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Shadow-resistant segmentation based on illumination invariant image transformation

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Abstract

Robust plant image segmentation under natural illumination condition is still a challenging process for vision-based agricultural applications. One of the challenging aspects of natural condition is the large variation of illumination intensity. Illumination condition in the field continually changes, depending on the sunlight intensity, position, and moving clouds. This change affects RGB pixel values of acquired image and leads to inconsistent colour appearance of plant. Within this condition, plant segmentation based on RGB indices mostly produces poor threshold result. Besides, when shadows are presented in the scene, which is not uncommon in the field, plant segmentation becomes even more challenging.

Excessive green (ExG) and other RGB indices have been widely used for plant image segmentation. Although ExG based segmentation is generally accepted as one of the most common and effective methods, it often provides poor segmentation results especially when the image scene contains an extreme illumination difference caused by dark shadows.

To build an automated mobile weed control system, within the framework of the SmartBot project with the focus on the detection and control of volunteer potatoes in sugar beet, the vision-based system should first be able to detect plants out from the soil background even under dark shadow region.

The objective of this research was to evaluate the segmentation robustness of illumination-invariant transformation in comparison with ExG method under natural illumination conditions. Using illumination-invariant transformation, global and local thresholds (Otsu with reconstruction) were assessed to segment plant images. The ground shadow detection process was implemented to remove ground shadow region and background. Global threshold outperformed ExG, and local threshold could effectively remove the soil background region. Even under extreme illumination difference in a scene including sharp dark shadows due to bright sunshine, the illumination-invariant transformation produced robust segmentation results.

Keywords: segmentation, image processing, illumination-invariant transformation, shadow

1 Introduction

One of the major issues for vision-based agricultural applications is how to cope with unpredictable and variable natural illumination (Jeon et al., 2009; Nieuwenhuizen et al., 2010b). The illumination condition in the field continually changes depending on the sunlight intensity and position as well as moving clouds. This illumination change affects RGB pixel values of acquired image and leads to inconsistent colour appearance of plant (Sojodishijani et al., 2010; Teixidó et al., 2012). Within this condition, plant segmentation based on RGB indices with fixed value mostly produces poor threshold result. Besides, plant segmentation becomes even more challenging when shadows are presented in the image scene.

To overcome the problem of variable natural illumination, several studies have proposed housing setup with cover and hood (Åstrand and Baerveldt, 2003; Lee, 1998; Nieuwenhuizen

et al., 2010a; Piron et al., 2010). The machine vision device was mounted under the hood to block outside illumination, and in some cases artificial lighting was created inside of the housing to provide constant level of illumination at all times. This helps to overcome any issues with shadows and enables to acquire field images with unchanging illumination regardless of outdoor natural conditions, thus provides consistent RGB colour appearance of objects. However, housing setup with artificial lighting typically requires an additional space and resource within the system. This may raise a critical issue in a mobile-based platform because available resource and space in mobile system are very limited.
Without using the housing and artificial lighting, shadows are inevitable in the field. Shadows can be created by mobile system, vision acquisition device, and/or nearby plants. Although Excess Green (ExG) based segmentation is widely used and generally accepted as one of the most effective methods (Gée *et al.*, 2008; Mathanker *et al.*, 2007; Swain *et al.*, 2011; Tellaeche *et al.*, 2008), it often provides poor segmentation results especially when the image scene contains an extreme illumination difference caused by dark shadows. This is due to the weak green value of RGB plant pixels under dark shadow region, as ExG takes advantage of the feature that vegetation plant pixels have a strong green component as compared to background soil pixels (Lin, 2009).
To build an automated mobile weed control system, within the framework of the SmartBot project with the focus on the detection and control of volunteer potatoes in sugar beet, the vision-based system should first be able to detect plants out from the soil background even under dark shadow region.
Recent study suggests that illumination-invariant images may provide reliable plant segmentation results under natural illumination condition (Lati *et al.*, 2013), as a logarithmic transformation followed by xyY colour space conversion can be used to remove shadows in the image scene (Bajcsy *et al.*, 1990). The objective of this research was to evaluate the segmentation robustness of illumination-invariant image transformation in comparison with the ExG under natural illumination conditions. Using illumination-invariant transformation, global and local thresholds (Otsu with reconstruction) were assessed to segment plant images. The ground shadow detection process was implemented to remove ground shadow region and background.

