Detecting maize leaf water status by using digital RGB images

Han Wenting [1,2*], Sun Yu [1], Xu Tengfei [1], Chen Xiangwei [3], Su Ki Ooi [4]

(1. College of Mechanical and Electronic Engineering, Northwest A & F University, Yangling 712100, China;
2. Institute of Soil and Water Conservation, China Academy of Sciences, Yangling 712100, China;
3. College of Food Science and Engineering, Northwest A&F University, YangLing 712100, China;
4. National ICT Australia, Victoria Research Lab., Department of Electrical and Electronic Engineering, The University of Melbourne, Parkville, VIC 3010, Australia)

Abstract: To explore the correlation between crop leaf digital RGB (Red, Green and Blue) image features and the corresponding moisture content of the leaf, a Canon digital camera was used to collect image information from detached leaves of heading-stage maize. A drying method was adopted to measure the moisture content of the leaf samples, and image processing technologies, including gray level co-occurrence matrices and grayscale histograms, was used to extract the maize leaf texture feature parameters and color feature parameters. The correlations of these feature parameters with moisture content were analyzed. It is found that the texture parameters of maize leaf RGB images, including contrast, correlation, entropy and energy, were not significantly correlated with moisture content. Thus, it was difficult to use these features to predict moisture content. Of the six groups of eigenvalues for the leaf color feature parameters, including mean, variance, energy, entropy, kurtosis and skewness, mean and kurtosis were found to be correlated with moisture content. Thus, these features could be used to predict the leaf moisture content. The correlation coefficient (R^2) of the mean-moisture content relationship model was 0.7017, and the error of the moisture content prediction was within ±2%. The R^2 of the kurtosis-moisture content relationship model was 0.7175, and the error of the moisture content prediction was within ±1.5%. The study results proved that RGB images of crop leaves could be used to measure moisture content.

Keywords: maize leaf, moisture content, image processing, color feature extraction, texture feature extraction
DOI: 10.3965/j.ijabe.20140701.005

Citation: Han W T, Sun Y, Xu T F, Chen X W, Ooi S K. Detecting maize leaf water status by using digital RGB images. Int J Agric & Biol Eng, 2014; 7(1): 45－53.

1 Introduction

As water scarcity intensifies and more agricultural water is diverted to other uses, irrigation systems must employ advanced technology and equipment so that the limited water resources can meet the needs of farmland irrigation. Real-time monitoring of crop water requirements is a prerequisite for the accurate and rapid evaluation of water requirements, and such monitoring lays the foundation for decision-making and management of precision irrigation[1,2].

Crop moisture information can be obtained in real time by methods such as measuring crop leaf water potential, sap flow, transpiration rate, canopy temperature and hyper-spectral images[3-5]. Ballester[6] used a handheld infrared thermal imager to study leaf moisture content in citrus trees and persimmon trees. Wang and Omasa[7] used RGB (Red, Green and Blue) images to detect tree leaf wilt in an orchard. Kim[8] used a hyperspectral camera installed in a greenhouse above apple saplings that had been through different irrigation treatments to obtain tree images, and the study found that there were certain relationships between the moisture content of fruit trees and their spectral reflectance images. In recent years, studies have found that the crop water

Received date: 2013-05-02 **Accepted date:** 2014-02-16
Biographies: Yu Sun, PhD student, College of Mechanical and Electronic Engineering; Email: sunyu_nwsuaf@163.com. **Xu Tengfei,** PhD student, College of Mechanical and Electronic Engineering; Email: xa8318sy@163.com. **Chen Xiangwei,** PhD, College of Food Science and Engineering; Email: chenxiangwei@126.com. **Su Ki Ooi**, PhD, Email: suki@unimelb.edu.au.
***Corresponding author: Han Wenting,** PhD, Professor, Institute of Soil and Water Conservation, Northwest A & F University; Tel: 029-87091325; Email: hanwt2000@126.com.

deficit will directly affect the biochemical processes and morphology of crops and that this effect can be observed in the color changes of the crop leaves. Therefore, some scholars began to study ways to rapidly determine leaf moisture content using leaf images. Wang et al.[9] used a 5-megapixel digital camera to obtain digital images of field cotton under natural light conditions. The lens was 2 m above the ground and perpendicular to the ground. The focal length was fixed, and the resolution was 2 592 ×1 944 pixels. The image format was JPEG. Regression models were constructed using the G-R parameter of the RGB color system, as well as the moisture content of cotton and the moisture content index. The prediction accuracies were up to 90.7% and 91.0%, respectively. Song and Xie[10] used a 4-megapixel digital camera and a 6-megapixel digital camera to capture nasturtium leaf images under natural light with a fixed eye distance, and they extracted the three color components (RGB), their respective coefficients (r, g, b) and the chroma H values for analysis. These researchers used artificial neural network modeling and fuzzy judgment to derive the relationships of these parameters with water deficit time. Zakaluk[11] used a 5-megapixel digital camera to capture RGB digital images of potato seedlings and determine the relationship between leaf water potential and image features.

