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Wavelet based multi-spectral image analysis of maize leaf chlorophyll content

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Abstract

With recent advancement in precision farming, the need for variable rate technology has become apparent. Variable rate technology can improve the efficiency of farm operations and lessen farm's environmental impact. To implement effective variable rate applications, it is essential to gather and process information on crop nitrogen level reliably. This research is intended to develop an image-processing method to assess crop nitrogen level based on multi-spectral images of maize plants. This method first removed unnecessary information from the image and then converted the image into a one-dimensional (1D) signal representing the reflectance of the maize plant across leaves. The obtained data was further processed using the wavelet packet transform to find specific patterns that correspond to crop nitrogen stress. To implement wavelet analysis, the 1D signal was deconstructed into packets of narrow frequency bands to find the lowest level approximations at different levels. The maximum wavelet coefficients were identified for interested signal bands and then compared to SPAD meter readings, which were used as the ground-truth corn nitrogen level. Analysis results indicated that the db4 wavelet at a level 8 deconstruction had the highest linear regression coefficient ($R^2 = 0.78$) with a high correlation coefficient ($r = 0.88$) for corn nitrogen levels.

Keywords: Crop nitrogen stress sensing; Multi-spectrum image; Wavelet analysis

1. Introduction

The last decade of agriculture has seen a variety of changes occur. One of these is in the use of variable rate application of fertilizers and chemicals (Tian, 2002). There are many advantages to variable rate application with the two main benefits being cost effectiveness and less environmental impact (Robert et al., 1995). To implement variable rate application, one needs information about the field and crop characteristics. These characteristics are then used to determine how much fertilizer or chemicals are needed in a particular area of the field. One way of determining these characteristics is by spectral analysis of the crop (Kim et al., 2000). The methodology of this research is to relate the reflectance of the crop to the amount of nitrogen in the plant. A similar experiment was conducted with a camera mounted to a variable rate sprayer (Noh et al., 2005).

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Nomenclature

CCD	charged couple device
CIR	red-green-near-infrared spectrum
d.f.	degrees of freedom
LSD	least significant difference
MSE	mean squared error
N	nitrogen
NIR	near-infrared
r	correlation coefficient
r^2	linear regression coefficient
RGB	red-green-blue spectrum
RMS	root mean square error
R1	the first reproductive stage of maize when silks first appear
SPAD	soil plant analysis development
V8	vegetative growth stage of maize and 8 is the number of leaves
α	confidence parameter

The goal of this research is to further the development of this technology with a newer mathematical technique. The wavelet packet transformation converts signals and images into frequency and spatial or time based domains (Marchant, 2003). This technique has not been used to detect the nitrogen content of maize crops, but its properties make it a useful tool in analysis of images and signals with transient information. The wavelet transform has a unique property in that it can detect spatial features in a signal as well as the frequency information that the Fourier transform can detect. The hypothesis of this research is that the distribution patterns of chlorophyll content on maize leaves are correlating to nitrogen stress of maize crop, such chlorophyll pattern variations across maize leaves are detectable in a multi-spectral image, and wavelet transform analysis can enhance the detectability of chlorophyll pattern variation for assessing the nitrogen stress of maize crop.

Multi-spectral images contain a number (two or more) of monochrome images (Gonzalez and Woods, 2002). Each monochrome image contains the amount of light reflected off the objects in the picture for a particular spectral band. A variety of techniques on multi-spectral images have been used for a multitude of purposes. Kleynen et al. (2005) used multi-spectral imaging to inspect apples and Hahn (2002) used this technology to predict maturity in un-ripened tomatoes. Other uses include the inspection of poultry carcasses (Park and Chen, 2001) and the detection of chlorophyll content of potatoes (Borhan et al., 2004). Multi-spectral analysis has also been used in row crops for nitrogen detection in maize (Kim and Reid, 2002; Noh et al., 2005), nitrogen detection in rice (Huang et al., 2003), weed detection in cotton fields (Alchanatis et al., 2005), and leaf surface wetness detection in maize (Ramalingam et al., 2003).

