

## Tobacco Plant Recognizing and Counting Based on SVM

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**Abstract**—Tobacco plants recognizing and counting accurately is very important in the tobacco plant management. In this paper, we propose an algorithm for tobacco plants recognizing and counting which consists of four main steps: first, we apply the unmanned aircraft to acquire the tobacco images. Second, the tobacco image is converted into the Lab color space, and then  $b$  channel in Lab space is processed based on morphological reconstruction. Third, the candidate regions which might contain tobacco plants are extracted based on the processed  $b$  channel. Finally, SVM(Support Vector Machine) is employed to classify the candidate regions as tobacco plants or not. The proposed method has been evaluated on a tobacco image data set. Experimental results (96.1% of accuracy and 94.3% of sensitivity) showed that the proposed method is feasible.

**Keywords**-Tobacco Recognition; Machine Learning; Lab color space; SVM;

### I. INTRODUCTION

The tobacco output in China accounts for about 41.5% in the world [1]. In China, tobacco is an important economic crop, and is one of the main source of tax revenue. In order to manage the tobacco planting better, one key issue is to predict the yield of tobacco. The yield of tobacco is usually calculated by estimating the tobacco growing area [2], or manually counting the number of tobacco plants. However, it is lack of precision and efficiency.

Aerial photography technology has been widely used in production, especially for precision agriculture. The aerial images of planting regions are photographed by the unmanned aerial vehicle. Aerial images are used to monitor the growth status of crops. The image processing technology can help to recognize and segment objects quickly [3] [4] [5] [6]. With the combination of aerial photography technology and image processing technology, we can estimate the yield of tobacco.

A RGB color image of the tobacco field is shown in Figure 1. It is clear that there are many other kinds of plants in the picture. Therefore, it needs to classify the plants into tobacco and non-tobacco plants. On the other hand, the leaves of tobacco plants are connected together, and these make it more difficult to separate the tobacco plants. In order to count the tobacco plants, the connected tobacco plant has to be divided into many single plants. The main work of



Figure 1. Aerial image of the tobacco planting region

this paper is to identify and count the tobacco plants in the images.

The rest of the paper is organized as follows. The proposed method is described in Section II. The experimental results are presented in Section III, followed by a discussion & conclusion in Section IV.

### II. METHODS

The framework of the proposed method is given in Figure 2. The unmanned aerial vehicle is applied to collect the images of the tobacco plants. Then the preprocessing is carried out to extract the candidate regions. The process of the preprocessing is given in Figure 3, which consists of color space conversion, segmentation and KNN(k-Nearest Neighbor) algorithm. Finally, a classifier trained by SVM is adopted to classify the candidate regions as tobacco or not.

#### A. Converting to Lab color space

The first step in the preprocessing is to convert the RGB image as Lab [7] image. The reason we do so is that the plants can be distinguished in the  $b$  channel of the Lab space. Figure 4 gives an example where Figure 4(a) is a sub-image cropped from the original image (Figure 1) and Figure 4(b) is the  $b$  channel of Figure 4(a).