In our study, a Canon digital camera was used to collect images of the detached leaves of heading-stage potted maize plants cultivated in a greenhouse under different irrigation treatments. The leaf texture feature parameters and color feature parameters were extracted, and their correlations with leaf moisture content were studied using image processing technology, including analysis of gray-level co-occurrence matrices (GLCMs) and gray histograms. The correlations were used to construct a prediction model.

2 Materials and methods

2.1 Irrigation treatment of maize

Maize was chosen as the subject of study. Maize samples were cultivated in plastic buckets with a height of 30 cm and a diameter of 25 cm in the greenhouse. Base fertilizers of nitrogen, phosphorus, potassium, etc., were applied to ensure that sufficient nutrition was provided for maize growth. The 90 maize plants that were raised were divided into three groups, with 30 plants per group. Water volumes of 1 500 mL, 1 200 mL and 900 mL were applied to Group I, Group II and Group III at each watering, respectively. Before collection, samples were watered once every five days, and irrigation was strictly controlled to cultivate samples with different levels of moisture.

2.2 Leaf image collection

A Canon IXUS 110 camera with 4×optical zoom and 12.1 effective megapixels was used to collect maize leaf images. The fifth leaf from the top of the jointing stage plants was photographed. The collecting time was 10:00 am to 11:00 am, Beijing Time. The background color was white, and a fluorescent background light source was used. The lens was positioned 5 cm away from the leaf. Acquired images were 1 600 × 1 200 true-color images stored as JPEG files. There were 90 images in total. Thirty-four images with uneven illumination were excluded. The remaining 56 sets of sample data were divided into three groups. The first group had 16 sets of sample data and was used to determine the feature parameters. The second group had 20 sets of sample data and was used to establish the prediction model. The third group had 20 sets of sample data and was used to verify the model.

To reduce the impact of external noise on the image processing results, images were filtered before analysis. Linear spatial filtering was used. The *imfilter* function in the MATLAB image processing toolbox was used to perform linear spatial filtering.

2.3 Leaf moisture measurement

The collected leaf samples were weighed immediately after their images were taken. Immediately after weighing the fresh leaves, the samples were dried to obtain dry weights, and the moisture content values were calculated. The dryer temperature was 74℃, and the drying time was 4 hours. The dried leaves were weighed, and the results were recorded. Then, the leaves were dried again for 1 hour and weighed again. When the dry weight difference between two adjacent measurements was less than 0.002 g, then the measured dry weight was regarded as the leaf's dry weight. Moisture content was calculated using the following equation:

$$v = \frac{w_1 - w_2}{w_1} \times 100\% \tag{1}$$

where, v is the moisture content of the maize leave sample; w_1 is the fresh weight of maize leaf; and w_2 is the fresh dry weight of the maize leaf after drying. The leaf moisture content distribution is shown in Figure 1.

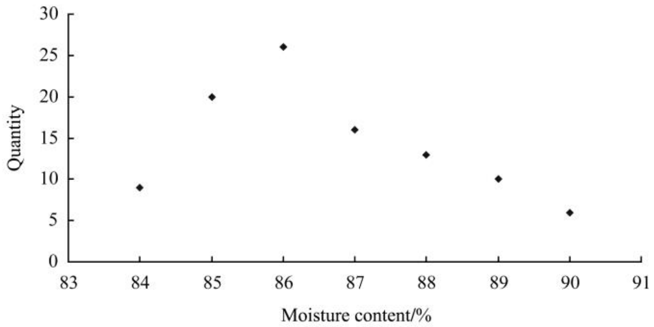

Figure 1 Leaf moisture distribution

2.4 Maize leaf texture feature extraction method

The maize leaves had a natural texture but did not display particular patterns or shapes. Instead, they showed an irregular distribution of color and grayscale intensities. The leaves did show certain overall regularities that could be treated as a quasi-regular texture. Therefore, the texture features were described based on pattern recognition in our study. The GLCM texture analysis method was used. The GLCM analyzes the grayscale relationship between two pixels in image space that are separated by a certain distance and then randomly extracts the leaf texture feature information based on probability characteristics. The texture description was achieved with statistical analysis[12-14].