The focus of this research was to develop an analytical technique to bring out the necessary features to detect nitrogen content of maize crops. Noh et al. (2005) worked on an experiment that focused on the reflectance changes due to changes in overall luminance. This included changes involving the solar zenith angle and cloud cover. His research developed an algorithm to correct for those variations by using a reflectance panel with four sections each with a known reflectance. His research also observed the need for segmentation of the image to separate the soil background from the maize plants and an image mask method was developed to separate the useful reflectance data from the background. Other researchers used alternative means to account for the ambient changes in the amount of sunlight. Kim et al. (2000) developed a system that included an illumination sensor to account for the changes. Later, Kim and Reid (2002) focused on illumination changes due to changes in solar zenith angle. A correction algorithm accounts for response changes due to the change in the solar zenith angle. Sui et al. (2005) developed a special sensor with an artificial light source so that the illumination of the crop would be artificial. This particular sensor detected nitrogen content in cotton. Image analysis techniques have also been used outside the determination of nitrogen content in maize. Manh et al. (2001) used an analysis technique to detect the green foxtail weeds in spectral images. His technique fitted a parametric model to leaf outlines in images. In this way, he could segment out images of weed leaves even when partially obstructed by other plant leaves.

Our research explores an innovative image-processing method to assess crop nitrogen stress based on multi-spectral images of maize plants. This method first removed unnecessary information from the raw image and then converted the crop image into a one-dimensional (1D) reflectance pattern across leaves of the maize plant. These patterns then underwent a wavelet packet transformation to bring out the specific features associated with nitrogen deficient of maize plants. The following sections will describe the process and the validation of this discovery research. The experimental results indicated that the method could successfully correlate the reflectance patterns across maize leaves to SPAD meter readings taken of maize plants, and verified that it is possible to assess maize crop nitrogen stress in by means of real-time multi-spectral image-processing.

2. Materials and methodologies

2.1. Crop samples preparation

In order to gain better control of nitrogen levels on maize to support the development of the proposed research, maize plant samples were grown in a controlled greenhouse environment. The maize variety used in this research was a cross between FR1064 and FR4318, a typical field maize variety being planted in the fields in Illinois, USA.

To ensure a variety of nitrogen stress in the crops, a set of pre-defined treatments were implemented in preparing the crop samples. A total 36 pots were split into 3 blocks: each block contains 12 pots of 4 levels of nitrogen treatment with 3 repetitions. Every plant received a specific amount of nitrogen based on its designed treatment level each week. The nitrogen was provided by applying different amounts of Miracle-Gro® 15-30-15 all purpose plant food (Scotts, Marysville, OH). Treatments HIGH received 1.0 g Miracle-gro®, MEDIUM received 0.75 g, LOW received 0.5 g, and CONTROL received none per week. Watering of the plants was done as needed and did not limit the uptake of nutrients.

To collect images of individual plants at different stages, image acquisitions were taken on four separate dates of 36, 43, 52 and 58 days after planting. The corresponding development stages of those maize plants were V8, V9, V10 and R1. SPAD meter readings were also taken from each plant the same day the images were recorded to provide the baseline measure of nitrogen content. Each baseline measure was averaged from four readings taken on the last fully unrolled leaf of the measured plant. The collected maize plant images were used to support the proposed methodology development.

2.2. Multi-spectral sensor and crop image collection

As illustrated in Fig. 1, the leaf reflectance of nitrogen deficient maize crop presents a higher value than that of nitrogen sufficient or average stressed maize crops over the entire spectrum. However, the leaf reflectance differences between nitrogen sufficient or average stressed maize crops are not as consistent as those of nitrogen deficient maize crop. From Fig. 1, one may also find that the leaf reflectance has no significant difference between nitrogen sufficient and moderate nitrogen stressed maize crops in the low band of the spectrum (<500 nm). Within the spectrum between 525 and 725 nm, the leaf reflectance of maize crops with sufficient nitrogen shows a lower value than those with only average nitrogen stress. Very interestingly, such reflectance difference flipped as the spectrum goes above 740 nm.

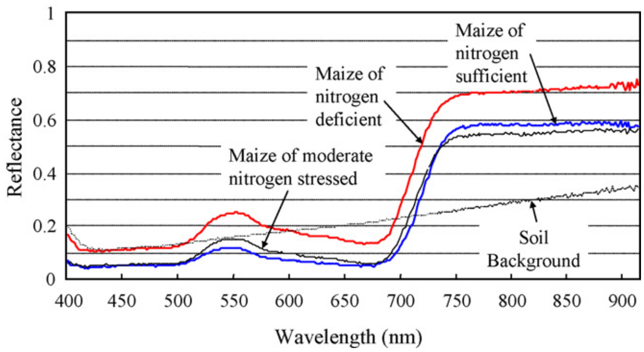

Fig. 1. Reflectance spectrum of maize leaf measured using a handheld spectro-radiometer.

