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Intra-row weed recognition using plant spacing information in stereo images

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Abstract. *Crop/weed recognition is a crucial step for selective herbicide application. A machine vision based sensing system was developed to detect intra-row weeds when crops were at their early growth stages. The proposed methods used color feature to extract vegetation from the background, whilst height and plant spacing information analysis techniques were applied to discriminate between crops and weeds. Firstly the identification of the weeds that were lower than crops was done by a height-based segmentation method using a stereo vision system. During the stereo matching process, correspondence search was performed on edged stereo images and disparity calculation was applied only to the edge pixels. This strategy could largely reduce the correspondence search range, thereby enhanced the weed recognition speed and accuracy. Afterwards, the higher weeds were distinguished from the crops by utilizing plant spacing characters. The histogram of plant pixels and their peak position were calculated from each pixel row of the segmented disparity image. Then plant centers were located and each weed region was further extracted based on the interplant distance in a row.*

Keywords. *Stereo vision, intra-row weed recognition, height feature, plant spacing information.*

Introduction

Site-specific weed control techniques, which can minimize herbicide usage and reduce environmental pollution caused by excessive use of chemical application, have been studied extensively. Development of a visual method for crop/weed recognition under the highly variable conditions is a hard job. Researchers have mostly investigated different imaging sensors for the purpose of applying herbicides selectively, and some machine vision systems have been developed.

Weed control consists of two separate areas: inter-row and intra-row weeding. Intra-row weeding is much more difficult than inter-row weeding due to the difficulty in discrimination between crops and weeds.

Automated intra-row weeding calls for robust sensing systems. Stereo vision can provide the depth information missing in the conventional planar image, which can attain more accurate plant detection. Piron et al. studied the detection of in-row weed by analyzing multispectral stereoscopic images. A method for corn plant detection and plant center position estimation using stereo vision was reported by Jin and Tang. Rovira-Más et al. used a compact stereo camera mounted on a remote controlled helicopter to acquire stereo images of a maize field and represent the crop information in a 3D crop map. Andersen et al. developed a method for computing geometric plant properties such as plant height and leaf area using stereo vision.

With the development of automated planters, crop is usually sowed with a precision drill, interplant spacing in crop rows became precise enough to allow the introduction of weed and crop discrimination utilizing plant spacing information. Shrestha et al. described a vision system that measures plant population using the regularity of the corn plants in the row. Two features were extracted from each pixel row of the segmented images: total number of plant pixels, and their median position. Cordill designed and tested an intra-row mechanical weeding machine for corn. The maize stalks were distinguished from the weeds by utilizing the typical vertical quasi-cylindrical stalk of the maize plant, the limited range of maize stalk diameters and by assuming constant plant spacing.

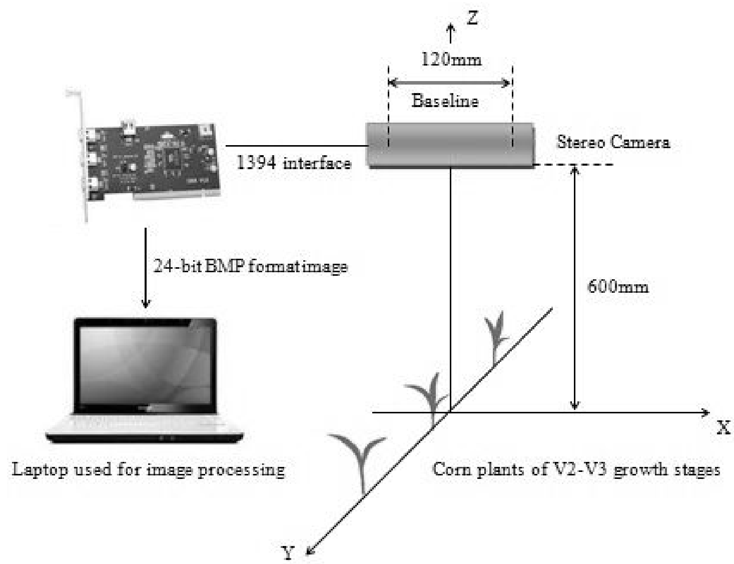
The main objective of this research is to develop an image processing algorithm for crop and intra-row weed discrimination at early growth stages utilizing stereo vision and interplant spacing information. The specific objectives were to 1) develop a real-time stereo matching algorithm that is capable of yielding accurate disparity measurements with a much lower computational cost. 2) identify and segment the crop plants using height and plant spacing information, then the remaining green objects in the segmented image were considered as weeds.