In the GLCM extraction process, different chosen step lengths will lead to different distances and different directions between pairs of pixels. For an image, choosing a different step length produces different GLCM results. After the step length and angle between pixels is chosen, an $n \times n$ GLCM with a certain step length and direction can be generated, as described by Equation (2).

$$p_d = \begin{pmatrix} p_d(0,0), p_d(0,1), & \cdots & p_d(0, G-1) \\ p_d(1,0), p_d(1,1) & \cdots & p_d(1, G-1) \\ \vdots & \cdots & \vdots \\ p_d(G-1,0),\cdots\cdots & \cdots & p_d(G-1, G-1) \end{pmatrix} \tag{2}$$

Element $P_d(i, j)$ in the GLCM P_d denotes the number of occurrences for different grayscale pixels in the entire grayscale image. The pixels have the same step length (d) in the same direction.

The GLCM has 15 feature parameters in total. Based on the meaning of each feature parameter and a comparison of the results, we selected four parameters, including contrast, correlation, entropy and energy, to study the texture features[15-17]. Energy (angular second moment) reflects the roughness distribution and texture image, and it is calculated as follows:

$$ASM = \sum_i \sum_j P(i, j)^2 \tag{3}$$

The contrast reflects the transparency and the depth of the image and the texture, and it is calculated as follows:

$$CON = \sum_i \sum_j (i-j)^2 p(i, j)^2 \tag{4}$$

The correlation reflects the degree of correlation in the local grayscale image, and it is calculated as follows:

$$COR = \frac{\sum_i \sum_j \left((ij) p(i, j) - \mu_x \mu_y\right)}{\sigma_x \sigma_y} \tag{5}$$

In the following equations, entropy reflects the random number of the image texture:

$$u_x = \sum_{i=0}^{l-1} i \sum_{j=0}^{l-1} p(i, j)$$

$$u_y = \sum_{j=0}^{l-1} j \sum_{i=0}^{l-1} p(i, j)$$

$$\sigma_x = \sum_{i=0}^{l-1} (i - u_x)^2 \sum_{j=0}^{l-1} p(i, j)$$

$$\sigma_y = \sum_{j=0}^{l-1} (j - u_y)^2 \sum_{i=0}^{l-1} p(i, j)$$

Entropy is calculated as follows:

$$ENT = -\sum_i \sum_j p(i, j) \log p(i, j) \tag{6}$$

2.5 Extraction method for leaf color features

Because the captured images are RGB images and the features of each pixel are described with three values, the image processing workload is heavy. When using image processing to extract valid information, the color information is usually projected onto gray space. Therefore, grayscale features correspond to the color features of the image. The grayscale features of the image are not sensitive to size or direction, and thus, they are quite robust. The grayscale histogram is a function of the grayscale image; it represents the number of pixels at each grayscale intensity and reflects the occurrence frequency of each grayscale pixel in the image. The grayscale histogram of the image can be defined with the following equation:

$$H(i)=\frac{n_i}{N},\ i=0,1,2,\cdots,L\text{-}1 \tag{7}$$

where, i denotes the grayscale intensity; L denotes the number of unique grayscale values; n_i is the number of pixels with grayscale value i; and N is the total number of pixels in the image. The horizontal coordinate of the histogram is grayscale intensity, and the vertical coordinate is the frequency of occurrence for this grayscale intensity value.

The image histogram provides a global description of the appearance of the image. The features extracted from the histogram are rotation, scale and translation (RST) independent. Thus, this method is widely used in image classification and recognition. The conventional histogram method considers only the number of pixels at each grayscale value. However, if the shape and size of the leaves change and external factors interfere, the color feature parameter also changes accordingly. The effects of leaf shape and size can be eliminated by using the percent histogram for the leaf image statistics.

The grayscale histogram-based statistical features include the mean, variance, energy, entropy, skewness and kurtosis, among other features. The mean reflects the average grayscale value of an image. The mean is calculated as follows:

$$\mu=\sum_{i=0}^{L\text{-}1} iH(i) \tag{8}$$

where, i denotes the grayscale level of the image; μ is the mean image grayscale value, and $H(i)$ is the frequency of a pixel with a grayscale level of i.

Variance reflects the discrete distribution of grayscale values of an image. Energy reflects the degree of uniformity of the grayscale distribution. Energy is higher when the grayscale distribution is more uniform. Entropy reflects the uniformity of the grayscale distribution in a grayscale histogram. Skewness reflects the degree of distribution asymmetry in a grayscale image histogram. A greater skewness indicates a more asymmetric distribution in the grayscale histogram, and a lower skewness indicates a more symmetric distribution. Kurtosis reflects the approximate state of the grayscale image when the grayscale distribution is around the mean. It is used to determine whether the grayscale distribution concentrates around the mean grayscale value. Lower kurtosis indicates a more concentrated distribution, and higher kurtosis indicates a more dispersed distribution. Kurtosis is calculated as follows:

$$u_k=\frac{1}{\sigma^4}\sum_{i=0}^{L-1}(i-u)^3 H(i)-3 \tag{9}$$

where, σ^2 is variance and u_k is the kurtosis of the image.

