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Prediction Model of Lettuce Nitrogen Content Based on Color Images

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Abstract: In order to facilitate intelligent precise nitrogen fertilizer management, a model of lettuce leaves' nitrogen content is constructed. In this article, the lettuce samples of several nitrogen levels were cultivated. At Rosette stage, color images of lettuce leaves with every nitrogen level were collected and preprocessed and the texture features and the color features were extracted. Through the correlation analysis, principal component characteristics were extracted and image feature vectors were constructed after being screened and optimized. The regression equations of image feature vector and lettuce leaf nitrogen content were constructed by the principal component regression analysis method and the multiple linear regression method respectively. Based on the same test samples, prediction error rates of two expression models were computed. Results showed that the average error ratio of the principal component regression expression model is 9.30% and the one of multiple linear regression expression is 12.66%. The root mean square errors (RMSEP) of PCR model was 0.4577 and the RMSEP of MLR model was 0.6284. It is also shown that the prediction result of the principal component regression expression model is better than the one of the latter and it can be applied to the nondestructive testing intuitive expression model of the nitrogen content of lettuce leaf. This study provides a basis or way to fertilize and manage nitrogen fertilizer precisely for lettuce or other crops.

Key words: Color image, lettuce, nitrogen content rate, expression model

INTRODUCTION

Lettuce contains rich protein, carbohydrate, vitamin and some minerals, being highly popular at home and abroad and its planting should be concerned. The reasonable application of nitrogen fertilizer is very important to the lettuce's yield and quality and accurate nitrogen management is on the basis of accurate detection of the crop nutrition elements (Zeng *et al*., 2004). For a long time, crop nitrogen nutrition diagnosis is mainly based on the routine testing in laboratory (Sun and Yang, 2008) but these methods' time efficiency is very low, which affects crop growth and against popularization and application. Crop nitrogen deficiency or excess can lead to physiological and morphological characteristics changes, therefore and change the crop color (spectrum), texture, lightness. Many scholars made quantitative analysis on crop nutrition level by spectral technology (Huang *et al*., 2012; Zhu *et al*., 2006; Zhang *et al*., 2010; Zhang and Mao, 2009; Sun *et al*., 2010; 2009) but the blade spectrometry test range is smaller and it is strict to choose test site. In recent years, nondestructive detection technology based on image technology has been applied in crop nitrogen nutrition diagnosis and it is fast, convenient and nondestructive. Hyperspectral image has the perfect information but its storage is too large and characteristic bands extraction and data processing are more complex (Wang *et al*., 2010; Cai *et al*., 2009a; Cai *et al*., 2009b; Shi *et al*., 2011; Zhang *et al*., 2008). Color image information is surface information and its processing procedure is easier than hyperspectral image, so it is convenient to develop the practical nondestructive testing instrument.

LiMinZan and ZhangYanE, the professors of China Agricultural University, collected the images of cucumber leaves in greenhouse under daylight conditions and analysed the correlativity of RGB, chroma, saturation, brightness index and leaf nitrogen rate, phosphorus rate and moisture content rate in the RGB and HSI color model respectively (Zhang *et al*., 2005). Cheng and Jia established the relation model of canopy green depth and the total nitrogen content of plant at the jointing stage and booting stage, respectively by digital cameras (Jia *et al*., 2004). Pagola analyzed the color images of

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barley leaves with different nitrogen nutrition levels and predicted the nitrogen nutrition (Pagola *et al*., 2009). Mao Hanping *et al*. studied the deficit detection recognition of nutritional elements such as nitrogen, potassium, calcium, magnesium of tomatoes, cucumbers and other crops in the visible light range based on computer vision technology (Mao *et al*., 2003). Song SY collected cucumber canopy images by digital cameras and analyzed the relationships between the cucumber canopy image parameters and nitrogen fertilizer, soil inorganic nitrogen and plant nitrogen nutrition in different nitrogen level (Song and Wang, 2008). Yang *et al*. (2010) used CCD camera and special filters to investigate the growth parameters of cucumber plants, the nitrogen content (Yang *et al*., 2010). In all the literatures above, the relationship of colors and nitrogen nutrition level of some crops had been researched but there were few literature reports about lettuce nitrogen content expression models based on color image information. In this study, the nitrogen content expression of the lettuce leaves based on the color image information will be studied, which will provide a reference or basis for nondestructive detection for other crop nitrogen nutrition elements.

