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Non-destructive Moisture Content Detection of Corn Leaves Based on Dielectric Properties and Regression Algorithm

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Abstract: Moisture content is a major index in the healthy growth of crops. It is beneficial to water and fertilizer management when the crop moisture content is detected timely. The dielectric properties (relative dielectric constant ε' and dielectric loss factor ε'') of 280 pieces of corn leaves with different moisture contents were measured with a self-made clamping capacitor and an LCR measuring instrument at 36 discrete frequencies over the frequency range of 0.06 ~ 200 kHz and the moisture content of the corn leaves were measured by drying weight method. To obtain the moisture content of corn leaves, linear regression methods (the combination of SWR and MLR) and nonlinear regression methods (SPA and SVR) were used to establish models to get the relationship between the moisture content and dielectric parameters (ε', ε'' and the combination of ε' and ε''), and the leave one out cross validation (LOOCV) was used to select the best models. The results showed that contrasted with the linear regression method, the nonlinear regression method had better predictive ability. The highest coefficient of determination (0.804) and the lowest root mean square error (0.017 6) were obtained by using the nonlinear regression model with the variable in the combination of ε' and ε'', which simplified the model with variables reduced from 72 to 10 and eliminated the overlap variables, and the complexity of the model was decreased effectively. The study indicated that it was feasible to detect the corn leaf moisture content non-destructively, and the results provided a credible method for rapid non-destructive detection of physiology information in crops.

Key words: corn leaves; moisture content; non-destructive detection; dielectric properties; regression algorithm

0 Introduction

In recent years, there are mainly two methods, the traditional measurement of wet basis moisture content and spectral measurement technology, of detecting the moisture content of crop leaves at home and from overseas. The traditional measurement of wet basis moisture content is a drying method, which the crop leaves are dried by oven, then the dry weight and wet weight are measured, and the moisture content can be calculated. Because the method is destructive and long time-consuming, and destroys the shape and internal features of the crop leaf, it is obviously not conducive to be promoted. Numerous studies have been conducted to detect the moisture content of crop leaves by spectroscopic techniques at home and from overseas. Different modeling methods are applied to precisely predict the moisture content of different crops, which are time-saving and labor-saving compared with drying method. However, in practical applications, the sample information measured by spectral instrument can not stand better for the whole sample information. Thus, the prediction accuracy needs to be improved.

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Dielectric technology measures the general information within the sample, thus it is more convincing compared with spectroscopy. Dielectric properties are defined that one kind of response produced by substance in the electric field, and it is characterized by relative dielectric constant ε', dielectric loss factor ε'', dielectric loss tangent $\tan\sigma$ and dielectric impedance, etc.

The technology of dielectric properties is applied to various fields of moisture content, and especially it plays a very important role in the nondestructive detection of fruit's internal quality grade and grain moisture content detection. Meanwhile, the study based on dielectric property principle has made a certain progress in detecting the moisture content of leaves. However, there are still not too many researches on crop leaves based on dielectric properties, mainly because LCR measuring instrument and parallel electrode plate are often used to measure dielectric properties of crop leaves. LCR measuring instrument belongs to sensitive instruments, which is easily influenced by subtle changes in the electrode plate. So it needs very high measurement accuracy.

Therefore, corresponding dielectric parameters at different frequencies (relative dielectric constant ε' and dielectric loss factor ε'') of different moisture contents of the corn leaves were measured with a LCR measuring instrument and a self-made clamping parallel electrode plate. Linear regression methods (combination of SWR and MLR) and nonlinear regression methods (SPA and RBF - SVR) were used to establish prediction models to get the relationship between moisture content and dielectric parameters of corn leaves, then the best regression model can be selected according to two kinds of criteria (R_p^2 and RMSEP) to predict moisture content of unknown corn leaves.

1 Experiment and methods

1.1 Experiment and data acquisition

1.1.1 Instruments and equipment

HPS2816B LCR digital bridge measuring instrument developed by Changzhou HPS Technology Company was used to measure parameters, such as capacitance, resistance, inductance and capacitance loss factor. The measuring frequencies were 60 Hz, 80 Hz, 100 Hz, 120 Hz, 150 Hz, 200 Hz, 250 Hz, 300 Hz, 400 Hz, 500 Hz, 600 Hz, 800 Hz, 1 kHz, 1.2 kHz, 1.5 kHz, 2 kHz, 2.5 kHz, 3 kHz, 4 kHz, 5 kHz, 6 kHz, 8 kHz, 10 kHz, 12 kHz, 15 kHz, 20 kHz, 25 kHz, 30 kHz, 40 kHz, 50 kHz, 60 kHz, 80 kHz, 100 kHz, 120 kHz, 150 kHz and 200 kHz. The other main instruments were micro-balance measuring instrument with resolution of 0.001 g (Hangzhou Wante Weighing Limited Company), thickness measuring instrument with accuracy of 0.01 mm, electric oven blast and a self-made clamping parallel electrode plate.

1.1.2 Self-made clamping parallel electrode plate

Traditional electrode plate is often used to measure solid or not easily deformed objects, and the electrode plate should be in close contact with the measured object. Due to the softness and easy deformation of leaves, pressure on the leaf can not get controlled. The pressure between two electrode plates are too small to clamp the leaf, so that mixed air between the plates affects the measurement accuracy; the pressure between two electrode plates are too big to deform the leaf and increase measurement error. Thus, making a kind of electrode plate with suitable pressure is particularly important.

Homemade holding parallel electrode plates is a simple portable parallel electrode plates, which can perform the following functions: no damage to the leaf structure under the condition of clamping; in the measurement of samples, ensuring the data measured by LCR measuring instrument get gradually stable; measuring the same sample at the same position several times, and ensuring that the measured results are similar.

(1) Performance standards of self-made clamping parallel plate

The performance of the designed instruments includes: the greatest pressure that leaves can bear when holding parallel electrode plates clamp leaves; whether the count of LCR measuring instrument connection is stable or not when electrode plates clamping leaf samples, etc. The above performance will be measured by some indirect methods.

The self-made parallel electrode plates used in this experiment should meet the following three kinds of performance standards: ① Two electrode plates were used to clamp the leaf, kept it stable for 5 min or so, and took out the leaf. The leaf and contact pressure between the electrode plates should not be damaged if there was no trace of extrusion on the surface of the leaf. ②After two electrode plates were used to clamp the leaf for a period of time (30 s), gradually forced the leaf out from the two electrode plates. The leaf can not be pulled out from the two electrode plates and it was still not damaged, which indicated that the electrode plates were very close to the leaf and the air gap between the contact surfaces was negligible. ③When the held sample was tested, the self-made clamping parallel plate should be kept stable to facilitate LCR to record data, because the electrode plate was connected with the LCR measuring instrument, and small changes would lead to changes in parameters, the electrode plate and sample to be tested should be ensured stable; the reading of LCR measuring instrument which was connected with the parallel electrode plates should be gradually steady. In the instrument making process, if three measured results of a parameter with the same leaf at the same position in the case of stable reading were little different, it would explain the stability of the instrument.

Among them, the performance standards ① and ② reflected the steady performance of self-made instrument, and the performance standard ③ reflected the dynamic performance.

(2) Structure of self-made clamping parallel plate

The self-made clamping parallel plate used in the experiment consisted of a small plastic clip with weak holding force, two hard circular copper plates with diameter of 20 mm and thickness of 1.5 mm, two slender cylindrical metal strips and two wires.

(3) Concrete structure: one side of two plates was respectively polished to be smooth enough, and centers of the other sides were connected with two short metal strips by soldering. Then the two short metal strips were put into the center hole dug at top of the two jaws of plastic clips, the size of this small hole was in agreement with the cross-section size of the short and small metal strips. Rotating and controlling the metal strip position made the two smooth electrode plates fully align and close with each other at the same time. At this time, the self-made clamping parallel plate was measured, if it met the three performance standards, metal strips would be fixed with plastic clips with an adhesive. The instrument was finally carried out. The concrete object was shown in Fig. 1.

