People's Choice Poster Award

Weed detection among soybean plants in artificial lighting environment using multispectral images and Computer Vision

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ABSTRACT

Precision Agriculture stands out as one of the most promising areas for the development of new technologies around the world. Some advances from this area include the mapping of productivity areas and the development of sensors for climate and soil analysis, improving the smart use of resources during crop management and helping farmers during the decision-making stages. Among the problems of modern agriculture, the intensive and non-localized use of herbicides causes environmental issues, contributes to elevated costs in farmers' budgets and results in applications of chemical substances in non-target organisms. Although there are many selective herbicide spraying systems available for use, the majority working principle is based upon chlorophyll detectors, thus not being able to distinguish crop plants from weeds with high accuracy in crop's post-emergence herbicide applications ("green-on-green" application). The main objective of this study is to develop a multispectral camera system for in-crop weed recognition using Computer Vision techniques. The system was built with four monochromatic CMOS sensor cameras with monochromatic wavelength bandpass filters (green, red, near infrared and infrared) and a RGB camera. Soybean and weed plants images were captured in a controlled environment using an automated v-slot rail system to simulate the movement of a spray tractor in the field. Infrared images presented higher precision (90.5%) and recall (89.3%) values compared to the other monochromatic bands, followed by RGB (87.0% and 86.1%, respectively) and near infrared images (83.6% and 87.9%), suggesting that infrared wavelengths plays an important role in plant detection and classification. Our results state that the combination of Computer Vision and multispectral images of plants is a more efficient approach for targeting weeds among crop plants for post-emergence herbicide applications.

Keywords: Weed detection, multispectral images, Artificial Intelligence, Precision Agriculture

1. INTRODUCTION

Precision Agriculture (PA) has gained global significance for optimizing natural resource utilization and crop yield while reducing losses and waste.[1] PA involves data collection to quantify spatial and temporal variations in agricultural units, serving as a site-specific management strategy employing information technologies to aid crucial decisions in crop production.[2] Recent advances in Internet of Things (IoT) and Machine Learning are enhancing PA's accuracy, increasing benefits in quantity and quality of production, reducing farmers' costs and contributing to a more sustainable agriculture.[3]

A major challenge in modern agriculture is weed control, where undesired plants compete with crops for resources like water, light, nutrients and growth space.[4] Herbicide resistance, often due to continuous chemical applications, leads to environmental harm and threatens ecosystem species. The rise of resistant weeds has drawn attention from farmers and specialists due to its causes related to herbicide application practices and genetic

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variation.[5] These factors contribute to the need for more precise methods such as localized input applications and advanced PA technologies to address these issues.

Farmers' interest in herbicide selective spraying systems is becoming high as these equipments rise as an efficient, affordable, sustainable and rentable technology.[6] While most available systems use chlorophyll detectors for weed detection, these methods are limited in distinguishing crops from weeds in pre-emergence herbicide applications, since this technique detects green (weeds) on a fallow ground. Computer Vision has emerged as a promising solution for image-based weed detection and recognition among crops for selective spraying herbicides in both pre and pos-emergence. YOLO ("You Only Look Once") algorithm, known for its real-time object detection capabilities, has been widely used in weed recognition tasks, showing success across various applications and different weed species.[7–12]

Multispectral imaging consists of capturing images of the same scene using different wavelengths. It has been widely used for remote sensing for productivity areas mapping,[13] weed mapping[14] plant density[15] and plant disease detection and diagnosis.[16] For detection tasks in artificial and natural lighting conditions, plants spectral signature plays an important role since different light wavelengths are reflected in distinct intensities and ways by plants' leaf structure.[17]

In this paper, it is described the use of multispectral images for in crop weed recognition using YOLO algorithm and an artificial lighting environment. Three important weed species were used (*Amaranthus viridis* L., *Bidens pilosa* L. and *Digitaria horizontalis* wild) and soybean (*Glycine max* L.) was chosen as a crop plant due to its economic importance in Brazil's agriculture. Plants were grown in an indoor greenhouse and a dataset containing 3,775 images was built using a multispectral camera system containing five cameras: RGB, green (G), red (R), near infrared (NIR) and infrared (IR).

