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Automatic Counting of Rice Plant Numbers After Transplanting Using Low Altitude UAV Images

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ABSTRACT

Rice plant numbers and density are key factors for yield and quality of rice grains. Precise and properly estimated rice plant numbers and density can assure high yield from rice fields. The main objective of this study was to automatically detect and count rice plants using images of usual field condition from an unmanned aerial vehicle (UAV). We proposed an automatic image processing method based on morphological operation and boundaries of the connected component to count rice plant numbers after transplanting. We converted RGB images to binary images and applied adaptive median filter to remove distortion and noises. Then we applied a morphological operation to the binary image and draw boundaries to the connected component to count rice plants using those images. The result reveals the algorithm can conduct a performance of 89% by the F-measure, corresponding to a Precision of 87% and a Recall of 91%. The best fit image gives a performance of 93% by the F-measure, corresponding to a Precision of 91% and a Recall of 96%. Comparison between the numbers of rice plants detected and counted by the naked eye and the numbers of rice plants found by the proposed method provided viable and acceptable results. The R^2 value was approximately 0.893.

Key words: *Rice Plant, Low Altitude Image, UAV, Morphological Operation, Connected Component.*

1. INTRODUCTION

Rice is an important crop for an enormous part of the world's population especially in Asia, because it is the staple food of the people in this region. Rice growth, quality, and yield are affected not only by genetics but also environmental factors and planting methods [1]. Different studies showed that there are notable effects on rice yield due to rice plant spacing and density. Researchers explained that rice seedling density affects both its growth and yield [2]. Competitive characteristics of plant vegetation and reproductive development are highly affected by plant density, which shows a great impact on rice growth and yield [3]. Proper plant spacing and optimum plant density ensure the proper solar light, nutrient uptake, and tiller formation that provide the best growth and yield of rice [1], [4]-[6]. It is already known that rice grain yield increases linearly with plant density without any vying effect [7]. Hence, the monitoring of rice from transplant to harvesting is important to get desirable growth and yields, and the number of plants per area is very important to yield estimation. However, manual field-based plant monitoring is labor intensive, expansive, and time consuming; as such, there is a need for an easier, simpler and cheaper means.

Remote sensing and digital image processing techniques are widely used in agriculture [8], [9]. The use of the unmanned aerial vehicle (UAV) platform for remote sensing applications has given several advantages over conventional methods [10],

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[11]. Recently, numerous studies have been exhibited for remote sensing and related applications using unmanned aerial vehicles, including vegetation cover assessment [12], [13], crop monitoring [14], [15], crop mapping [16]-[18], etc. The data is collected in real time and has the flexibility for optimizing the operation.

Counting plants, trees, or flowers by using images is much more convenient than counting on the ground [19]. Extracting objects from the background and isolating objects with respect to overlap or touch are the most disputed aspects of the automatic counting of objects using digital image processing. Research on different image processing methods has already been done for automatic detection and/or counting of plants, trees, fruits, flowers, etc.

An image processing technique was introduced [8] to automatically count wheat seedlings using UAV images. Morphological processing, binary masking, segmentation and skeleton analysis were applied to count the wheat seedlings. An image processing method was discussed [20] on counting the number of trees in a high spatial resolution satellite image using a texture approach. Another automatic method [21] was proposed for individual fruit tree identification using multispectral satellite images. They used a four-step algorithm with spatial transforms and functions like an asymmetrical smoothing filter, a local minimum filter, a mask layer, and a spatial aggregation operator. Mathematical morphology was used [22] as a tool to count trees using satellite images. In this method, the satellite image was read into a MATLAB workspace and converted to a grayscale image, and then morphological operations were applied to the grayscale image. A novel application of computer vision and color image segmentation was discussed [23] using a threshold for automating the precise yield prediction process of the gerbera flower. They used HSV color space and a histogram analysis to define the color of flowers. The identification and classification of a maize crop row in the maize field using UAV images was approached [24]. They developed an object-based image analysis. A new citrus tree identification and counting system from high spatial resolution satellite images was introduced [25]. Satellite imagery with low- and high-density trees was tested. The citrus plant's region was extracted using spectral information, and then a morphological operator was used to initially setup the tree position. A genetic algorithm was subsequently used to optimize the position and canopy diameter. Morphological dilation [26] and erosion [27] process also were applied to count small objects and pea grain, respectively by using digital images.