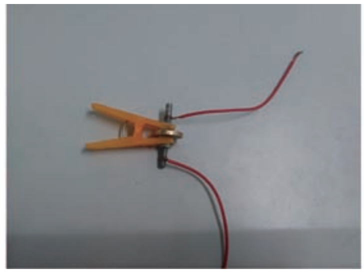

Fig. 1 Physical instrument of self-made parallel electronical plate

1.1.3 Experimental materials

Corn was cultivated in a farmland of Dantu Road Jingkou District of Zhenjiang City, corn variety was Suyu 19. All corn plants were fertilized properly before the grain formation period. In order to get corn leaves with different moisture contents, all corn plants were randomly divided into four groups after the grain formation period, three groups among which were fertilized according to adequate, appropriate, a small amount of three kinds of irrigation once 2 d for 10 d. The remained one group was not fertilized. In the first 10 d, 70 strains were selected from each group, and 280 corn leaves were picked out from the same position (middle part of the corn plant) of each plant. Because the corn leaf area was very large, a rectangular sample of side length 30 mm × 35 mm in the middle of each plant was cut out before experiment. A total of 280 samples were collected.

1.1.4 Experimental methods and procedures

The LCR measuring instrument was opened and adjusted to $C_p - D$ (C_p for measuring shunt capacitance, D for loss factor) block, and the self-made clamping parallel plate was connected with LCR measuring instrument, and it was stayed for 10 min to make the whole device stable.

The whole device was put into a 25℃ environment, and the full frequency was open circuit cleared, after which samples were put between self-made clamping parallel plates. Then LCR measuring frequency was adjusted to 60 Hz. When the error of C_p reading data was less than 0.5% (C_p data would be convergent gradually and smoothly, and measuring all the frequencies cost about 100 s), the data of C_p and D were recorded; then the frequency was adjusted to 80 Hz for 3s, and the data of C_p and D were recorded;

until the frequency was adjusted to 200 kHz, the data was recorded. Then, a mark was made at the edge of the leaf in contact with the electrode plate, the leaf next was removed from the electrode plate, and according to the mark, the thickness of four positions and the central part of contact points was measured. Finally, the quality of the leaf sample was measured. At this point, a sample data measurement was completed. All samples were processed in accordance with above steps. Eventually all leaves were placed in the oven and dried for 10 h at 120℃. And leaf dry mass of different samples was recorded sequentially.

1.1.5 Calculation of relative dielectric constant ε' and dielectric loss factor ε''

Sample parallel capacitance and loss factor were first measured by self-made parallel electrode plates and digital LCR measuring instrument; area was calculated according to the size of the fixed parallel plate electrode; five faceted thickness of samples were measured by the thickness measuring instrument, and the average thickness was treated as its thickness; the relative dielectric constant ε' and dielectric loss factor ε'' of corn leaves can be calculated according to the principle of parallel plate capacitor.

1.1.6 Moisture content measurement

Water situation of corn leaves can be judged by moisture content. Moisture content of corn leaf can be calculated as

$$M = \frac{M_0 - M_1}{M_0} \times 100\%$$

where M represents moisture content; M_0 represents fresh weight of corn leaves; M_1 represents dry weight of corn leaves.

1.2 Principles and methods

1.2.1 Sample division

Totally 280 moisture content of corn leaves containing the corresponding ε' and ε'' sample data were collected in the experiment. To observe the data, some of the abnormal data generated by experiment (mainly due to the lack of open circuit cleared and other reasons) were eliminated, and 267 sets of data were remained. Sample data of 50 groups were randomly selected from each group of different water content samples as training samples, and a total of 200 training samples were obtained. The remained 67 sets of sample data were treated as test samples.

1.2.2 Modeling method

To fully understand the relationship between moisture content of corn leaves and the corresponding dielectric parameters, three variables of corn leaves, i. e., ε', ε'' and fusion information of both variables, were applied respectively to establish the prediction model of moisture content. Among them, each of ε' and ε'' contained 36 characteristic variables corresponding to measurement frequencies. The fusion information of ε' and ε'' was a combination of the two parameters, namely 72 characteristic variables.

Full frequency variables (36 single variables corresponding to frequencies or 72 variables corresponding to frequencies of fusion information variables) can be selected for data model. However, because there was a certain correlation between the full frequency variables, a frequency corresponding to the variable information can be explained by several other groups of frequency variables. That was, this set of variables would become redundant information or useless information, and they would increase the complexity of the model. In order to remove redundant information or useless information in the data and achieve the purpose of streamlining the model, two methods were selected by characteristic frequency variables, which were stepwise regression and successive projection algorithms, and they were used to compare and analyze the forecasting results of models, which were established by the combination of characteristic frequency variables and total frequency variables with the corresponding regression algorithm.

In statistics, regression algorithm was mainly divided into two categories: linear and nonlinear. Linear regression can be used to accurately measure the contribution of each variable to the regression fitting and the degree of correlation among the variables, and it can reflect the linear causal relationship between the independent variable and the dependent variable so as to facilitate analysis. While nonlinear regression, through a nonlinear mapping, can convert a low dimensional nonlinear problem into a high dimensional linear problem. Compared with linear regression, nonlinear regression can enhance correlation between variables through the nonlinear mapping, but it also increased the complexity of the regression model. Two kinds of regression algorithm, multiple linear regression

(MLR) and support vector regression (SVR) were used to fit the regression relationship between two kinds of information variables of corn leaves (ε', ε'' and their fusion information) and the moisture content and the comparative analysis of the effects of linear and nonlinear regression on modeling was made.

The modeling method was a combination of characteristic frequency variable selection and the regression algorithm. Linear modeling and nonlinear modeling were used. Linear modeling was combined with SWR and MLR, and nonlinear modeling was a combination of SPA and SVR. By these methods, the two modeling methods can be analyzed to compare the prediction effects on the moisture content of corn leaves.

Linear modeling was combined with stepwise regression (SWR) and multiple linear regression (MLR). Stepwise regression (SWR): the implementation process of SWR was that the contribution (partial regression quadratic sum) of all variables not introduced into the regression equation should be calculated in each step, then one variable with the greatest contribution would be selected to do F significance test. If the result was significant, the variable would be introduced into the regression equation, otherwise, it would be eliminated. Next, the contribution of all variables introduced into the regression equation was calculated in order to eliminate variables which were not significant to dependent variables. All steps above should be repeated until that no new variables can be introduced and all the variables in the regression equation were not far removed. Stepwise regression consisted of characteristic variable selection method and multiple linear regression. Only characteristic variable selection method was used to compare the effects on regression modeling of the full frequency variable and characteristic frequency variable. Therefore, the selection of characteristic frequency variable and multiple linear regression should be separated. Multiple linear regressions (MLR): when linear prediction or estimation, the factors influenced dependent variables were often decided by a plurality of interdependent and inter-effected variables. The linear method which was predicted by a number of independent variables and estimated dependent variables was called multiple linear regression.

Nonlinear regression was combined with successive projection algorithm (SPA) and support vector regression (SVR). Successive projection algorithm (SPA): a forward loop variable selection method, each cycle was from a variable, and the size of projection on the other unselected variables was calculated. Then the variable with the greatest projection vector would be introduced into the wavelength combination until cycled for N times. When the number of variables selected met the setting requirements, the combination of variables with a minimum of redundant information would be picked out to solve issues of overlapping information and collinearity and so on. Support vector regression (SVR) was a generalization of application of support vector machine for regression fitting. The main idea was that a low-dimensional inseparable problem can be transformed into a high dimensional linear separable problem through a nonlinear mapping. Compared with the traditional fitting method, kernel function was used in SVR to adapt to the nonlinearity of the training sample set and reduce the risk of over fitting through adjustable parameters. Replacing the linear term in the linear equation by using the kernel function can make the original linear algorithm become nonlinear. The RBF (radial basis function) kernel function was used to analyze the dielectric parameters and moisture content of corn leaves.

1.2.3 Leave one out cross validation method

Due to the limitation of the total number of samples collected, using a training set and testing set to model was accidental to a certain extent. In order to reduce the chance of modeling, results of modeling prediction were evaluated and compared by using the method of leave one out cross validation. The so-called left one method was to divide samples into N copies, the first copies was selected as a test set, and the remained $N-1$ samples were used as training samples for modeling analysis; then the second copies was selected as a testing set; until all the N samples were tested and set up as a model, finally N different models were obtained. The N models were analyzed and a model with the optimal performance was selected as the final model of this modeling method.

2 Results and analysis

2.1 Effect of frequency on relative dielectric constant ε' and ε'' of corn leaves under different moisture contents

The changing curves of ε' and ε'' with measurement frequency under different moisture contents were shown in Fig. 2 and Fig. 3, respectively. Within the frequency range of 60 Hz ~ 200 kHz, ε' and ε'' of corn leaves were decreased with the increase of measurement frequency. Compared with the change of ε' at low frequency, ε' at high frequency was decreased slowly. As shown in Fig. 3, ε'' was changed stably. At the same frequency, ε' and ε'' of different samples were influenced differently by the moisture content. Generally, the higher the moisture content of corn leaves was, the bigger ε' and ε'' at the same frequency were, which was mainly because the influence of moisture content of corn leaves on the dielectric properties was more significant than other factors.