Materials and Methods

Image Acquisition

A binocular stereo camera (BB2-08S2C-38, Point Grey Research, Inc., Vancouver, British Columbia, Canada) with two lenses of 3.8 mm focal length and 12 mm baseline was used in this research. The camera generated two (left and right) 320 × 240 color images at 48 Hz frame rate. Smaller resolutions were selected to minimize image processing effort. The stereo vision system was operated from a laptop with a Intel(R) Core(TM)2 Duo T6600@2.20GHz central processing unit (CPU) connected through an IEEE 1394 (FireWire) interface. The camera was pre-calibrated for lens distortions and camera misalignments. Therefore, there was no need for in-field camera calibration.

Schematic description of the stereo vision system arrangement was shown in figure 1. The camera was mounted 600 mm above the ground and top-view stereo images were taken directly above the plants. Image acquisition was performed when the plants were V2-V3 growth stages, as herbicide application at that early stage would minimize weed competition. The image processing and stereo matching algorithm were implemented in C++ using the OpenCV library (version 1.0). Figure 2 shows the main steps of the image processing.



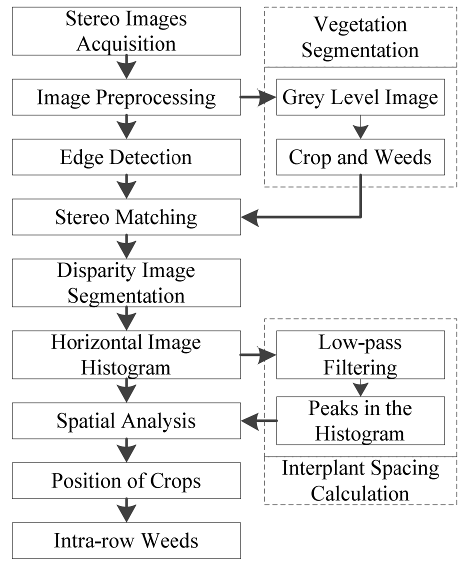


Figure 1. Schematic description of the stereo vision system arrangement. Figure 2. Main steps of the image processing.

Vegetation Segmentation

To extract vegetation from other elements of the scene (i.e. soil, residues). The normalized excess green index (ExG) introduced by Woebbecke et al. was used with some modifications:

$$ExG = \begin{cases} 0 & \text{if}(\ g < r \ || \ g < b\ ) \\ 2g\text{-}r\text{-}b & \text{Otherwise} \end{cases} \tag{1}$$

$$r = \frac{R}{R+G+B}\ ,\ g = \frac{G}{R+G+B}\ ,\ b = \frac{B}{R+G+B} \tag{2}$$

where r, g and b are the normalized RGB coordinates ranging from 0 to 1.

This index, based on normalized RGB coordinates, is therefore insensitive to the intensity of the light source as well as the viewing and illumination angles.

The grey level image was transformed into a binary image using Otsu method, which is based on an analysis of the histogram resulting from the gray level image calculation. Then, a 3-by-3 median filter was applied to segmented images to eliminate random noise in the image. Edges of crop and weed in the binary stereo images were detected using the canny operator. Stereo process was then performed on edged stereo images.

Region of intra-row weeding

Since the overall goal of this research was to develop a machine vision system that was capable of detecting intra-row weeds, a region of intra-row weeding (ROIW) was defined as a narrow strip formed around the centerline of the processing image, which was based on the assumption/fact that crop plant row was approximately located along the image's centerline. The ROIW width was defined to enclose the crop plant row with a width of ±50 mm (on both sides of the crop plant, determined empirically through observations). Objects that inside the ROIW were considered as crops or intra-row weeds, and image processing algorithm was applied only to the ROIW.

Stereo image processing

Binocular stereo vision uses two parallel lenses to capture images of the same object from different viewpoints. The objects perceived through these two lenses will result in offsets within the obtained images. Once these offsets are known, the depth information of each image point can be calculated by triangulation.

During the stereo matching process, correspondence search was performed on edged stereo images and disparity calculation was applied only to the edge pixels. This strategy can largely reduce the correspondence search range; thereby enhance the weed recognition speed and accuracy.