All previous research showed a good result for tree or flower counting. However, these methods cannot be easily applied to rice plant counting or plant detection. Compared with other kinds of trees, fruits, or flowers, the morphological structure of a rice plant is very irregular and depends on cultivation methods. Moreover, the density of plant leaves increases continually with time. Therefore, we proposed an image processing technique to detect and count rice plants using low altitude UAV images. The main objective of the present study was to develop an image processing technique using images obtained from a UAV for automatic counting and detection of rice plants in the usual field condition just after transplanting.

2. MATERIALS AND METHODS

2.1 Study Area

The study area for this experiment was located at Jeollanam-do Agricultural Research and Extension Services, Naju, South Korea (Latitude 35°1'34.24" N and Longitude 126°49'14.21" E). The main experimental field area was 2184 m^2 and the crop was rice (*Oryza sativa* L.). The rice transplant date was May 25, 2016. Study area, position and other information are shown in Fig. 1. We captured images with an interval of two weeks using a UAV mounted RGB camera during the rice growing season.

Fig. 1. Study area and **its** position.

2.2 Data Acquisition

Images from the field were taken from just after the transplantation. We used a Sony Alpha a5100 digital camera (lens: Sony E 16 mm F 2.8). The camera was 24.3 MP with a complementary metal-oxide-semiconductor (CMOS) image sensor. The maximum resolution was 6000×4000. Images of the rice crops were taken under clear and sunny days and the height of the camera was 10 m from the canopy. The camera was mounted on a rotary wing type UAV (model: DJI-S1000; Geospatial Information Co. Ltd.) (Fig. 2(a)). The forward flying speed of travel was 2.5 m/s. A notebook was connected to the UAV by a wireless datalink connector (model: LK 900, dji, 900 MHz). All specifications of UAV and RGB camera are listed in table 1.

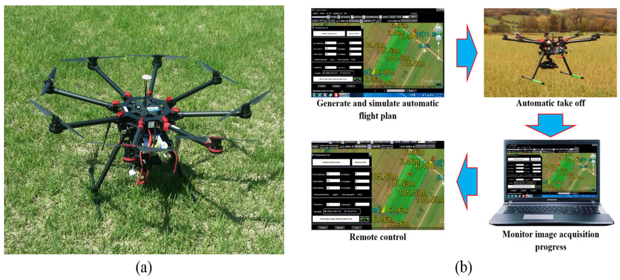


Fig. 2. (a) Rotary wing type UAV (model: DJI-S1000), (b) Automatic flight simulation path for UAV.

An automatic flying path (Fig. 2(b)) was set and the UAV flew automatically over the rice field and captured the images. After finishing the process, it flew back to the home location. After the digital images (format: RGB) were taken, they were transferred to the notebook from the camera and the plants were counted manually or with the naked eye. Then the images were processed using MATLAB 2016a (MathWorks, Inc., USA) software for further steps.

Table 1. Parameters that were used for UAV and camera to acquire data from the field.

Rotary wing UAV (model: DJI-S1000)		Camera (Sony Alpha a5100)	
Parameters		Parameters	
Altitude (m)	10	Image sensor	CMOS
Flying speed (m/s)	2.5	F-stop	f/2.8
Ground sampling distance (cm/pixel)	0.2	Exposure time	1/2500 s
Time for image acquisition (min/ha)	15	ISO	200
Max. flight time (min)	15	Focal length	16 mm

2.3 Image Processing

In this section, different steps of our proposed rice plant counting algorithm will be elaborated on. The following subsections will be described step by step.

2.3.1 RGB to Gray and Binary Image Conversion: The first step of the image processing method is to convert RGB images into grayscale images. Here, we convert the true color image, RGB, to the grayscale intensity image. Conversion is accomplished by removing the hue and saturation while maintaining the luminance of the image. The input is an RGB image, class uint8. The output image is of the same class as the input image. This conversion converts RGB values to grayscale values by forming a weighted sum of the R, G, and B components as in Eq. (1) [28]:

$$G_{gray} = 0.3\,R + 0.59\,G + 0.11 \quad (1)$$

After converting the RGB image to a grayscale image, we use an adaptive median filter to remove noise and distortion from the image.

