Computers and Electronics in Agriculture 140 (2017) 461–468

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

journal homepage: www.elsevier.com/locate/compag

Original papers

Early detection of water stress in maize based on digital images

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ARTICLE INFO

Article history:
Received 16 January 2017
Received in revised form 15 June 2017
Accepted 22 June 2017
Available online 7 July 2017

Keywords:
Early maize
Water stress
Image segmentation
Feature extraction
Gradient boosting decision tree

ABSTRACT

Early water stress detection is of great significance in precision plant breeding and agricultural production. In the field, outdoor cameras would be an applicable tool for early drought stress detection with high-resolution images. Based on image analysis, we presented a model to detect water stress of maize in the early stage. In the red-green-blue (RGB) color space, a simple linear classifier was proposed to extract green vegetation from maize images. After color image segmentation, fourteen-dimensional color and texture features were extracted from each image. Three water treatment levels (well-watered, reduced watered and drought stressed) were applied to maize plants. We adopted a two-stage detection model trained with different feature subsets to evaluate the water stress. The water stress detection model was based on a supervised learning algorithm, gradient boosting decision tree (GBDT). The recognition accuracy of three water treatments (ATWT) was 80.95% and the accuracy of water stress (AWS) reached 90.39%. Results showed that the proposed method had an effective detection performance between water suitability and water stress conditions in the maize fields.

1. Introduction

Water stress is the main environmental constraint that adversely affects agricultural crop production around the world. Maize plants are sensitive to water stress. Drought stress at different stages will strongly affect vegetative and reproductive growth of maize (Cakir, 2004). Water deficit leads to decrease in leaf extension rate, leaf number, leaf area and plant height, which finally causes serious losses in production (Li et al., 2012). Precise detection of plant water stress is critical for irrigation strategies and sustainable agriculture.

Soil moisture sensors provide an objective and consistent means to monitor plant water status. However, these single-point field measurements are subject to installation location, which may not account for spatial plant variability within the whole field (Mangus et al., 2016). Leaf physiological methods are more objective and directly to assess crop drought stress. Water stress can be detected by leaf area analysis (Maki et al., 2004), leaf stomatal conductance measurements, or stem water potential, respectively (Pu et al., 2003; Berni et al., 2009). Generally, these techniques are practically destructive, limited under controlled laboratory environment with a time-consuming process and unsuitable for real-time water status assessment (Kim et al., 2011).

The latest imaging techniques are investigated to detect early signs of crop water stress, allowing fast and non-destructive phenotyping in plants. Fluorescence, thermography and multi-spectral imaging are currently the most highly developed of these methods. Under water stress, the photosynthetic apparatus of leaves was affected directly, such as an increase in chlorophyll fluorescence (Lichtenthaler and Miehé, 1997). An ultraviolet laser-induced fluorescence imaging system was proposed to assess the photosynthetic activity of leaves in a non-invasive manner (Lichtenthaler and Miehé, 1997). For early water stress detection, a new and much cheaper flash-lamp induced chlorophyll fluorescence imaging system was constructed (Lichtenthaler and Babani, 2000). However, fluorescence imaging detecting early stress in plants before visual symptoms was restricted to the leaf area (Chaerle and Van Der Straeten, 2000). Thermography allows a large crop area to be measured. Compared with normal growth, plant leaves under soil water deficit display higher leaf temperature and more infrared radiation is emitted. These changes undetectable by human eyes were visible at near-infrared images (Fensholt and Sandholt, 2003). Therefore infrared thermography has the potential to detect water stress. O'shaughnessy et al. (2011) found a significant negative linear correlation between an empirical crop water stress index (CWSI) and leaf water potential using digital infrared thermography. Canopy temperature (Tc) was measured with a infrared thermographic camera to evaluate

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http://dx.doi.org/10.1016/j.compag.2017.06.022
0168-1699/

water stress on citrus and persimmon trees in the field (Ballester et al., 2013). Thermal imaging was also applied for phenotyping to screen water stress-tolerant maize varieties (Romano et al., 2011). It was suggested that infrared thermography could be a non-destructive measurement to assess drought tolerant genotypes. Compared with fluorescence imaging, thermography can not detect presymptomatic change in temperature, which is affected by different environmental conditions. A hyperspectral camera is of great value to measurements and analysis of reflectance. Some indices calculated from spectral bands are highly correlated to water stress, such as normalized difference index (NDVI) and Red Edge NDVI (Sims and Gamon, 2002). The photochemical reflectance index (PRI) was developed to detect xanthophyll cycle pigment at a canopy level under water stress (Suárez et al., 2008). These indices can be distorted by illumination changes, view angles and backgrounds. A new study combined multispectral imaging to detect early water stress in plants (Kim et al., 2011). Empirical and radiative transfer models were proposed to estimate water content by using airborne Multispectral Infrared and Visible Imaging Spectrometer (MIVIS) data (Colombo et al., 2008). These laboratory imaging techniques for crop water detection are almost non-invasive, non-destructive, and can be applied for automation.