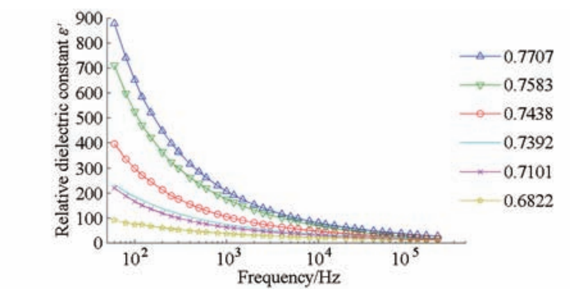

Fig. 2 Influence of frequency on ε' of corn leaves at different moisture contents

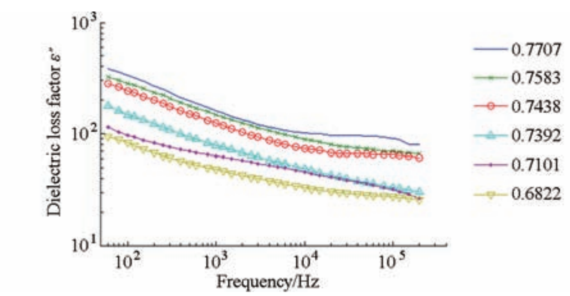

Fig. 3 Influence of frequency on ε'' of corn leaves at different moisture contents

2.2 Modeling

Leave one out cross validation method was used to establish the model, and the model which was the most suitable for different modeling methods was selected. The original 200 training samples were divided into 10 parts, each of which consisted of 20 samples (5 samples were randomly selected from each kind of water situation). In the use of leave one out cross validation method, 9 samples were selected from 10 samples as the cross training sets, and the remaining one sample was used as the cross validation sets. Ten different models were established successively, and the best model was selected as the final model of the modeling method according to the cross validation set decision coefficient R^2_{CV}. Finally, the performance of the model was verified by 67 test samples.

2.2.1 Linear modeling

(1) Characteristic variables selection by SWR

Stepwise regression method can be used as a modeling method of variable selection method andcombined with multiple linear regression method, but only the variable selection method was used here.

By leave one out cross validation method and SPSS software, stepwise regression was used in the cross-training set data to select frequency variables, and the confidence interval was set as 95%. If the significance test coefficient F was greater than 3.84, the variable would be sent into the model. When the variable was returned to the sentence, the variable of the test coefficient $F < 2.71$ was eliminated. Increase of variables selected led to increase in model complexity, which may affect the model prediction accuracy, therefore, in order to guarantee a significant model, the variables should be selected as few as possible to select characteristic variables.

The result showed that the characteristic variables of 10 models selected by the method of leave one out cross validation were all consistent. Among them, the parameters of characteristic variables selected by one of the models were shown in Tab. 1. It showed the indicators and results of characteristic variables selected by stepwise regression of ε', ε'' and three information variables of their fusion information.

As shown in Tab. 1, the significant index Sig. showed the effect of models in linear analysis. The confidence interval was set as 95%, and the significant level α was 0.05. If the value of Sig. was smaller than α, the linear equation would be valid and the effect of the model was significant. And the smaller the value of Sig. was, the better the effect of the model would be. The values of Sig. were all zero in Tab. 1, which showed that the dielectric parameters ε' and ε'' can characterize the moisture content significantly. That was, the stepwise regression method can be better used to extract the characteristic frequency points, select the variable combination of the complementary information and eliminate variables of the information overlapping. Finally, fewer variables can be used to represent the information of the whole model, which can simplify the data and reduce the complexity of the model.

Tab. 1 Feature variables selection by using stepwise regression method (α = 0.05)

Variables	Number of variables selected	Model sequence	R_C^2	RMSEC	Sig.
ε'	6	1	0.503	0.030 9	0
		2	0.618	0.027 9	0
		3	0.715	0.023 5	0
		4	0.765	0.021 7	0
		5	0.792	0.018 1	0
		6	0.814	0.016 1	0
ε''	5	1	0.453	0.032 5	0
		2	0.591	0.028 8	0
		3	0.725	0.023 7	0
		4	0.738	0.022 8	0
		5	0.746	0.020 0	0
ε' and ε''	6	1	0.532	0.032 4	0
		2	0.613	0.026 6	0
		3	0.754	0.023 0	0
		4	0.825	0.018 8	0
		5	0.848	0.016 9	0
		6	0.861	0.015 6	0

Overall, the model established by the information fusion of ε' and ε'' was the best. The original 72 frequency points were reduced to 6 through the combination model, which extremely reduced the model complexity, obviously enhanced R_C^2 of the model compared with the signal information variable of ε' or ε'' and obviously weakened RMSEC. Although the single object modeling can achieve good results, the effect of two object modeling was significantly better than the single object modeling, which indicated that frequency variables existed in each of the two objects to prompt another object to be complementary.

(2) Regression model establishment by MLR

By use of leave one out cross validation method, three information variables of corn leaves, ε', ε'' and fusion information of both variables, were used to select full frequency variables and SWR characteristic frequency variables, which would be both used to establish multiple linear regression model. Among them, the cross training set was used to establish the model, and the cross validation set was used to validate the model. And the best R_{CV}^2 and RMSECV would be set as the standard of selecting the model with the best performance. Then the testing samples were used to validate the training model. In the end, the testing set decision coefficient R_P^2 and the root mean square error of testing set RMSEP were set as the standard of evaluating the model. Tab. 2 showed the best MLR model and its performance parameters under different variables obtained by use of leave one out cross validation method. Wherein, R_{CV}^2 and RMSECV were respectively the determinant coefficient of cross validation set and the root mean square error of selecting the best model.

Tab. 2 showed the modeling parameters of full frequency variables and SWR characteristic frequency variables of the three information variables by use of MLR. The testing set decision coefficients R_P^2 were all greater than 0.5, which illustrated that all models can partly reflect the internal information of the sample. And the maximum R_P^2 (0.684) and RMSEP (0.024 4) were obtained by applying the fusion information of ε' and ε'' and the combination of SWR and MLR.

As seen from R_P^2 and RMSEP, under the full frequency variables, the highest R_P^2 (0.644) and RMSEP (0.024 0) were obtained though the MLR model established by the fusion information of ε' and ε''. Under the characteristic variables extraction of SWR, the highest R_P^2 (0.684) and RMSEP (0.024 4) were obtained though the MLR model established by the fusion information of ε' and ε''. Therefore, the information fusion variables of ε' and ε'' can better predict the moisture content of corn leaves than single information variable.

The fusion information of ε' and ε'' can more accurately and comprehensively reflect the relationship between the dielectric properties and the moisture content.

As seen from the comparison between R_{CV}^2 of the cross validation set and R_P^2 of the test set, in a certain extent, R_{CV}^2 outperformed R_P^2, mainly because the cross validation set contained 20 samples, and the difference

Tab. 2 Parameters of MLR model

Variables	Variable selection	Number of variables	Training set		Cross validation set		Test set	
			R_C^2	RMSEC	R_{CV}^2	RMSECV	R_P^2	RMSEP
ε'	Full frequency	36	0.738	0.023 5	0.645	0.027 8	0.596	0.029 4
	SWR	6	0.814	0.016 1	0.663	0.026 9	0.635	0.028 5
ε''	Full frequency	36	0.745	0.019 2	0.582	0.027 1	0.543	0.028 2
	SWR	5	0.746	0.020 0	0.629	0.027 7	0.584	0.026 5
ε' and ε''	Full frequency	72	0.828	0.019 2	0.683	0.022 5	0.644	0.024 0
	SWR	6	0.861	0.015 6	0.735	0.021 8	0.684	0.024 4

between samples was very small; while the test set contained 67 samples, the difference between which was relatively large. Therefore, the performance of the cross validation set was slightly higher than that of the test set.

As seen from full frequency variables and characteristic frequency variables selected by SWR, although full frequency variables preserved the original information of data completely, some problems such as noise interference, data overlap still existed, and they led to the increase of the model complexity and reduced the accuracy. At the same time, SWR eliminated a large number of overlapping information variables and increased the model fitting degree, but the values of R_P^2 were not larger than 0.70, and the prediction accuracy needed to be improved.