The adaptive median filtering algorithm used two processing levels, as level A and level B as follows [29]:

Level A: If $I_{min} < I_{med} < I_{max}$, then the median value is not an impulse, go to Level B.
Else the size of the window is increased
If window size $\leq S_{max}$, repeat level A
Else output I_{med}

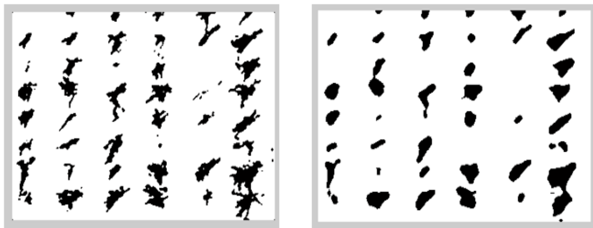
Level B: If $I_{min} < I_{xy} < I_{max}$, output I_{xy}
Else output I_{med}

where, S_{xy} is the image being processed, I_{min}, I_{med}, I_{max} are the minimum, median and maximum intensity value in S_{xy}, respectively, I_{xy} is the intensity value at coordinates (x,y) and S_{max} is the maximum window size.

Then we convert the grayscale image to a binary image by thresholding. The threshold value was 0.51. The output binary image has values of 1 (white) for all pixels in the input image with luminance greater than the threshold level and 0 (black) for all other pixels. The morphological operation is then completed after finishing the binarization of the image.

2.3.2 Morphological Image Processing: Morphological image processing is a set of non-linear processes related to the shapes or morphological characteristics in an image, and it is broadly used in image processing methods like feature detection, segmentation, denoising, and object distinction [22]. Morphological operations depend not on the arithmetic values of pixels but the relative ordered pixel values; this process is very much suitable for binary image processing. Dilation and erosion are the basic morphological processing operations and are the basic elements of many algorithms [30]. These operators are used on an image with a set of pixels of interest called the structuring element (SE). The SE contains both a shape and an origin. All types of morphology operators can be defined in terms of combinations of erosion and dilation. In our proposed method, we use only the closing morphological operation. The closing operation consists of two steps: dilation followed by erosion, applying the same SE for both steps. The closing of image X by structuring element Y, denoted by XY, consists of dilation followed by erosion as in Eq. (2) [31]:

$$X \cdot Y = (X \oplus Y) \ominus Y \quad (2)$$



(a) (b)

Fig. 3. An illustration of morphological closing. (a) Original filtered binary image, (b) After morphological closing operation.

After the binarization process, we use the closing morphological operation to get a good shape of rice plants in the image (Fig. 3). The closing operations will smooth the contoured sections, and combine the tiny cracks and long thin gaping holes. In addition, they will remove the small holes and fill the gaps in the contours. Then the adaptive median filter is applied again to eliminate more noise.

2.3.3 Connected Component: In an image, pixel connectivity or connected component is called as an individual and independent object. Independency depends on the connectivity between the objects. In digital images, a pixel can be valued as a binary number 1 or 0. A value of 1 represents the objects and 0 represents the background of the image. To find the objects in a digitalized form, we need to detect groups of black pixels that are connected to each other. A connected component in a 2D imaging format is 4-connected or 8-connected. In our experiment, we used 8-connectivity or an 8-connected component (Fig. 4). For a pixel, in 8-connected case, the neighboring set of coordinates will be in the following set (Eq. (3)) [32]. All the elements in the coordinates of that set will be a part of the same connected component.

$$\{(x-1, y-1), (x-1, y), (x-1, y+1), (x, y-1), (x, y+1), (x+1, y-1), (x+1, y), (x+1, y+1)\} \quad (3)$$

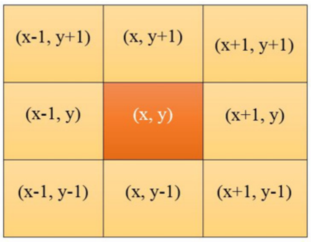


Fig. 4. An illustration of 8-Connectivity

We obtain the sets of foreground pixels then threshold them to make a set of binary points. These foreground binary pixels showing the object and background are portioned into regions by a connected component algorithm, which provides a set of smooth blobs corresponding to each of the objects.

