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Automated robust crop-row detection in maize fields based on position clustering algorithm and shortest path method

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ABSTRACT

Crop row detection is critical for precision agriculture and automatic navigation. In this paper, a novel automatic and robust crop row detection method is proposed for maize fields based on images acquired from a vision system. As the image quality is easily affected by weed pressure and gaps in the crop rows, the proposed method was designed with the required robustness in order to deal with these undesirable conditions, and it consists of three sequentially linked phases: image segmentation, feature points extraction, and crop row detection. The image segmentation is based on the application of a modified vegetation index and double thresholding combining the Otsu method with the particle swarm optimization, thus achieving a separation between the weeds and crops. During the procedure of crop row detection, the position clustering algorithm and shortest path method were applied successively to confirm the final clustered feature point set. Finally, a linear regression method based on least squares was employed to fit the crop rows. The experimental results show that the detection accuracy of this proposed method is 0.5°, which out-performs the classical approach based on the Hough transform.

1. Introduction

Automatic detection of crop rows in natural fields is essential for precision farming and automatic navigation and for agricultural robots. It has a wide range of applications such as planting, fertilization, plant protection, weeding, and harvesting (Jiang et al., 2015). With accurately detected crop rows from the camera images, these processes can be easily automated by guiding an autonomous vehicle according to the detected rows (Vidović et al., 2016). Obviously, automatic navigation is quite beneficial as it would reduce the operator fatigue and improve the vehicle positioning accuracy, which would lead to higher productivity (Gerrish et al., 1997). Therefore, the development of reliable and real-time crop row detection methods is of great significance in the field of precision farming.

This important issue primarily concerns crop-row and weed detection, which has attracted much attention (Montalvo et al., 2012). Different imaging-based methods have been used for detecting crop rows (García-Santillán et al., 2017a). Typically, these methods fall into a few categories according to their detection principle, such as Hough transform (HT), linear regression, blob analysis, stereo vision, and horizontal strips.

The Hough (1962) is one of the most commonly used machine vision methods for identifying crop rows (Slaughter et al., 2008). It is a feature extraction technique used in digital image processing, image analysis, and computer vision (Duda, 1972). The core concept of the HT is the accumulation of the votes and detection of the peaks in the parameter space. In order to speed up the calculation, Xu et al. (1990) proposed a randomized HT (RHT) algorithm. The special idea involved in locating lines with the RHT is that it randomly selects two edge pixels each time with equal probability in the image space. However, high weed pressure and serious crop loss would cause the incorrect detection of the lines or even inability to detect the lines.

The linear regression method was used to detect lines fitted to outliers as a method of identifying the crop-row guidance information (Billingsley and Schoenfisch, 1997). In addition, Søgaard and Olsen (2003) located barley crop rows using weighted linear regression. This is a feasible approach that is applicable when pixels of crop rows are well separated from those of the weeds. Moreover, Montalvo et al. (2012) and Guerrero et al. (2013) predicted the expected position of the crop rows and then adjusted the position through the Theil-Sen estimator. However, its effectiveness is highly affected by the pixels of the weeds. Therefore, linear regression is only feasible if the pixels of the weeds and crops have been separated.

The blob analysis method is used to identify and characterize regions of contiguous pixels of the same value in a binaries image (Fontaine and Crowe, 2006). The gravity centers of these regions

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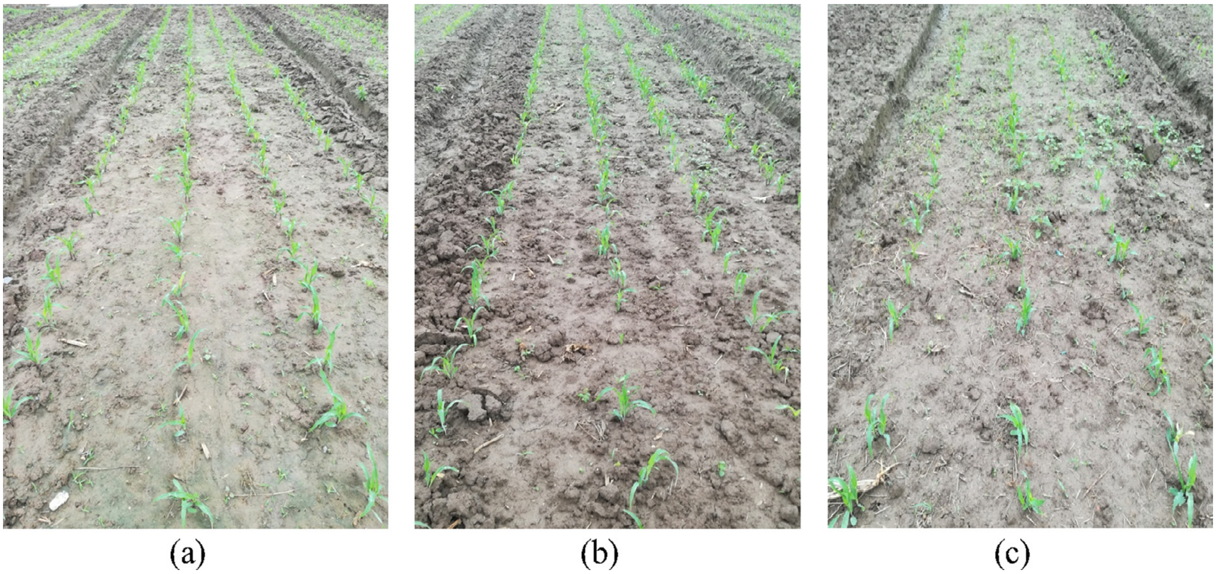

