Color Segmentation using Multi Layer Neural Network and the HSV Color Space

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Abstract

This paper presents the results of studying color segmentation using machine learning algorithm and color space analysis. RGB (red, green, blue) color space data points from an image are projected into HSV (hue, saturation, value) color space to provide data points that are insensitive to the variations of illumination in outdoor environment. Multi layer neural network trained using backpropagation algorithm is used to segment the color image. The results show that the algorithm is able to segment the images reliably with less appearance of small blobs. This will help improve the accuracy and minimize the processing time of the subsequent processes in the robot vision system where real-time issue is of important.

I INTRODUCTION

This paper presents the results obtained in one of the steps involved in a project to develop a robot vision for an intelligent real-time robotic chemical control system called Putrabot. The aim of the robot vision is to detect crops (in this case young corn trees), locate the position of the closest crop, and calculate angle for the robot navigation. Using the information given by the vision system, the robot will navigate towards the detected target and control the application of chemical product with the right dose to the right spot.

There are four main modules involved in the robot vision system. Those are image pre-processing module, image post-processing module, feature extraction module and object recognition module. Color segmentation process is part of image pre-processing module, where the accuracy of this process reflects the success of the whole vision system. Inaccurate segmentation may result in inaccurate recognition of the crops. To develop a robust robot vision system for outdoor field conditions, algorithms must be developed to extract useful information in the presence of noise associated with unstructured lighting conditions.

Color information has more disambiguity power than intensity values. Therefore, obtaining image features using color information has some specific robustness properties. Since real-time requirement is of important here, colors that are known a priori are chosen to ease this task. This kind of color segmentation is known as supervised color segmentation.

A. Precision farming

The ability to locate and identify crops and weeds automatically in digital images could lead to many useful inventions. In recent years, modern farming relies on chemical control apply to crops, weeds, pests, and diseases. Economic pressure, environmental concerns, and increased consumer demand for organic foodstuffs had led to the development of precision agriculture techniques to reduce and optimized chemical use. Precision agriculture has also enabled reduction of the area of management from the whole farm field down to sub field level. Due to the increased data processing required to cover a complete field at the individual plant level, only certain operations could be carried out using human intervention and therefore different forms of automation, especially in high value crops, are needed.

In recent years, the development of autonomous vehicles in agriculture has received increased interest to meet these opportunities. This development has led many researchers to start exploring the possibilities to develop more rational and adaptable vehicles based on

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a behavioral approach [4]. Research into autonomous vehicles in agriculture started in the early 1960s, mainly developing automatic steering systems [5]. Robotic applications in agriculture, forestry and horticulture have been developed for various applications [6][7]. However, there are less scientific references to fully autonomous vehicles in agriculture, such as the automated harvesting system Demeter [8] as well as in semi-autonomous tractors [9][10]. There are a number of field operations that can be executed by autonomous vehicles, giving more benefits than conventional machines. These autonomous platforms would be used for cultivation and seeding, weeding, scouting, application of fertilisers and chemicals, irrigation and harvesting [11].

II METHODOLOGY

A. Image resizing

The system starts by receiving a 320x240 image frame from the Creative WebCam Live!TM Ultra attached to the robot. The first step upon receiving the input image is to reduce the size of the image to half of its original size. The resulting image size would be 160x120. This is done to reduce the computational burden during the image processing steps and feature extraction steps. The image will be further divided into two sections, which is the top half of the image and the bottom half of the image. Since the objective is to find the closest young corn tree to the robot, only the bottom half of the image will be considered for further processing. The process of image resizing is illustrated in Figure 1. After resizing process, the image is converted from RGB color space to HSV color space. This is done to ensure the system can tolerate to the variations of illumination in outdoor environment.

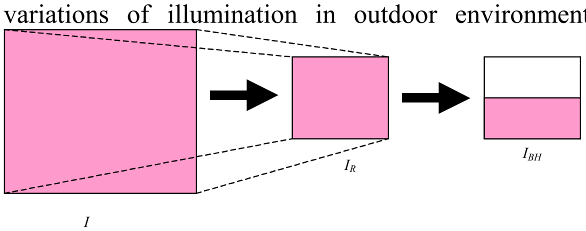

Figure 1. Image of size 320x240 sub-sampled to 160x120 and only the bottom half of the sub-sampled image is considered.

B. RGB to HSV

A color can be represented by the red, green and blue (RGB) components. In digital images, the RGB values are between 0 and 255. Since the accuracy of the color detection affects the results of locating the base of the corn trees, choosing the suitable color space for color segmentation is very important. In this sense, RGB color space is not suitable because it is very sensitive to the variations of intensity. Since the segmentation results must be insensitive to the strength of illumination, color segmentation based on hue, saturation and value (HSV) has been chosen as suitable for this research.

The HSV coordinate system, proposed originally in Smith [1], is cylindrical and is conveniently represented by the hexcone model shown in Figure 2 [2][3]. The saturation is a measure of the lack of whiteness in the color, while the hue is defined as the angle from the red color axis, and value refers to the brightness. The motivation for using the HSV space is found in experiments performed on monkeys and anthropological studies, because it corresponds more closely to the human perception of color. This user-oriented color space is based on the intuitive appeal of the artist's tint, shade, and tone.