The following criteria were specified when the plant disparity was calculated:

1) Stereo matching was performed on edged stereo images and disparity calculation was applied only to the

edge pixels;

2) As the camera was calibrated for lens distortions and camera misalignments, each row is an horizontal epipolar line, so the matching location in the right image must be along the same row as in the left image;

3) In order to increase the matching accuracy and reduce ambiguity, the range of the disparity search is limited to 49 (dmin) to 65 (dmax) pixels, corresponded to a longest range of 600mm and a shortest range of 450mm in which the system could detect the potential plant, respectively;

4) The correspondence search always starts at the dmin point and moves to the right for the set number of disparities.

Figure 3 illustrates the correspondence search in stereo images.

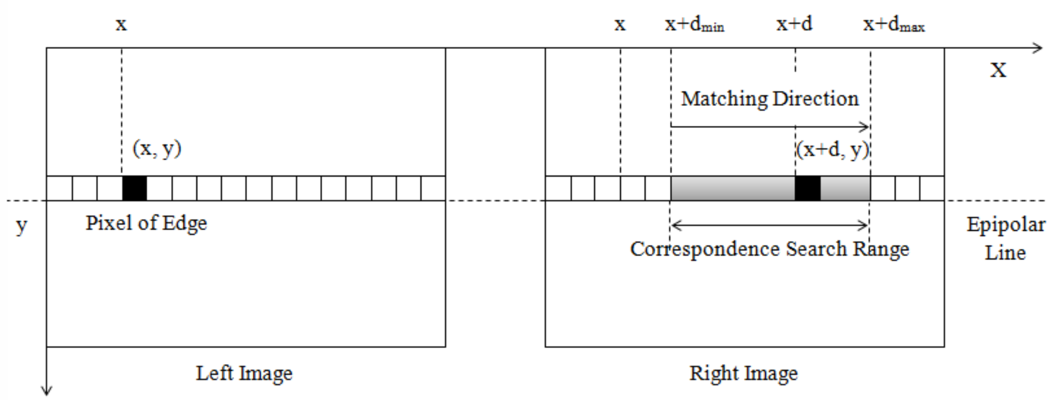


Figure 3. Illustration of correspondence search in stereo images.

Weed detection using plant spacing information

In a crop row, assuming that the crops are normally distributed (250mm), the plant spacing information could be extract to discriminate between crop and weeds. A histogram was found by summing the plot along the plant row direction (X-axis). Peaks in the histogram should correspond to the center location of plants (crop/weed). Due to irregular growth of plants and weeds in an arable field, a low-pass filter was used to improve the tracking of plants. Afterwards, the plant center position and plant width were determined.

Once the location of plants (crop/weed) are found, the distance between the plants and previous crop can be calculated. The plant whose distance away from the previous crop nearest to the assuming constant spacing is considered as crop, otherwise marked as weed.

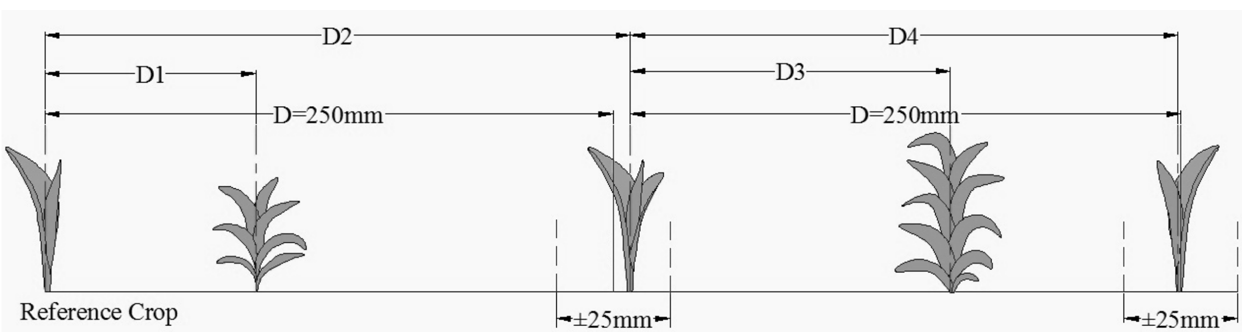


Figure 4. Weed detection using plant spacing information. The dash-dot lines indicate estimated plant centers. D (250mm) represents assuming constant plant spacing.

