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Development of ExG, ExR, ExGR, HSV, CIELAB Images from RGB Images Using Image Segmentation Algorithm in Computer Vision Based Herbicide Spraying Applications

Koduru Koteswara Rao [a++*], Raj Kiran B [a#], Srinivasa Rao [a#] and Lavanya K [b#]

[a] Department of Farm Machinery and Power Engineering, Dr. NTR College of Agricultural Engineering, Bapatla, India.
[b] Department of Processing and Food Engineering, Dr. NTR College of Agricultural Engineering, Bapatla, India.

Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

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[++] *M. Tech Student;*
[#] *Assistant Professor;*
**Corresponding author: E-mail: kkrntr2000@gmail.com;*

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ABSTRACT

Weed management in agriculture is critical for preventing crop yield losses, with traditional methods often leading to environmental harm and increased production costs. This study explores the development of color indices and models for weed detection in computer vision-based herbicide spraying applications. Among the all sensors, RGB colour cameras offer several advantages, including low cost and wide availability of image processing libraries tailored for RGB image analysis. In present study a Logitech C270 webcam was used for acquiring the RGB images and a specially python algorithm was developed for image segmentation based on color. Excess Green (ExG), Excess Red (ExR), Excess Green minus Red (ExGR), HSV, and CIELAB color model images are developed by using algorithm. The research demonstrates that while ExG and ExGR indices are effective under specific conditions, the CIELAB model offers superior segmentation results across varying lighting environments. Among all these color indices and models, particularly CIELAB, can enhance the precision of weed detection in automated herbicide applications, thereby reducing environmental impact and improving agricultural efficiency.

Keywords: Color indices; computer vision; weed detection; RGB image; mask image.

1. INTRODUCTION

A plant other than the main crop or a plant in the wrong place is considered a weed. Immediate action to remove weeds once they emerge is an essential task of weed management because weeds compete with the main crop for water, sunlight and nutrients. Otherwise, substantial yield loss may be encountered. The yield loss due to weeds alone was reported at 37% [1]. Mechanical and chemical weeding methods have been more commonly used than other weeding methods for weeding of large agriculture fields. The entire field was tilled in the case of the mechanical method of weeding or weedicides were applied uniformly to the entire field in the case of the chemical method of weeding. Since, over application can lead to environmental damages. This increases farmer’s production cost and prone to groundwater contamination. With the rapid growth in high resolution vision systems, image processing techniques and embedded computing devices [2,3], the imaging sensors playing vital role in precision agriculture. The digital colour camera stores colour information in RGB colour space. In case of traditional image processing most of the cases the image background has been segmented by converting RGB image to grayscale image. This technique is possible only when the grayscale values of background and foreground elements are different. For example, if colour image contains black and white pixels and converting colour image into grayscale image the white pixels intensity values approximately more than 200 and black pixels intensity values approximately less than 100. In this situation by placing threshold values as 125 one can convert grayscale image into binary image. In case of weeds and soil pixels classification the above technique is not possible. It was reported that directly converting RGB pixels values into grayscale scale do not yield a good segmentation because plant and soil background contain similar grayscale values. Hence, visible spectral colour indices derived from RGB image have been employed for weed and soil pixels classification [4]. Color indices have been suggested to be less sensitive to in lighting variations, and may have the potential to work well for different residues backgrounds [5]. A disproportionate amount of redness from various sources may overcast a digital image, making it more difficult to identify green plants with simple indices [6]. For example, image redness may be related to digital camera operation and background illumination, but may also be related to redness from the soil and residue itself. An alternate excess red vegetative index ($ExR=1.4r-b$) was pro posed by Meyer et al. [7], but has not tested well in later studies. A widely used colour index [8], (Vidović et al., 2016), has been called excess green (ExG) [9]. Excess green index provides a near-binary intensity image, hence it was commonly employed for weed and soil pixels classification by several studies [10,8,9] (Yang et al., 2015). Then, with the help of a suitable threshold value, each set of images were segmented into foreground and background pixels. Colour indices have been recommended and extensively used for vegetation identification as they can work under different crop residue conditions and were less sensitive to lighting variations [5]. Excessive redness from several sources may be overcast and hamper digital image quality, making it more difficult to identify green plants with simple colour indices [7]. Performance of several vegetation indices, i.e. Excess green index (ExG), excess red index (ExR), excess green minus red index (ExGR) on green vegetation segmentation accuracy was studied [3]. The objective of this paper is to describe an improved color vegetation index with an automatic threshold and to determine its accuracy using plant-soil-residue images. The main objective of this paper is to determine the colour vegetation indices of GBR images in computer vision based spraying applications.