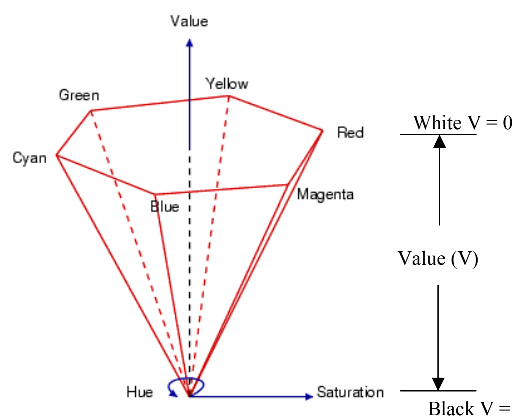

Figure 2. The HSV Color Space

The set of equations listed below are used to transform a point in the RGB coordinate system to the appropriate value in the HSV space.

$$H_1 = \cos^{-1}\left\{\frac{\frac{1}{2}\left[(R-G)+(R-B)\right]}{\sqrt{(R-G)^2+(R-B)(G-B)}}\right\} \quad (1)$$

$$H = H_1 \text{, if } B \le G \quad (2)$$

$$H = 360° - H_1 \text{, if } B > G \quad (3)$$

$$S = \frac{\max(R,G,B)-\min(R,G,B)}{\max(R,G,B)} \quad (4)$$

$$V = \frac{\max(R,G,B)}{255} \quad (5)$$

The RGB values presented here are between 0 and 255.

C. Color Training and Color Segmentation using Multi Layer Neural Network

Before color segmentation is applied, sample color pixels of the plants and the background are analyzed to determine their positions in the color space. Interactive procedure is done by first manually outline the colors of interest in the image with polygonal boundaries. (All the polygonal approximations can be done interactively using computer mouse.) Figure 3 shows two color images taken from two different illumination environments. Figure 4 and Figure 5 show the sample color pixels of plant and soil, which have been manually outlined.

Figure 3. Two images taken in different illumination environment.

Figure 4. Sample color pixels of the plant selected from Figure 3.

Figure 5. Sample color pixels of the soil selected from Figure 3.

To analyze and determine the positions of the sample color pixels, the sample color pixels of both plant and soil in RGB (Figure 6) plane and HSV (Figure 7 and Figure 8) plane is plotted.

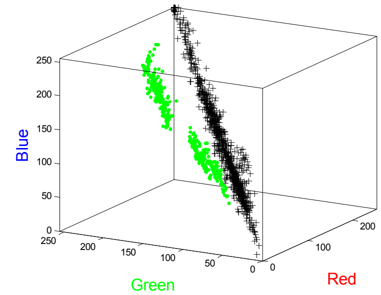

Figure 6. Sample color pixels of plant and soil in RGB plane. The green points are the plant pixels, and the black points are the soil pixels.

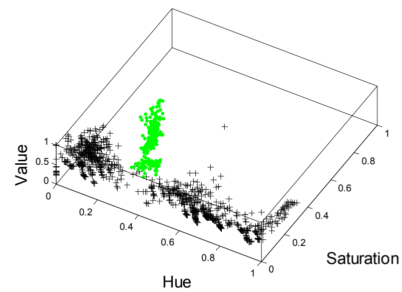

Figure 7. Sample color pixels of plant and soil in HSV plane. The green points are the plant pixels, and the black points are the soil pixels.

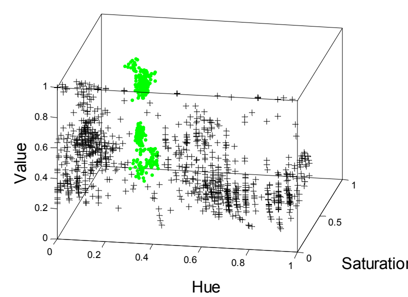

Figure 8. Sample color pixels of plant and soil in HSV plane viewed at different angle. The green points are the plant pixels, and the black points are the soil pixels.

By analyzing the sample color pixels that lie in 3-dimensional spaces like RGB plane and HSV plane, learning system such as Artificial Neural Network (ANN) can be used to classify or to segment any pixel point in the image according to which partition it lies in.

Pattern vectors were generated by converting the RGB values of an image into the HSV values. The resulting HSV vectors will be the inputs to the three-layer feedforward ANN shown in Figure 9 denoted by ANN_{CS}. The number of neuron nodes in the first layer was chosen to be 3, corresponding to the dimensionality of the input pattern vectors (which is the hue, saturation, and value). The single neuron in the third layer corresponds to the outputs, either plant or soil (background). The number of neurons in the middle layer is heuristically specified as 6. There are no known rules for specifying the number of nodes in the internal layers of a neural network, so this number is chosen arbitrarily and then refined by testing. An offline training process using backpropagation algorithm is performed on the ANN_{CS} using the manually selected sample color pixels. The trained ANN_{CS} structure will be used for the color segmentation.