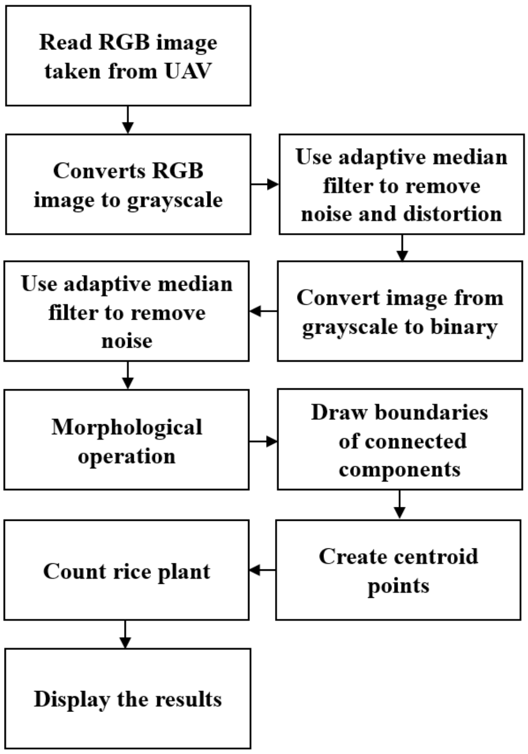


Fig. 5. Flow chart of the rice plant counting algorithm

Fig. 5 shows the flow chart of rice plant counting algorithm. First, we read the RGB image taken from the UAV mounted camera into the MATLAB workspace and convert it to a grayscale image. We then apply adaptive median filters to the grayscale image which is then converted into a binary image so that morphological operations can be applied. In this method we use the closing morphological techniques on the binary image. After the closing operation, we draw the boundaries of the connected components, and then create the centroid point for each connected component. Each centroid point counts as a rice plant number; this gives us the total number of plants. Finally the results are displayed.

2.4 Performance Evaluation

For performance measure, we chose Precision, Recall, and F-Measure for this experiment. We calculated them with the following Eq. (4), (5) and (6) [33], [34]:

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \quad (4)$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \quad (5)$$

$$\text{F} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision+Recall}} \quad (6)$$

where, TP is the number of accurately detected rice plants, FN is the number of accurately detected non-rice plants and FP is the number of non-rice plants detected as rice plants. By using this set of performance measures, we can analyze the performance of our method.

3. EXPERIMENTAL RESULTS

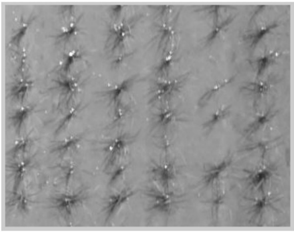
3.1 Dataset

All the images were taken under a clear sky at a height 10 m from the rice plant canopy using a UAV. All images were RGB images, and after they were transferred to the notebook the sample images were sorted-out randomly. We selected 15 images for this experiment. We counted the plant number using the naked eye as a real data set from those sample images. Then we used our algorithm to count it automatically. Both, the number of rice plants detected and counted by our method and by the naked eye (ground truth) are listed in table 2.

3.2 Counting of Rice Plants

The first four steps of the image-processing algorithm were for the basic conversion of the image format and use of filters to remove noise. All these processes were used before the morphological process. Grayscale (Fig. 6 (b)) and binary images (Fig. 6 (d)) showed good results for the removal of noise. After this morphological closing operation was performed. In this step, the binary pixels (0s and 1s) represent the components in the image. The "1s" represent the black pixels as the rice plants. The "0s" represent the background of the image. Thus, the "1s" permit the visualization of the centroid of each individual rice plant. By applying the filter after the closing operation on the image, clearer and better-shaped plant centroids were obtained, as shown in Fig. 6 (f). After this process, we drew the boundaries of the connected components comprised of the black connected pixels. Then, we made the centroid point for each connected component and counted the centroid as a rice plant. We finally counted the total number of plants and showed the results.

