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Maize and weed classification using color indices with support vector data description in outdoor fields

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ABSTRACT

An automated method for maize and weed detection is very important to efficiently remove weeds and precisely calculate the quantity of maize. Color features were used in this study to investigate a simple maize-detection method using a color machine-vision system. Conventional image segmentation methods based on RGB values cannot separate maize from weeds because of the highly similar image RGB values of these plants. Thus, a post-processing algorithm was developed to distinguish maize from weeds after image preprocessing. Color indices were used to develop a classification model. The nine optimal features were selected by principal component analysis to reduce the effect of illumination. Finally, support vector data description was used as a classifier to differentiate maize from the mixes of different species of weeds. Pictures were taken by a commercial camera and used to verify the stability of the algorithm. Results show that the overall accuracy for three years is 90.19%, 92.36% and 93.87%, respectively. And the color indices used in this work were stable under various weather conditions and over time.

1. Introduction

Expert systems are widely applied in agricultural studies, of which plant recognition has been increasingly applied in automatic control systems to meet the demand of automatic supervision for large areas with crops. Thus, expert systems for crop-plant recognition have become highly important to hasten and facilitate agricultural tasks.

Maize production worldwide is approximately 875 Mt (Kurtulmuş and Kavdir, 2014), and maize can be planted in any climate. Maize is agriculturally important because of its nutritional value and high consumption by humans. Excessively high or small number of maize planted per unit area will reduce agricultural production. Moreover, the maximum production of maize depends on the nutritional supply of the fields where maize grows. Several studies have shown that plant density is related to the yield in fields (Dai et al., 2015; Yang et al., 2014). Under the same fertilizer level, rational close planting and increasing the basic seedlings contribute to promote yield.

Weeds are spread in cropland in every growing period of maize, and they compete with maize for water and nutrient (Westerman et al., 2008). Weeds should be removed throughout crop growth, especially in maize seedling, to reduce loss. Using herbicides is the most common method for weeds removal because of its high efficiency in controlling weeds (Ali et al., 2014). However, blanket spraying of herbicides will leave pesticide residues and lead to environmental pollution. The proper application of herbicides should be studied to reduce the use of herbicides and protect the field environment. Thus, plant recognition is important in crop fields to locate plant more accurately and calculate the coverage of crops more precisely. In traditional methods, observing maize fields and removing weeds manually is time-consuming and vulnerable to mistakes. These limitations can be avoided using machine visual technology to detect maize in fields.

Numerous studies have applied in-field computer vision methods to recognize plants. Shape features can be used after background separation or a combination of color and shape features. Golzarian and Frick (2011) presented an approach to classify images of wheat, ryegrass and brome grass species using color, texture and shape features. These features were reduced to three descriptors by principal component analysis (PCA), and the results show accuracy of 88% and 85% in the differentiation of ryegrass and brome grass from wheat, respectively. Sujaritha et al. (2017) designed a classification system to extract leaf textures and employ a fuzzy real-time classification technique, and the system detected weeds with 92.9% accuracy over a processing time of

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0.02 s. Torres-Sospedra and Nebot(2014) used a new training procedure with noisy patterns for ensembles of neural networks to detect weeds. Bansal et al. (2013) used fast Fourier transform leakage values to detect green citrus. An agricultural mobile robot for mechanical weed control was equipped with two vision systems, namely, one gray-level vision that can recognize the row structure formed by crops, and the other is color-based that can identify a single crop among weed plants (Åstrand and Baerveldt, 2002). Kurtulmuş and Kavdir (2014) proposed a computer vision algorithm to detect cutting locations of corn tassels in natural outdoor maize canopy. In this process, conventional color images and computer vision were used with a minimum number of false positives. Color (vegetable) indices, shape, and texture features were used to reduce false positives, reaching 81.6% correct detection rate for the test set. However, plant detection based on shape features could become quite complex because of variations in leaf shapes of diverse species at different growth stages. Moreover, in actual field conditions, the following complex cases may occur: (1) leaf overlap; (2) leaf orientation variation; (3) shooting angle variation, causing changes in the shape of leaves; or (4) leaf movement along with the wind, blurring boundaries in images. Most of these factors may also affect textural analysis and cause greater difficulties in analysis.

Color vegetation analysis is probably the most efficient method for machine vision-based location of crops and weeds. El-Faki et al. (2000) established a simple weed-detection method using a color machine-vision system, and four types of relative color indices formed by RGB gray levels were designed. The most effective combinations of these color indices were selected, and the final classification accuracies for wheat and soybean were 54.9% and 62.2%, respectively. Vegetation indices were used in image segmentation, which was oriented to detect crop rows in images from maize fields with high weed concentration (Montalvo et al., 2012). Raw RGB channels and extracted vegetation indices were used primarily to detect vegetation against background. Kazmi et al. (2015) used 14 vegetation indices to detect creeping thistle in sugar beet fields.