2.6 Prediction model construction

Simple linear regression was used to construct the image eigenvalue moisture-content model. The following equation was used:

$$y=ax+b \tag{10}$$

In this equation, a and b are the regression coefficients determined by the observed data: (x_1, x_2, …, x_n) and (y_1, y_2, …, y_n); x is the image eigenvalue, and y is the moisture content.

3 Results and analysis

3.1 Moisture content distribution in the leaf samples

After collecting the leaf images, we measured the moisture content immediately using the drying method. The results shows that the leaf moisture was within a narrow range of 84% to 90%, mainly concentrated at approximately 86% (Figure 1).

3.2 Leaf texture feature extraction

We randomly selected eight maize leaves with moisture content values within two ranges, 84%-85% and 89%-90%, as the test samples to extract feature parameters. To reduce the computational load in the image GLCM extraction, the maize leaf grayscale images were compressed from 256 levels to 16 levels. A GLCM with the directions of 0 degrees, 45 degrees, 90 degrees and 135 degrees and 10 step lengths from 1 to 10 was extracted from each maize leaf image. The feature parameter extraction program was written in MATLAB to calculate the following feature parameters: energy, entropy, contrast and correlation. After comparison, GLCMs with a direction of 90 degrees and step length of 1 were chosen to extract feature parameters.

Results show that there are overlaps and no obvious distinctions between these feature parameters (correlation, entropy, energy and contrast) (Figure 2). Therefore, it is difficult to use texture features to predict maize leaf moisture content.