2.2.2 Nonlinear modeling

(1) Characteristic variables selection by SPA

By use of leave one out cross validation method, the cross training set and cross validation set were used to carry outsuccessive projection algorithm (SPA) based on the Matlab software to get 10 models of the number of variables selected by SPA. In order to ensure the accuracy of model performance, the number of variables selected was ranged from 3 to 20, and under the premise of ensuring the stability of the performance of the model, the number of variables should be as few as possible. The root mean square error (RMSEC) was used as the criterion of the number of variables selected by SPA, and the smaller the RMSEC was, the better the model of the number of variables selected was. When RMSEC was decreased to a certain degree and tended to be stable, the number of variables and the corresponding frequency points were selected.

The change of characteristic variables selected by SPA applied in one of thefusion information of $\varepsilon'$and ε'' was shown in Fig. 4, and RMSEC was set as its evaluation standard. It can be seen from the figure that RMSEC was gradually decreased with the increase of number of selected variables. When the number of selected variables was 10, RMSEC was changed very little. Thus 10 variables were selected, and the smallest RMSEC(0.029 17) was obtained.

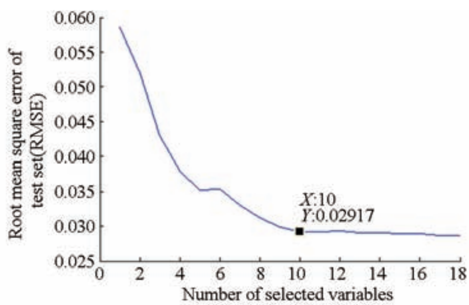

Fig. 4 Change of RMSEC with selected characteristic variables by SPA

For different information variables and leave one cross validation model, the selected feature variableswere not the same.

(2) Regression model establishment by SVR

RBF kernel function with good stability and accuracy was selected as SVR kernel function. When applying RBF – SVR regression method to establish a model, in order to ensure the optimization of the parameters of the model, parameters of the training set by 40 fold grid search (2^{-10} to 2^{10} interval $2^{0.5}$) were optimized to determine the SVR penalty factor c and kernel parameter g.

Three information variables, ε' and$\varepsilon''$of corn leaves and the fusion information of both variables were used to select full frequency variables and SPA characteristic frequency variables by leave one out cross validation method. SVR models with the best parameters optimization were respectively established by using two frequency variables, among them, the cross training set was used to establish the model, and the cross validation set was used to validate the model. R_{CV}^2 and RMSECV were set as the standard of selecting the model with the best performance. Then the model was verified by the test set and two parameters, the determination coefficient R_P^2 and the root mean square error of test set RMSEP were set as the standard of evaluating the model. Tab. 3 was the best SVR model and its performance parameters under different variables obtained from the leave one out cross validation method. Among them, R_{CV}^2 and RMSECV were decisive factors and root mean square error of cross validation set for selecting the best model.

Tab. 3 Parameters of combined SPA and SVR model

Variables	Variable selection	Number of variables	Parameter optimization		Training set		Cross validation set		Test set	
			c	g	R_C^2	RMSEC	R_{CV}^2	RMSECV	R_P^2	RMSEP
ε'	Full frequency	36	8	2	0.935	0.011 2	0.754	0.023 9	0.748	0.024 3
	SPA	8	5.657	4	0.917	0.012 8	0.769	0.022 7	0.762	0.023 7
ε''	Full frequency	36	90.510	0.088 4	0.735	0.024 8	0.584	0.024 9	0.561	0.0259
	SPA	9	326.038	0.022 1	0.753	0.023 8	0.586	0.025 4	0.588	0.024 9
ε' and ε''	Full frequency	72	5.657	0.442	0.942	0.011 8	0.795	0.019 9	0.783	0.019 5
	SPA	10	4	8	0.953	0.010 8	0.815	0.018 8	0.804	0.017 6

Tab. 3 showed the parameters of the model established by SVR through three information variables selected by full frequency variables and SPA characteristic frequency variables. From R_P^2 of the test set, it can be seen that all models can reflect the internal information of the sample to a certain extent. Overall, the best model can be established with the fusion information of ε' and ε'' by application of modeling method of SPA and SVR, among which, R_P^2 was 0.804 and RMSEP was 0.017 6, and it had higher accuracy and lower error than other models.

From the optimization of parameters c and g, results of different information variables in parameter optimization were different, which was because the grid c and g coordinate parameters were substituted into SVR training modeling in the 40 fold grid search, and the best c and g parameters were selected by selecting the minimum of root mean square error in the training test. Since different information variables had different modeling data of the training set, the optimal c and g parameters were also different.

From the information variables in the research, the fusion information of ε' and ε'' had better prediction ability of the moisture content than single information variables. Because the integration of information between the combination of ε' and ε'' can achieve the complementary to a certain extent. When selecting the best variables by SPA, the complementary variables can be combined together so that it had smaller root mean square error to improve the performance of the model and reflect more accurately and comprehensively the relationship between dielectric properties and moisture content.

From the point of view of variable selection, three kinds of information variables by SPA modeling simplified variable data to a certain extent and improved the prediction accuracy of the model. Among them, the fusion information of ε' and ε'' can reduce the original 72 variables to 10 and obtain the highest rate of application of variable.

Through the above analysis, ε' and ε'' can both predict and analyze the moisture content of corn leaves to a certain extent; compared with the single variable, two variables fusion information can better achieve complementary regression and increase the prediction accuracy of the model. Both linear regression and nonlinear regression can reflect the relationship between dielectric properties and moisture content in a certain degree, overall, the nonlinear regression model can be used to get a better model. However, fewer modeling variables can be obtained by using linear regression, and the model can be expressed in the form of formula more intuitively and specifically.

The best model can be obtained by using nonlinear regression model with the highest prediction accuracy and the minimum root mean square error. Finally, the modeling method of the fusion information of ε' and ε'' by application of SPA and SVR was selected to study the relationship between the dielectric properties and moisture content of corn leaves. The effect of the test set after modeling through the fusion information of ε' and ε'' by nonlinear regression was shown in Fig. 5.

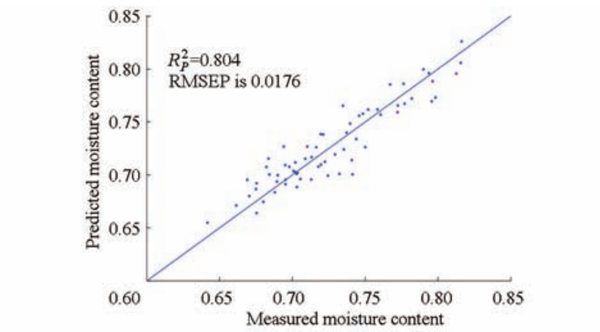

Fig. 5 Result of predicted test in nonlinear regression with fusion information of ε' and ε''

3 Conclusions

(1) Between 60 Hz and 200 kHz, with the increase of test frequency, the dielectric constant and dielectric loss factor of corn leaves were monotonically decreased; the moisture content of corn leaves and test frequency had significant effect on the dielectric parameters.

(2) Compared the two modeling methods, linear regression and nonlinear regression, of the dielectric parameters and the moisture content of corn leaves, the nonlinear regression was better than linear regression. Among them, the highest test determination coefficient R_P^2 (0.804) and the minimum test root mean square error RMSEP (0.017 6) can be obtained through the fusion information of ε' and ε'' by using nonlinear regression.

(3) Compared full frequency variables modeling with characteristic frequency variables modeling, the selected method of using characteristic frequency variables can effectively reduce the complexity of the model, increase the accuracy and improve the performance.