2. MATERIALS AND METHODS

2.1 Weed Detection Sensor

A Logitech C270 webcam served as the weed detection sensor (Picture 1). Unlike traditional digital color cameras, the Logitech C270 webcam lacks an internal memory chip. Instead, it immediately transmits captured images to a computer or microcontroller. The webcam is equipped with a USB 2.0 port cable, which both supplies power to the device from the computer or microcontroller and transfers the digital information captured by the webcam to the computer.

Picture 1. Logitech C270 web camera

2.2 Image Acquisition by Using Algorithm

A set of colour digital images of a single plant were acquired. The images were acquired by using Logitech C270 web camera which is connected to a laptop under natural sunlight. The camera was set to operate in the automatic mode and best quality image resolution (640×480 pixels). Capture the images of different single plants in the way to minimize shadows of plant. Image acquisition was done by using web camera by a specialized algorithm.

2.3 Image Segmentation by Using Algorithm

The plant segmentation method includes classifier and threshold value. Visible spectral colour indices and colour models used as a classifier for plant and soil pixel classification are formed by combining the RGB values through simple arithmetic operations. In present study excess green index (ExG), excess red index (ExR), excess green minus red index (ExGR), hue-saturation-value (HSV) and CIELAB colour model models were used for plant and soil pixel classification. These are colour model images are developed by a specialized algorithm in python language.

2.3.1 Excess Green Index (ExG)

It was widely employed and simple to calculate. The sensitivity of this method to background and lighting issues was low. In a natural environment, it exhibited strong adaptability. It performs poorly when the light was too bright or too dim.

Excess Green can be calculated by using following formula,

Excess Green [9] Exg = 2*G-R-B

2.3.2 Excess Red Index (ExR)

Computing it was simple. It still extracts green pixels despite relying only on the red component. Both high and low light conditions degrade its performance. Compared to exg, it was less precise.

Excess Red can be calculated by using following formula,

Excess Red [7] Exr=1.4×R-G

2.3.3 Excess Green minus Excess Red Index (ExGR)

It showed a high degree of environmental adaptability. This method was capable of extracting green by using exg and removing background noise by using exr. It performs poorly when the light was high or low. It segments the pixel of shadow as a plant pixel.

Excess Green minus Red can be calculated by using following formula,

Excess Green minus Excess Red (exgr) [8] Exgr = exg – exr

2.3.4 Hue Saturation Value (HSV)

HSV color model is a kind of method to define color according to the three basic features of the color: hue, saturation and luminance. Hue(H) is the basic feature of color, and is just the color name, such as: red, yellow. According to the position in the standard color wheel, it ranges from 0 to 360. Saturation(S) is the color purity. Higher the value is, purer the color is . And it ranges between 0 and 100%. Luminance (V) is also named brightness, it ranges from 0 to 100%.

2.3.5 CIELAB

L*a*b* color model determines the color depending on its position in a3d color space the L* components is the lightness of the color (when L* =0 means black and when L* =100 referred to while) and the chroma*(for positive values indicate red and for negative values indicate green) and the hue b* (positive values refer to yellow while negative values refer to blue).

3. RESULTS AND DISCUSSION

In the present study, weed coverage percentage in the input image was extracted using excess green index (ExG), excess red index (ExR), excess green minus red index (ExGR), HSV and CIELAB. Since opencv represents images as numpy arrays in reverse order, the input image in a RGB format. The exg and exgr were computed using python code from RGB image. Opencv-Python library consists of one separate module for colour model conversion. ExG and ExrR mask images is developed by using a specialized python code [11-13].

The developed ExG images are shown below:

Plate 1. RGB image

Fig. 1. ExG mask image

Plate 2. RGB image

Fig. 2. ExG mask image

Plate 3. RGB image

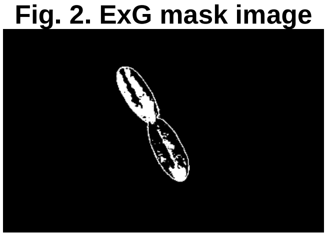

Fig. 3. ExG mask image

The developed ExR images are shown below:

Plate 4. RGB image

Fig. 4. ExR mask image

Plate 5. RGB image

Fig. 5. ExR mask image

Plate 6. RGB image

Fig. 6. ExR mask image

The developed ExGR images are shown below:

Plate 7. RGB image

Fig. 7. ExGR mask image

Plate 8. RGB image

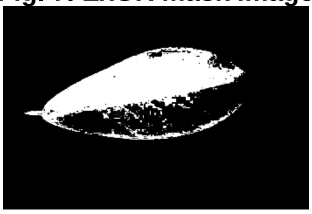

Fig. 8. ExGR mask image

Plate 9. RGB image

Fig. 9. ExGR mask image

The RGB image was converted to HSV image using cv2.cvtcolor (image, cv2.COLOR_BGR2HSV). This method generally indicates its Hue (H), Saturation (S), Value (V). Though it shows betters results but developed masked image was not perfectly segmented.