CULTIVATION TEST AND MEASUREMENT OF NITROGEN CONTENT

Lettuce samples were cultivated by soilless culture technology using perlite. Nitrogen nutritive element was controlled precisely in order to get the pure samples which have different nitrogen stress levels, under the normal situation of other nutrient elements. Experiments were made in Venlo type greenhouse of Jiangsu university modern agricultural equipment and technology province department and cultivation started in April and ended in May of 2011. Italian resistance bolting lettuces were chosen as test variety. Six nitrogen levels were set respectively as 200, 166, 133, 100, 66, 33% of the standard formula nitrogen mass fraction and each level 20 strains, a total of 120 strains.

The AutoAnalyzer3 type continuous flowing analyzer produced by British SEAL Company was selected to detect the samples' total nitrogen content based on the kjeldahl determination. The total nitrogen content of lettuce sample was calculated by Eq. 1:

$$N = \frac{c}{m \times (1-w)} \times 100\% \tag{1}$$

In it, N expresses total nitrogen mass fraction (%), C expresses instrument observation value(mg), m expresses the quality of the test sample (mg) and w expresses the moisture content of test sample (%).

COLOR IMAGE ACQUISITION AND PREPROCESSING

Image acquisition device: Image acquisition device consisted of a digital camera and a frame. The frame is 50cm high and IXUS 500 HS Canon digital camera fixing on the frame, the camera CCD providing 1 0.1 million pixels, with 12x optical zoom and 1/2.3 inch sensor, 28~336 mm equivalent focal length, F3.4~F5.6 aperture range. The shadow points may exist, due to the lettuce leaf surface is uneven and lack of light, which can be preprocessed by the subsequent image processing methods. In short, the condition of image acquisition is stable and consistent to improve test repeatability.

Lettuce nitrogen deficiency can cause the color turn light green, stems be short and thin, blade be thin and some older leaves turn yellow. In all the lettuce growth period, color images of 20 lettuce leaves in each nitrogen level, a total of 120 leaves, were collected.

Image preprocessing: Lettuce leaves images collected with a digital camera are 24 bit true color images, which consist of R, G, B three monochromatic mix colors. The grayscale images were conversed according to the corresponding relation between gray value Y and RGB color through the Eq. 2 (Zhang and Lv, 2011):

$$Y = 0.299R+0.587G+0.114B \tag{2}$$

Otsu algorithm was chosen to complete image binarization, which was a kind of global threshold method based on one dimensional gray histogram. Otsu algorithm was simple and need calculating only one dimension gray histogram of the zero order and first order cumulative moment. The basic idea of Otsu algorithm was expressed as below. If the image has L grayscale, a threshold T was chosen to divide the image pixel into two categories such as C1 and C2. The gray value of C1 is greater than the threshold T and the one of C2 is less than the threshold T and the variance between class σ_B and variance in classes of two kinds of classes σ_w pixels are computed and the threshold T is found to make two variance ratio's σ_B/σ_B be largest. Lastly, the threshold T is the best threshold value of the binary image (Song and Wang, 2008; Zhang and Lv, 2011; Otsu,1979).

Test environment of image processing is listed as below. HP Corporation is chosen as computer, Intel (R) Pentium (R) Dual E2180 @ 2 G is chosen as CPU, 1 G memory is chosen as memory and Matlab6.5 is chosen as processing software.

The black and white noise interferences were produced after image threshold segmentation and the image processing method of mathematical morphology such as inflation, corrosion treatment was needed to remove obvious noise interference.