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基于介电特性与回归算法的玉米叶片含水率无损检测

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摘要: 利用0.06~200 kHz范围内拥有36个频率点的LCR测量仪及自制夹持平行电极板,测量280片不同含水率玉米叶片的相对介电常数ε'及介电损耗因子ε'';利用干燥法测量玉米叶片的湿基含水率。利用逐步回归法(SWR)与多元线性回归(MLR)结合的线性建模方法和连续投影算法(SPA)与支持向量回归(SVR)结合的非线性建模方法,分别建立玉米叶片介电参数(ε'、ε''及两者融合信息3种参数)与湿基含水率的关系模型,并应用留一交叉验证法选取2种建模方法的最佳关系模型。分析表明,非线性模型较线性模型具有更高的预测能力,且基于ε'与ε''的融合信息运用连续投影算法(SPA)与支持向量回归(SVR)相结合的非线性建模方法使模型原72个变量精简到10个,剔除了模型中冗余度较高的变量,有效降低了模型的复杂度,得到最高的测试集决定系数R_p^2(0.804)和最小的测试集均方根误差RMSEP(0.017 6)。结果表明基于介电特性的玉米叶片含水率无损检测方法是可行的,为快速检测其他农作物的生理信息提供了一种可靠的方法。

关键词: 玉米叶片; 湿基含水率; 无损检测; 介电特性; 回归算法

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Non-destructive Moisture Content Detection of Corn Leaves Based on Dielectric Properties and Regression Algorithm

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Abstract: Moisture content is a major index in the healthy growth of crops. It is beneficial to water and fertilizer management when the crop moisture content is detected timely. The dielectric properties (relative dielectric constant ε' and dielectric loss factor ε'') of 280 pieces of corn leaves with different moisture contents were measured with a self-made clamping capacitor and an LCR measuring instrument at 36 discrete frequencies over the frequency range of 0.06 ~ 200 kHz and the moisture content of the corn leaves were measured by drying weight method. To obtain the moisture content of corn leaves, linear regression methods (the combination of SWR and MLR) and nonlinear regression methods (SPA and SVR) were used to establish models to get the relationship between the moisture content and dielectric parameters (ε', ε'' and the combination of ε' and ε''), and the leave one out cross validation (LOOCV) was used to select the best models. The results showed that contrasted with the linear regression method, the nonlinear regression method had better predictive ability. The highest coefficient of determination (0.804) and the lowest root mean square error (0.017 6) were obtained by using the nonlinear

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regression model with the variable in the combination of ε′ and ε″, which simplified the model with variables reduced from 72 to 10 and eliminated the overlap variables, and the complexity of the model was decreased effectively. The study indicated that it was feasible to detect the corn leaf moisture content non-destructively, and the results provided a credible method for rapid non-destructive detection of physiology information in crops.

Key words: corn leaves; moisture content; non-destructive detection; dielectric properties; regression algorithm

引言

近年来,国内外对农作物叶片含水率检测主要集中在传统湿基含水率测量和光谱测量技术2种方法。传统湿基含水率测量方法为干燥法:通过干燥箱将作物叶片干燥,测量叶片净重与干重,计算得到湿基含水率,此方法破坏了农作物叶片形状及内部特征[1],且耗时周期长,为有损检测方法,不利于推广。国内外学者已经应用光谱技术对农作物含水率检测进行了大量的研究[2-4]。运用不同建模方法准确预测了不同农作物的含水率,较干燥法省力节时,但在实际应用中,光谱仪器测量的是样本点信息,不能较好地代表整个样本信息,预测精度有待提高。

介电技术测量的是样本内部的整体信息,较光谱技术更具有说服力。介电特性主要是指物质在电场作用下产生的一种响应特性[5],通常用相对介电常数 ε′、介电损耗因子 ε″、介电损耗角正切 $\tan\sigma$ 和介质阻抗等参数来表征。

介电特性技术已应用于多个领域的含水率测量[6-11],其中,对水果内部品质无损分级[12]和粮食含水率的检测[13-14]起到了重要作用。基于介电特性原理对茶鲜叶叶片含水率的研究也有一定进展[15]。但基于介电特性技术对农作物叶片的研究仍然较少,主要是因为在测量农作物叶片介电特性参数时,常用的仪器是LCR测量仪和平行电极板,LCR测量仪属敏感仪器,细微的电极板变化都会使其测量值产生很大的变化,故对测量精度要求很高。

本文应用LCR测量仪及自制夹持平行电极板测量不同湿基含水率的玉米叶片在各频率下对应的介电参数(相对介电常数 ε′和介电损耗因子 ε″)。运用线性(逐步回归法(SWR)与多元线性回归法(MLR)结合)和非线性(连续投影算法(SPA)和基于RBF核函数的支持向量回归(RBF-SVR)结合)2种回归方法建立玉米叶片的介电参数与湿基含水率预测模型,根据测试集决定系数(R_{P}^2)及测试集均方根误差(RMSEP)2种评判标准选取最佳回归模型,以期达到预测未知玉米叶片的湿基含水率的目的。

1 实验与方法

1.1 实验与数据采集

1.1.1 仪器与设备

采用常州海尔帕科技公司研发的HPS2816B型LCR数字电桥测量仪,此仪器可测量电容、电阻、电感及电容损耗因子等参数,测量频率分别为:60 Hz、80 Hz、100 Hz、120 Hz、150 Hz、200 Hz、250 Hz、300 Hz、400 Hz、500 Hz、600 Hz、800 Hz、1 kHz、1.2 kHz、1.5 kHz、2 kHz、2.5 kHz、3 kHz、4 kHz、5 kHz、6 kHz、8 kHz、10 kHz、12 kHz、15 kHz、20 kHz、25 kHz、30 kHz、40 kHz、50 kHz、60 kHz、80 kHz、100 kHz、120 kHz、150 kHz、200 kHz。其他主要仪器有:分辨率为0.001 g的微量天平测量仪(杭州万特衡器有限公司),精确度为0.01 mm的厚度测量仪,电热鼓风干燥箱一台及自制夹持平行电极板。

1.1.2 自制夹持平行电极板

传统的电极板常用于测量固体或不易形变的物体,且在测量物体时需要电极板与被测物体紧密接触。由于植物叶片柔软且易形变,传统的电极板测量叶片时,无法控制叶片受到的压力大小,易出现两电极板间压力太小,无法夹紧叶片,使两极板间混入空气而影响测量精度;两电极板间压力过大,使叶片受损形变,增大测量误差。因此,自制一种压力合适的电极板尤为重要。

本文自制夹持平行电极板为一种简易便携式平行电极板,能够完成以下功能:在夹紧叶片的前提下不损伤叶片结构;在测量样本时,能保证LCR测量仪测出的数据逐渐稳定;且测量同一样本同一区域多次时,能够保证测量数据结果相近。

(1)自制夹持平行电极板性能标准

文中设计仪器的性能包括:夹持平行电极板夹紧叶片时,叶片所能承受最大的压力;电极板夹紧叶片样本时,与之连接的LCR测量仪计数是否稳定等。文中通过一些间接方法测量以上性能。

应用于本实验的自制平行电极板应满足以下3种性能标准:①两电极板夹住叶片,稳定5 min左右,取出叶片,若叶片表面没有挤压的痕迹,说明叶

片没有受损形变,电极板与叶片接触压力不损伤叶片。②两电极板夹住叶片一段时间(30 s)后,逐渐用力将叶片抽出两电极板间,若即使叶片损坏也无法将叶片抽出两电极板间,说明两电极板与叶片接触很密切,接触面间的空气间隙可忽略不计。③自制平行电极板夹持待测样本时,应保持稳定,以便LCR 记录数据(因为与电极板连接的是 LCR 测量仪,细小的变化都会引来参数的变化,因此需保证电极板与待测样本保持稳定);与此平行电极板连接的 LCR 测量仪读数应逐渐收敛稳定;且在仪器制作时,测量同一片叶片同一处位置的参数 3 次,若读数稳定时其 3 次测量结果差别不大,即可说明此仪器稳定。

其中,性能标准①、②体现了自制仪器的稳态性能,性能标准③体现了自制仪器的动态性能。

(2)自制夹持平行电极板的结构

实验采用的自制夹持平行电极板由夹持力较弱的塑料小型夹子,2 片直径 20 mm、厚约 1.5 mm 的坚硬圆形铜板,2 个细长的圆柱形小金属条及 2 根导线构成。

具体结构:分别打磨两电极板的其中一面使其足够平滑,将两极板非打磨面中心与两短小金属条用锡焊连接。将塑料夹子顶部两夹口中心都挖出 1 个小孔(此小孔大小与短细小金属条横截面大小吻合),将两短小金属条分别装入塑料夹口中心的小孔处。旋转控制金属条方位使两光滑的电极板各部位能够完全对齐且同时闭合。并且,测试此时自制平行电极板是否符合 1.1.2 节中的 3 个性能标准,若符合,将金属条与塑料夹子用粘合剂固定,仪器完成。具体实物图如图 1 所示。