Figure 4 shows the schematic description of weed detection using spatial analysis. The algorithm assumes that the first plant in the sample image is crop (reference crop), the distance between the reference crop and next plants were calculated (D1, D2). The plant who at the D±25mm distance away from the reference crop was determined as crop (±25mm is used to offset the inaccuracies in the drilling of the crop, which usually cause variation in crop plant spacing). The detected crop was then marked as reference crop, and interplant distances between the plant pair (D3, D4) were obtained and compared with D±25mm. If there is a skip in a row section and a corn plant is not planted (missed crop), the position that is exactly at the constant spacing (D=250mm) distance away from the previous crop was then assumed as reference crop plant center. The machine vision system sequences the acquired images into one mosaicked image, after that, the above process was applied repeatedly to the mosaicked image. The flowchart of the overall image processing for crop and intra-row weed discrimination at early growth stages utilizing a stereo vision system is shown in figure 5.

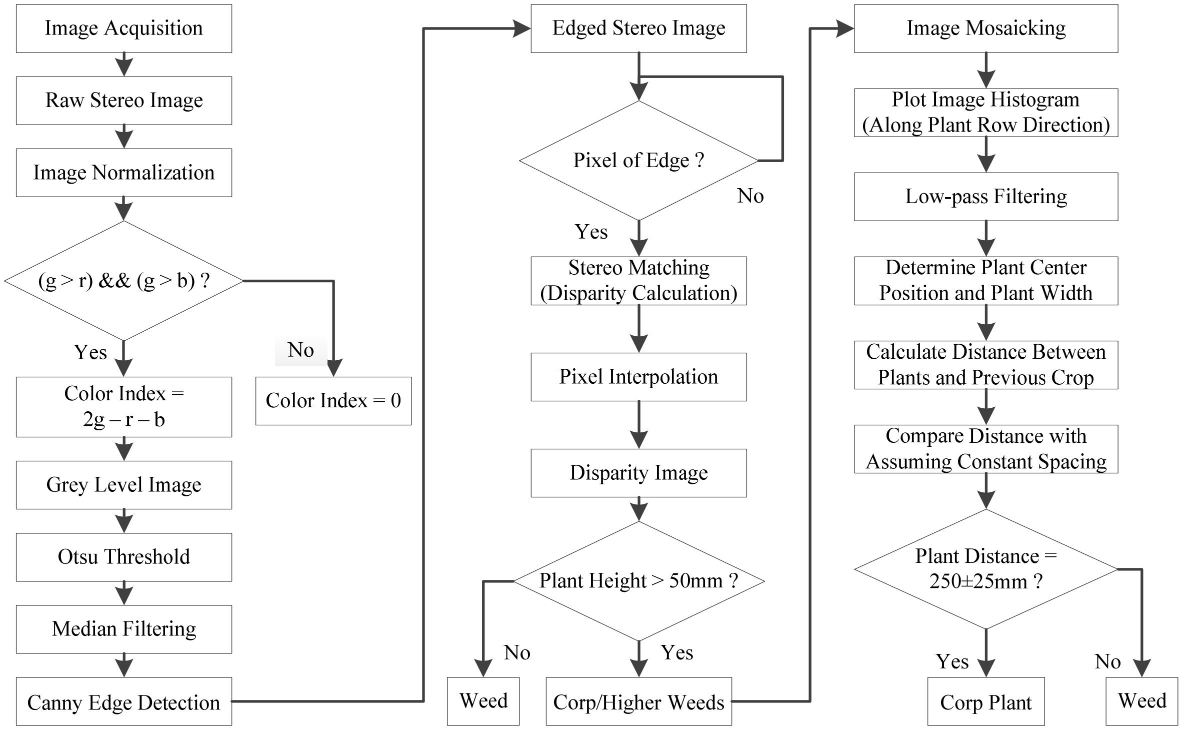
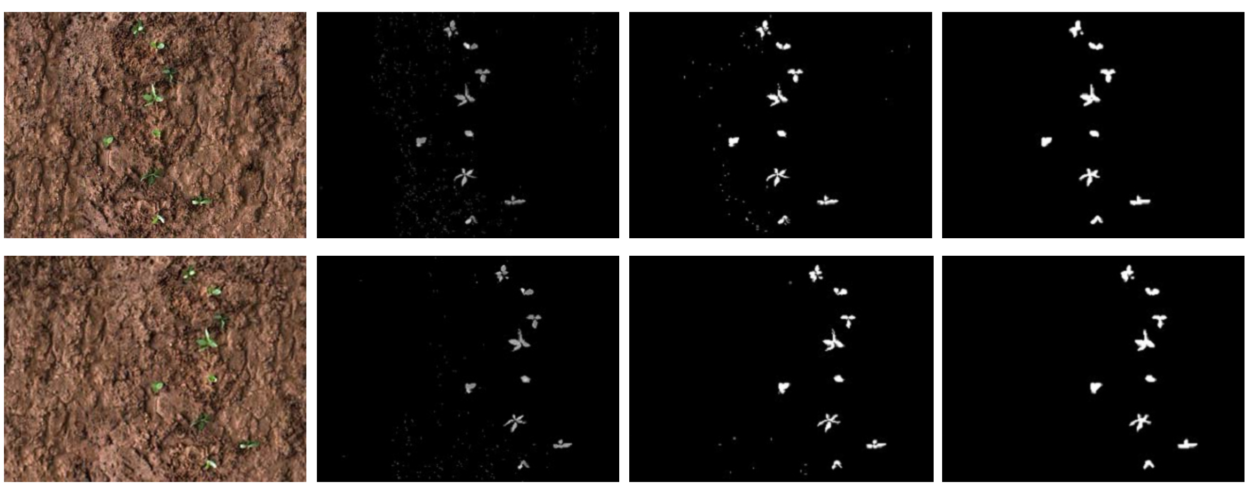