IMAGE FEATURE VECTOR EXTRACTION

Plant physiology and plant nutrition research showed that nitrogen nutrition deficiency can cause leaf surface macroscopic characteristics such as color and texture characteristics change. The features of lettuce leaf image in this study include the texture characteristics and color characteristics.

Texture statistical measures characteristics: The image gray-gradient symbiotic matrix is calculated to reflect the gray-gradient distribution of the pixel pair having specific space connection and to build texture descriptor for further. The image gray series are set as L and the gray histogram is expressed as h (i), i = 0, 1,..., L-1. Gray mean value is expressed as m, so the n order center statistics for the moment is expressed as Eq. 3:

$$u_n = \sum_{i=0}^{L-1} (i-m)^n h(i) \quad n = 2, 3, 4 \tag{3}$$

In Eq. 3 u_2 expresses variance measuring the gray contrast ratio, u_3 expresses histogram partial slope, u_4 describes the histogram of the relative flatness. The six texture statistical characteristics are shown as:

$$m = \sum_{i=0}^{L-1} ih(i) \tag{4}$$

$$\sigma = \sqrt{u_2} \tag{5}$$

$$R = 1\text{-}1/(1+u_2) \tag{6}$$

$$L_3 = u_3/L^2 \tag{7}$$

$$U = \sum_{i=0}^{L-1} h^2(i) \tag{8}$$

$$V = \sum_{i=0}^{L-1} h(i) \log h(i) \tag{9}$$

In above formulas, m expresses mean value, σ expresses standard deviation, R expresses smoothness, L3 expresses three moments and U expresses consistency, V expresses entropy.

Color features: Color features are described commonly by color histogram and they are directly computed according to all the pixel gray value or color value of the image, reflecting the global features of image color. The pixel value of i th color component and j th pixel of color image are assumed as p_{ij} and the number of pixels of image is N. The one order central moment is shown as Eq. 10:

$$e_i = \frac{1}{N} \sum_{j=1}^{N} p_{ij} \tag{10}$$

The third order central moment is shown as Eq. 11:

$$s_i = \left(\frac{1}{N} \sum_{j=1}^{N} \left(p_{ij} - e_i \right)^3 \right)^{\frac{1}{3}} \tag{11}$$

In above eqution, N expresses total pixel points of image and three color components have 6 color characteristics. e_i expresses one order central moment of color component and s_i expresses three order central moments of color components.

The texture characteristics and color features are integrated and initial feature vector is (x_1, x_2 and x_3... x_{12}). x_1 expresses the first order center moment of color R, x_2 expresses the third order center moment of color R, x_3 expresses the first order center moment of color G, x_4 expresses the third order center moment of color G, x_5 expresses the first order center moment of color B, x_6 expresses the third order center moment of color B, x_7 expresses gray mean m, x_8 expresses gray standard deviation, x_9 expresses texture smoothness, x_{10} expresses gray three moment, x_{11} expresses grey consistency and x_{12} expresses grey entropy. From the test data, there are obvious differences among lettuce leaves image features of different nitrogen levels.

PREDICTION MODEL AND VALIDATION

Based on rosette stage, the lettuce nitrogen content was forecasted by principal component regression analysis method and the multiple linear regression method and 105 lettuce leaves samples were chosen as calibration samples and the remaining 15 lettuce leaves samples were used as test samples for the prediction model.

Principal component regression model: Principal Component Regression (PCR) is a widely used regression model for data having a large degree of covariance in the independent or predictor variables. Principal component regression analysis method combined the original variables into a new set of independent several variables, from which a few less comprehensive variables can be taken out to reflect the original variable information according to actual requirement. Most of the original data information is compressed into less principal component, in order to realize the data's dimension reduction. Principal component analysis method was used to evaluate nitrogen content of lettuce leaves in this study, determining the relationship expression of y. y represents nitrogen content of lettuce leaf and $x_1, x_2, ..., x_{12}$ represent 12 characteristic value.

Hundred groups of the training sample data were used in the study and the Matlab software was used to calculate the correlation coefficient between 12 indicators and the correlation coefficient matrix was shown in Table 1.