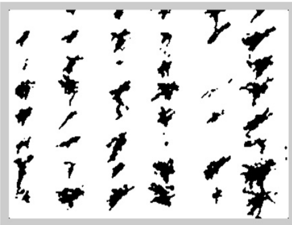
(a) Read RGB image.



(b) Grayscale image.

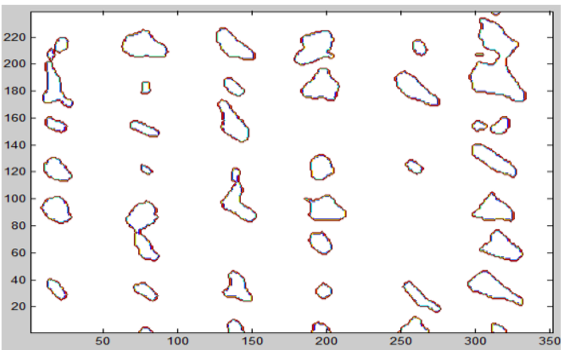
(c) Filtered grayscale image.

(d) Binary image.

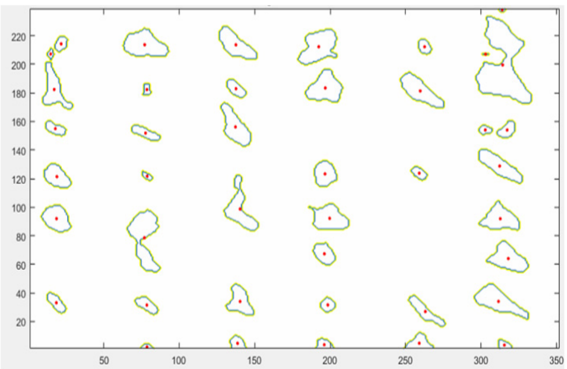


(e) Filtered binary Image

(f) Binary image - morphological process



(g) Boundaries of connected components.



(h) Count the centroid as rice plant.

Fig. 6: Schematic diagram for each step of rice plant counting algorithm

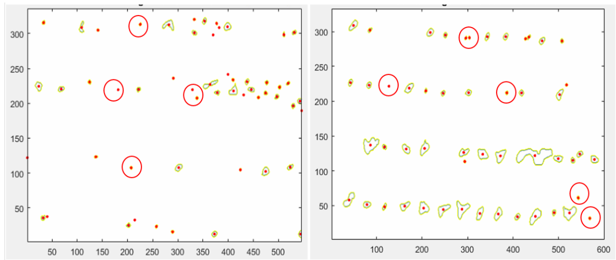


Fig. 7. Example of false positive position error.

3.3 Performance Evaluation

Fifteen test images were randomly selected to test the proposed algorithm. The true positive, false positive, and false negative numbers of rice plants were also counted. Recall, Precision, and F-measure were calculated using Eq. (4), (5), and (6). The results indicated that the algorithm could carry out a performance of 89% by the F-measure, corresponding to a Precision of 87% and a Recall of 91%. The best-fit image gives a performance of 93% by the F-measure, corresponding to a Precision of 91% and a Recall of 96%. Some error may be due to the false positive position error shown in Fig. 7. The correlation of the rice plant count between the proposed method and ground truth is shown in Fig. 8. The R^2 value was found to be around 0.893.

Though the result shows a good performance of the proposed method, there is opportunity to improve it and make it more accurate for different conditions, such as sunlight reflection, image blurring, distortion, drone shadow, obstacles in the rice field, etc.