Computer vision and machine learning are widely developed in agricultural growth management (Schirrmann et al., 2016; Kruse et al., 2014). Support vector data description (SVDD) technique, a one-class classifier based on the principle of support vector machine (SVM), was developed for the weed/corn recognition using imbalanced weed/corn image samples (Liu et al., 2010). Artificial neural network proved its good performance on predicting leaf population chlorophyll content from cotton plant images (Suo et al., 2010). The simplex volume maximization (SiVM), an unsupervised classification approach, was applied to hyperspectral data for early drought stress detection in cereals (Römer et al., 2012). Based on image analysis, these machine learning algorithms recognize crop patterns effectively. These identification techniques are applied in a suitably climate controlled greenhouse (Moshou et al., 2014). To the best of our knowledge, there is little research on detecting water stress in maize using machine learning methods.

In this study, we employed an automatic classification algorithm to assess water stress in early stage of maize. For this purpose, color images were collected from fields. A simple linear classifier was presented to segment maize plants from background objects. A set of candidate features were extracted from the segmented images, including color and texture. Three different levels of water treatment were applied, and we proposed a two-stage model to detect maize water stress. The first selected feature subset was regarded as input vectors to construct a gradient boosting decision tree (GBDT) model. When maize was detected to be water stress, another GBDT trained with the second feature subset was used to assess water stress level, which was reduced watered or drought stressed. The experiment results showed that the proposed detection model could provide an effective recognition in the field and natural light conditions.

2. Materials and methods

2.1. Maize species and experimental conditions

In the field scale, maize was planted at an experimental agricultural site in central China. The product ZhengDan958 was the most popular type of maize cultivated in China planting area, having excellent agronomic characters. The maize plants were sowed on June 18, 2014. At the early stage of maize growth, water and other nutrients were well supplied to make sure normal sprout. Until July 3, the maize grew to be jointing stage from three-leaf stage. On July 22, the maize was going to be in the huge bellbottom stage. From June 27 to July 22, soil water content was controlled manually with different irrigation treatments. The image data acquisition was conducted from July 3 to July 22.

In the early growth stage, there were three water treatments: (a) 65–80%FC (well-watered treatment), %FC represented the percentage of soil moisture content at field capacity, (b) 40–50%FC (reduced watered treatment), (c) 30%FC (drought stressed treatment). Each treatment was set in two plots. The soil volumetric water content was measured by a soil moisture sensor every five minutes. The soil moisture sensor with type of TDC210I was installed and fixed in the field to a depth of up to 40 cm before seeding, which used parallel distributed metal probes in the soil to realize the measurements. The moisture determination was based on volumetric water content of local soil region surrounding the metal probes. Irrigation and water stress treatments were controlled by reducing the total amount of water during June 27 and July 22. When soil moisture content was on lower bound, it could reach upper bound through irrigation. So the soil water potential remained at an interval. Except controlled water stress, other growth conditions kept consistent with local agricultural production. After July 22, all of the treatments were well-watered.

2.2. Image data acquisition

Six experimental fields were under the natural outdoor environment. There were 12 maize plants (2 rows and 6 plants/row) in a planting density of 6 plants/m^2. We divided experimental fields into two groups, namely A and B. In each group, three treatments were applied in different fields, including well-watered, reduced watered and drought stressed treatments. The distinction between groups A and B was the view of the camera. A set of image acquisition system with type of WV-SW396AH produced by Panasonic was applied. The camera with a focus length of 3.3–119 mm employed a new type of MOS sensors. It was available for rotary position with a pan-tilt technique, which controlled cameras elevation angle in the range between -15° and 185°. The camera was installed 4.5 m away from the ground and the ground resolution was about 1.5 mm. There was an Ethernet module in the image acquisition system. As a result, it was convenient to access the camera and transmit digital images through the internet.

From 6 am to 18 pm during July 3 and July 22, maize plant images were gathered every two hours. The gathered image resolution was 640×480 in JPG storage format. Because of the irrigation applied to control soil water content, the image acquisition system was shut down during this period. As a consequence, some images were not captured. The number of maize images from different fields was shown in Table 1. From the image examples depicted in Fig. 1, it could be seen that there were kinds of background objects such as bare soil, wheat straw residue, bricks and cables. Besides, the placement and angle of the cameras were different for A and B.

2.3. Image segmentation

The maize images collected in early stage contained various objects such as maize plants, soil, pool wall and sensors. For the

Table 1
The number of maize images.

Group	The number of maize images		
	Well watered	Reduced watered	Drought stressed
A	111	110	110
B	108	108	109