The observed spectrum indicates that the sensitive spectrum band is between 550 and 700 nm for detecting nitrogen stress level of maize crop in terms of leaf reflectance. It may also been seen that the reflectance of soil background is within the variation range of the leaf reflectance with different nitrogen stress levels in the most sensitive band of the spectrum. However, the reflectance difference between the maize leaf and the soil background is very significant in the high band of the spectrum. Analytical Spectral Devices (ASDs) hand held spectro-radiometer (FieldSpec Hand held, ASD, Boulder, CO) was used to create Fig. 1. This spectro-radiometer makes quantitative measurement of radiant energy at each wavelength from 325 to 1075 nm in radiance, irradiance, reflectance or transmission, which covers the spectral range from visual to near-infrared.

To support the image collection, a mobile image collection platform was created for this research. Two multi-spectral cameras, one RGB MS3100 and one CIR MS3100 (Duncan Tech, San Diego, CA), were mounted on a John Deere Gator (Moline, IL) to form the mobile platform. In this research, only the images collected using the CIR camera were used to sense maize canopy reflectance in different bands. This Duncan CIR camera consists of three CCD channels of green (G, central band 550 nm), red (R, central band 660 nm) and near-infrared (NIR, central band 800 nm) with a 25 mm focal length and a 14.6° field of view. Each channel can capture a separate image with a pixel resolution of 656 × 494. The camera was controlled by a PC-based camera control system, which could automatically control both camera gain and exposure using an iterative method. This iterative camera control method kept the average pixel value in the green channel at a grey level of 60. A digital frame grabber (IMAQ PCI-1424, National Instrument, Austin, TX) was used to record the multi-spectral images captured using this camera. One hundred and forty-four maize crop images were collected in a 4-week image-collecting period.

2.3. Image pre-processing

To enhance the sensitivity of the image analysis based nitrogen stress assessment, it is essential to perform an image pre-process to extract only the usable signals from each image for analysis. This pre-process consisted of two procedures of background segmentation for removing the soil background and leaf reflectance averaging for transforming the two-dimensional leaf reflectance into a one-dimensional leaf reflectance. The core analysis of this research was to use a wavelet packet transformation to identify the leaf reflectance patterns across the total length of maize leaves as an indication of the nitrogen stress in a maize plant.

The background segmentation was done by using a reflectance panel as a reference (Noh et al., 2005). This reference panel was painted with four levels of grey going from light grey to almost black and placed in the top of every image (Fig. 2). Rather than using a computationally expensive histogram function for segmentation, an index was created based on the average value found in the reflectance panel. A linear model was then developed to relate this index to the segmentation value. This allows the system to segment images even if the overall illumination changes due to cloud cover or to a change in solar zenith angle.

The second process was to transform the image data from a two-dimensional (2D) distribution to a one-dimensional pattern. It is a critical step for preparing the raw data suitable for performing a 1D-wavelet packet transform analysis.

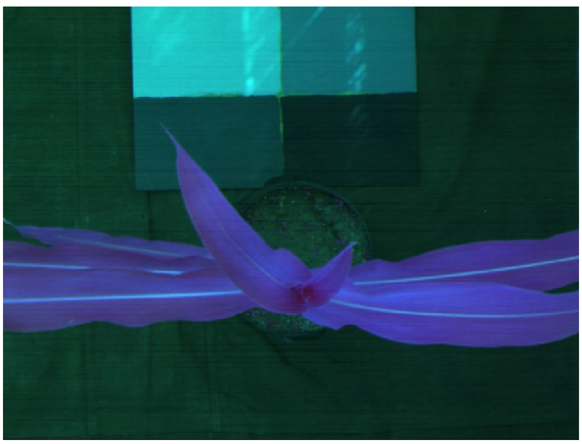

Fig. 2. Example of an original CIR image of a maize plant recorded with green, red, and NIR channels. Image was collected 36 days after planting.

When a plant image is collected, it can be seen that most of the color/reflectance variations are in one direction along the long axis of the leaves (Fig. 2). For this reason, a 1D signal was created from every image in the horizontal direction. Because maize plants tend to grow in a horizontal direction when viewed from above, averaging the pixels by column should be able to accurately represent the reflectance variances in the leaf. Every pixel value of interest was extracted and averaged by column.

An automated image-processing program was written in Visual Studio Net® (Microsoft, Redmond, WA) to extract the data from the images. This program first converts the images from the native JPEG format into a bitmap so that the pixel values can be extracted, and then saves the extracted pixel values to form a new segmented image. Figs. 2 and 3 show an original image and the segmented image. The pixel values are then averaged by column in every channel to produce three 1D signals for every picture. The center point of the plant is recorded by inspecting each image and clicking the corresponding pixel. This procedure allows all plants being evaluated to be compared in terms of their center points. The outputs of this program are one text file containing the column averaged leaf reflectance data for each channel and another text file containing the coordinates of plant center point. These text files were imported into Matlab® (MathWorks, Natick, MA) for performing the wavelet analysis.