2 Materials and methods

Colour pixels in ColorChecker® were selected and analyzed with illumination-invariant transformation under different outdoor illumination conditions. Based on the pixel value difference among selected colours, a global threshold value was determined to differentiate between soil- and plant-related colours. Two threshold procedures were implemented with acquired field images to extract plant pixels. First, global threshold based on fixed threshold value was implemented, and its performance was compared with ExG method. Second, local threshold with ground-shadow detection procedure was implemented to have adaptive threshold value depending on the image scene.

2.1 ColorChecker® image acquisition

ColorChecker® (X-Rite, Grand Rapids, MI, USA) images were acquired with a colour camera (NSC1005c camera, New Imaging Technologies, France) on different days under different outdoor illumination conditions. The image resolution was 1280 x 720 pixels. ColorChecker® images on the Unifarm field in Wageningen, Netherlands were taken at various times during daylight in June, August, and October 2013 (Fig. 1).

Figure 1: Acquired ColorChecker® images in different illumination conditions

As shown in Fig. 2, six colours in the ColorChecker® were selected to analyse colour pixel values, of which three colours were related to plants (Foliage, Yellow Green, and Green) and three colours were related to soil and background (Dark Skin, Moderate Red, Magenta). The selected colours were processed with following steps for illumination-invariant transformation: first, RGB colour values were converted into XYZ space (Eqs. (1)) (Stokes *et al.*, 1996); second, X,Y, and Z values were normalized using Eqs. (2) to obtain x and y values in xyY space; and third, a double logarithmic transformation ($log(x/y)$, $log(Y/y)$) was applied to the x, y, Y components (Lati *et al.*, 2013). Based on the distinction between plant (green-related pixels) and soil-related colour pixels, segmentation value for global threshold was set.

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} 0.4124 & 0.3576 & 0.1805 \\ 0.2126 & 0.7152 & 0.0722 \\ 0.0193 & 0.1192 & 0.9505 \end{bmatrix} \begin{bmatrix} R_{sRGB} \\ G_{sRGB} \\ B_{sRGB} \end{bmatrix} \tag{1}$$

$$x = \frac{X}{X+Y+Z}, y = \frac{Y}{X+Y+Z}, z = \frac{Z}{X+Y+Z} \tag{2}$$

Figure 2: Six selected colours (marked with a red square) in ColorChecker®.

2.2 Field image acquisition

Crop images were acquired in two experimental sugar beet fields in Wageningen, Netherlands. One experimental field was a sandy soil site and the other was clay soil site. Sugar beets were sown in experimental fields on May 2, July 26, and September 3, 2013, and each time on different plots. Crop images were obtained on different days under different illumination conditions, as a manually-controlled mobile-device was driven through the fields at various times during daylight in June, August, and October 2013. Several different illumination conditions were considered, including extreme illumination scene caused by direct sunlight and shadow.

2.3 Plant segmentation by thresholding

2.3.1 Global threshold with fixed threshold value

The acquired field images were processed to evaluate the plant segmentation performance of the specified threshold value with the illumination-invariant transformation as well as with the conventional ExG method. Segmentation based on global threshold was performed to extract plant pixels.

2.3.2 Local threshold (Otsu) with ground-shadow subtraction

Segmentation to remove background soil pixels was based on a local thresholding technique, smoothing (pre-processing) followed by Otsu with reconstruction (Gonzalez *et al.*, 2004; Otsu, 1979). The same procedure in Sec 2.1 was implemented to acquired field images to remove background soil pixels.
To detect shadows that are rendered on the soil background, a ground-shadow detection process was performed as a simultaneous and concurrent process along with local threshold (Fig. 3). A logarithmic transformation ($log(x * y/Y)$) was applied in xyY components, and Otsu 3-threshold was performed to extract ground-shadow region. This extracted ground-shadow region is subtracted from the segmentation output of local threshold. All calculations and image-processing procedures were implemented with MATLAB. Segmentation results were manually examined.