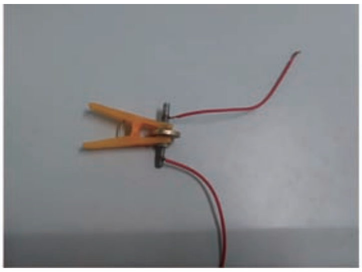

图 1　自制平行电极板实物图

Fig. 1　Physical instrument of self-made parallel electrode plate

1.1.3　实验材料

玉米栽培于江苏省镇江市京口区丹徒路某农田,玉米品种为苏玉 19。在籽粒形成期之前,对所有玉米适量施水。为得到不同含水率的玉米叶片,在进入籽粒形成期后,将所有玉米植株分成 4 组,对其中 3 组玉米依次按照充足、适量、少量 3 种灌溉程度进行施水,并 2 d 浇一次水,持续 10 d;剩余 1 组不施水。第 10 天,选取每组玉米 70 株,每株玉米采用 1 片同叶位(玉米株的中部)叶片,共采取 280 片玉米叶片。因整个玉米叶片面积很大,故在实验前将每片叶片中部剪出 1 个尺寸为 30 mm × 35 mm 的矩形样本,共采集 280 个样本。

1.1.4　实验方法与步骤

打开 LCR 测量仪,将其调节到 $C_p - D$(C_p 为测量并联电容、D 为损耗因子)挡位,将自制夹持平行电极板与 LCR 测量仪连接,等待 10 min 使整个装置稳定。

将整个装置置于 25℃ 环境中,进行全频率开路清零。开路清零结束后将样本放入自制夹持平行电极间,并将 LCR 测量仪测量频率调至 60 Hz,待 C_p 读数数据变化误差小于 0.5%(C_p 数据随着时间会逐渐平稳收敛,且所有频率点都测量完成总耗时为 100 s 左右)时,开始记录 C_p 与 D 数据;然后调节频率至 80 Hz 稳定 3 s 记录 C_p 与 D 数据;…;直至调节频率至 200 kHz 记录数据。然后,将叶片与电极板接触边缘做一个标记,将叶片从电极板处取下,根据标记处测量叶片与电极板接触处 4 个方位及中心部位的厚度。最后,测量叶片样本的质量。至此,一个样本数据测量完毕。将所有样本按照上述步骤处理,最终将所有叶片放入 120℃ 干燥箱内干燥 10 h,并依次记录不同样本对应的叶片干质量。

1.1.5　相对介电常数 ε' 和介电损耗因子 ε'' 的计算

由自制平行电极板及 LCR 数字测量仪测得样本并联电容及损耗因子;根据平行板电极大小计算面积;由厚度测量仪测出样本的 5 个方位的厚度,以平均厚度作其厚度。根据平行板电容器原理即可计算得出玉米叶片的相对介电常数 ε' 和介电损耗因子 ε''。

1.1.6　湿基含水率的测量

以湿基含水率来评判玉米叶片的含水状况。湿基含水率为

$$W = \frac{M_0 - M_1}{M_0} \tag{1}$$

式中　W——湿基含水率

M_0——玉米叶片鲜质量,g

M_1——玉米叶片干质量,g

1.2　原理与方法

1.2.1　样本划分

实验一共得到 280 组玉米叶片湿基含水率及其对应的 ε' 与 ε'' 样本数据。对数据进行观察,剔除一些因实验原因产生的异常数据(主要是实验时因未开路清零等原因导致),剩余 267 组数据。分别从每组不同含水率的样本数据中随机选取 50 组样本数据作为训练样本,共得到 200 组训练样本;剩余

67 组样本数据作为测试样本。

1.2.2 建模方法

为了充分了解玉米叶片湿基含水率与对应的介电参数的对应关系，本文分别应用玉米叶片的 ε'、ε'' 及两者融合信息变量 3 种信息变量建立玉米叶片湿基含水率的预测模型。其中，ε' 与 ε'' 各含有 36 个测量频率对应下的 ε'（ε''）特征变量，ε' 与 ε'' 的融合信息为两者参数的组合，即 72 个特征变量。

数据建模时，可以选择全频率变量（全频率变量即单一的 ε'（或 ε''）36 个频率点对应的变量或融合信息变量的 72 个频率点对应的变量），但由于全频率变量间存在一定的相关性，往往某频率对应的变量信息可由其他几组频率变量共同解释，因此该组变量便成为冗余信息或无用信息，且此变量增加模型的复杂度[16]。为去除数据中的冗余信息或无用信息，达到精简模型的目的，本研究采用逐步回归法（Stepwise regression, SWR）与连续投影算法（Successive projection algorithm, SPA）2 种特征频率变量选取的方法，比较分析特征频率变量和全频率变量与对应回归算法结合的建模预测效果。

统计学中，回归算法主要分为线性和非线性两大类。线性回归可准确地计量各变量对回归拟合的贡献度及各变量间的相关程度，且能够反映自变量与因变量间的线性因果关系，便于分析。非线性回归是通过一个非线性映射，将一个低维非线性问题转换为高维线性问题，将此问题再进行线性分析。较线性回归，非线性回归通过非线性映射可增强各变量间的相关性，但也增加了回归模型的复杂度。本文采用多元线性回归（Multiple linear regression, MLR）和支持向量回归（Support vector regression, SVR）2 种回归算法拟合玉米叶片 2 种信息变量（ε'、ε'' 及两者结合的融合信息）与湿基含水率之间的回归关系，比较分析线性与非线性回归对建模的影响。

建模方法由特征频率变量选取方法与回归算法结合而成，本文分为线性建模和非线性建模 2 种。线性建模由 SWR 与 MLR 相结合，非线性建模由 SPA 与 SVR 结合。以此比较分析 2 种建模方法对玉米叶片湿基含水率的预测影响。

线性建模由逐步回归法（Stepwise regression, SWR）与多元线性回归（Multiple linear regression, MLR）结合而成。逐步回归法（SWR）：逐步回归分析的实现过程是每一步都要对未引入回归方程的所有变量计算其贡献（即偏回归平方和），选一个贡献最大的变量，进行 F 显著性检验，如果显著则引入回归方程；如不显著则剔除。然后对已引入方程内的所有变量进行贡献计算，剔除对因变量不显著的变量。然后再次重复上述操作，直至无新变量可以引入且回归方程中的所有变量都不能剔除为止[17]。逐步回归法由特征变量选取方法与多元线性回归构成，本文仅用到其特征变量选取功能，因为在文中要比较全频率变量与特征频率变量对回归建模的影响。因此将特征频率变量的选取与多元线性回归分开。多元线性回归（MLR）：进行线性预测或估计时，影响因变量的因素往往由多个相互依存、相互影响的变量共同决定。这种由多个自变量预测或估计因变量的线性方法被称为多元线性回归。

非线性回归由连续投影算法（Successive projection algorithm, SPA）与支持向量回归（Support vector regression, SVR）结合而成。连续投影算法（SPA）——一种前向循环变量选择方法：从一个变量开始，每次循环，并计算此变量在其他未选入变量上投影的大小，将投影向量最大的变量引入到波长组合，直到循环 N 次。当选入的变量数量符合设定要求时，选取冗余信息最少的变量组合，以解决信息重叠、共线性等问题[18]。支持向量回归（SVR）：支持向量回归是支持向量机应用于回归拟合的一种推广形式。主要思想是通过一个非线性映射将一个低维不可分问题转换到高维使其线性可分的问题。与传统的拟合方法相比，SVR 采用核函数思想，不仅能够适应训练样本集的非线性，还可通过可调参数降低过拟合的风险。用核函数代替线性方程中的线性项可使原来的线性算法非线性化[19-20]。本研究应用 RBF（径向基函数）核函数对玉米叶片的介电参数与湿基含水率进行分析。

1.2.3 留一交叉验证法

由于采集的样本总数有限，采用一个训练集和测试集建模具有一定的偶然性。为降低建模的偶然性，采用留一法交叉验证评价比较模型预测结果。所谓留一法就是将样本均分为 N 份，选取第 1 份作为测试集，其余 $N-1$ 份样本作为训练样本，进行建模分析；然后再选取第 2 份作为测试集，…，直到所有 N 份样本全部都作为测试集并建立模型，共得到 N 份不同的模型。对 N 份模型进行分析，选出最佳性能的模型作为此建模方法的最终模型[21]。

2 结果与分析

2.1 不同湿基含水率下频率对玉米叶片相对介电常数 ε' 与 ε'' 的影响

图 2、图 3 分别是不同湿基含水率下 ε' 与 ε'' 随测量频率的变化曲线。在 0.06 ~ 200 kHz 频率范围内，玉米叶片的 ε' 与 ε'' 随着测量频率的增大而减