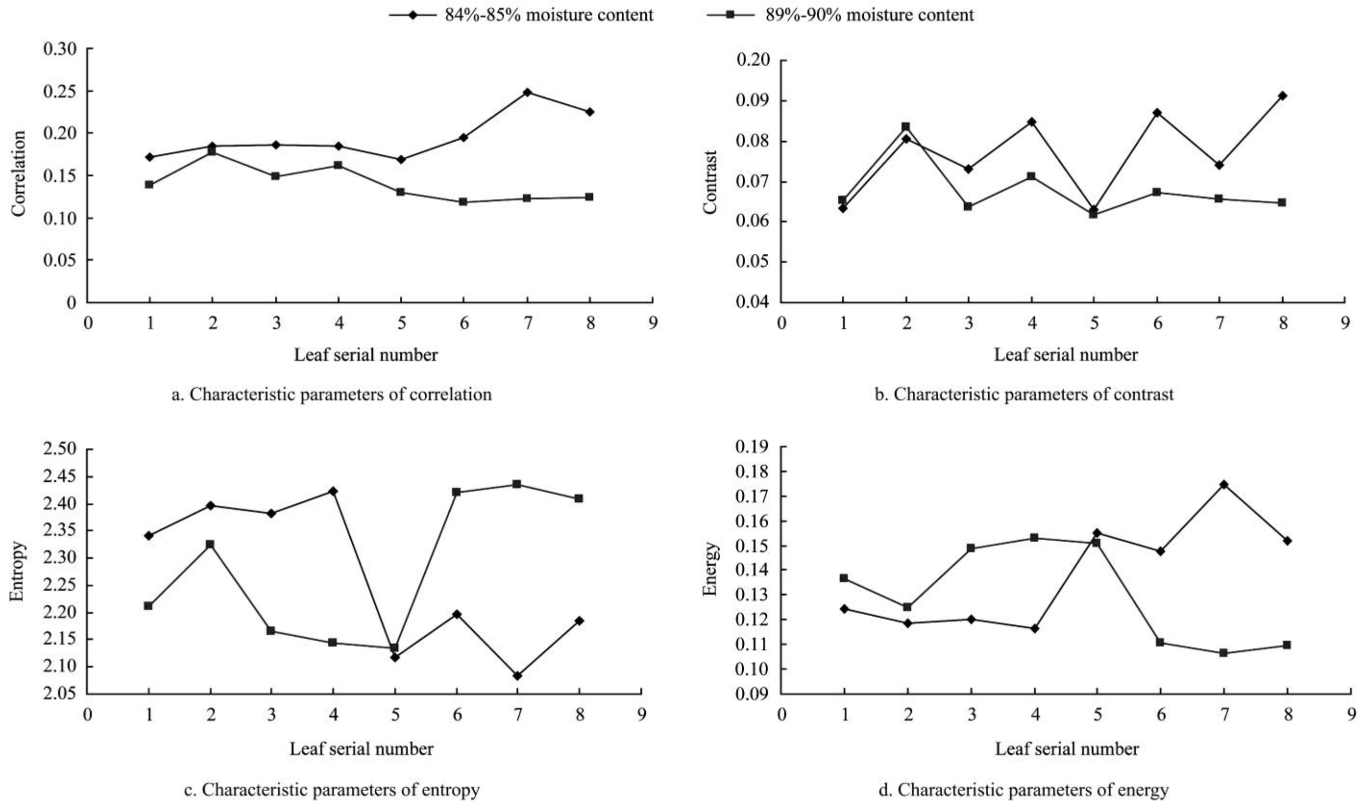

Figure 2 Feature parameters of the leaf texture gray-level co-occurrence matrices (GLCM) at different moisture contents

3.2 Color feature parameter extraction

The leaf grayscale histogram is calculated based on the definition of a grayscale histogram. Figure 3 is an example of a crop leaf image grayscale histogram.

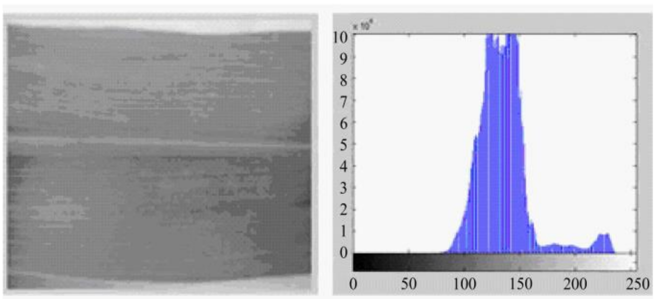

Figure 3 Grayscale histogram of maize leaf

Grayscale histogram feature parameter analysis was performed on eight groups of leaf samples with moisture contents in the ranges of 84%-85% and 89%-90%. The feature parameters of the sample grayscale histogram were calculated with equations to determine the mean, variance, energy, entropy, skewness and kurtosis. The results are shown in Figure 4. In the figure, the horizontal coordinate is the sample leaf serial number, and the vertical coordinate is the extracted eigenvalue of the mean of the sample leaf images. Different serial numbers denote leaves with different moisture content.

As suggested by the mean parameters in Figure 4a, the mean image grayscale value of maize leaves with higher moisture content was larger than that of maize leaves with lower moisture content. The kurtosis parameter in Figure 4f suggests that the leaf image grayscale distribution of a leaf with higher moisture content is more concentrated around the mean grayscale value. However, the four feature parameters (variance, energy, entropy and skewness) overlapped with each other and could not be used to predict moisture content. In addition, there was no correlation between mean and kurtosis; they were relatively independent of each other and were useful for measuring maize leaf moisture content. Therefore, we chose mean and kurtosis as feature parameters to predict the moisture content. A mean-moisture content relationship model and a kurtosis-moisture content relationship model were constructed to predict the maize leaf moisture content.

3.3 Prediction model construction

The 20 groups of leaf samples in the second part of the study were used to construct the prediction model. Data are shown in Table 1.