Figure 5. Flowchart of the overall image processing for crop and intra-row weed discrimination.

Results and discussion

Figure 6 gives an example of vegetation segmentation using color information, which shows that the modified excess green index improved the contrast of the test areas of the interest between the plants and background, and the median filter was successful in eliminating random noise in the image.



(a) (b) (c) (d)

Figure 6. Example results of image processing (upper (left image) and lower (right image)): (a) raw stereo images, (b) modified excess green index, (c) binary image created with the Otsu's method, (d) binary image after median filter.

Stereo image processing is given in figure 7, where figure 7(a) shows that edged stereo images were effectively obtained from segmented stereo images using canny operator. and figure 7(b) displays the result created from the edged stereo images (gaps in the edges were filled by linear interpolation), note that image processing algorithm was applied only to the ROIW. The height information is coded by grey intensity on the disparity image, brighter pixels indicate higher disparity. These are areas that are closer to the cameras. Dark areas have lower disparity, and are further away.

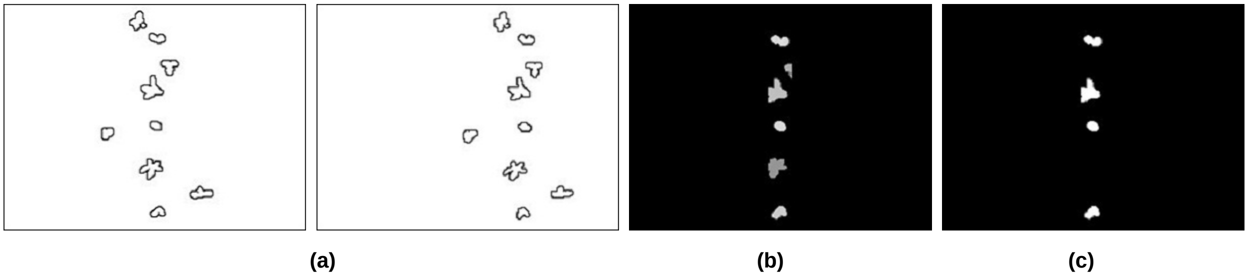


Figure 7. Stereo image processing: (a) edged stereo images (left and right), (b) disparity image created from the edged stereo images (gaps in the edges were filled by linear interpolation), (c) disparity image after segmentation.

Generally, a corn plant of V2-V3 growth stages is taller than 50mm, while weed is shorter than 50mm. Thus, 50mm was chosen as the height threshold so that any object lower than 50mm would be considered as weed. Figure 7(c) shows the plants higher than 50mm, in this case, only corn plants and few higher weed exist in the segmented image. To further detect the higher weed, plant spacing information was extracted and analyzed.