小。相比低频率下的 ε' 变化，高频率下的 ε' 减小幅度较慢。从图 3 中可以看出，ε'' 变化较为稳定。同一频率下，不同样本的 ε' 与 ε'' 受湿基含水率的影响不同。一般情况下，玉米叶片湿基含水率越高，同频率下的 ε' 与 ε'' 越大。这主要是由于介电特性受玉米叶片湿基含水率的影响较其他因素更为显著。

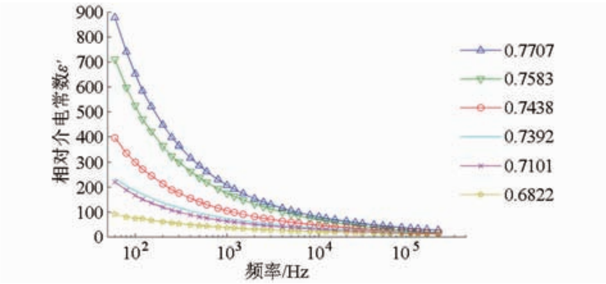

图 2　不同湿基含水率下频率对玉米叶片相对介电常数 ε' 的影响

Fig. 2　Influence of frequency on ε' of corn leaves at different moisture contents

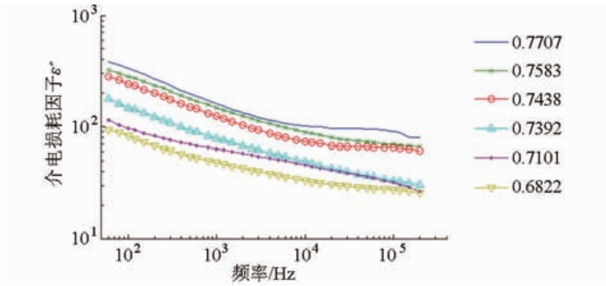

图 3　不同湿基含水率下频率对玉米叶片介电损耗因子 ε'' 的影响

Fig. 3　Influence of frequency on ε'' of corn leaves at different moisture contents

2.2　建模

采用留一交叉验证法建立模型，选出最适合不同建模方法的模型。将原 200 个训练样本平均分成 10 份。其中，每份 20 个样本（每组含水状况下随机选取 5 个样本）。运用留一交叉验证法，10 份样本中选取 9 份作为交叉训练集，剩余 1 份作为交叉验证集。依次建立 10 份不同的模型，以交叉验证集决定系数 R_{CV}^2 选取最佳的模型作为此建模方法的最终模型。最终，用 67 个测试样本验证模型性能。

2.2.1　线性建模

（1）应用 SWR 选取特征变量

逐步回归法本身即可作为一种变量选取方法与多元线性回归方法相结合的建模方法，本文只运用逐步回归法的变量选取方法。

利用留一交叉验证法，应用 SPSS 软件将交叉训练集数据进行逐步回归法（SWR）选取特征频率变量，设置置信区间为 95%，显著性检验系数 $F>3.84$ 时变量进入模型；变量回判时，将显著性检验系数 $F<2.71$ 的变量剔除出模型。由于选取变量个数的增加导致模型复杂度上升，可能会影响模型的预测精度，因此，在保证模型显著性的情况下，选择尽量少的变量个数，据此条件进行特征变量的选取。

结果表明：运用留一法交叉验证建立的 10 份模型选取的特征变量均一致。其中，表 1 为其中一份模型选取特征变量的参数。

表 1　逐步回归法选取特征变量（$\alpha=0.05$）

Tab. 1　Feature variables selection by using stepwise regression method（$\alpha=0.05$）

参数	选取变量数	模型序列	决定系数 R_C^2	均方根误差 RMSEC	Sig. 值
ε'	6	1	0.503	0.030 9	0
		2	0.618	0.027 9	0
		3	0.715	0.023 5	0
		4	0.765	0.021 7	0
		5	0.792	0.018 1	0
		6	0.814	0.016 1	0
ε''	5	1	0.453	0.032 5	0
		2	0.591	0.028 8	0
		3	0.725	0.0237	0
		4	0.738	0.022 8	0
		5	0.746	0.020 0	0
ε' 和 ε''	6	1	0.532	0.032 4	0
		2	0.613	0.026 6	0
		3	0.754	0.023 0	0
		4	0.825	0.018 8	0
		5	0.848	0.016 9	0
		6	0.861	0.015 6	0

表 1 为 ε'、ε'' 及两者融合信息的 3 种信息变量进行的逐步回归法特征变量选取的指标及结果。

表 1 所示，显著性指标 Sig. 值表明线性分析中模型的效果，文中设置的置信区间为 95%，显著性水平为 $\alpha=0.05$，Sig. 值若小于 α，说明线性方程有效，模型效果显著，且 Sig. 值越小，表明模型的效果越佳。由表中 Sig. 值均为 0 可以看出介电参数 ε' 与 ε'' 均能对湿基含水率进行十分显著的表征，说明逐步回归法可较好地提取特征频率点，选取信息互补的变量组合并剔除信息重叠的变量。最终可用较少的变量代表整个模型的信息，达到简化数据，降低模型复杂度的目的。

总体来看，ε' 与 ε'' 结合的融合信息建立的模型效果最好，组合模型将原有的 72 个频率点变量精简到 6 个，极大地降低了模型的复杂度，并且模型的 R_C^2 较 ε' 或 ε'' 单个信息变量有明显的增强，且其 RMSEC 较 ε' 或 ε'' 单个信息变量有明显的减弱。表明虽然单一对象建模能够取得良好的效果，但 2 种对象建模的效果明显优秀于单一对象，说明 2 种对

象之间均有促使另外一种对象互补的频率变量。

(2)应用 MLR 建立回归模型

运用留一交叉验证法将玉米叶片 ε'、ε''及两者结合的融合信息 3 种信息变量分别进行全频率与 SWR 特征频率变量选取,将两种不同频率变量分别建立多元线性回归模型。其中,以交叉训练集建立模型,以交叉验证集验证模型,并根据最佳 R_{CV}^2 和 RMSECV 作为选取最佳性能模型的标准。并用测试样本验证训练模型。最终,以测试集决定系数 R_P^2 及测试集均方根误差 RMSEP 2 种参数作为评测模型的标准。表 2 为运用留一交叉验证法得到的不同变量下的最佳 MLR 模型及其性能参数。其中,R_{CV}^2 与 RMSECV 为选取最佳模型的交叉验证集的决定性系数与均方根误差。

表 2 MLR 模型参数

Tab.2 Parameters of MLR model

参数	变量选择	变量数	训练集		交叉验证集		测试集	
			R_C^2	RMSEC	R_{CV}^2	RMSECV	R_P^2	RMSEP
ε'	全频率	36	0.738	0.023 5	0.645	0.027 8	0.596	0.029 4
	SWR	6	0.814	0.016 1	0.663	0.026 9	0.635	0.028 5
ε''	全频率	36	0.745	0.019 2	0.582	0.027 1	0.543	0.028 2
	SWR	5	0.746	0.020 0	0.629	0.027 7	0.584	0.026 5
ε'和 ε''	全频率	72	0.828	0.019 2	0.683	0.022 5	0.644	0.024 0
	SWR	6	0.861	0.015 6	0.735	0.021 8	0.684	0.024 4

表 2 为应用 MLR 对 3 种信息变量的全频率变量及 SWR 特征频率变量建模参数。表中测试集决定系数 R_P^2 均大于 0.5,说明所有模型均能在一定程度上反映样本的内部信息。并且,应用 ε'与 ε''结合的融合信息经 SWR 与 MLR 结合建模得到最大 R_P^2(0.684)及其 RMSEP(0.024 4)。

从 R_P^2 与 RMSEP 可以看出,在全频率变量下,ε'与 ε''结合的融合信息经 MLR 模型得到最高的 R_P^2(0.644)及其 RMSEP(0.024 0);在进行 SWR 特征变量提取下,ε'与 ε''结合的融合信息经 MLR 模型得到最高的 R_P^2(0.684)及其 RMSEP(0.024 4)。因此,ε'与 ε''结合的融合信息变量较单一信息变量更能较好地预测玉米叶片的湿基含水率。这是由于 2 种单一信息变量之间在一定程度上能够互补,增大变量之间的相关性。ε'与 ε''结合的融合信息能够更加精确全面地反映介电特性与湿基含水率之间的关系。

从交叉验证集 R_{CV}^2和测试集 R_P^2 比较可看出,在一定程度上,R_{CV}^2优于 R_P^2,主要是因为交叉验证集含有 20 个样本,其样本间的差异性较小,而测试集含有 67 个样本,其样本的差异性相对较大。因此,会出现交叉验证集的性能略高于测试集性能。