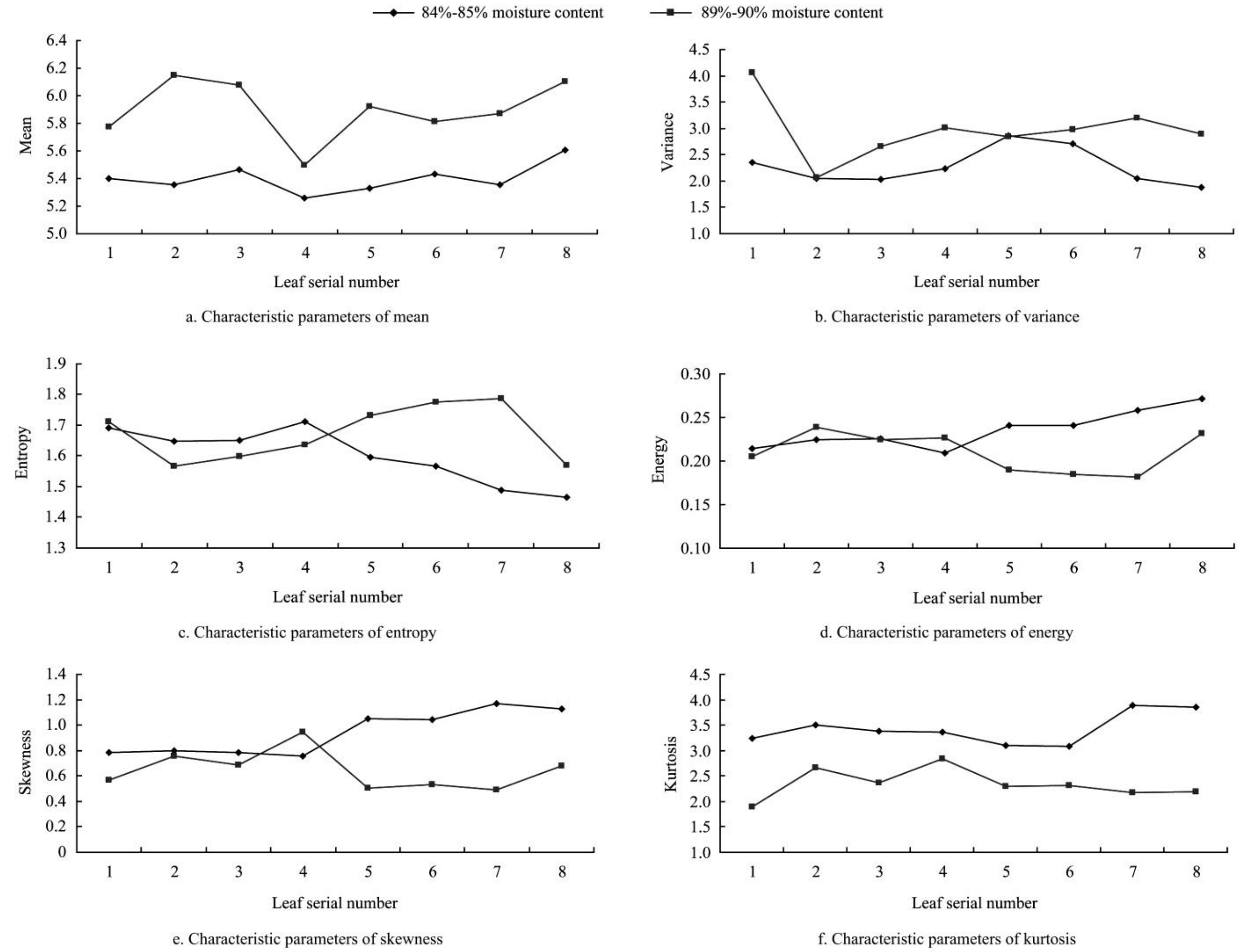

Figure 4 Comparison of the feature parameters of leave at different moisture contents

Table 1 Sample eigenvalues of the established model

Parameter	Leaf serial number																			
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Moisture content/%	84.99	84.23	85.35	85.7	85.07	85.27	86.25	86.49	86.31	86.34	87.89	87.06	87.19	87.62	88.07	88.16	89.65	89.8	89.34	89.05
Mean	5.4524	5.4315	5.4785	5.7172	5.7759	5.4890	5.4816	5.5893	5.8700	5.9881	5.7446	5.5663	5.6315	5.6106	5.7954	5.6804	5.8537	5.7530	6.1052	5.9290
Kurtosis	5.4226	4.4831	5.057	3.436	2.8267	4.5425	4.4459	4.229	2.1266	2.9847	2.7698	3.3284	2.8501	3.0869	2.9788	3.0285	2.7884	2.6695	2.2135	2.2400

Because the color of the leaf image information in groups 5, 9 and 10 changed, resulting in noisy image information, these groups were excluded and were not used in model construction. The relationship between the leaf moisture content and the mean leaf eigenvalue was obtained by simple linear regression based on the remaining 17 sets of data. The following regression line was obtained:

$$y = 0.0791x + 0.4235 \tag{11}$$

In this equation, x is the extracted eigenvalue, and y is the moisture content predicted based on the eigenvalue.

The correlation coefficient (R^2) was 0.7017. The correlation was significant, so the model can be used to determine maize leaf moisture content. The relationship between the mean and the moisture content is shown in Figure 5.

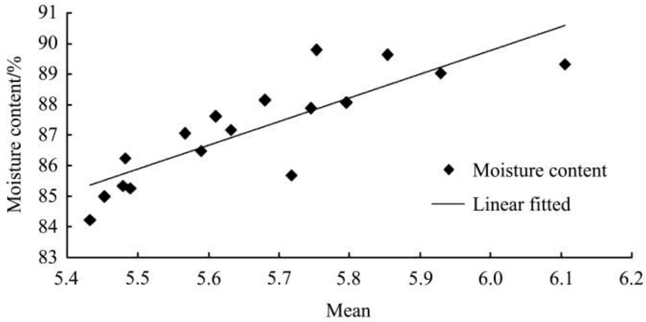

Figure 5 Relationship between the leaf moisture content and the mean

The relationship between the kurtosis and the leaf moisture content is as follows:

$$v = -0.0147u_k + 0.9226 \tag{12}$$

where, v denotes the maize leaf moisture content, and u_k denotes the kurtosis of the maize leaf image histogram feature parameters.