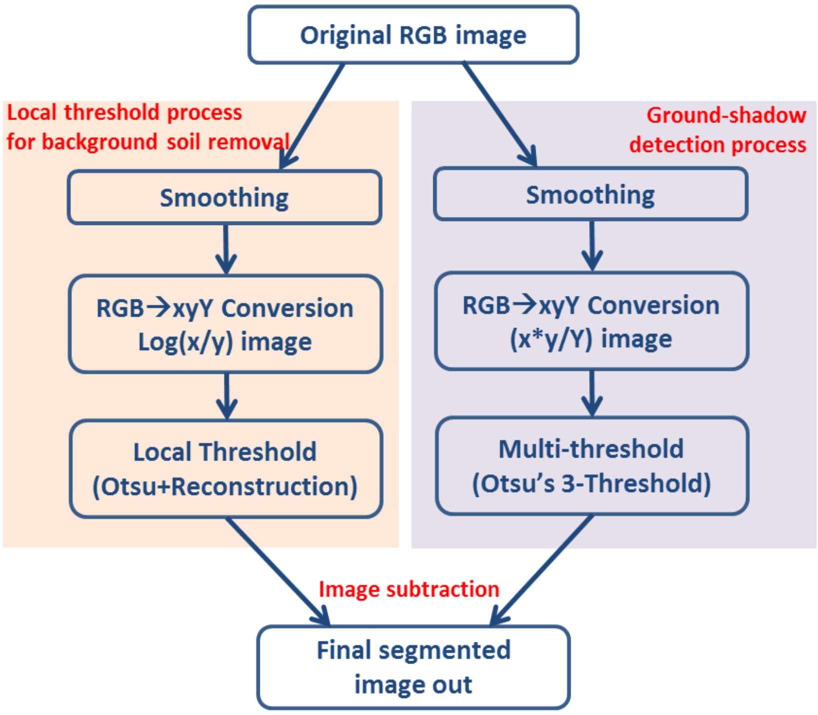


Figure 3: Flowchart of local threshold and ground shadow detection process

3 Results

3.1 Selected ColorChecker® colours

With illumination-invariant transformation, the green-related pixel values extracted from the ColorChecker® were clearly distinct from those of the soil- and background-related ones regardless of illumination intensity. Green-related pixels were easily separated from other colours. The pixel values derived from selected colours are shown in Fig. 4. The $log(x/y)$ value of green-related pixels was above 0.42 while the $log(x/y)$ value of soil- and background-related ones was below 0.4.

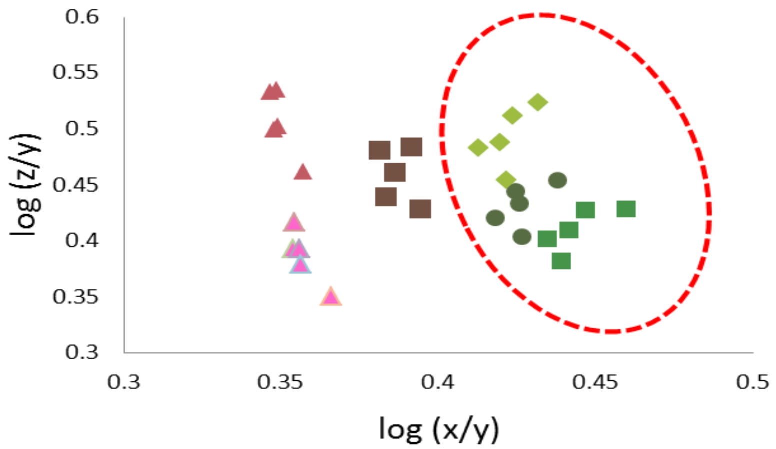


Figure 4: Hue projection of selected colours with illumination-invariant transformation. The points in the dashed oval represent the green related squares and the other points the soil related squares of the ColorChecker®.

3.2 Global threshold with fixed threshold value

Plant segmentation performance was manually assessed between illumination-invariant transformation with a global threshold and ExG method. Global threshold values were set from ColorChecker analysis in Sec 3.1. As shown in Fig. 5, the illumination-invariant transformation with global threshold produced more effective segmentation results for the field images than the ExG method did. Even under extreme illumination differences in a scene including sharp dark shadows due to bright sunshine, the illumination-invariant transformation provided a clear extraction of plant material, while excessive green provided no plant image extraction.