Table 2. Results of the proposed image processing and visual counting (ground truth) methods for different images

Sample	Ground truth	No of plant	TP	FP	FN	Recall	Precision	F-measure
Img 01	37	38	31	6	5	0.86	0.84	0.85
Img 02	43	44	38	6	6	0.86	0.86	0.86
Img 03	43	45	35	5	6	0.85	0.88	0.86
Img 04	36	38	33	6	5	0.87	0.85	0.86
Img 05	35	37	33	4	3	0.92	0.89	0.90
Img 06	40	44	38	6	4	0.90	0.86	0.88
Img 07	48	46	42	8	5	0.89	0.84	0.87
Img 08	42	43	36	6	2	0.95	0.86	0.90
Img 09	51	49	43	4	2	0.96	0.91	0.93
Img 10	49	51	42	9	3	0.93	0.82	0.88
Img 11	51	52	47	6	3	0.94	0.89	0.91
Img 12	51	49	45	7	5	0.90	0.87	0.88
Img 13	49	51	43	4	2	0.96	0.91	0.93
Img 14	39	42	36	4	2	0.95	0.90	0.92
Img 15	42	47	37	7	4	0.90	0.84	0.87
Average						0.91	0.87	0.89

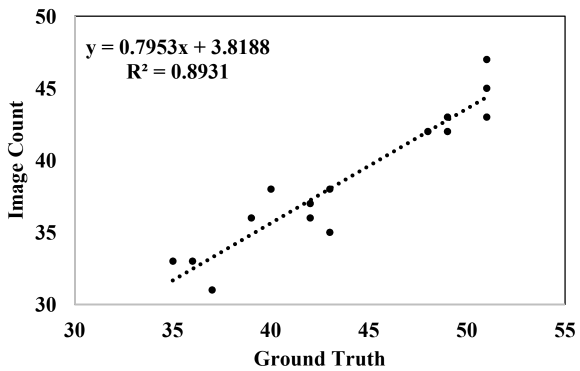


Fig. 8. Relation between ground truth and proposed method in terms of rice plant count

3.4 Comparison with Previous Work

Most of the method previously reviewed were related to trees, fruits, or flowers counting using different image acquisition techniques like satellite imaging, digital imaging, and UAV imaging with high altitude. In our method, we used very low altitude images to count rice plant. And the conditions and circumstances were also different with different methods. There were no direct work to count rice plant from field image using UAV. We applied some similar methods to our images and the accuracy of the proposed method and previous works are shown in table 3 and Fig. 9.

Table 3. Comparison between proposed method and previous work

Method	Accuracy*
Binary conversion and Dilation processing with labeling [26]	83.08%
Morphological reconstruction and watershed transform [22]	87.77%
Binary conversion and Erosion processing with labeling [27]	89.14%
Our proposed method	94.99%

*Accuracy ={1-((|proposed method count – actual count|)/actual count)}*100 [19]

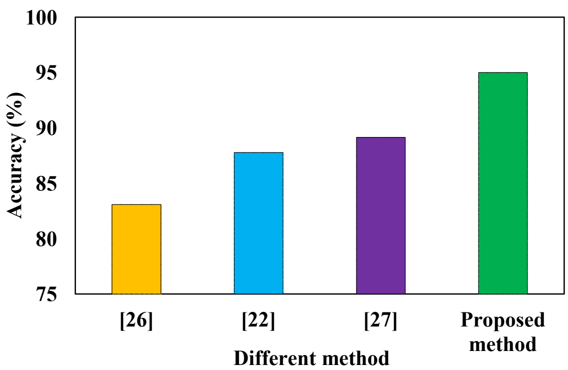


Fig. 9. Accuracy comparison between previous work and proposed method

4. CONCLUSION

In this paper, we proposed an image processing technique that relies on a morphological operation to detect and count the number of the rice plants in a field automatically, using RGB images obtained from a digital camera mounted on a UAV. We implemented a UAV platform (DJI SW1000 octocopter) along with a common digital camera (Sony Alpha a5100) and GPS system to collect very high-resolution RGB images during pre-programmed automatic flights. Next, we converted RGB images into binary images and removed the noise. Using those images, we applied a morphological operation and drew boundaries of the connected components to count the rice plants. The result shows that the algorithm can carry out a performance of 89% by the F-measure, corresponding to a Precision of 87% and a Recall of 91%. The best-fit image gives a performance of 93% by the F-measure, corresponding to a Precision of 91% and a Recall of 96%. The comparison provided good and acceptable results. The R^2 value was found to be around 0.893. The method was found to be efficient to detect and count the number of rice plants. The proposed method has demonstrated that it is able to detect and count rice plants without any mechanical interferences and it may be used as an automated tool for different crops.

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