The R^2 of the model was 0.7650. The correlation was significant, so the model can be used to determine maize leaf moisture content. The relationship between the kurtosis and moisture content is shown in Figure 6.

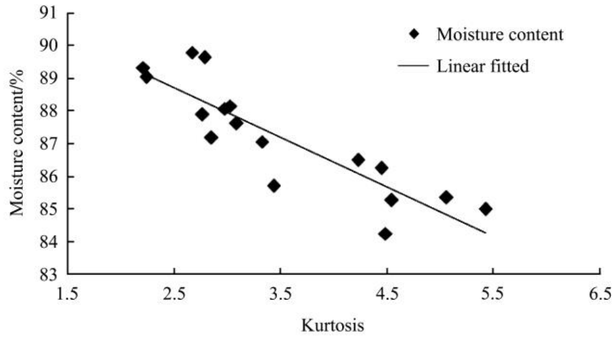

Figure 6 Relationship between leaf moisture content and kurtosis

Based on the results shown in Figures 5 and 6 and the fact that the correlation coefficients of the two models are significant, we are confident that these models can be used to predict and diagnose maize leaf moisture content.

3.4 Model verification

The mean and kurtosis of the grayscale histograms were extracted from the 20 maize leaves with different moisture contents in the third group, and the values were inserted into Equations (15) and (16) to predict leaf moisture content. The measured moisture contents and the predicted moisture contents of the 20 sample leaves are shown in Table 2. The results are shown in Figures 7 and 8.

Table 2 Verification results for the leaf moisture content prediction model

Parameter	Leaf serial number																			
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Mean	5.5233	5.358	5.6093	5.7028	5.3556	5.5453	5.5651	5.4027	5.8346	5.8246	5.7264	5.7174	5.6260	5.6106	5.7953	5.6804	5.7469	5.5593	5.8537	6.1052
Kurtosis	5.2150	4.8915	5.0361	4.7905	4.7867	4.6950	4.5637	4.0194	3.7348	3.4257	2.8341	3.2839	2.7035	3.0688	3.1384	3.4135	2.5898	2.5690	2.5742	2.1898
Measured moisture content/%	84.99	84.23	85.35	85.7	85.07	85.27	86.25	86.49	86.31	86.34	87.89	87.06	87.19	87.62	88.07	88.16	89.65	89.8	89.34	89.05
Moisture content predicted by the mean model/%	86.07	84.79	86.74	87.47	84.77	86.24	86.4	85.13	88.49	88.42	87.65	87.58	86.87	86.75	88.19	87.29	87.81	86.35	88.64	90.60
Moisture content predicted by the kurtosis model/%	84.59	85.06	84.85	85.28	85.28	85.35	85.58	86.41	86.77	87.22	88.01	87.53	88.41	87.86	87.75	87.33	88.58	88.48	88.47	89.19

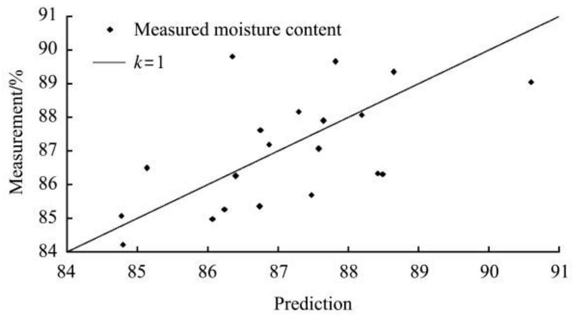

Figure 7 Measured values and values predicted by the mean prediction model

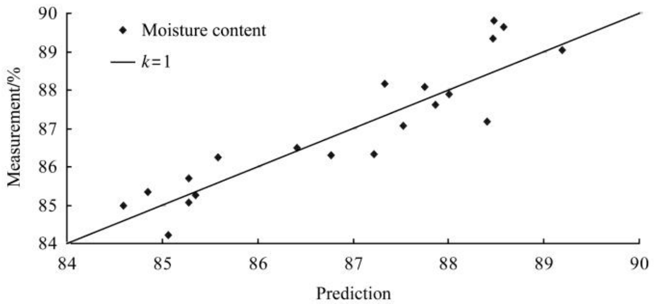

Figure 8 Measured values and values predicted by the kurtosis prediction model

Figures 7 and 8 contain points that are distributed on both sides of the line with slope k=1. The differences between the leaf moisture content values calculated with the regression prediction model and the actual measurements were small. The error of the mean prediction model was within ±3.8%, and the error of the kurtosis prediction model was within ±1.4%.