2.4. Wavelet analysis

Wavelet theory was created for extracting finite characteristics in wave-form signals. For this reason the wavelet analysis approach was selected to extract characteristics from the images that could indicate nitrogen stress on maize plants. Much of the basis of wavelet theory comes from the well-known Fourier transform and its applications. The Fourier transform transfers a signal from a time–amplitude to a frequency–amplitude scale by multiplying the signal by a sinusoidal basis and then integrating it over the entire frequency range from negative infinity to positive infinite as defined by the equation below:

$$F(\omega) = \int_{-\infty}^{\infty} f(x)\, e^{i\omega x}\, dx \qquad (1)$$

Although information such as the frequency components of the signal are gained in this way, it has some very serious limitations for real world signal processing. When performing a Fourier transform, the information from the whole set of signals is blended together making it impossible to distinguish where a certain event took place in the signal. This is because the signal or kernel being compared to, the sinusoid, is time-invariant (Marchant, 2003). Therefore, it is impossible to distinguish where singularities like discontinuities or spikes are. In contrast, when comparing the signal to a time-variant kernel such as wavelet, it will allow singularities to be evaluated more easily since the time-variant kernel is closer in appearance to a real signal.

Wavelets are, in essence, small waves that exist on a smaller time scale than the signal it is being compared to and have a mean value of zero. When doing continuous analysis with the Fourier transform, the signal is broken into

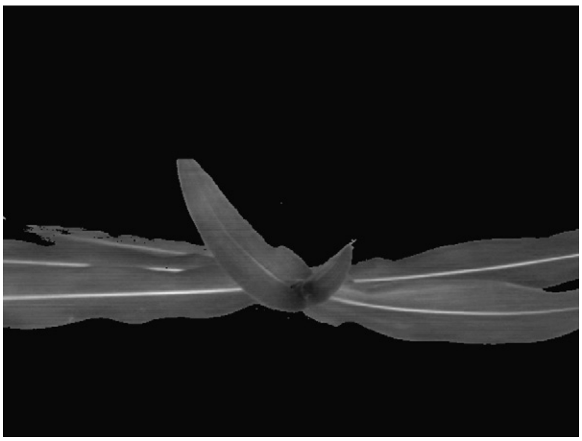

Fig. 3. Segmented monochrome image of a maize plant (green channel).

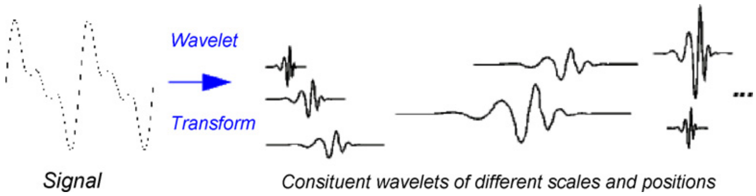

Fig. 4. The wavelet transform breaks a signal into constituent wavelets much like a Fourier transform breaks a signal into constituent sinusoids (Matlab, 2004).

several sinusoidal waves that, when multiplied by the Fourier coefficients and added together, form the original wave. Similarly, in continuous wavelet analysis, the signal is broken down into various wavelets that when multiplied by wavelet coefficients and added back together form the complete signal (Fig. 4). In performing the wavelet analysis, the algorithm will compare a selected mother wavelet to the beginning of the signal being analyzed. It will then shift the wavelet length down and compare the shifted mother wavelet to the signal again. Every time it compares the mother wavelet to the signal it will assign a number (often c) that correlates how closely the two resemble each other (Misiti et al., 1997). Once the comparison of the entire signal segment is completed, the wavelet will be scaled to a new size and the whole process could be done again. Often the wavelet analysis is performed for many scaling factors until a 2D array of numbers is achieved with 1D of the array being time and the other scale. Wavelet analysis can find aspects like trends, breakdown points, discontinuities in higher derivatives, and self-similarity. This is because of its unique ability in finding both high and low frequency information.

Comparing to the continuous transformation, the discrete transformation only takes certain scales or certain shifts. If the discrete steps follow a particular pattern there would be no loss of information and the transformation will take a lot less computing power. This is called the dyadic scale:

$$a = 2^j \tag{2}$$

$$b = ka \tag{3}$$

where a is the scale, b the dyadic translation, j denotes the level, and k denotes the time interval.