从全频率变量与 SWR 选取的特征频率变量可以看出,全频谱变量虽较好完整地保留数据的原始信息,但仍然存在一定的噪声干扰、数据重叠等问题,导致模型复杂度增大,精确度降低。同时,SWR 虽消除了大量的重叠信息变量,增大了模型的拟合度,但 R_P^2 均未超过 0.70,预测精度仍待提高。

2.2.2 非线性建模

(1)应用 SPA 选取特征变量

运用留一交叉验证法将交叉训练集与交叉验证集根据 Matlab 软件进行连续投影算法(SPA)运算,共得到 10 份 SPA 选取特征变量数的模型。为了保证模型性能的准确度,预设选取变量数范围在 3 ~ 20 之间,并在保证模型性能稳定的前提下,选取尽可能少的变量数。以均方根误差(RMSEC)作为 SPA 选取变量数的标准,即 RMSEC 越小表示对应选取的变量数建模越优良。当 RMSEC 下降到一定程度趋于稳定时,选取此时的变量数及对应的频率点变量。

图 4 为其中一份 ε'与 ε''结合的融合信息应用 SPA 选取特征变量的变化曲线,以 RMSEC 作为其评判标准。从图中可以看出,随着选取的变量数的增加,RMSEC 逐渐降低。当选取变量数为 10 后,RMSEC 变化甚微。故选取 10 个变量,并得到最小的 RMSEC(0.029 17)。

对于不同的信息变量及留一交叉验证模型,选

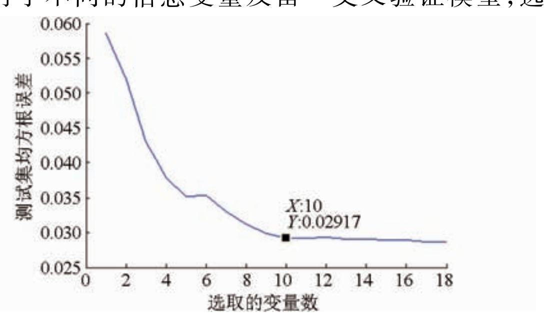

图 4 RMSEC 随 SPA 选取特征变量数的变化

Fig.4 Change of RMSEC with selected characteristic variables by SPA

取的特征变量也不尽相同。

(2)应用 SVR 建立回归模型

选择稳定性和准确性较好的 RBF 核函数作为 SVR 核函数。应用 RBF - SVR 回归方法建立模型时，为保证模型的参数优化，将训练集通过 40 折网格搜索($2^{-10}\sim2^{10}$，间隔 $2^{0.5}$)对参数进行寻优，确定 SVR 的惩罚因子 c 和核参数 g。

运用留一交叉验证法将玉米叶片 ε'、ε''及两者结合的融合信息 3 种信息变量分别进行全频率与 SPA 特征频率变量选取。运用 2 种不同频率变量分别建立最佳参数优化的 SVR 模型，其中以交叉训练集建立模型，以交叉验证集验证模型，并以 R^2_{CV} 和 RMSECV 作为选取最佳性能模型的标准。并用测试集验证此模型，以决定系数 R^2_P 及测试集均方根误差 RMSEP 2 种参数作为评测模型的标准。表 3 为运用留一交叉验证法得到的不同变量下的最佳 SVR 模型及其性能参数。其中，R^2_{CV} 与 RMSECV 为选取最佳模型的交叉验证集的决定系数与均方根误差。

表 3　SPA 与 SVR 模型预测参数

Tab. 3　Parameters of combined SPA and SVR model

参数	变量选择	变量数	参数优化		训练集		交叉验证集		测试集	
			c	g	R^2_C	RMSEC	R^2_{CV}	RMSECV	R^2_P	RMSEP
ε'	全频率	36	8	2	0.935	0.011 2	0.754	0.023 9	0.748	0.024 3
	SPA	8	5.657	4	0.917	0.012 8	0.769	0.022 7	0.762	0.023 7
ε''	全频率	36	90.510	0.088 4	0.735	0.024 8	0.584	0.024 9	0.561	0.025 9
	SPA	9	326.038	0.022 1	0.753	0.023 8	0.586	0.025 4	0.588	0.024 9
ε'和 ε''	全频率	72	5.657	0.442	0.942	0.011 8	0.795	0.019 9	0.783	0.019 5
	SPA	10	4	8	0.953	0.010 8	0.815	0.018 8	0.804	0.017 6

表 3 为 3 种信息变量经全频率变量与 SPA 特征变量选取由 SVR 建模的参数表。从表中测试集 R^2_P 可看出所有模型均能在一定程度上反应样本的内部信息。整体来看，ε'与 ε''两者结合的信息变量应用 SPA 与 SVR 结合建模方法建立最佳的模型，其中 R^2_P 为 0.804，RMSEP 为 0.017 6，较其他模型拥有更高的准确度及更低的误差。

从 c、g 参数优化来看，不同信息变量在进行参数优化时结果也不同，主要是由于在进行 40 折网格搜索时，将网格 c、g 坐标参数代入 SVR 进行训练集建模，并选择训练集中最小的均方根误差来选择最佳 c、g 参数。由于不同信息变量拥有不同的训练集建模数据，因此优化的最佳 c、g 参数也不同。

从研究的信息变量看，ε'与 ε''结合的融合信息变量较单一的信息变量拥有更好的预测湿基含水率的能力。主要是由于 ε'与 ε''结合的融合信息变量之间在一定程度上能够达到互补，经 SPA 选取最佳变量时，可以将互补的变量结合在一起，使其拥有更小的均方根误差，提高模型的性能，更加精确全面地反映介电特性与湿基含水率之间的关系。

从变量选取角度观察，3 种信息变量经 SPA 建模均能在一定程度上精简变量数据，并提高模型的预测精度。其中 ε'与 ε''结合的融合信息运用 SPA 可将原 72 个变量精简到 10 个，得到最高的变量应用率。

通过上述分析，ε'与 ε''在一定程度上均能对玉米叶片湿基含水率进行预测分析；相比较于单一变量，2 种信息融合变量更能在一定程度上达到回归互补，增加模型的预测准确率。线性回归与非线性回归都能够在一定程度上反映介电特性与湿基含水率之间的关系，总体来看，应用非线性回归建模能够得到更好的模型。但在一定程度上，运用线性回归可得到更少的建模变量，并能在一定程度上用公式的形式将模型表达出来，更加形象、直观、具体。

运用非线性回归建模能够得到最佳的模型，拥有最高的预测精度和最小的均方根误差。最终选定以 ε'与 ε''结合的融合信息应用 SPA 与 SVR 联合建模的方法作为研究玉米叶片介电特性与湿基含水率的关系的方法。ε'与 ε''结合的融合信息经非线性回归模型测试集的效果如图 5 所示。

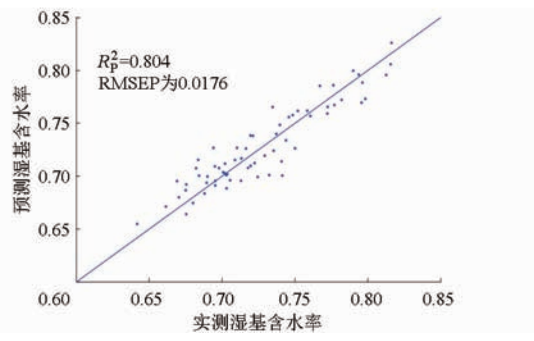

图 5　ε'与 ε''融合信息的非线性回归模型测试集结果

Fig. 5　Result of predicted test in nonlinear regression with fusion information of ε' and ε''

3　结论

(1)在 0.06 ~ 200 kHz 间，随着测试频率的增

大,玉米叶片的介电常数与介电损耗因子均单调递减;玉米叶片的湿基含水率及测试频率对其介电参数均有显著的影响。

(2)在对玉米叶片的介电参数与湿基含水率进行线性和非线性2种回归建模比较时,可以看出,非线性回归优于线性回归。其中,运用 ε' 与 ε'' 结合的融合信息经非线性回归可得到最高的测试决定系数 R_P^2(0.804)和最小测试均方根误差 RMSEP(0.017 6)。

(3)从全频率变量与特征频率变量的建模比较,表明运用特征频率变量选取方法可有效降低模型的复杂度,增加模型的精确度,提高模型性能。

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