Based on principal component analysis, the principal components of original characteristic value were computed. The cumulative contribution of the first 8 principal components was 0.9917, containing the vast majority information of original variable information, so the first 8 principal components were chosen as the principal component variables. The regression equation was calculated by Principal component regression analysis method, shown as Eq. 12:

$$\begin{aligned} y = {} & 2940.924173 - 0.024038*x_1 - 0.026250*x_2 \\ & +0.029927*x_3 + 0.085099*x_4 + 0.001923*x_5 \\ & +0.004873*x_6 + 0.007908*x_7 - 0.004882*x_8 \\ & -2942.376265*x_9 + 0.059430*x_{10} \\ & -2.425177*x_{11} - 0.113026*x_{12} \end{aligned} \tag{12}$$

In the above eqution, y expresses the prediction value of lettuce leaf nitrogen rate and $x_1, x_2, ..., x_{12}$ represent for 12 characteristic values.

Multiple linear regression model: Multiple Linear Regression Analysis (MLR) method was used to analyze the linear relationship between independent variable and dependent variable, based on the analysis about two or more independent variables and a dependent variable in this study (Liu and Niu, 2010; Sun *et al*., 2012).

The regression equation is shown as Eq. 13:

$$\begin{aligned} y = {} & 901.8552 + 0.4871*x_1 + 0.0878*x_2 \\ & +1.0109*x_3 + 0.2865*x_4 + 0.1832*x_5 \\ & +0.0260*x_6 - 1.6531*x_7 - 0.3419*x_8 \\ & -906.6572*x_9 + 0.2898*x_{10} \\ & +1.0584*x_{11} + 0.1155*x_{12} \end{aligned} \tag{13}$$

In the formula, y expresses the prediction value of lettuce leaf nitrogen rate and $x_1 \sim x_{12}$ express 12 characteristic value.

Model test: The rest twenty sample data were forecasted by the principal component regression equation and multiple linear regression equation:

$$R_{err} = \frac{|Y_{fore} - Y_{obs}|}{Y_{obs}} \times 100\% \tag{14}$$

In the formula, Y_{fore} expresses the prediction value of lettuce leaf nitrogen rate, Y_{obs} expresses the actual value of lettuce leaf nitrogen rate, R_{err} expresses prediction error rate. The prediction results of principal component regression analysis and multiple linear regression analysis method are shown in Table 2.

From Table 2, it is known that the average error rate of the prediction by the principal component regression analysis expression model is 9.30% and the error rate of the prediction by multiple linear regression expression model is 12.66%. The error rate of principal component regression analysis expression model is 2.26% and the error rate of multivariate linear regression expression model is 5.99%.The forecast effect of principal component regression analysis expression model is better than that of multiple linear regression expression model.

The principal component information is the linear combination of 12 features information, so the principal component regression model and multiple linear regression model are both multiple linear modeling based on 12 features information but their difference is the regression coefficient in each feature information.