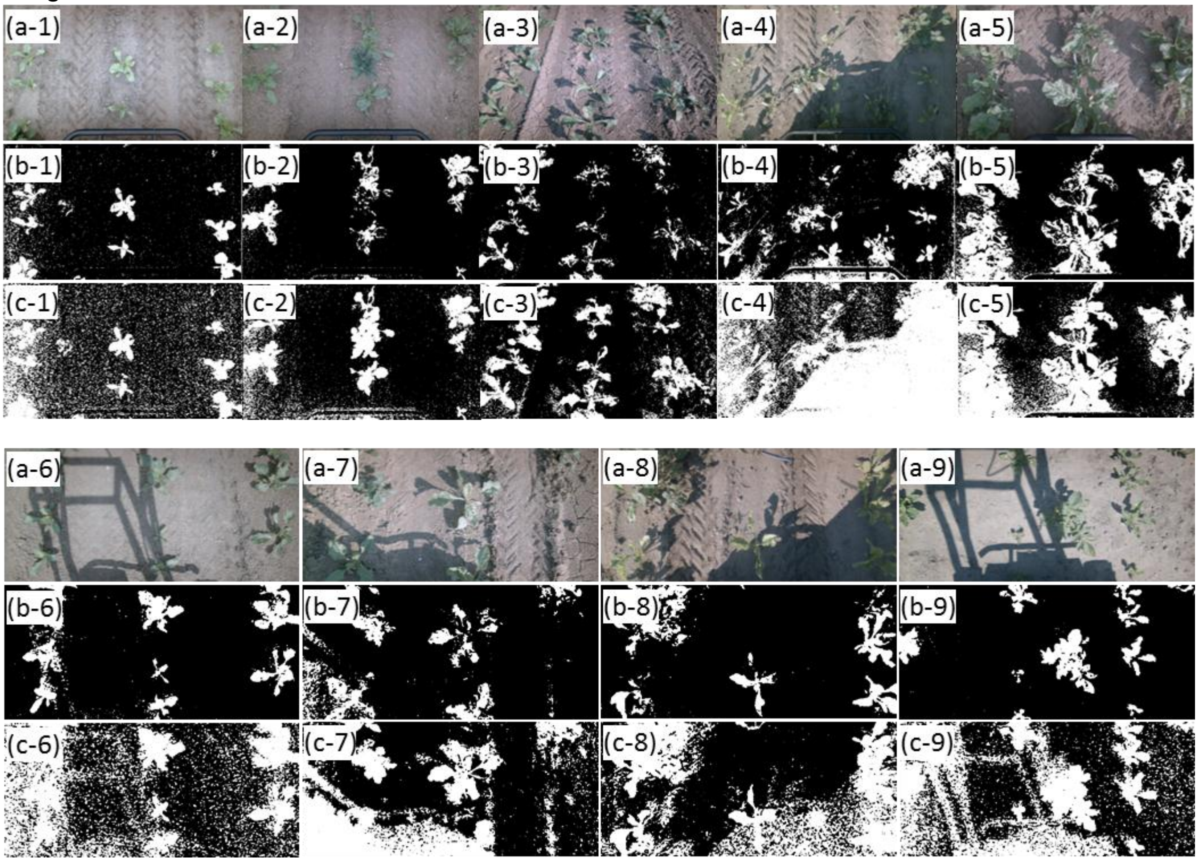


Figure 5: Plant segmentation under natural illumination condition. (a) Original field images, (b) segmented images based on illumination-invariant transformation, (c) segmented images based on ExG.

3.3 Local threshold (Otsu) with ground-shadow subtraction

Local threshold based on Otsu's method removed the background soil region. Both shadow and green pixels were extracted with the local threshold if the image scene contains any shadow region, while only green pixels were extracted if the image scene had no shadows. As a concurrent procedure along with the local threshold, the ground shadow region was identified based on Otsu's 3-threshold (Fig. 6). Otsu's 3-threshold segments the image scene to three different regions based on maximum inter-region variance. The ground-shadow region was subtracted from the segmentation output of local threshold. As shown in Fig. 7, green plant pixels were clearly extracted even under sharp dark shadows. The average processing time for one image was 0.42 seconds.

