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Detection of maize drought based on texture and morphological features

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ABSTRACT

The greatest impact on maize growth and yield at present is vegetation water stress. Therefore, a timely drought detection in maize is beneficial in arranging irrigation and ensuring the final return. Some methods use spectral reflection, infrared temperature measurement and chlorophyll fluorescence for drought detection. However, these types of equipment are bulky, incur high cost and cannot be widely used in an in-field environment. To alleviate these issues, we propose herein a method for detecting drought in maize from three aspects: colour, texture and plant morphology via computer vision. Compared to other methods, the average angle and dispersion of maize leaves are first calculated using a superpixel method. The morphological features of maize are then effectively described. Tamura and grey-level co-occurrence matrix is applied to extract the texture feature. Finally, we build a drought detection model using a support vector machine. Three water level datasets consisting of 1297 images is constructed to verify the method effectiveness. The final recognition rate is 98.97% by experiment, and it has good adaptability to light conditions in different periods of the day.

1. Introduction

Maize is presently regarded as an important food source in the world. It is responsible to provide 1/2 of the calorie consumption worldwide (Liang et al., 2017). Researchers focus on drought detection of maize, which plays an important role in maize production and the development of the world economy. The accurate detection of plant drought has been the focus studies, and has attracted much attention from learners every year (Peters et al., 2002).

In the past century, population growth and changes in the environment have posed a threat to global food security. To deal with these challenges, we must use fewer means of production to maintain a high maize output and meet the food and fuel demand (Fahlgren et al., 2015). One of the most threatening environmental factors is drought, and maize is more sensitive to drought stress. Some studies shown that water stress occurring during the vegetative and tasseling stages reduce plant height and cause 28–32% loss in the final dry matter weight. Much greater losses of 66–93% could be expected as a result of prolonged water stress during tasseling and ear formation stages (Çakir, 2004). Drought stress has drastic effects on elongation and expansion growth, leaf water content, leaf area and photosynthesis of maize seedling (Anjum et al., 2003; Bhatt and Rao, 2005; Kusaka et al., 2005; Shao et al., 2008; Barnabás et al., 2008; Naveed et al., 2014). The water deficit on maize in different growth periods also has different effects, and the reduction degree of maize not is only related to the drought stress level but also affected by the growth period of maize with drought stress. The demand for water for maize plants is low at the early stage of growth and reaches its peak during the reproductive period. An adequate water supply during this period can ensure maize production (Darby and Lauer, 2004). Drought detection before the arrival of the reproductive period is extremely important because determining plant drought before the reproductive growth period can have sufficient time for the water replenishment operation, which reduces the probability of drought in the reproductive period. A several studies shown that water stress in plants can be detected. Liu et al. (2010) estimated the maize water stress and growth condition using multi-temporal remote sensing data. These data were derived from the Compact Airborne Spectrographic Imager and the Thematic Mapper Plus sensors. Modelling work was used to detect the water stress of plants using high-resolution thermal and hyperspectral imagery (Zarco-Tejada et al., 2012). Ge et al. (2016) used RGB images and hyperspectral imaging to quantify the water use efficiency and the plant leaf water content. In recent years, studies also applied the chlorophyll fluorescence technique to detect plant drought. Ni et al. (2015) used chlorophyll fluorescence to measure the fluorescence of leaves, which determined the moisture content of plants through plant photosynthesis. These techniques measure drought degree by detecting the plant surface reflectance, temperature, RGB information of visible light, soil

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moisture and other data. However, similar methods still have some problems, such as relatively high cost, difficult data acquisition and complicated operation. With the development of computer vision, an increasing number of researchers have begun to apply this technology to precision agriculture production. Compared to previous methods, computer vision has the advantages of a low cost and a good real-time data acquisition without plant contact to avoid causing damage to the plant. Computer vision also provides the possibility for continuous plant growth detection (Xiang and Tian, 2011). Some of the previous works with image-based researches included locating the ears of maize and collecting visible image samples with a digital camera (Lu et al., 2015), Yu et al. (2013) proposed a method for the automatic detection of three leaf seedlings and maize using computer vision and image processing technology.