2. METHODS

The experiments were conducted within an indoor greenhouse laboratory located at the São Carlos Institute of Physics from the University of São Paulo, ensuring controlled conditions with a temperature of 25 ℃ and a regulated photoperiod of 12 hours of light followed by 12 hours of darkness. The indoor greenhouse was equipped with ten LED lamps designed for plant growth and two white ceiling LED lights that offer visible spectrum illumination, along with ten halogen lamps that provide near-infrared spectrum lighting. The cumulative spectrum produced for both plant growth and image capture was assessed using a spectrometer from Ocean Optics (Ocean Optics, USA) and is presented in Figure 1.

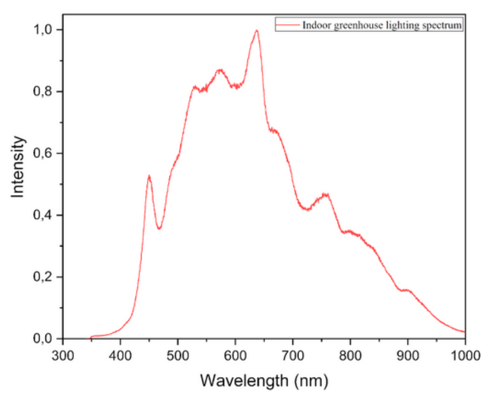


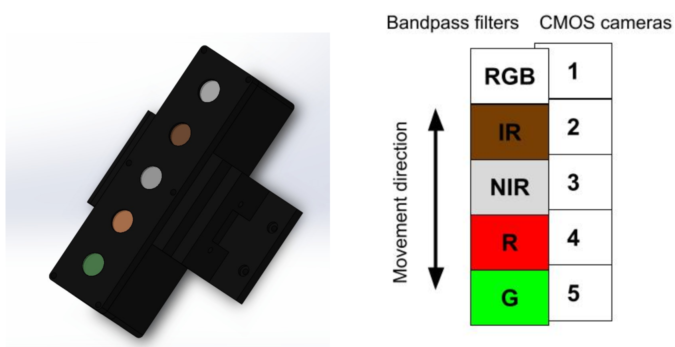
Figure 1: Indoor greenhouse lighting spectrum used for plant growth and image acquisition with the multispectral camera system.

For purpose of automating the image acquisition and emulating the motion of a spray tractor navigating through crop planting rows, a v-slot rail system was built using a wooden frame (see Figure 2). The architecture encompasses two v-slot rails affixed with cameras, a NEMA 17 stepper motor connected via GT2 belts and pulleys,

Figure 2: Automated v-slot rail system developed to automate image acquisition and to simulate the movement of a spray tractor in the field towards crop's planting rows.

and a CNC Shield housing an Arduino Nano to regulate the NEMA 17 motor's steps, thereby orchestrating the camera system's motion.

The camera arrangement comprises four monochromatic CMOS sensor cameras (ELP - OSMO B/W, China) and a colored RGB CMOS sensor camera (ELP-USBFHD01M, China), each equipped with a 6 mm focal distance lens. Both camera models feature 2 megapixels OV2710 CMOS sensors (1920×1080 pixels). Communication between the cameras and a desktop computer occurred through the USB 2.0 protocol. Three monochromatic bandpass filters designed to match green (G: $501 - 525$ nm), red (R: $654 - 674$ nm), and near-infrared (NIR: $761 - 829$ nm) wavelengths were placed over the lenses of three out of four monochromatic cameras, exclusively allowing light of predetermined wavelengths to reach each sensor. The fourth monochromatic camera employed an infrared longpass filter (IR: $>$ 780 nm) on its lens. The RGB camera didn't use additional filters, maintaining only the factory KG1 filter to obstruct infrared light from reaching the sensor. The camera support structure was designed using SolidWorks software (SolidWorks Corporation, USA) and produced via an Ender 3D printer (Ender, China) to ensure alignment of all five cameras in the same direction as the system's movement. Figure 3 shows the arrangement of the cameras on the support.