A discrete wavelet transform will be on a level-time domain instead of a scale-time domain. Every 1D wavelet family will have the following form:

$$\frac{1}{\sqrt{a}}\Psi\left(\frac{x-b}{a}\right) \tag{4}$$

making the wavelet transform appear as follows:

$$C(a,b) = \int_{-\infty}^{\infty} f(t)\frac{1}{\sqrt{a}}\Psi\left(\frac{x-b}{a}\right)\,\mathrm{d}t \tag{5}$$

In practice the wavelet transform uses two filters to deconstruct the signal, a wavelet to capture the high frequency information, details, and its associated scaling function for the low frequency information, approximations. Further deconstruction of the approximations allows analysis at lower scales. In order to deconstruct the details the wavelet packet transform must be used. The wavelet packet transformation is different from the standard transform in that both the approximation and detail coefficients can be deconstructed into lower scale approximation and detail coefficients. The wavelet packet transform was used in this research to dissect the data at many different frequencies.

MATLAB® wavelet toolbox (Mathworks, Notick, MA) was chosen to perform the wavelet analysis. A script was created for calculating the wavelet coefficients and then writing the results to a file. This research focused on finding the highest correlation between nitrogen deficient maize plants and their relative image signal data. Therefore, the maximum wavelet coefficient was recorded for each transformation. This script could also write all the coefficients for a particular packet and mother wavelet in one file. This makes it easier to determine which packet is best correlated for each mother wavelet. The mother wavelets used in this research include the Daubechies 1–10 (db1–db10) and using the lowest frequency packet of levels 5–10 for analysis. These levels were chosen to see which one could best separate the low frequency information describing nitrogen from the high frequency information.

2.5. Experimental data analysis

To determine which mother wavelet and level was the best, a least significant difference (LSD) test was performed on all the trials. The LSD test is useful for determining if the means of groups of data are statistically different from each other. Eq. (6) shows how the LSD is calculated for a data set:

$$\mathrm{LSD} = t_{\alpha/2,\mathrm{d.f.}}\sqrt{\frac{2\mathrm{MSE}}{n}} \tag{6}$$

where $t_{\alpha/2,\mathrm{d.f.}}$ is the Student's t value, MSE the mean squared error calculated in ANOVA analysis, and n is the sample size.

The degrees of freedom for this test were 11 and the selected α value was 0.05. This means there is a 5% chance of committing a type 1 statistical error. A type 1 error is committed if we reject the hypothesis that the means of the groups are equal when in fact they are equal. With this particular d.f. and α, the value of t was 2.201. After the LSD value was calculated, it was used to determine the difference between the means of two groups. If the difference in means of two groups is greater than or equal to the LSD value then the two groups are significantly different from each other. This test was also performed on the SPAD data to see how well the nitrogen treatments were separated. Afterwards, the maximum wavelet coefficients were plotted against the SPAD meter data and a linear model coefficient (r^2) was found using a least squares method. In order to reduce the number of plots, only those coefficients that were found to be significantly different between treatments were tested for a linear model.

3. Results and discussion

All collected images were analyzed using the methods developed in this research, and the obtained results indicated that it was theoretically applicable and technically feasible to use the wavelet analysis method in detecting maize plant nitrogen deficiency level in the early stage of maize plants growth. The software created in this research could effectively segment the soil background from the maize plant image and extract the wavelet coefficients representing the 1D array of leaf reflectance distribution.

In extracting the wavelet coefficients from the collected plant images, the first step is to convert the 2D distribution of leaf reflectance to a 1D array by averaging the reflectance data by column along the long axis of the plant to obtain the spatial features of the leaves reflectance variations in the green channel (Fig. 5). In the wavelet analysis process, it was found that several wavelets and levels worked well to distinguish between treatment levels. The wavelets and their levels that passed the LSD test were: db1 (level 9); db2 (level 7); db3 (levels 6 and 7); db4 (level 4); db5 (levels 7 and 8); db6 (level 7); db7 (level 7); db8 (levels 7 and 8); db9 (levels 7 and 8) and db10 (levels 7 and 8).

Fig. 6 shows an example of the 1D leaves reflectance distribution patterns generated by the column average method based on the leaf reflectance extracted from all the repetitions for images collected on the 36th day after planting. The results present some clearly distinguishable patterns among the images collected from different fertilization treatments which representing different levels of maize plant nitrogen stress. After comparing the sensitivity of using a few different wavelets with various levels, it was found that the db4 was the most sensitive wavelet in extracting maize plant nitrogen level information from leaf images. Fig. 7 shows the matching scaling function and the result indicates that the db4-based filter is very similar to the second half of the signal formed from an image of a nitrogen deficient main plant (Fig. 5). It can be concluded that when looking for an appropriate wavelet to describe low frequency signals it is important to look at the scaling function and not just the mother wavelet because the scaling function will determine how what low frequency signals are being searched for.