The present study designs a maize drought detection algorithm based on computer vision. The plant colour, texture and morphological characteristics are extracted from the image samples of maize to determine whether plants are subjected to drought stress or not. From the vision, plant with drought has a non-uniform leaf colour distribution. The leaf is thin and has a large blade angle. The Tamura texture and gray-level co-occurrence matrix is introduced to describe the texture distribution of plant leaves. The morphological part is measured by the average leaf angle and the discrete degree defined in this study. One of the main innovations in this study lies in adding the measurement of plant leaf morphology, when testing drought, colour and texture features are easily affected by illumination; hence, the correct rate of comprehensive decision when adding plant morphological characteristics will improve the detection.

2. Materials and methods

2.1. Maize cultivar

The experimental samples selected in this study were Zhengdan No. 958 grown in a pot under an in-house condition. Zhengdan has characteristics of high production, stable production, lodging resistance, disease resistance and wide adaptability, among others. Zhengdan is presently cultivated in the largest area in China. The plant height is 240 cm, and the average panicle height is 100 cm.

2.2. The pot information and soil type

The pot's height we selected in this study is 0.5 m and the upper diameter is 0.4 m, the bottom diameter is 0.3 m. The soil type is medium loam.

2.3. Moisture control

Table 1 shows the moisture control in the middle growth period. In the actual operation, the soil moisture sensor measured the moisture once every 5 min. When the measured soil moisture was lower than the lower limit, an irrigation was performed to control the upper limit. During irrigation, water metres were installed on the water pipe heads. Irrigation was then performed in strict accordance with the calculated irrigation amounts. When the water was irrigated, the water spraying head was uniformly moved according to the water flow speed; thus the irrigation area was equally distributed. When rainfall occurred, the canopy was timely closed, thereby achieving full control of the soil moisture.

Table 1
Scheme of the soil moisture control.

Water level	Soil moisture	Depth of moisture test (cm)
Suitable moisture	65–80%	20
Moderate drought	50–60%	20
Heavy drought	<40%	20

Table 2
Description of the maize plant vegetative growth period.

Growth stage	Feature description
V_E	Emergence
V_1	One leaf with collar visible
V_2	Two leaves with collar visible
$V(n)$	(n) leaves with collar visible
V_T	Last branch of tassel is completely visible

2.4. Collection of maize image samples

The growth stage of the maize selected in this paper was V_8 (eight visible leaves) ~ V_T (the last spike was visible). Table 1 shows the growth stage and description.

The samples used in this study were sown on 18 July 2015. The artificial control of the suitable water supply from sowing was performed in September 8th. We provided three water levels in manual control from the beginning of September 9th (see Table 2).

The selected image collection equipment was Canon Eos 700D. This camera has 18 million effective pixels. The actual collection of the maize image samples had a resolution of 5184×3456. However, the original picture resolution was compressed to 648×432 in the calculation to improve the computational efficiency. Each pot of maize was equipped with a camera having an initial installation height of 0.5 m. The camera angle and focal length were adjusted with the growth of the maize. A picture was taken every 5 min at 5:30 am to 18:30 pm. Considering that the plant variation within 5 min was quite small, the final sampling time selected was 30 min. The time of sample collection was from September 12 to 30, and corresponding maize growth stage was V_8 to V_T. Finally, the number of samples of the three water levels was 434,433 and 430.

2.5. Maize extraction

The image in our dataset showed the maize and the background. In a black curtain, the flowerpot and the other background maize plants were dominantly green. Therefore, a description based on the RGB colour space was first established. Two classifiers were then trained to separate the maize from the image.

We calculate the y_1 and y_2 features of all pixels for the maize image sample in RGB colour space.

$$\begin{cases} y_1 = 2G - B - R \\ y_2 = (B + R)/G \end{cases} \tag{1}$$

R,G and B denote the red, green and blue components of each pixel of the image, respectively. The green dominant point will have a high y_1 and a small y_2. We extracted 25 images from each sample group in different light conditions and manually marked the foreground and background points to establish a better segmentation model. We then calculate two features for each foreground and background. Fig. 1 shows two feature scatter plot.

We selected the following classification model function after the experiment:

$$f(x) = \sum_{i=1}^{n} a_i y_i k(x,y) + b \tag{2}$$

where α_i is the Lagrange multiplier, and b is bias. We used a linear kernel function to train the model.

$$k(x,y) = x \cdot y \tag{3}$$

Fig. 2 Presents the segmentation results.