Computers and Electronics in Agriculture 116 (2015) 211–220

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

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

Development of an android app to estimate chlorophyll content of corn leaves based on contact imaging ☆

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ARTICLE INFO

Article history:
Received 17 March 2015
Received in revised form 12 June 2015
Accepted 12 June 2015
Available online 10 July 2015

Keywords:
Smartphones
Chlorophyll content
App
SPAD
Contact image

ABSTRACT

In this study a new android app for smartphones to estimate chlorophyll content of a corn leaf is presented. Contact imaging was used for image acquisition from the corn leaves which captures the light passing through the leaf directly by a smartphone's camera. This approach would eliminate the needs for background segmentation and other pre-processing tasks. To estimate SPAD (Soil Plant Analysis Development) values, various features were extracted from each image. Then, superior features were extracted by stepwise regression and sensitivity analysis. The selected features were finally used use as inputs to the linear (regression) and neural network models. Performance of the models was evaluated using the images taken from a corn field located in West of Ames, IA, USA, with Minolta SPAD 502 Chlorophyll Meter. The R^2 and RMSE values for the linear model were 0.74 and 6.2. The corresponding values for the neural network model were 0.82 and 5.10, respectively. Finally, these models were successfully implemented on an app named SmartSPAD on the smartphone. After installing the developed app on the smartphone, the performance of the models were evaluated again using a new independent set of data collected by SmartSPAD directly from maize plants inside a greenhouse. The SmartSPAD estimation compared well with the corresponding SPAD meter values (R^2 = 0.88 and 0.72, and RMSE = 4.03 and 5.96 for neural network and linear model, respectively). The developed app can be considered as a low cost alternative for estimating the chlorophyll content especially when there is a demand for high availability.

1. Introduction

Determining the chlorophyll content of plants gives valuable information relevant to plant health and crop management. Chlorophyll is the main pigment in leaves and it is responsible for leaf greenness. Leaf colour is an indicator of plant health and also it can indicate plant nutrient status (Yadav et al., 2010; Muñoz-Huerta et al., 2013). For example, there is significant correlation between chlorophyll and nitrogen content of leaf tissues, thus by measuring chlorophyll content, nitrogen status can be assessed (Evans, 1989; Tewari et al., 2013). On the other hand, excess nutrients like nitrogen in an agricultural environment is a leading cause of water quality impairment (Turner and Rabalais, 1991). Therefore, managing and balancing agricultural nutrients use has economic benefits in addition to reducing the risk of water and environment pollution (Daughtry et al., 2000; Sawyer et al., 2004). Destructive methods like Kjeldahl tissue analysis to determine nutrients status, in addition to their high costs, cannot be used as a way for variable rate fertilising (i.e., real-time application) because of time lag between collecting tissue sampling and obtaining results (Piekielek et al., 1995; Muñoz-Huerta et al., 2013). Chlorophyll meters (CMs) have been used by many researchers as a non-destructive method to measure the chlorophyll content and estimate the nitrogen value of agricultural crops (Richardson et al., 2002; Chang and Robison, 2003; Murillo-Amador et al., 2004; Scharf et al., 2006; Uddling et al., 2007; Miao et al., 2009). CMs use two wavebands to assess chlorophyll content, infrared light centred 930 nm and red light centred 650 nm (Blackmer et al., 1994).

In recent years, additional non-destructive techniques based on spectral and hyperspectral reflectance have been investigated for estimating the chlorophyll content of plants. These methods were developed to achieve special purposes such as, real time and accurate nutrients status reporting (Feng et al., 2008; Fitzgerald et al.,

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http://dx.doi.org/10.1016/j.compag.2015.06.012
0168-1699/

2010; Tian et al., 2011). Because chlorophyll content affects visual features of leaves, using digital cameras or in other words RGB (red, green, blue) imaging as a low cost instrument in the visible range has also been used in nitrogen status estimation (Dutta Gupta et al., 2013; Lee and Lee, 2013; Wang et al., 2013).

Standard cameras are significantly lower in cost than other imaging systems and chlorophyll meters (Rorie et al., 2011a), which cost about $1500US, but there are some challenges in using them for this purpose; for example, different ambient lighting conditions or shadows on leaves will affect the images. To overcome these issues Tewari et al. (2013) used an experimental setup with a cover and an artificial light to estimate nitrogen content of a rice paddy crop. In addition, utilising independent indices extracted from images can be useful in reducing the effect of variation in light. Wang et al. (2013) used GMR (G–R), G/R, NGI (normalised green index), NRI (normalised red index) and Hue indices for estimating biomass, N content and leaf area index (LAI). They mentioned that in the GMR index, the colour of the plant canopy is sharply different from the background and it is feasible to set a threshold to segment rice plant from background. Moreover, GMR and G/R indices had a better correlation than the other indices to estimate biomass, N content and LAI. It seems that combinations of component values have better correlation with N content of plants. Karcher and Richardson (2003) found that the green value in RGB colour space cannot exactly represent how green the vegetation will appear, and that red and blue values also may change the appearance of the green colour of turfgrass. They introduce the dark green colour index (DGCI) based on HSB (hue, saturation, and brightness) colour space, and after calibrating HSB values, the DGCI showed a good correlation with N content. Further studies also reported the capability of DGCI to estimate N content of plants (Rorie et al., 2011a,b).