The obtained wave-form signals were a prime choice for doing a wavelet transformation. A steady trend was found that the center portion of the signal patterns increased as the lower the nitrogen treatment while the ends stayed relatively constant. The wavelet transformation was able to extract a maximum wavelet coefficient representing the alikeness in pattern between the scaling function and the examined leaf reflectance pattern. The obtained coefficients were then compared to the SPAD data taken for the plants. Fig. 8 shows the 1D signal formed from the wavelet coefficients and is equivalent to one line of a time-scale plot. This signal was made from the CIR image of plant 2 using a db4 wavelet at the lowest approximation packet of level 8. A spike in the wavelet coefficients indicates that the signal closely matches the scaling function used in the wavelet transform. For this reason, the maximum coefficients were taken for each signal and statistical analysis was performed on the data. It indicates when using a Daubechies-four wavelet (db4) at a

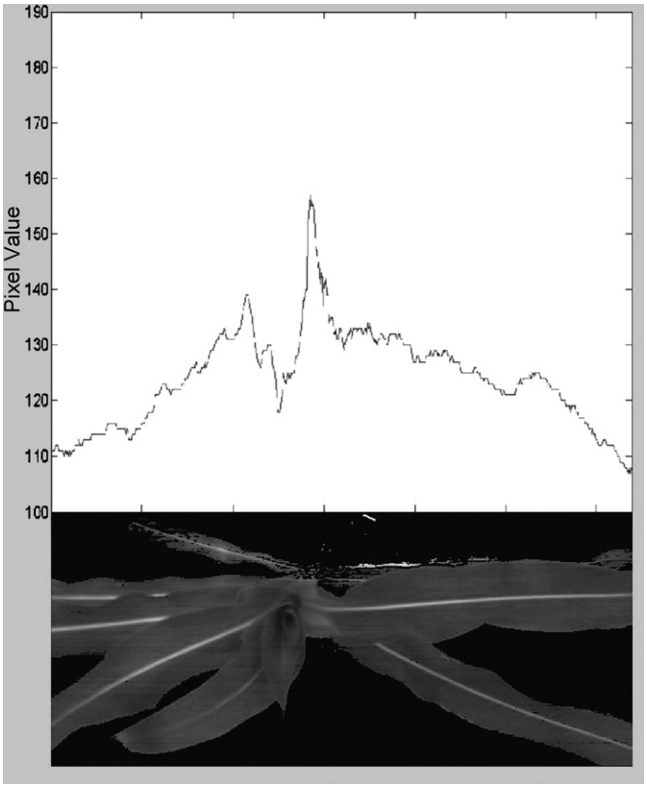

Fig. 5. An example of maize plant and its associated column-averaged leaf reflectance along the long axis of the leaves. Pixels values are the associated reflectance of the leaf given as a range between 0 and 255.

level 8 transformation it resulted the highest linear regression coefficient ($r^2 = 0.78$) with a high correlation coefficient ($r = 0.88$). This result was comparable to that obtained from a conventional image analysis as reported by Noh (2003) which had a regression coefficient of 0.74 who compared the average green pixel values of the leaves of maize plant with the similar fertilization treatments to SPAD readings.

A problem occurred when images were taken multiple weeks in a row. Fig. 9 shows a plant image taken 58 days after planting, and Fig. 10 is the averaged leaf reflectance patterns obtained from the images collected on that day. From the result, one may find there is a significant decrease in the trends comparing to the data obtained in day 36. As

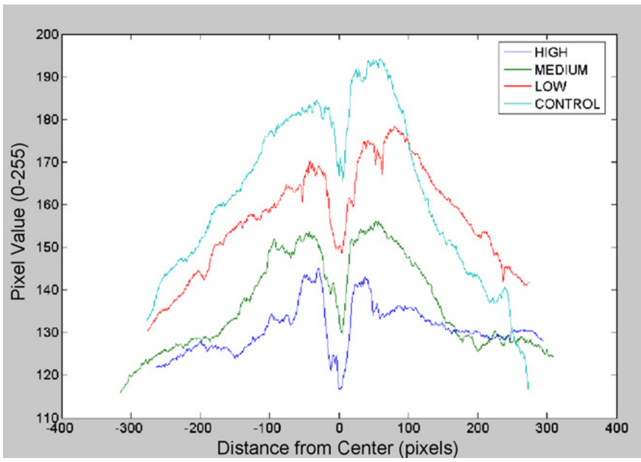

Fig. 6. One-dimensional leaves reflectance distributions from different fertilization treatments from images collected on day 36 after planting.

