THE RESEARCH OF IMAGE SEGMENTATION BASED ON COLOR CHARACTERISTIC

GUO-QUAN JIANG[1], CUI-JUN ZHAO[2], JUN-YAN QI[3]

[1,3]School of Computer Science and Technology, Henan Polytechnic University, Jiaozuo 454000, China
[2]School of Resources and Environment Engineering, Henan Polytechnic University, Jiaozuo 454000, China
E-MAIL: jiangguoquan@hpu.edu.cn, zhaocuijun@hpu.edu.cn, qjywl@hpu.edu.cn

Abstract:

Agricultural image segmentation is the basic work of computer vision technology in agriculture. This paper presents an image process method based on color characteristic. The algorithm separates the crop area from soil background according to the color feature, which is got by analyzing the color difference between crop and background. In order to translate the color images to gray ones effectively, fourth different transformation methods in RGB color space and three components of HSI were compared. Test results show that the excess green 2G- R- B is the best index for segmentation. This index has a characteristic of consuming little time, good quality of segmentation and not being influenced by sunshine intensity and can meet the real-time navigation in the target extraction.

Keywords:

Machine vision; Image segmentation; Color characteristic

1. Introduction

Potential benefits of automated agricultural vehicles include increased productivity, increased application accuracy, and enhanced operation safety [1]. Researchers have been interested in developing automated guidance for agricultural machinery since the early days of the tractor; this interest has increased recently because of the advent of precision agriculture, the emergence of which has been mainly attributed to the advances in computers and sensors [2].

In a vision-based vehicle guidance system, finding guidance information from crop row structure is the key in achieving accurate control of the vehicle. Among them, the main issue related with the application of machine vision methods is that concerning the image segmentation. Efficient and automatic segmentation of vegetation from images of the ground is an important step [3-5].

Many studies to achieve the segmentation with the image processing techniques have been reported. For examples, Reid et al. (1985) developed a binary thresholding strategy used Bayes classification technique to effectively and accurately segment crop canopy and soil background for cotton crop at different growth stages. Gerrish et al. (1985) concluded in their study that thresholded intensity images alone will not work in all cases, and they showed that the combination of noise filtering, edge detection, thresholding, and re-scaling was the most promise technique. Timmermann and Krohmann [6] used images formed in the infra red part of the spectrum to distinguish between vegetation and soil.

Lv Junwei et al. proposed a method which using Multi-spectral image fusion method to improve gray ratio in image. This method based on studying the gray level ratio with onion (crop) , mustard (weed) and soil in multi-spectral images, it was found that some modes of multi-spectral image fusion like b+ir-g-r give better results [7]. Yang Guobin et al. developed a Bayesian classification model which could discriminate tomatoes from the natural background using only color features in a digital color Image, because of the complexity of the image, the effect is not stable[8].

2. Materials and methods

2.1. Images

Wheat images in different growth stages and under a wide variety of conditions are employed as test images. Sampling operations were performed at the experimental farm of the Chinese Academy of Agricultural Sciences. The camera was located 110 cm above ground and tilted at an angle of 30^{o} to the vertical. The wheat height ranged from 5 to 12cm. The area covered by one image was 2.6m long in row direction and 1.0m wide. The resolution of image was 640×480 pixels. All acquisitions were spaced by five/six days, i.e. they were got under different conditions of illumination and different growth stages. The images were processed with Microsoft visual C++ 6.0. A set of 240

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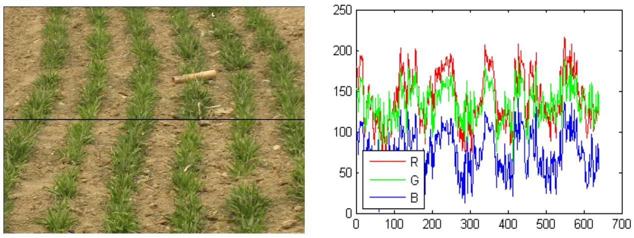
images were processed in the PC with a 1.8.GHz CPU.