4 Conclusions

The RGB images of detached leaves of heading-stage maize were collected with a digital camera. Leaf texture feature parameters and color feature parameters were extracted with image processing technology, including GLCM and grayscale histograms. Correlations of feature parameters with leaf moisture content were studied, and prediction models were constructed. In the experimental study, the texture feature parameters, including contrast, correlation, entropy and energy were not significantly correlated with moisture content. Those features could thus not be used to predict leaf moisture content. Of the 6 leaf color parameters considered (mean, variance, energy, entropy, kurtosis and skewness), the mean and kurtosis were found to be well correlated with moisture content and could be used to predict leaf moisture. The R^2 of the mean-moisture content relationship model was 0.7017, and the error of moisture content prediction was within ±3.8%. The R^2 of the kurtosis-moisture content relationship model was 0.7650 (R^2=0.7650), and the prediction error was within ±1.4%. Our results indicate that RGB images of leaves can be used to measure the moisture content.

Acknowledgements

This paper was founded by the National Science & Technology Supporting Plan (2012BAH29B04-02) and the Science and Technology Innovation Project from Northwest A & F University (Z109021202).

[References]

[1] Huang Y X, Han W T, Zhou L, Liu W S, Liu J D. Farmer cognition on water-saving irrigation technology and its influencing factors analysis. Transactions of the Chinese Society of Agricultural Engineering, 2012; 28(18): 113-120. (in Chinese with English abstract)

[2] Han W T, Wu P T, Feng H, Yang Q. Theoretical study on variable-rate sprinklers for high uniformity precision irrigation. Transactions of the Chinese Society of Agricultural Engineering, 2005; 21(10): 13-16. (in Chinese with English abstract)

[3] Chen X W, Han W T. Spectroscopic determination of leaf water content using linear regression and an artificial neural network. African Journal of Biotechnology, 2012; 11(10): 2518-2527.

[4] Thanh H N, Tateishi R. Persistent water, temporary water, partial water mapping using MODIS data 2008. The 32nd Asian Conference on Remote Sensing, 2011; volume 2, pp 977-982.

[5] Modzelewska-Kapitua M, Cierach M. Correlation of the attributes measured by computer vision with moisture and fat content of meat batters. Food Science and Technology Research, 2012; 18(6): 769-779.

[6] Ballester C, Jiménez-Bello M A, Castel J R, Intrigliolo D S. Usefulness of thermography for plant water stress detection in citrus and persimmon trees. Agricultural and Forest Meteorology, 2013; 168: 120-129.

[7] Wang F, Omasa K. Image measurements of leaf scorches on landscape trees subjected to extreme meteorological events. Ecological Informatics, 2012; 12: 16-22.

[8] Kim Y, Glenn D M, Park J, Ngugi H K, Lehman B L. Hyperspectral image analysis for water stress detection of

apple trees. Computers and Electronics in Agriculture, 2011; 77(2): 155-160.

[9] Wang F Y, Wang K R, Wang C T, Li S K, Zhu Y, Chen B, et al. Diagnosis of cotton water status based on image recognition. Journal of Shihezi University (Natural Science), 2007; 25(4): 404-408.

[10] Song Y J, Xie S Y. Application of machine vision in the irrigation for tropaeolum. Journal of Southwest Agricultural University, 2006; 28(4): 659-662.

[11] Zakaluk R, Sri Ranjan R. Predicting the leaf water potential of potato plants using RGB reflectance. Canadian Biosystems Engineering, 2008; 50(7): 1-7.

[12] Gao C C, Hui X Wei. GLCM-based texture feature extraction. Computer Systems and Applications, 2010; 19(6): 195-197.

[13] Moffett K B, Gorelick S M. Distinguishing wetland vegetation and channel features with object-based image segmentation. International Journal of Remote Sensing, 2013; 34(4): 1332-1354.

[14] Chung S O, Cho K H, Kong J W, Sudduth K A, Jung K Y. Soil texture classification algorithm using RGB characteristics of soil images. 3rd IFAC International Conference Agricontrol, 2010; Volume 3, Part 1, pp 34-38. DOI: 10.3182/20101206-3-JP-3009.00005.

[15] Hendrawan Y, Murase H. Image feature selection in machine vision for determining Sunagoke moss water content (bio-inspired approaches). American Society of Agricultural and Biological Engineers Annual International Meeting, 2010; volume 2, pp 976-993.

[16] Hendrawan Y, Murase H. Bio-inspired feature selection to select informative image features for determining water content of cultured Sunagoke moss. Expert Systems with Applications, 2011; 33(11): 14321-14335.

[17] Hendrawan Y, Murase H. Neural-Intelligent water drops algorithm to select relevant textural features for developing precision irrigation system using machine vision. Computers and Electronics in Agriculture, 2011; 77(2): 214-228.