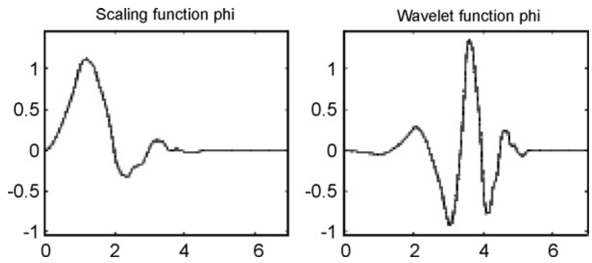

Fig. 7. Scaling and wavelet function for Daubechies-four with related filters.

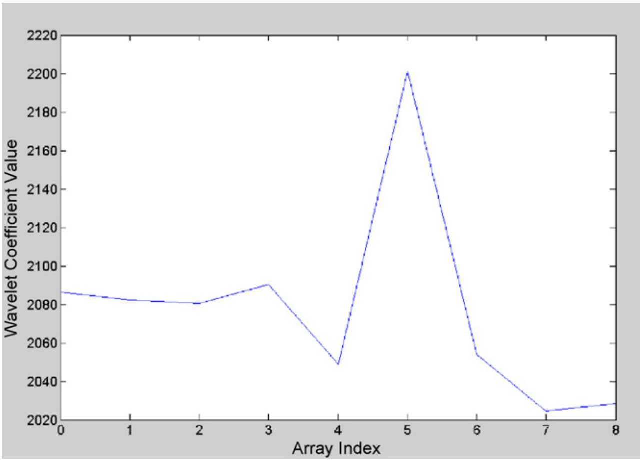

Fig. 8. Wavelet coefficients obtained from the wavelet analysis on the1D leaf reflectance pattern of maize plant 2 using the Daubechies-four (level 8) wavelet.

it can be seen from Fig. 6, the data for the first week follows a good trend. The signal for the healthy plants is low and flat; when there is an increase in deficiency, the signals become higher and show a curved high point near the center portion of the signal. The results also shows that as the location moves closer to the center of the plant it shows higher signs of stress than the extended portions due to the plant pushing the available nitrogen to the ends of the leaves where it can be used for the chlorophyll. However, there was no trend on the results obtained from the images collected on day 58 (Fig. 10). One possible explanation for this phenomenon might be the insufficient height of the test stand. The

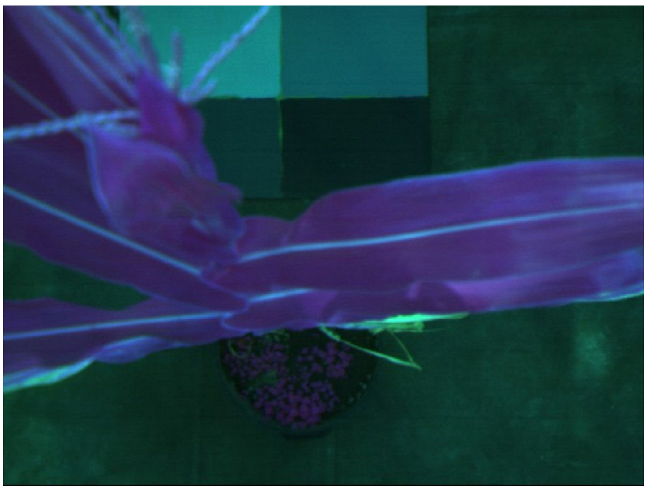

Fig. 9. Example of an original CIR image of a maize plant recorded 58 days after planting.

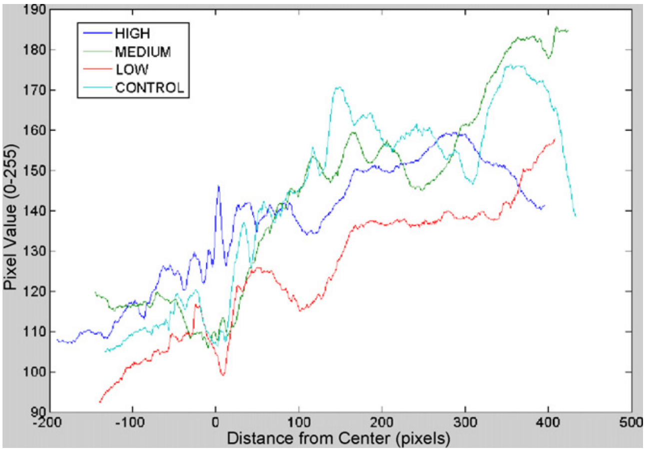

Fig. 10. One-dimensional leaves reflectance distributions from different fertilization treatments from images collected on day 58 after planting.