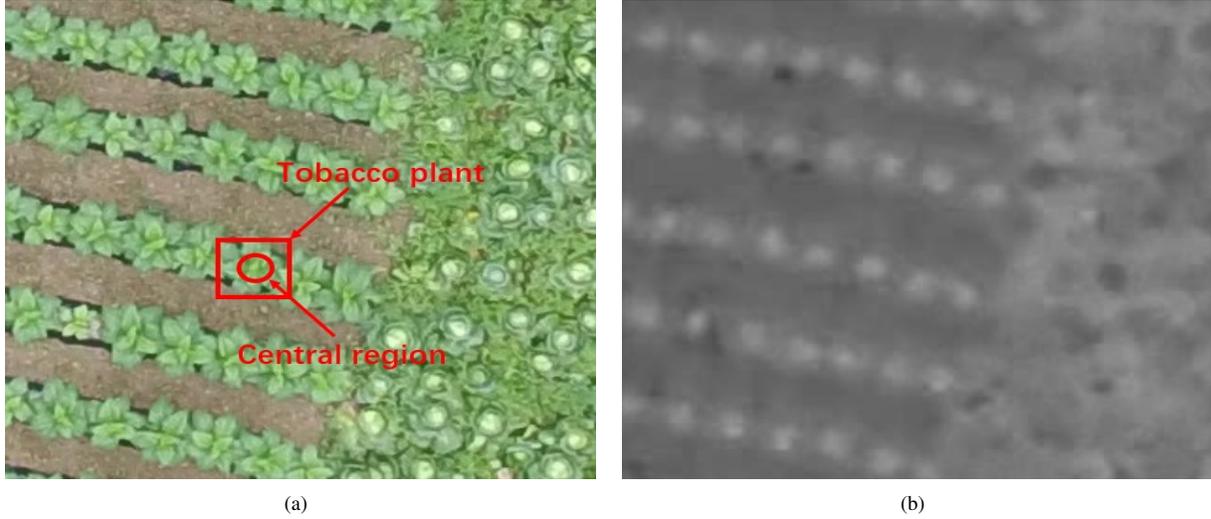


Figure 4. (a) The original image; (b) The  $b$  channel

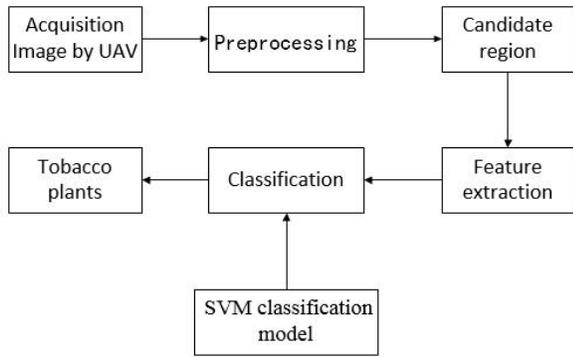


Figure 2. The flowchart of the proposed method



Figure 5. Each connected domain represents a central region of tobacco plant

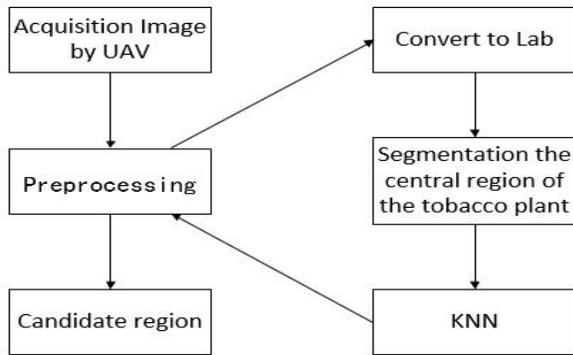


Figure 3. Preprocessing

### B. Extracting candidate regions

It should be noted that the central regions of the tobacco plants are brighter than the surrounding regions of the tobacco plants in the  $b$  channel, which is an available character to extract the tobacco plant candidate regions. In this work, we employ morphological reconstruction method to extract the candidate regions. Concretely, the  $b$  channel is eroded by a large structural element. Then the eroded image is processed by morphological reconstruction. Finally, the local maximum regions are segmented out. Figure 5 gives an example where each connected domain is regarded as the central of a candidate region.

After separating the central region, the whole tobacco plant should be separated in order to facilitate the classi-