Plate 10. RGB image

Fig. 10. HSV mask image

Plate 11. RGB image

Fig. 11. HSV mask image

Plate 12. RGB image

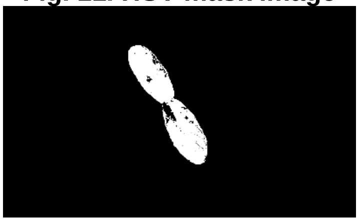

Fig. 12. HSV mask image

The RGB image was converted to CIELAB using cv2.cvtcolor (image, cv2.COLOR_BGR2LAB). Among the all models mentioned above only CIELAB model had got the better results in terms of conversion of RGB images into CIELAB masked images with good segmentation.

Plate 13. RGB image

Fig. 13. CIELAB mask image

Plate 14. RGB image

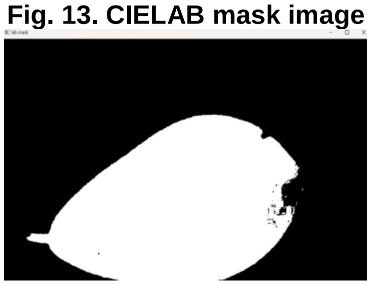

Fig. 14. CIELAB mask image

Plate 15. RGB image

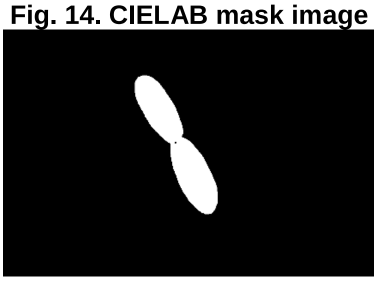

Fig. 15. CIELAB mask image

4. SUMMARY AND CONCLUSIONS

This study focuses on the development and application of various color indices and models for image segmentation in vision-based herbicide spraying applications. Weeds are a major concern in agriculture, competing with crops for resources and causing significant yield loss. Traditional methods of weed control, such as mechanical and chemical weeding, often lead to environmental damage and increased costs. Advances in imaging systems and image processing techniques offer new possibilities for precision agriculture, particularly in weed detection. RGB images, commonly used in digital cameras, are often converted to grayscale for image processing. However, this method is ineffective for distinguishing between weeds and soil due to their similar grayscale values. To overcome this, the study explores various color indices derived from RGB images, including Excess Green (ExG), Excess Red (ExR), Excess Green minus Red (ExGR), and color models like HSV and CIELAB, for better segmentation of weed and soil pixels. Using a Logitech C270 webcam, images of plants were captured and processed using Python algorithms. Among the all methods that ExG and ExGR indices perform well under certain conditions, while HSV and CIELAB color models offer better segmentation results under varying lighting conditions.

1. The study confirms that color indices like ExG, ExR, and ExGR are useful for weed detection in precision agriculture. However, their performance varies depending on the lighting conditions and the specific characteristics of the plants and soil.
2. Among the color models tested, the CIELAB model provided the best results for segmenting RGB images into masked images, offering superior performance in diverse lighting conditions. HSV also showed good results but was less effective in perfect segmentation.
3. The use of Python-based algorithms for image processing proved effective in developing ExG, ExR, ExGR, HSV, and CIELAB images, which can significantly aid in vision-based herbicide spraying applications.
4. The study highlights the importance of environmental adaptability in selecting and applying color indices and models, with CIELAB showing the most promise in this regard.

Suggestions for future work:

1. Implementing machine learning techniques, such as convolutional neural networks (CNNs), could improve the accuracy of weed detection.
2. Create easy-to-use software that helps farmers quickly set up and adjust weed detection algorithms in their spraying systems. This could include mobile apps or websites that offer real-time feedback and options for customization.
3. Explore the integration of the developed image segmentation techniques with unmanned aerial vehicles (UAVs) or ground-based robots.

DISCLAIMER (ARTIFICIAL INTELLIGENCE)

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc) and text-to-image generators have been used during writing or editing of this manuscript.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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