2.2. Image color characteristic analysis

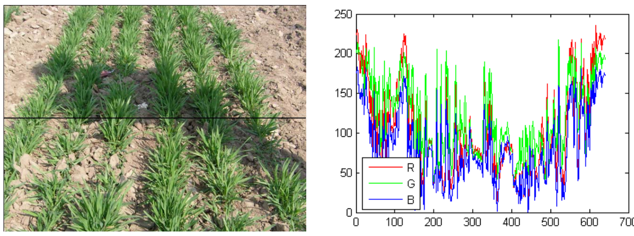
Wheat in different growth stages, as an organism, which has its own unique color characteristics. Figure 1.a is a wheat RGB image in cloudy day while Figure 2a is that in sunny days. Figure 1b and 2b is R, G, B color component with 1/2 height horizontal scan for Figure 1a , Figure 1b respectively.

For the crop image in growing period, crops' green component occupies the dominant position, but red components occupy the dominant position for background. This has provided the very good basis for the segmentation for the crops from the background. These can be seen clearly from Figure 1b, Figure 2b and table 1. So, Color indices have been developed to highlight crop from other elements of the scene. These indices were designed to highlight the differences between the spectral properties of plants and those of the rest of the scene (i.e. soil, stones, and shadow).



(a) Wheat image in cloudy day (b) Color distribution curve

Figure 1. Wheat RGB image and its R, G, B color statistical distribution curve in 1/2 high level



(a) Wheat image in sunny day (b) Color distribution curve

Figure 2. Wheat RGB image and its R, G, B color statistical distribution curve in 1/2 high level

2.3. RGB color model

- 2G-R-B

The principle is shown as formula (1).

$$pixel(x,y)=\begin{cases}0 & 2G \le R-B \\ 2G-R-B & others \\ 255 & 2G \ge R+B+255\end{cases} \tag{1}$$

Table 1. color component parameter in horizontal scan line for wheat image

Image number	Color component	Min value	Max value	Mean value
Figure 1a	R	65	216	142
	G	64	189	135
	B	2	141	74
Figure 2a	R	5	236	104
	G	24	217	120
	B	1	183	83

Where G,R,B are equal to the green, red and blue value of $po\text{int}(x,y)$ respectively in the color image, $pixel(x,y)$ denotes the grey value of $po\text{int}(x,y)$ in the grey image, and confined to [0, 255].

- excess green RGB color model

$$pixel(x,y)=\begin{cases}0 & R>G \text{ or } B>G \\ 2G-R-B & others\end{cases} \tag{2}$$

2.4. Normalized rgb

Color space normalization: given an original input image in the RGB color space, we applied the following normalization scheme, which is usually applied in agronomic image segmentation (G é e et al., 2008), obtaining the normalized spectral r, g and b components ranging in [0,1].

$$r=\frac{R}{R+G+B} \quad g=\frac{G}{R+G+B} \quad b=\frac{B}{R+G+B} \tag{3}$$

where $r+g+b=1$

- 2g-r-b

$$pixel(x,y)=\begin{cases}0 & 2g \le r+b \\ 2g-r-b & others \\ 255 & 2g \ge r+b+255\end{cases} \tag{4}$$

Where , $pixel(x,y)$ denotes the grey value of $po\text{int}(x,y)$ in the grey image.

- Excess green RGB color model

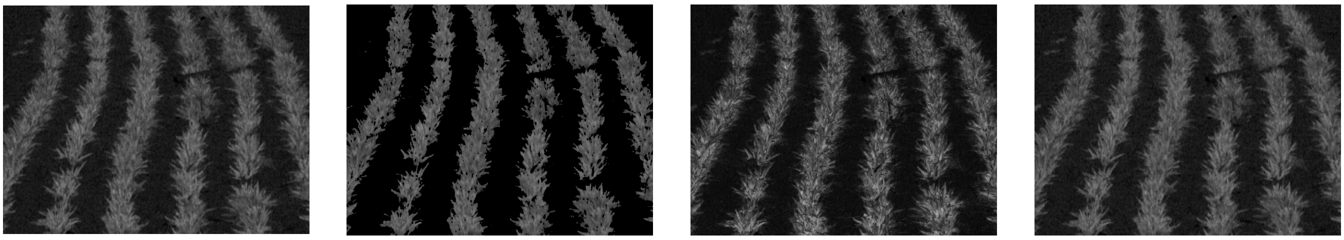
$$pixel(x,y)=\begin{cases}0 & r>g \text{ or } b>g \\ 2g-r-b & others\end{cases} \tag{5}$$

2.5. HSI Model

The HSI color system has a good capability of representing the colors of human perception, because human vision system can distinguish different hues easily, whereas the perception of different intensity or saturation does not imply the recognition of different colors.

