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Crop feature extraction from images with probabilistic superpixel Markov random field

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ABSTRACT

In the process of agriculture automation, mechanization and intelligentialization, image segmentation for crop extraction plays a crucial role. However, the performance of crop segmentation is closely related to the quality of the captured image, which is easily affected by the variability, randomness, and complexity of the natural illumination. The previously proposed crop extraction approaches produce inaccurate segmentation under natural illumination when highlight occurs. And specularity removal techniques are still hard to improve the crop extraction performance, because of the flaw of their assumption and the high requirement of the experimental configuration. In this paper, we propose a novel crop extraction method resistant to the strong illumination by using probabilistic superpixel Markov random field. Our method is based on the assumption that color changes gradually between highlight areas and its neighboring non-highlight areas and the same holds true for the other regions. This priori knowledge is embedded into the MRF–MAP framework by modeling the local and mutual evidences of nodes. Besides, superpixel and Fisher linear discriminant are utilized to construct the probabilistic superpixel patches. Loopy belief propagation algorithm is adopted in the optimization step. And the label for the crop segmentation is provided in the final iteration result. We also compare our method to the other state-of-the-art approaches. The results demonstrate that our method is resistant to the strong illumination and can be applied to generic species. Moreover, our approach is also capable of extracting the crop from the shadow regions. Statistics from comparative experiments manifest that our crop segmentation method yields the highest mean value of 92.29% with the lowest standard deviation of 4.65%, which can meet the requirement of practical uses in our agriculture automatic vision system.

1. Introduction

1.1. Problem statement

An increasing amount of automatic control systems have been applied in the field of agriculture industry to meet the demands of large areas of crop growth automatic supervision (Gebbers and Adamchuk, 2010; Zhang et al., 2002; Hushon, 1990). In the process of automatic monitoring, computer vision has been utilized to mine data from the captured image. It has many applications in agriculture automation field, such as physiological status estimation (Sakamoto et al., 2012; Soltani et al., 2011; Xiang and Tian, 2011), cover crop estimation (Cruz-Ramírez et al., 2012; Hervás-Martínez et al., 2010), crop or weed identification (Burgos-Artizzu et al., 2011; Guerrero et al., 2012b), crop row detection (Gée et al., 2008; Guerrero et al., 2012a; Kaizu and Imou, 2008), autonomous vehicles guidance (Bakker et al., 2008; Reid et al., 2000; Subramanian et al., 2006) and crop disease detection (Gonzalez-Andujar, 2009; Pang et al., 2011; Pugoy and Mariano, 2011).

In this paper, we mainly focus on crop extraction to separate the candidate's green plant material or regions of interest from the background. However, the natural illumination has a decisive influence on the captured image, due to its properties with uncertainty and instability. Fig. 1(a)–(c) displays images under different illumination intensity. In cloudy days, as shown in Fig. 1(a), two factors lead to misclassifying soil into crop. One is the reduction in red component owing to the dark illumination, and the other one is that the color of the soil is similar to dark green. In sunny days, the relative position of the sun and the object generates shadows in Fig. 1(b). This also causes misclassifying shadow pixels into crop category. In over-sunny days, as shown in Fig. 1(c), specular

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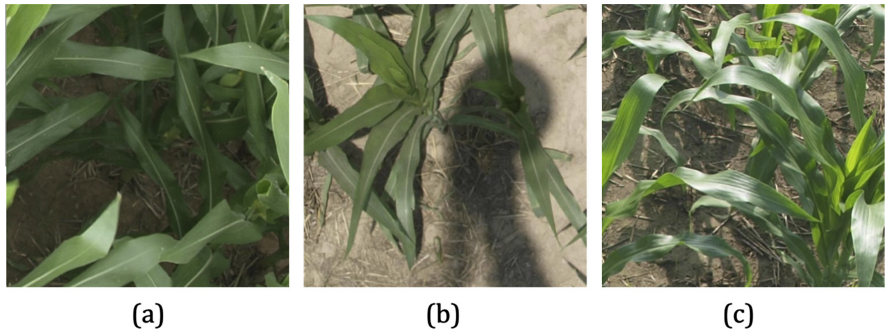

Fig. 1. The images under different illumination intensity: (a) lacking in enough illumination results in the soil of dark green; (b) the relative position of the sun and the object generates shadows in the image; (c) specular reflection produces white light spots in the leaf or soil. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

reflection produces white light spots in the leaf or soil. These result in misclassifying those highlight pixels into wrong category.

