XVIIth World Congress of the International Commission
of Agricultural and Biosystems Engineering (CIGR)

Hosted by the Canadian Society for Bioengineering (CSBE/SCGAB)
Québec City, Canada June 13-17, 2010

PREDICTION OF MELON FRUIT FIRMNESS USING VIS/NIR DIFFUSE REFLECTANCE SPECTROSCOPY

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CSBE101473 – Presented at Section VI: Postharvest Technology, Food and Process Engineering Conference

ABSTRACT Visible/near-infrared reflectance spectroscopy has shown usefulness for measurement of fruit internal quality, which is related to the chemical components of the fruit, because it measures spectral diffuse reflectance of the fruit. However, VIS/NIR spectroscopy cannot provide satisfactory measurement of fruit firmness, which is associated with the physical properties of the fruit. Thus, the goal of this study was to explore the possibility to measure melon firmness using VIS/NIR diffuse reflectance spectroscopy that is the modification of NIR spectroscopy. Melon samples were taken at different development stages and different growing seasons. Calibration models were built using partial least squares regression (PLSR) with nine pre-processed spectral data and raw spectral data. The highest R^2 value of calibration was 0.759. It was believed that NIR diffuse reflectance spectroscopy was potentially possible to measure firmness of melon. Finally, performance of prediction models developed with the mixed data of melon samples produced in different season was demonstrated and discussed to show their scope.

Keywords: muskmelon, firmness, diffuse reflectance, VIS/NIR spectroscopy

INTRODUCTION Firmness of fruit is one of important factors to assess internal quality of fruit, and various techniques have been tried to predict it in a non-destructive way. Visible and near infrared (VIS/NIR) spectroscopy, having a good correlation with some chemical components of fruits, has shown its usefulness to predict internal content of the component in a fruit non-destructively (He et al., 2005; Ruiz-Altisent and Ortiz-Canavate, 2005; Zude et al. 2006). Firmness of fruit, mostly associated with the physical properties of fruit, is known as a difficult one to predict by the optical technique (Nicolai et al., 2007; Bureau et al. 2009). Moreover, for a fruit of thick peel like muskmelon, the technique is expected as not easy to apply. The main objective of this study was to explore feasibility of VIS/NIR spectroscopy for predicting firmness of melon.

One of major difficulties of the VIS/NIR spectroscopic technique in predicting internal quality of fruits is that performance of models for the prediction is highly variable even for fruits grown in a similar environment. Because of the variable performance of the VIS/NIR spectroscopy for predicting internal quality of fruits, a prediction model built with mixed data collected from fruit samples grown in different environment could be developed to reduce the performance variation. A series of experiment was conducted to show the variation of performance of the developed prediction models for firmness of melons produced in a same area but in different seasons. In the remainder of the paper, performance of prediction models developed with the mixed data (Lu and Bailey, 2005) was demonstrated and discussed to show their scope.

MATERRIALS AND METHODS

Materials

Samples of melon were taken at different development stages and different growing seasons. Three lots of musk melon (cultivar: Sonata) cultivated in green houses during winter and spring at Naju, Chonnam, Korea, were harvested in February (48 units for experiment #11), March (45 units for experiment #12) and June (104 units for experiment #13) in 2009, and experimented one day after the harvests. Basic physical properties of the samples are shown in Table 1.

Table 1. Physical properties (mean±std. deviation) of the melons experimented.

Experiment #	Diameter (cm)	Weight (kg)	Firmness of fruit flesh (N)
11	14.6 ±0.7	1.6 ±0.3	16.9 ±3.6
12	15.9 ±0.6	2.0 ±0.2	27.6 ±4.7
13	-	1.7 ±0.3	26.4 ±4.1