(a) (b)

Figure 3: Multispectral camera system developed for acquisition of multispectral images of weeds and soybean plants. (a) Tridimensional concept; (b) bandpass filters array.

To facilitate plant growth, two trays filled with commercial soil were situated directly beneath the illumination bench and the v-slot rail system. Soybean plants were meticulously sown in two parallel rows, while weed plants were randomly distributed across the cultivation trays. Throughout the course of a month-long experiment, a total of approximately 3,775 images were acquired, with each camera contributing 755 images. These images were labeled utilizing the bounding box technique in the Computer Vision Annotation Tool (CVAT) software and they were labeled into three classes: soybean (Glycine max (L.) Merrill plants), weed (broadleaf weeds of the Amaranthus viridis L. and Bidens pilosa L. species), and grass (grassy weeds of the Digitaria horizontalis wild species). Figure 4 shows examples of images captured in the different bands.

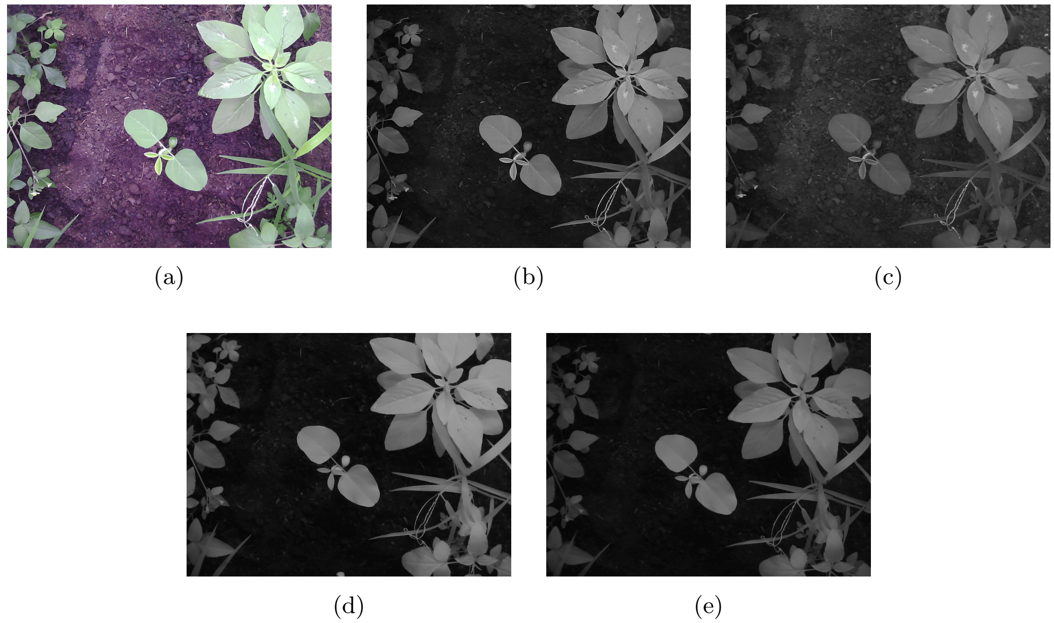


Figure 4: Example of images captured at different bands. (a) RGB; (b) green ($501 - 525$ nm); (c) red ($654 - 674$ nm); (d) infrared (> 780 nm); (e) near-infrared ($761 - 829$ nm).

The YOLO algorithm was employed, maintaining its fundamental architecture, for each of the individual spectral camera images as well as the RGB images. The dataset was splitted into three subsets: 70% of images for training, 20% for validation and 10% for testing, keeping the same amount of images for each band. Training was executed over $3,000$ epochs, using early stopping technique with patience value set to 100. To evaluate the performance of the different models, the following metrics were used: precision; recall; mAP(0.5); and mAP(0.5:0.95). Precision is a measure of how accurate the model is in classifying; recall calculates how many actual positives the model captures through labeling it is a true positive; and mAP is a metric that incorporates a trade-off between precision and recall.