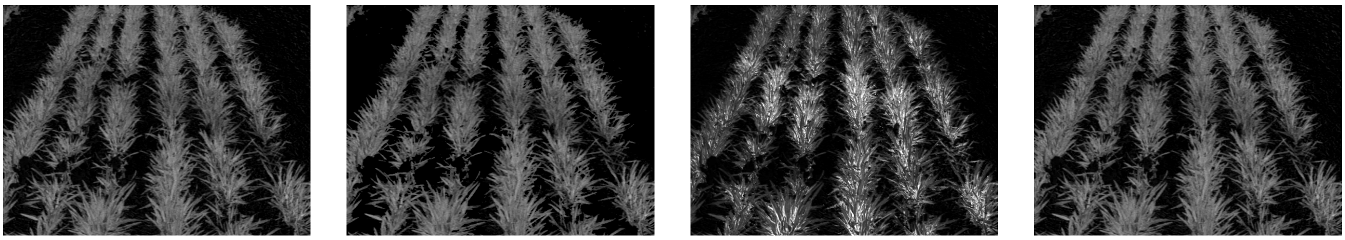
The HSI coordinates can be transformed from the RGB space. The formulas for hue, saturation, and intensity are:

$$H = \arctan\left(\frac{\sqrt{3}(G-B)}{(R-G)+(R-B)}\right),$$
$$S = 1-\frac{3}{(R+G+B)}\left[\min(R,G,B)\right], \quad I = \frac{1}{3}(R+G+B) \tag{6}$$



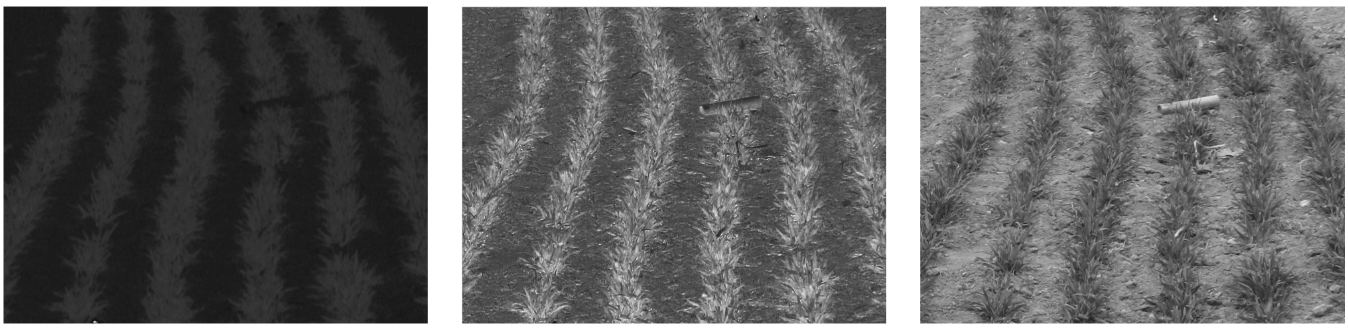
(a) 2G-R-B (b) excess green 2G-R-B (c) 2g-r-b (d) excess green 2g-r-b

Figure 3. Image segmentation result for Figure 1a



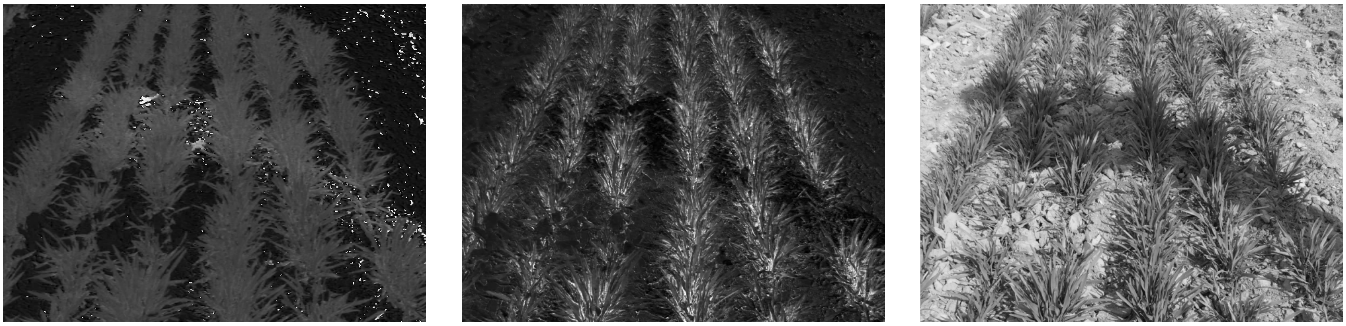
(a) 2G-R-B (b) excess green 2G-R-B (c) 2g-r-b (d) excess green 2g-r-b