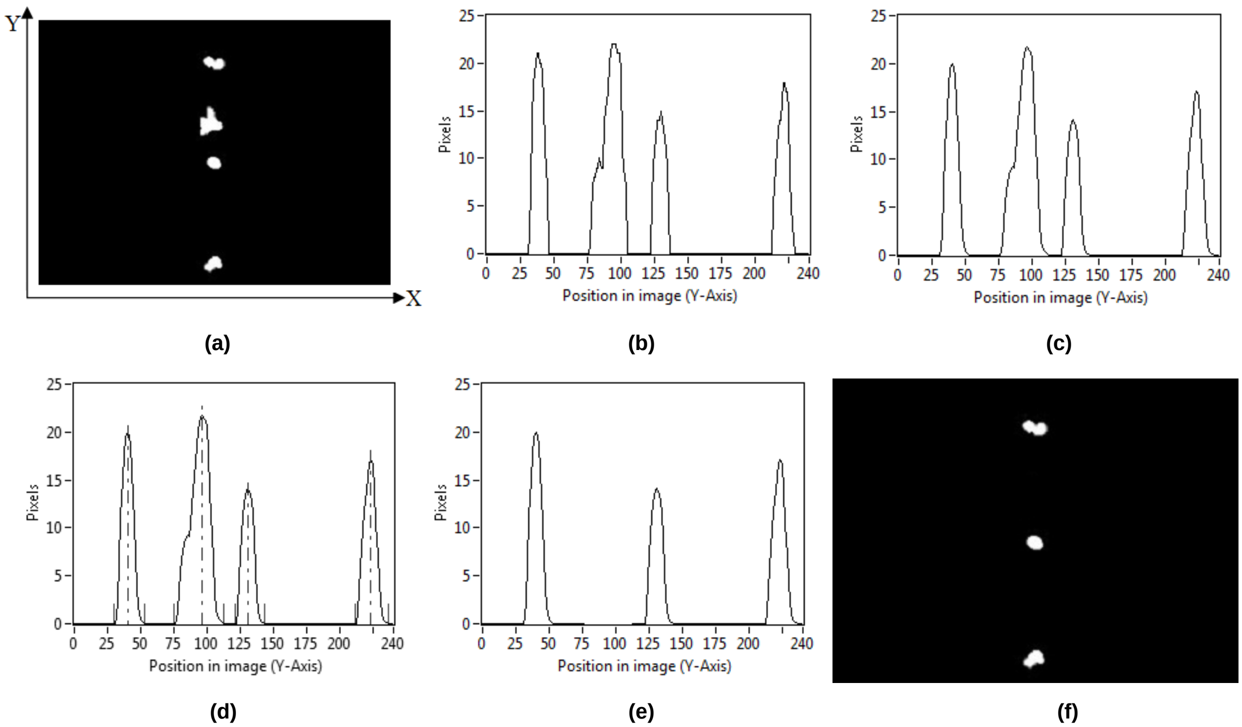


Figure 8. Crop and higher weed discrimination using plant spacing information: (a) segmented disparity image, (b) histogram of the sample image (plant pixels are summed in the direction of the x-axis), (c) histogram after low-pass filtering process. (d) location of plants (the dash-dot lines denote estimated plant centers, the solid lines represent plant width). (e) histogram of detected crop plant. (f) final image with identified crop plant.

Example result images of crop and higher weed discrimination using plant spacing information are shown in figure 8. As can be seen the peaks in the filtered histogram image give a quite good approximation of the actual position of the plants. Furthermore, better result was obtained with a more advanced growth stage due to the fact that at this stage plants tend to have smaller canopies and their leaves do not extend very much, which assure that the plant center locations were generally at the position of peaks in the histogram.

Conclusion

In this study, an image processing algorithm for crop and intra-row weed discrimination at early growth stages utilizing a binocular stereo vision system was developed and evaluated. The image processing was depicted in two steps. The modified excess green index was used to extract vegetation from the background. Then height and plant spacing information were applied to discriminate between crop and weeds.

For the relatively lower height intra-row weeds, the algorithm presented was shown to have promising performance. On the other hand, the use of interplant spacing information overcame the difficulties involved with using stereo vision system to detect the higher weeds.

The stereo matching algorithm yielded accurate disparity measurements with a much lower computational cost compared to the result of stereo correspondence in raw stereo images, which renders it suitable to real-time image processing.

The use of stereo vision system combined with prior information of plant spacing information proved successfully in identifying crop plants with higher classification accuracy. The proposed method has the ability to detect intra-row weeds for target oriented herbicide applications.

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