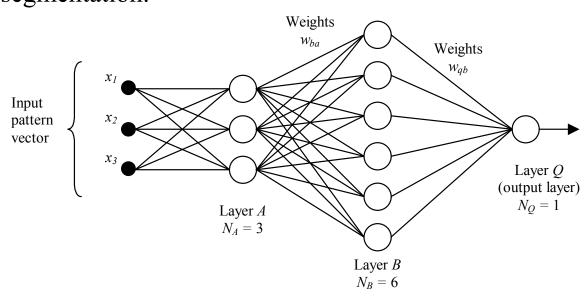

Figure 9. Three-layer ANN ANN_{CS} used for color segmentation.

III RESULTS

A. *Results of Image Resizing*

Upon receiving the input image, the first thing to do is to sub-sample the image. The original size of the image is 320x240. By considering the trade-off between processing time and the quality of the image, the image will be reduced to half of the original size. The resulting image would have the size of 160x120. Figure 10 shows an image before and after the sub-sampling process. In this process, nearest neighbor interpolation method is used. Although this process is said to be not as accurate as bicubic or bilinear interpolation method, but it is considered to be the simplest and the fastest. Furthermore, the result shown after the sub-sampling process still retains the details and quality of the image.

Figure 10. Image of size 320x240 sub-sampled to 160x120.

Figure 11. Bottom half portion of the sub-sampled image.

The task of the vision system is to locate the base of the young corn tree, and in addition to that, it must also find the closest young corn tree to the robot. Therefore, to further reduce the processing time, the top half portion of the image is discarded. Figure 11 shows the bottom half portion of the image taken from the sub-sampled image.

B. *Results of Color Segmentation using Multi Layer Neural Network*

Bottom half of the sub-sampled image will first need to be converted from RGB color space to HSV color space. After the conversion process, the converted image will be fed to the ANN for color segmentation to segment the image into binary image. Figure 12 shows example of some images after color segmentation. The white pixels in the binary image indicate the foreground (young corn trees), whereas the black pixels indicate the background (soil).

Clearly, it can be seen from Figure 12 that the algorithm is able to segment the images reliably even though the green colors of the leaf are not uniform. Some of the leaf colors are yellowish and some are dark green. The speckles of white appear in the binary images because the soil is not of uniform color. These small regions or also called small blobs are quite small and therefore it can be easily filtered out using morphological opening process.

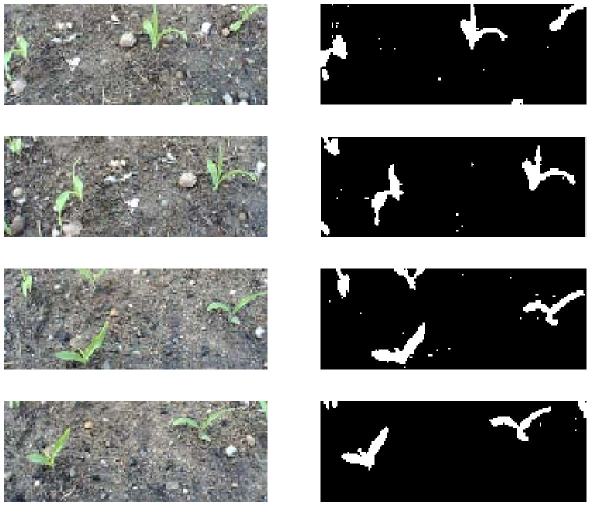

Figure 12. Resulting binary image after color segmentation.

TABLE 1. AVERAGE PROCESSING TIME FOR EACH PROCESS ON AN IMAGE. ALL VALUES IN MILLISECONDS.

	RGB-HSV	Segmentation
Average	12.5	44.3

Table 1 shows the average processing time needed to convert an image from RGB color space to HSV color space. This experiment were simulated in Matlab 7.0 (R14) running on an Intel® Pentium® M processor 1.73GHz laptop, with 256 MB of RAM.

IV CONCLUSION

Image segmentation is a must when dealing with digital images especially for object recognition. This process is a crucial step to prepare the image for further processing. From the resulting images, it can be observed that this algorithm can provide good segmentation. This can be seen on the last image on Figure 12 where there is less appearance of small blobs. The background of the original image on the last image on Figure 12 is more uniform compared to the background of the others. For these kinds of images, the processing time needed to perform the subsequent processing stages would decrease due to less number of unnecessary regions in the images.

The robot vision has been implemented successfully during the Field Robot Event 2006 competition held between 24th and 26th June 2006 at Universitat Hohenheim, Stuttgart, Germany. The algorithm proposed in this paper, is an improved version of the one implemented during the competition where we managed to win the first place during the free style session. In this session, each robot had to demonstrate their unique capabilities. Putrabot chose to demonstrate its capability to recognize a small plant, navigate towards the plant and spray water onto the plant. Results of the competition can be seen at http://www.uni-hohenheim.de/fieldrobot.

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