Table 1
ANOVA results comparing the four nitrogen test groups between each other

Groups	Count	Sum	Average	Variance	Difference	LSD
HIGH	3	6582.8	2194.3	3,722.7	165.9	148.89
MEDIUM	3	7080.4	2360.1	1,258.8	284.6	
LOW	3	7934.3	2644.8	13,070.1	325.0	
CONTROL	3	8909.2	2969.7	9,401.3		

Source of variation	SS	d.f.	MS	*F*	*P*-value	*F* crit.
Between groups	1,042,532.00	3	347,510.55	50.63	1.51E−05	4.07
Within groups	54,905.69	8	6863.21			
Total	1,097,437.69	11				

cameras were set to approximately 2.74 m above the ground for every test. During the later weeks, the maize grew so tall that the camera could not take a picture containing most of the leaves of a plant. As seen in Fig. 9, the picture mainly consists of the center whirl of the maize plant and does not contain much of the leaf. In order for the proposed process to work, a large portion of the leaf must be present. Pictures like these do not lend themselves to good data transformation. For this reason, only the images collected in the early weeks of this study were kept for study.

An LSD test was also performed on the wavelet coefficients. As an example, Table 1 lists the ANOVA and LSD data for level 8, wavelet db4. Each column represents the repetitions for each nitrogen treatment, the maximum wavelet coefficients for this wavelet and level for images taken 36 days after planting. The ANOVA information is listed just above this. The entries in the difference column are found by subtracting the mean of the next group from the current group. So the difference entry for column one is the average of column one minus the average of column two. The LSD value is 148.9 and the difference between every group is greater than or equal to this value. Based on the obtained results, it can be concluded that the groups are statistically different from each other. The statistically significant maximum wavelet coefficients for the 12 CIR images from the test date 36 days after planting were graphed against the SPAD data taken from each plant. Fig. 8 shows the coefficients from a level 8 deconstruction using a db4 wavelet. This level and wavelet was found to have the highest correlation coefficient of 0.88.

4. Conclusions

This research has investigated an innovative image-processing method for extracting nitrogen stress information from maize leaves using a wavelet analysis approach. Field test results successfully proved that this method could reliably extract maize plant nitrogen stress information from leaf images. To obtain maize plant samples with sufficient

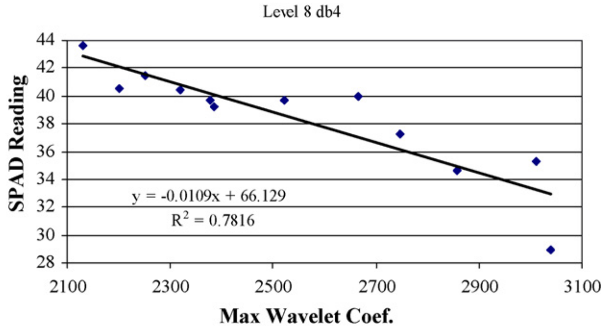

Fig. 11. Correlation of maximum wavelet coefficients vs. SPAD data.

nitrogen level variation, the plants were grown in a controlled environment inside a greenhouse with different soil nitrogen treatments. The raw data were collected and analyzed using in-house developed image pre-process methods for this research. The data signal then undergoes a wavelet transformation to bring out specific spatial features. The feature of interest was a large increase in reflectance of the leaf the closer the signal was to the center of the plant. This kind of signal indicates there is a lot of stress in a plant because the leaf color is brighter the closer it comes to the center of the plant and is darker at the tip of the leaf. Plants with less stress do not have this feature and are more likely to be uniform across the whole leaf. Using trial and error, a particular wavelet and level was found that best brings out this feature to be able to distinguish between the various levels of nitrogen treatment. Another approach would be to choose those wavelets and their corresponding scaling functions that approximate those features that are being searched for. This would involve extending this research to include other wavelet families besides the Daubechies wavelet family.

The maximum wavelet coefficient for each signal was found and then plotted against each plant's respective SPAD value (Fig. 11). It was found that using a db4 wavelet at level 8 transformation had the best liner regression coefficient ($r^2 = 0.78$) and a high correlation factor ($r = 0.88$). The results were comparable with Noh's (2003) results. This developed method was fairly effective in finding correlations between wavelet packet coefficients and SPAD data. This research shows considerable promise in the ability for wavelet analysis to assist in determining nitrogen content in real-time, on-board systems.

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