Fig. 1. Original images with various weed distribution situations: (a) low weed pressure, (b) presence of gaps, and (c) high weed pressure.

determine straight rows by associating an equation with each crop row (García-Santillán et al., 2017a). Based on these associations and the direction and displacement of the tractor, crop rows were detected (Burgos-Artizzu et al., 2011; Bengochea-Guevara et al., 2012). Jiang et al. (2015) presented an algorithm based on small regions of interest and least squares fitting while taking into consideration known inter-row spaces in fields of wheat, corn, and soybean. However, this algorithm does not distinguish between blobs caused by weeds and crops well in weedy areas.

The stereo vision method is usually used when the heights of the weeds and crop plants above ground are highly visible and when the weed and crop plants differ in height (Romeo et al., 2012). Kise and Zhang (2008) developed a stereo-vision-based crop-row tracking navigation system for agricultural machinery. Stereo-image processing is used to determine the 3D position of the field of the object of interest from the obtained stereoscopic image. Furthermore, Rovira-Más et al. (2008) applied precision vision to other areas of precision agriculture. However, this method is only feasible if the crop or weeds in the 3D scene have relevant heights.

The horizontal strips method determinates crop rows through image analysis without segmentation. Søgaard and Olsen (2003) firstly divide the color image into its red, green, and blue channels and then extract the living plant tissue by applying well-tested methods (Woebbecke et al., 1995). Lastly, after the transformation, the gray-level images are divided into 15 horizontal strips, and the vertical sum of the gray values for each strip are calculated. Moreover, Sainz-Costa et al. (2011) developed a strategy for identifying crop rows based on the analysis of video sequences. The above methods work well in the case of low weed pressure. However, in complex conditions comprising high pressure or a severe shortage of available images, the strip features generally cannot be detected accurately.

However, as mentioned above, it is obvious that complex outdoor agricultural environments have a significant influence on the image processing. Gaps may appear in the crop rows owing to a lack of germination, the occurrence of defects, or the presence of pests/diseases during planting. Different plant heights and volumes are mapped under image perspective projection with different widths (García-Santillán et al., 2017b). In addition, a high ratio of weed density with spectral components of similar color to crops can be present in the inter-row spaces and close to the real crop rows, thus resulting in false widths in the imaged crop rows and, hence, fake crop rows during detection (García-Santillán et al., 2017a).

While extending the advantages of the existing methods described above, we design a new crop row detection method that can cope with complicated conditions with a focus on weed pressure and crop gap treatment. The designed automation method comprises three main modules: image segmentation, feature point extraction, and crop row detection. In the first module, a modified vegetation index and double thresholding combining the Otsu method with the particle swarm optimization (PSO) method were used to obtain a good segmentation result. Subsequently, the vertical projection method is applied to divided horizontal strips in order to extract the feature points that indicate the crop row centers. The clustered point sets are then obtained based on the position clustering algorithm and shortest path method. Lastly, the crop rows are detected using least squares fitting. Therefore, the main contributions of this paper are the creation of a new vegetation index and optimization of the double thresholding method to improve the effect of segmentation; in addition, we apply the position clustering algorithm and shortest path method in order to make the least squares method (LSM) feasible, which further improves the robustness of the method.

2. Materials and methods

2.1. Image acquisition

Maize crop images in the seedling stage were selected in this study. A Samsung S850 color camera was mounted on a farm vehicle and the 300 images were captured during May 2017 in the same maize fields in the countryside. The proposed algorithm is developed using Microsoft Visual C++ 6.0 and the free computer vision library OpenCV 1.0. Furthermore, the digital images were stored as 24-bit color images with resolutions of 3264 × 2448 pixels and saved in RGB (red, green, and blue) color space in the JPEG format. Camera setting was: pitch and roll angles of 30° and 0° with the camera placed at a height of 1.5 m from the ground. In order to reduce the amount of calculation required, sample processing is performed on the image by applying a pixel area relationship resampling method. As this method can prevent the occurrence of ripples when the image is zoomed out. Subsequently, the image size is shrunk to 793 × 595 pixels. In addition, Fig. 1 displays three illustrative examples at different growth environments of maize in conditions comprising (a) low weed pressure, (b) the presence of gaps in crop rows, and (c) high weed pressure.