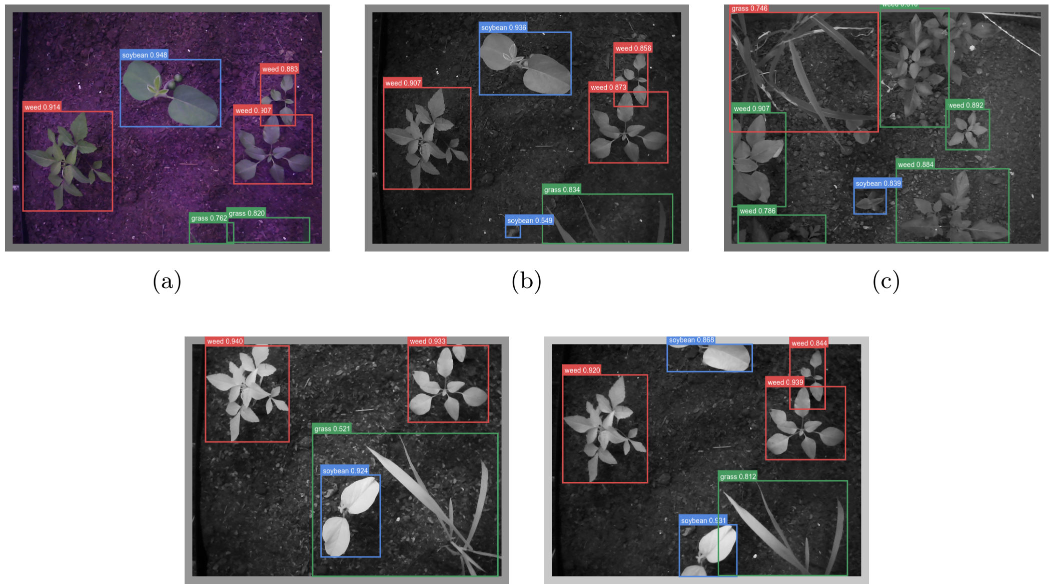
3. RESULTS

The five models were evaluated using the same 375 images (75 for each band and for the RGB images). Table 1 summarizes the results, presenting the metrics for each model.

Table 1: Results from tests performed for images in different bands and RGB.

Band	**Precision**	**Recall**	**mAP(0.5)**	**mAP(0.5:0.95)**
RGB	0.870	0.861	0.874	0.679
G	0.851	0.845	0.881	0.661
R	0.761	0.733	0.798	0.589
IR	**0.905**	**0.893**	**0.928**	**0.725**
NIR	0.836	0.879	0.875	0.641

Experimental results indicate best performance for IR band with precision of 90.5%, recall of 89.3%, mAP(0.5) of 92.8% and mAP(0.5:0.95) of 72.5%. Figure 5 presents examples of detection and classification weeds and soybean in the different bands.



(a) (b) (c)

(d) (e)

Figure 5: Example of detection and classification of plants in the different bands. (a) RGB; (b) green; (c) red; (d) infrared; (e) near-infrared.

4. CONCLUSION

In this paper, the development of a multispectral camera and a v-slot rail system to capture images of plants in an indoor greenhouse with artificial lighting is described. A multispectral image dataset consisting of $3,775$ images of weeds and soybean plants was assembled using four monochromatic bands (G, R, NIR, and IR) and an RGB camera. The YOLO algorithm was employed to conduct weed detection among soybean plants utilizing the five types of acquired images. Experimental results reveal that the longpass infrared band achieved superior precision and recall values (0.905 and 0.893, respectively) followed by RGB (0.870 and 0.861, respectively) and the near-infrared band (0.836 and 0.879, respectively), demonstrating a good performance of infrared wavelengths for weed recognition within crop settings. Furthermore, it was demonstrated that Computer Vision offers a promising avenue for addressing post-emergence herbicide applications, given its ability to differentiate between crop plants and weeds.

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