The proposed algorithm in this study was developed to detect maize in natural outdoor fields using conventional color pictures and computer vision with a minimum number of false positives in a real-time monitoring system. Conventional image segmentation methods based on RGB values can separate maize from background. However, these methods cannot separate maize from weeds because of the high similarities in their image RGB values. We discovered that the color indices of these plants differ in contrast. Thus, color indices were used to distinguish maize and weeds in our study. According to the characteristic of real-time supervision system, the samples in the training set of this algorithm were collected only one day during the early growth stage of maize in 2011, and the training model was used to recognize the samples after several days. The test set consisted of images for 12 days in the same year, and images in following two years were tested to verify the stability of the algorithm. As a one-class classifier, support vector data description (SVDD) was used in our task (Tax and Duin, 1999), because weed species vary in the field and the features of all kinds of weeds are difficult to be extracted. The main objective of this study was to develop and test classification models based on color indices for identifying maize and weeds using color digital images.

2. Material and method

2.1. Image acquisition

RGB images were taken in a maize field located in Gucheng, Hebei province, China, using a digital camera (E450 Olympus) with a resolution of $3648 * 2736$ pixels and focal length of 16 mm. The camera within the protection cover was fixed on a bracket at height of 6 m from the ground. The pitch and roll angles of camera were 30° and 0°, respectively. The images used in this study were captured in July 9–July 21 in 2011, July 1–July 16 in 2012, and July 13–July 27 in 2013. The image was collected one time per hour from 8:00 to 17:00 in each day. During image acquisition, the growth state of maize was varied from seeding stage to jointing stage. The experimental pictures were collected from the different years, illumination, weather, and crop growth state, which can be more comprehensive and fully verify the performance of the proposed algorithm in this study.

2.2. Image preprocessing and extraction of color indices

In this study, color images of weeds and maize were assumed to contain three types of objects (three classes): (1) weed leaf, (2) maize leaf, (3) soil. The ultimate goal was to separate these classes accurately. As a result, a crop extraction algorithm needs to be robust enough to account for both outdoor light condition and weather.

The first task is soil background elimination. Due to obvious differences in color between soil background and plants in the acquired images, Excess Green (ExG) was used to separate green plants from soil, which utilized three components (RGB) of the image according to certain combination 2G-R-B (ExG) to make the difference of green crops and soil background expanded (Wu et al., 2011). After ExG was calculated for each pix in image, the Otsu threshold was used to produce a complete binary image segmenting the vegetation against the background. Dilation and erosion were then applied to erase the blurs and noises in the binary image. As shown in Fig. 1, there were a number of independent sub-regions in the binary image, each sub-region represented an individual plant (maize or weed).

In order to accurately identify the plant in each sub-region, the feature extraction was needed. Extensive researches shown that vegetation indices were powerful features for crop/weed classification. Compared with the shape features, the vegetation indices are easy to calculate, and are not affected by variations in leaf shapes of diverse species at different growth stages (Woebbecke et al., 1995). Hence, the vegetation indices including relative single-color indices (Rn, Gn and Bn), two-color contrast indices (ExR and GB), and three-color contrast indices (Gray, ExR, CIVE, ERI, EGI and EBI) were used in this study to classify maize and weeds. The formulas for calculating vegetation indices were given in Table 1. Vegetation indices were extracted by averaging only the unmasked pixels in each sub-region, hence, a total of 12 features were obtained for one plant.

2.3. SVDD

SVDD is used for one-class classification problems. This process can locate a spherically shaped boundary from N normal training samples $\{x_i, i = 1, \dots, N\}$. The boundary consists of the center μ and radius R, which envelops as much normal observations as possible and simultaneously has as small minimum volume as possible. When one or a few remote vectors are in the data set, a very large sphere is obtained which will not represent the data very well. Outliers in training data are unavoidable. Thus, a variable ξ_i is introduced as a slack variable for the largest distance between x_i and μ. First, the primary formulation of an optimization problem is given as follows:

$$\begin{aligned} &\min_{R,\mu,\xi_i} \quad R^2 + C\sum_i \xi_i \\ &s.t. \quad \|x_i - \mu\|^2 \leqslant R^2 + \xi_i, \quad \xi_i \geqslant 0, \quad \forall i \end{aligned} \tag{1}$$