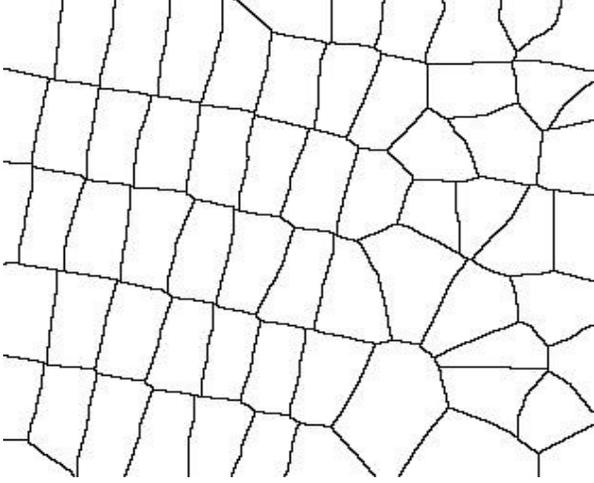


Figure 6. KNN, pixel is classified into a central region based on its Euclidean distance to the central region

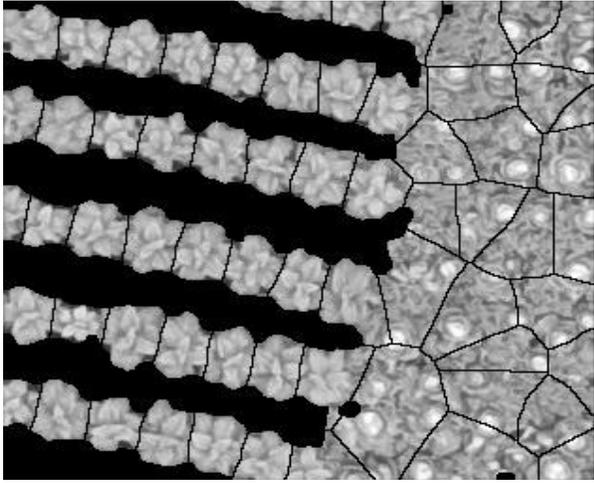


Figure 7. Candidate regions of tobacco plant, each candidate region represents a candidate tobacco plants

fication. In this paper, a simple segmentation method named KNN is employed [8]. The idea of the KNN segmentation method is to assign a pixel into the nearest central region based on the Euclidean distance. Figure 6 gives an example where the image is segmented into many connected domains by the KNN segmentation method.

Each connected domain in Figure 6 contains a tobacco plant. However, some of the connected domain contains non-green part, such as soil, which should be removed. In this paper, we use the ex-green method [9] to remove the non-green parts. The principle of the ex-green method can be illustrated by Equation 1.

$$I_{green\_region} = I_g - I_r > diff_{gr} \& I_g - I_b > diff_{gb} \quad (1)$$

where  $I_{green\_region}$  means the connected domain contains

non-green part if it equals to 0,  $diff_{gr}$  and  $diff_{gb}$  are constants. Usually  $diff_{gr}$  and  $diff_{gb}$  are greater than 0. This two parameters can control the depth of the green.  $I_g$  means the green channel,  $I_r$  the red channel and  $I_b$  the  $b$  channel. Figure 7 gives an example after removing the non-green parts. In Figure 7, each connected region is regarded as a candidate tobacco plant.

### C. Candidate Regions Classification

Feature extraction is an essential procedure in the classification of the candidate regions. In this work, nine features are extracted which include texture features and color features. Table I lists the extracted features and the corresponding intuitive reason.

The second step of the candidate region classification is feature selection. Since the Relief algorithm [11] does not depend on heuristics, is accurate even if features interact, and is noise-tolerant, so it is used to select the features in this work. The main idea of the Relief is assign a weight for each feature using statistical method [12].

Finally, the Support Vector Machine algorithm [8] [13] [14] is used to classify the candidate regions as tobacco plants or non-tobacco plants.

## III. EXPERIMENTAL RESULTS

The proposed method has been validated in the data set which collected by our group. The data set contains 12 tobacco field images of  $4000 \times 3000$  pixels obtained by Phantom 4 [15].