1.2. Related work

Previous studies document a variety of approaches for crop extraction. All these methods demonstrate good performance under plain and simple environments with soft illumination and clear soil conditions. Most approaches fall into two broad categories. One is the color-index-based algorithm, and the other is the learning-based algorithm. Both categories have their own advantages. In the color-index-based methods, color is an intuitionistic and easy characteristic, which is utilized to distinguish the crop from the background. In the learning-based algorithm, it employs the learning process from the training samples, which to a certain extent shows adaptability to the changing illumination. For simplicity, in this paper, R, G, and B are defined to represent red, green, and blue color components of the RGB color space respectively.

In the color-index-based algorithm, the excess green index ($ExG = 2G - R - B$) (Woebbecke et al., 1995) is based on the hypothesis that the green component is more salient in green crop extraction. The excess green minus excess red index ($ExGR = ExG - ExR$, $ExR = 1.4R - G$) (Meyer et al., 1999; Neto, 2004) inhibits the red component by subtracting the ExR index (Meyer et al., 1999). Similarly, the normalized difference index ($NDI = (G - R)/(G + R)$)(Perez et al., 2000; Woebbecke et al., 1993) uses both green and red components and then improves the performances through a region growing process. And the color index of vegetation extraction ($CIVE = 0.441R - 0.811G + 0.385B + 18.78745$) (Kataoka et al., 2003) and the vegetation index ($VEG = G/(R^a \times B^{1-a})$, where a is set to be a constant) (Hague et al., 2006) use all three color components. In all, they accentuate the role of green component and adopt the combination of channels from RGB color space. Then the combination results are converted into the gray images. And the fixed threshold for segmentation is obtained through Otsu (1975) method for the ExG, NDI, CIVE methods. In the VEG method, the process of binarization is carried out by the mean value. In short, a fixed threshold is required for a single image for all above color-index methods. However, these threshold methods may fail to generate appropriate thresholds for crop extraction because of the presence of highlights, noted by (Perez et al., 2000). Their occurrences violate the surmise and in fact the green channel may not be salient than other two channels under these situations. Therefore, thresholding can only be applied in only limited situations.

In the learning-based algorithm, they mainly have two steps, training and classification. In the EASA method (Ruiz-Ruiz et al., 2009; Tian and Slaughter, 1998), the training process begins with clustering and ends with Bayesian classifier. And the classification process is completed through a look-up table. In AP-HI approach (Yu et al., 2013a), their AP-HI method is based on the assumption that the histogram of hue under certain intensity is similar to the Gauss distribution curve. Its training process is to calculate the mean value and the standard deviation of each hue level and then to build up the corresponding look-up table (LUT). And the classification process is through a discriminant function checking with the LUT. In (Zheng et al., 2009), mean sift algorithm and back propagation neural network (BPNN) have been utilized for segmentation. In (Guo et al., 2013), decision tree and image noise reduction filters are used for crop extraction. In (Montalvo et al., 2013), support vector machine (SVM) has been applied for crop identification. In (Bai et al., 2013), the vegetation segmentation method based on particle swarm optimization (PSO) clustering and morphology modeling in CIELAB color space are introduced. All these methods can adapt to the change of illumination to some extent. Nevertheless, their performances rely on the size of training samples to cover the characteristic of different illumination. Since the change of illumination happens all the time without rules and regulations, the training samples are limited and the classification results cannot be guaranteed, especially when highlight takes place.

To demonstrate their different segmentation performances, one image captured under strong illumination is shown in Fig. 2(a) and their corresponding results are demonstrated from Fig. 2(b)–(g). The highlight spots occurring in the leaf are tagged by red cycle in the original image. And the misclassified regions in the processing images are labeled as well. From Fig. 2, we observe that all these labeled highlight regions are misidentified.

Thus, the methods above do not perform well enough when highlight occurs. This is because that they work in the premise of perfect diffuse reflection and that they normally consider the specular pixels (highlights) as outliers or noise (Artusi et al., 2011). Hence, specularity removal techniques have been analyzed to improve the performance of crop extraction under strong illumination. These techniques can enhance the image quality in the premise that the image is captured under controlled illumination. Based on the type of input data, they can be classified into two categories: single-image and multi-image methods.

In the single-image category, both color reflection model (CRM) (Klinker et al., 1987, 1988) and S space method (Bajcsy et al., 1996) carry out the specularity removal process through the analysis of distribution of the diffuse and specular components in the color space. But the requirements of manual involvement and the estimation of illumination color from the CRM method limit its application in automatic vision system. Besides, the flaw of the assumption and segmentation limits noted by (Bajcsy et al., 1996) is another factor confining the application of the S space