Table 1: Correlation coefficient matrix of characteristics

	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	x_{10}	x_{11}	x_{12}
x_1	1.0000	0.6425	0.9666	0.1700	0.9553	0.8374	0.9861	0.6214	0.6563	-0.2310	0.9262	-0.9618
x_2	0.6425	1.0000	0.6886	0.5889	0.7284	0.8463	0.6894	0.9312	0.8812	0.0254	0.6540	-0.6794
x_3	0.9666	0.6886	1.0000	0.0595	0.9560	0.8327	0.9941	0.5901	0.6377	-0.2193	0.9116	-0.9633
x_4	0.1700	0.5889	0.0595	1.0000	0.1750	0.4414	0.1132	0.7923	0.6489	-0.0267	0.2208	-0.1174
x_5	0.9553	0.7284	0.9560	0.1750	1.0000	0.7973	0.9744	0.6486	0.6877	-0.1487	0.9223	-0.9790
x_6	0.8374	0.8463	0.8327	0.4414	0.7973	1.0000	0.8378	0.8682	0.8539	0.0788	0.7060	-0.7815
x_7	0.9861	0.6894	0.9941	0.1132	0.9744	0.8378	1.0000	0.6163	0.6593	-0.2136	0.9285	-0.9768
x_8	0.6214	0.9312	0.5901	0.7923	0.6486	0.8682	0.6163	1.0000	0.9312	0.0535	0.5930	-0.5934
x_9	0.6563	0.8812	0.6377	0.6489	0.6877	0.8539	0.6593	0.9312	1.0000	0.1196	0.5819	-0.6107
x_{10}	-0.2310	0.0254	-0.2193	-0.0267	-0.1487	0.0788	-0.2136	0.0535	0.1196	1.0000	-0.4764	-0.2158
x_{11}	0.9262	0.6540	0.9116	0.2208	0.9223	0.7060	0.9285	0.5930	0.5819	-0.4764	1.0000	-0.9489
x_{12}	-0.9618	-0.6794	-0.9633	-0.1174	-0.9790	-0.7815	-0.9768	- 0.5934	-0.6107	-0.2158	-0.9489	1.0000

Table 2: Test result

	Principal component regression model		Multiple linear regression model		
	Prediction result of of nitrogen rate	Error rate (%)	Prediction result of nitrogen rate	Error rate (%)	Real value of nitrogen rate
1	4.6010	1.37	4.3737	3.64	4.5387
2	4.4595	5.01	4.4749	4.68	4.6945
3	4.6779	5.98	4.8413	9.68	4.4141
4	4.8999	7.22	3.9589	13.37	4.5699
5	4.6841	1.80	4.1406	10.01	4.6011
6	4.4256	0.44	3.6989	16.79	4.4453
7	6.1043	25.85	3.8234	21.17	4.8503
8	4.7070	7.70	3.6844	27.75	5.0995
9	4.7234	11.82	4.5261	7.15	4.2241
10	4.2568	13.35	3.9966	18.65	4.9126
11	4.5989	7.29	4.6304	8.02	4.2864
12	4.6445	1.00	4.6879	0.7	4.6914
13	4.5554	4.17	4.6082	3.06	4.7537
14	4.5327	4.23	4.5348	4.28	4.3487
15	4.5345	11.07	4.4976	11.80	5.0991
Average value		7.22		10.72	
Variation		2.26		5.99	

From Table 1, it can be seen that, there is linear phenomena among some characteristic variables. In multivariate linear regression method, the original variables are directly use as variables to establish regression model and there are possibly redundancies among variables. However, the principal component regression analysis can eliminate the multicollinearity, although the calculation is more complex than multiple linear regression method but the results are more reliable and accurate.The Root Mean Square Errors (RMSEP) of PCR model was 0.4577 and the RMSEP of MLR model was 0.6284.

Because principal component analysis constructs a new variable combination according to the original all variables, these new variables as far as possible not only keep back the original information but also ensure each other uncorrelated. Adverse effects of the redundant information in estimating the results are reduced through calculating the regression coefficient by principal component analysis regression.

On the other hand, it is seen from the test result table, the error discrete degree of some test results is relatively large. One of the reasons is that the modeling method is to be improved, in addition, the lettuce leaves are rough and cameras can't adjust automatically and some similar objective factors lead to the decrease of the quality of the image acquisition, even the color value of the same nitrogen level blades is different which lead to nitrogen diagnosis error. So if the image quality can be improved, the prediction accuracy of lettuce nitrogen rate will be promoted.

CONCLUSION

On lettuce rosette stage, the color images of different nitrogen level of lettuce were gathered and lettuce image feature vectors were constructed after preprocessing and feature extraction. The principal component regression analysis method and multiple linear regression method were used respectively to construct nitrogen regression expression and the same samples were tested. The results show that, the prediction error rate of principal component regression analysis regression expression is 9.30%, which can be used as a lettuce nitrogen nondestructive testing intuition expression model and is convenient to develop practical nondestructive testing instrument. At the same time, a simple and reliable way is provided for information nondestructive testing of other crops.

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