In order to use any of the above strategies or similar, computer processing is required. With the advent of smartphones, the camera and the processor exist in the same device, opening new opportunities for image capture and data generation. Gong et al. (2013) developed and evaluated an app for android smartphones that can estimate the citrus yield two weeks before harvest time. They use a phone-implemented image processing technique for identifying fruits in an image of a tree by segmenting and clustering. Confalonieri et al. (2013) developed an app called PocketLAI, which used smartphone images to estimate LAI, one of the principal indices for assessing crop water requirements and photosynthetic primary production. The authors note that their approach is an inexpensive and highly portable alternative to commercially available LAI devices.

Recently, developments in smartphones especially in their processors with built in sensors like cameras have brought us an opportunity that in addition to using their sensors as measurement tools, computation and analysis can be done on them without any additional attachment. Yet to date, no standalone android apps for measuring leaf chlorophyll content have been developed. In this study we designed and implemented an app for android smartphones named SmartSPAD to estimate the SPAD value of corn plants. In order to increase practicality and accuracy in real conditions, a new method of imaging is introduced. Overall performance of the app is compared with Minolta SPAD-502 chlorophyll meter.

2. Materials and methods

2.1. Data collection

The data were collected from maize (Zea mays) plots at the Iowa State University Field Extension Education Laboratory, Ames, IA (USA) during the 2014 growing season. Various levels of nitrogen deficiency were induced by using different fertiliser treatments: 0, 56, 112, 168, and 224 kg ha^{-1} (0, 50, 100, 150, 200, pounds per acre). Each treatment was applied on two of the 55 m $\times$ 27 m plots since 2011, and N treatment was replicated in 6 rows. Both plots of each treatment were corn–corn rotation; the east plot had no tillage and the west plot was ploughed by chisel in falls of 2012 and 2013.

A set of validation data were collected from maize plants inside a greenhouse located in Iowa State University (Agronomy Department). These plants were fertilised by nitrogen at different levels and leaf images with corresponding SPAD observations were collected among them randomly.

2.2. Image acquisition and SPAD determination

To take images from the plant leaves, a LG E975 smartphone with CCD sensor camera was used. To avoid or reduce effects of ambient conditions on images, a new method of smartphone imaging is presented which we refer to as contact imaging. In this method, unlike standard picture-taking, leaves are held to the camera lens of the smartphone and the camera captures the light passing through the leaf (Fig. 1). Compared to standard image capturing, this method of contact imaging has several advantages including:

- No interference from the background: One of the main steps in using image processing techniques in leaf imaging is segmenting the background. A variety of methods exist for distinguishing the target from the background, but the possibility of misclassification always exists (Teimouri et al., 2014), and even a small misclassification rate can affect the results. With contact imaging, however, there is no need to remove the background, and the entire image can be used as an input data.
- No variation in the distance between leaf and sensor: Generally, for robust use of cameras in either the lab or field, predefined distances are assumed; to keep this distance between the target and the sensor constant during image capture, frames or other setups have been used. Contact imaging eliminates the need for any other attachments.
- No differences in image focus or blur: The nature of contact images overcome this problem. Because in this method there is no space between leaf and camera, there is essentially no difference between a focused image and an unfocused image.
- Lower influence of different ambient conditions: Cloudy or sunny lighting conditions, shadows, and wind conditions can affect the success of using cameras in field conditions. Sun position also affects the reflectance of vegetation indices of plants (de Souza et al., 2010). But in contact imaging, only low lighting condition has some influence on the resulting images; as described below, we reduce this effect by adding luminance factor to the features used in computing the SPAD estimates. Other field conditions like shadow, sun position, and wind, have no effect on contact images.
- An additional benefit of contact imaging is that the effects of camera-to-camera variation are minimal. Because of the nature of contact imaging and the image processing described below, differences in sensor size or camera focusing algorithms will not have an effect on the results of the contact image.

About 480 contact images in RGB colour space were captured by the smartphone and were transferred to a desktop computer for further analysis and model development. Images were intentionally taken from all plots under different light conditions (clear and cloudy sky) and at different times of the day. During image acquisition, field meteorological conditions including solar radiation, air temperature and relative humidity were varied from 200