In this work, we use the accuracy and the sensitivity to evaluate the performance of the proposed algorithm. The definition of the accuracy and the sensitivity are given in Equation 2 and 3 respectively. The accuracy indicates the proportion of true positive in the classification results. The sensitivity indicates the proportion of true positive in the ground truth. Both of them are equal to 1 when the performance of the algorithm is perfect.

$$accuracy = \frac{detection\_result - error\_detection}{detection\_result} \times 100\% \quad (2)$$

$$sensitivity = \frac{real\_true - missing\_detection}{real\_true} \times 100\% \quad (3)$$

In Equation 2,  $detection\_result$  is the number of tobacco plants detected by the algorithm. The  $error\_detection$  is the number of detected tobacco plants by the algorithm but not belong to the ground truth.

In Equation 3, the  $real\_true$  represents the actual number of tobacco plants in the ground truth and the  $missing\_detection$  is the number of missing detected tobacco plants by the algorithm which belong to the ground truth.

To train and test the SVM classification model, the database is divided into training set and test set. We randomly selected two images from the data set as the training

Table I  
TEN FEATURES EXTRACTED BY THE USER

Features	Intuitive Reason
Local Binary Patterns [10] in the gray image	They contain the multiresolution gray scale and rotation invariant texture information of the tobacco plant.
The mean and variance of the candidate regions in $I_g$ , $I_h$ and $I_s$	These features are the color feature. Because different plants have different green.
The mean and variance of the candidate regions in the first derivative of $I_g$	These features are texture feature. Tobacco is dicotyledonous plant. To distinguish the different shapes of leaves.

Table II  
THE CLASSIFICATION RESULTS

Image_number	Real_true	Detection_result	Missing_detection	Error_detection	accuracy	sensitivity
Training_set_01	1754	1809	31	86	0.952	0.982
Training_set_02	1767	1813	34	80	0.955	0.980
Test_set_01	2457	2413	94	50	0.979	0.961
Test_set_02	3099	2718	410	29	0.989	0.867
Test_set_03	2866	2648	281	63	0.976	0.901
Test_set_04	2297	2348	81	132	0.943	0.964
Test_set_05	1677	1796	34	153	0.914	0.979
Test_set_06	2564	2429	155	20	0.991	0.939
Test_set_07	2054	1995	119	60	0.969	0.942
Test_set_08	1208	1263	10	65	0.948	0.991
Test_set_09	3282	3460	87	265	0.923	0.973
Test_set_10	3430	3195	296	61	0.980	0.913
Test_set_average	\	\	\	\	0.961	0.943

set. The rest of 10 images as the test set. 3000 candidate regions (consists of 1500 positive samples and 1500 negative samples) were randomly selected from the training set. Figure 8 gives an example where the red squares indicate the detected the tobacco plants. Table II summarizes the experimental results where we can see that the proposed method achieves 96.1% of average accuracy and 94.3% of average sensitivity.

#### IV. DISCUSSION & CONCLUSION

In this paper, we proposed a new method for recognizing and counting tobacco plants based on the SVM. The  $b$  channel in the Lab color space is employed to extract the candidate regions based on morphological reconstruction. Ten features for each candidate region are designed by hand and some of them are selected by Relief algorithm. Finally, we apply SVM to classify the candidate regions as tobacco plants or not. The experimental results (96.1% of accuracy and 94.3% of sensitivity) show that the proposed method can distinguish and count the tobacco plant efficiently.

To improve the performance of the proposed algorithm, two aspects should be considered in the future work. One is the candidate region extraction, which will affect the subsequent steps directly. In this work, we utilize the character that the the central regions of tobacco plants are brighter than the surrounding regions in the  $b$  channel of Lab color space to extract the candidate regions. However, we found that there is similar phenomenon in the other color spaces, such as YCBCR color space [16]. So whether we can fuse the information in the different color spaces to make

the candidate region extraction more correctly? It is one of our future work. The other is feature extraction. Nine features, including color features and texture features, are designed for each candidate region by hand in this work. However, the plants have very similar characteristics which is a challenge to look for the distinguishable features among the plants. Although the results obtained by the proposed method illustrated that the features in this work are feasible, they still should be improved in the future work.

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Figure 8. The red square indicates the detected tobacco plants

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