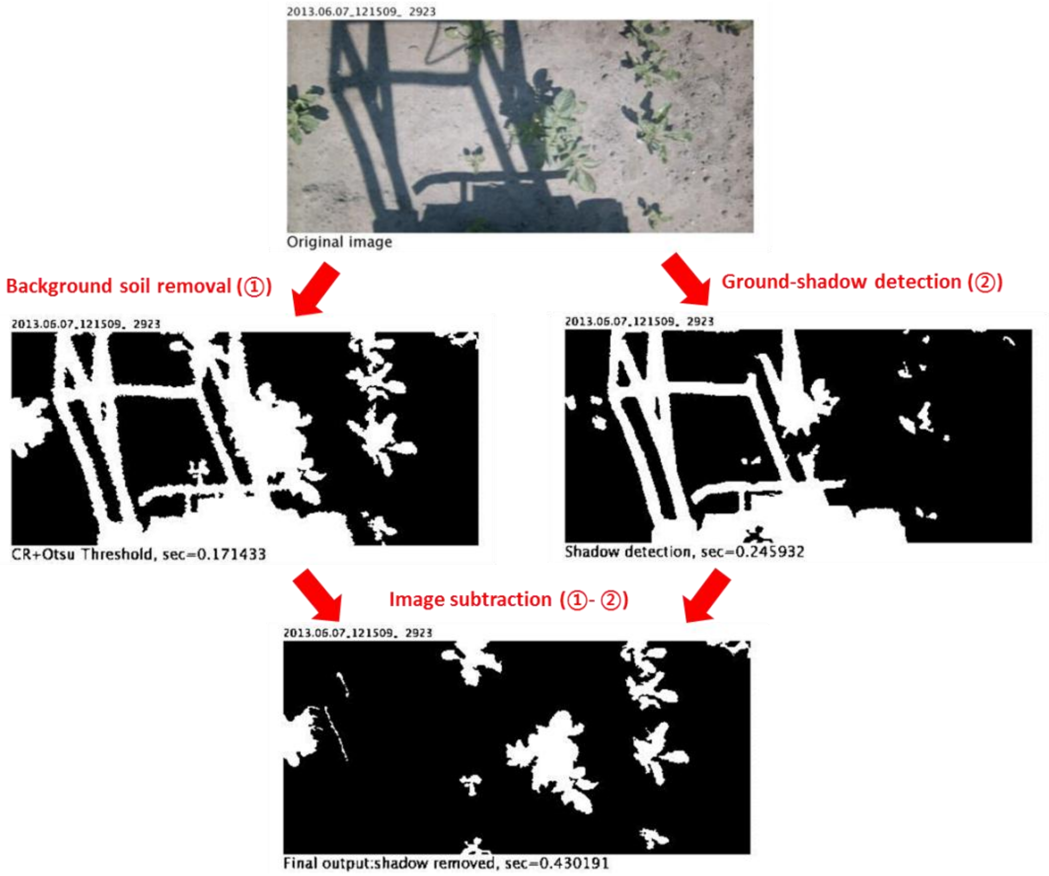
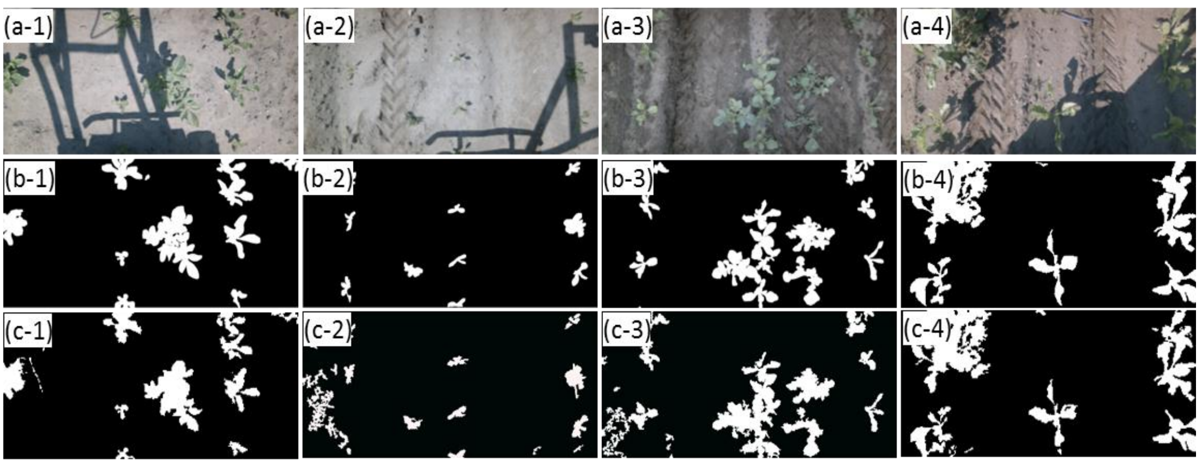