Figure 4. Image segmentation result for Figure 2a



(a) H component Image (b) S component (c) I component

Figure 5. Segmentation result with HSI model for Figure 1a



(a) H component Image (b) S component (c) I component

Figure 6. Segmentation result with HSI model for Figure 2a

The hue is undefined if the saturation is zero, and the saturation is undefined when the intensity is zero.

Table 2. Consume time and image segmentation result evaluation with different days

Model	Consume time(ms)	Image Segmentation result Evaluation	
		Wheat (in Cloudy)	*Wheat (in Sunny)*
2G-R-B	1	bad	good
Excess green 2G-R-B	1	good	good
2g-r-b	16	bad	bad
Excess green 2g-r-b	25	bad	good
H component of HSI	56	good	bad
S component of HSI	8	bad	bad
I component of HSI	1	can't segment	can't segment

3. Results and discussion

In order to test the goodness or badness of image segmentation, we adopt the image processing time and processing effect to evaluate the above several kinds color characteristic.

- The image processing time

According to the table 1, the image processing time has a great difference. The fast processing time is 1ms, and the corresponding image segmentation model is 2G-R-B, the excess green 2G-R-B, and the component I of HSI model.

- The image segmentation effect

From Figure 3, 4, 5, 6 and table 2, the segmentation effect can be seen clearly. For wheat images in different growth stages, or in different climates whether it is cloudy, sunny image, or in different image noises, the excess green 2G-R-B has a good evaluation. It achieves very good results under a wide variety of conditions.

According to the above analysis, it is not difficult to draw a conclusion. Under the full consideration the image processing time and image segmentation effect, the excess green 2G-R-B is the best choice for green crop.

4. Conclusions

Because the red component of background occupies the dominant position while the green component of crops occupies the dominant position, which provides the very good basis for recognition between crops with the non-crops background. Integrate segmentation time-consuming and the segmentation results two factors, we find excess green 2G-R-B is the best division factor. Test results shows the algorithm is not sensitive to light intensity and less time-consuming, which can meet the agricultural production of real time intelligence requirements.

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References

[1] S. Han, Q. Zhang , B. Ni, J.F. Reid, "A guidance directrix approach to vision-based vehicle guidance systems", Computers and Electronics in Agriculture, Vol. 43, pp. 179-195, 2004.

[2] Reid, J. E., Zhang, Q., Noguchi, N., and Dickson, M, "Agricultural automatic guidance research in North America", Computers and Electronics in Agriculture, Vol. 25, pp. 155-167, 2000.

[3] Onyango, C.M., Marchant, J.A., "Segmentation of row crop plants from weeds using colour and morphology",. Computers and Electronics in Agriculture, Vol. 39, pp. 141-155, 2003.

[4] Tellaeche, A., Burgos-Artizzu, X., Pajares, G., Ribeiro, A., Fernández-Quintanilla, C., "A new vision-based approach to differential spraying in precision agriculture", Computers and Electronics in Agriculture, Vol. 60, pp. 144-155, 2008

[5] Tellaeche, A., Burgos-Artizzu, X.P., Pajares, G., Ribeiro, A., "A vision-based method for weeds identification through the Bayesian decision theory", Pattern Recognition, Vol. 41, pp. 521-530, 2008.

[6] Timmermann, C., Krohmann, P., "First detect weeds, then control them: From automatic weed recognition to field-sector specific treatment", Mais, No. 3, pp. 114-117, 2000.

[7] Lv Junwei, Ma Chenglin, Yu Yongsheng, "Multi-spectral image fusion to increase gray level ratio between crop and weeds in image", Transactions of The Chinese Society of Agricultural Engineering, Vol. 21, No. 11, pp. 99-102, 2005

[8] Yang Guobin, Zhao Jiewen, Xiang zhongpin, "Discriminating Tomatoes Based on Computer Vision Technology in Natural Outdoor Scenes", Journal of Agricultural Mechanization Research, Vol. 1, pp. 60-62, 2003.