Figure 6: Local threshold with ground-shadow subtraction



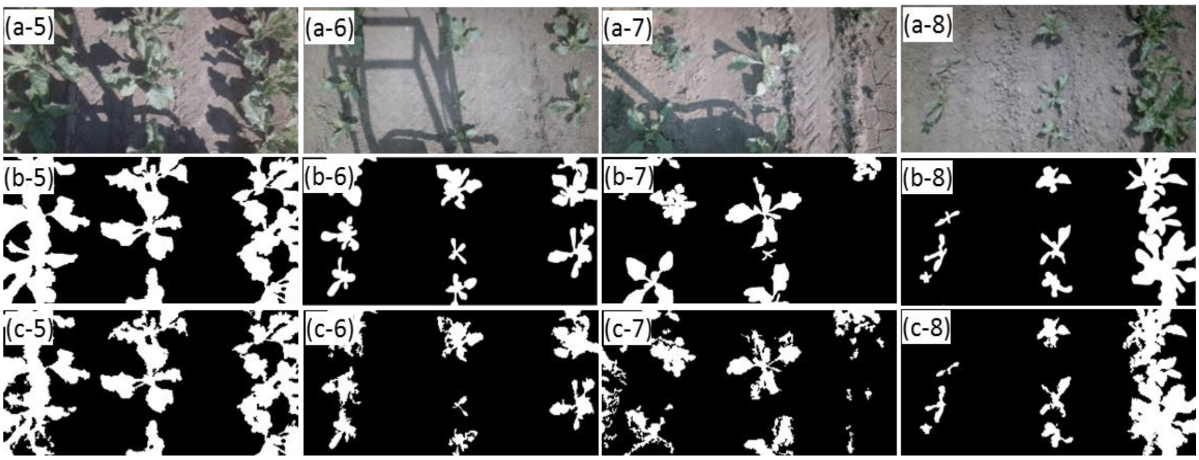


Figure 7: Plant segmentation results. (a) Original field images, (b) ground-truth images, (c) segmented images based on ground-shadow removal

4 Discussion & conclusion

In this study, performance of illumination-invariant transformation and ExG were assessed under natural illumination conditions. The acquired crop field images were processed to evaluate plant segmentation performance by specified threshold with illumination-invariant transformation as well as with ExG. Illumination-invariant transformation has shown robust plant segmentation performance under outdoor natural illumination conditions, and outperforms ExG method. ExG method has long been used as a general solution for various vision-based agricultural applications. However, ExG could not be used in practical field operation as it provides poor segmentation results especially when the image scene contains dark sharp shadows. Since shadows are inevitable and unavoidable in the field, they should be removed or compensated not only for plant segmentation process but also for individual plant identification. Illumination-invariant transformation has important implication for developing vision-based automated system. However, the mechanism in the illumination-invariant transformation process with colour space conversion has not yet been fully understood in agricultural domain. Future studies on this topic are therefore recommended. Deeper knowledge and understanding of colour science may additionally be required to build robust image processing procedures for agricultural field applications.
All output images were manually examined. Manual evaluation of segmentation performance may raise a potential issue of human error. To provide solid performance evaluation, quantitative performance criteria should be developed and introduced. Further work is required to establish this.
Based on the obtained results, it was concluded that the illumination-invariant transformation is a promising technique that provides a robust segmentation under natural illumination conditions.

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