Instrumentation

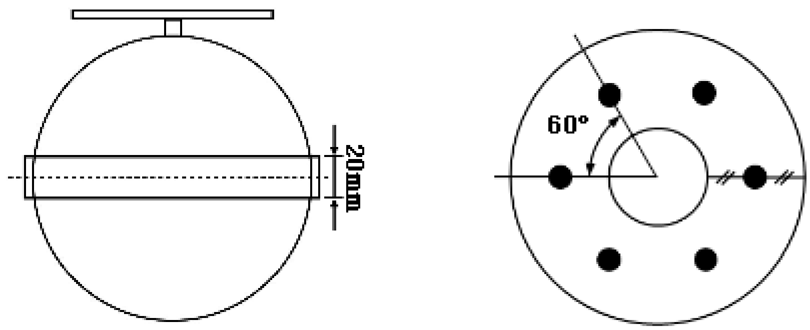
A VIS/NIR spectral data acquisition system was composed of a light source, 2 light guide lines of optical fiber for incidence and collection, a spectrometer (USB 4000, Ocean Optics, USA) having a measuring range of wave length as 471~1160 nm, and a personal computer.

The light source was constructed with 4 tungsten-halogen lamps (JCR, Ushio Inc., Japan) of 100 W, of which intensity of light was controllable using a power supply. A convex lens was installed at the end of the light guide for focus lighting on the fruit in a certain distance and a collimating lens (UV-74, Ocean Optics, USA) was set at the entrance of the light guide for collection of light from a wider area.

Methods

<u>Acquisition of spectral data:</u> Spectral data were collected at evenly distributed 6 points in the equator line of a melon. In order to acquire spectral data of a melon at the point, the collecting part of light guide line was placed close to the point.

Measurement of melon firmness: To measure melon firmness, doughnut shaped fruit flesh of melon was cut from middle part along with equator line of melon with a thickness of 20 mm as shown in Figure 1-a. On the surface of the flesh cut, 6 points where the spectral data were collected, were pointed on a center circle of fruit flesh as shown in Figure 1-b. Firmness of melon flesh was measured at the 6 points with a small material testing machine (1-I, Multi-Test, Mecmesin, UK) having a capacity of 1000 N. A probe of 8 mm in diameter was used to penetrate specimen of the melon flesh at a speed of 24 mm/min (ASABE Standards s368.4, 2004) up to 15 mm, and maximum force was recorded as the firmness. Data from the 6 points were averaged to represent firmness of a melon.



(a) (b)

Figure 1. Location of firmness measuring points of a melon: (a) cut of specimen at middle of a melon, (b) location of firmness measuring points on the middle cut.

Spectral data analysis: Collected spectral data within a band of 475~1100 nm were preprocessed by 9 kinds of preprocessing methods; normalizations by mean, maximum and range, multiplicative scatter correction (MSC), standard normal variant (SNV), 1st and 2nd order differentiation of Savitzky-Golay, and Norris Gap. To the 9 preprocessed data sets and collected spectral raw data, partial least square regression (PLSR) routine was applied to develop prediction models (calibration) for firmness of melon.

Coefficients of determination of the calibration (R_c^2) and standard error of the calibration (SEC) were noted to compare performance of the developed prediction models. All the developed models were tested by the cross-validation and the coefficients of determination in the cross-validation (R_{cv}^2) and the standard error of the cross-validation (SECV) were recorded also for the comparison of performance between the developed models.

RESULTS AND DISCUSSION

Performance of VIS/NIR spectroscopy to predict firmness of melon

The indices of performance, R_c^2 and R_{cv}^2, of the PLSR models developed using the various preprocessing methods in each experiment are varied widely according to the preprocessors; the ranges of the variation of R_c^2 are 0.089~0.455, 0.275~0.759 and 0.198~0.719, and range of R_{cv}^2 are 0.011~0.094, 0.196~0.653 and 0.001~0.439 for the experimental data of #11, #12 and #13, respectively.

A model showing the highest R_c^2 and R_{cv}^2 in each experiment was selected and performance of the selected PLSR models is shown in Table 2. The preprocessors that resulted in the highest R_c^2 and R_{cv}^2 in each experiment are listed. The table shows that the preprocessor of the best result in each experiment is not same. This means all the preprocessors have to be tried to find the best model for the prediction for any lot of melon.

Table 2. Preprocessors and performance of the best models to predict firmness of melon in each experiment.

Experiment	Preprocessor	Calibration		Cross Validation	
		R_c^2	SEC (N)	R_{cv}^2	SECV (N)
#11	Savitzky-Golay-1st deri.	0.455	2.7	0.094	3.6
#12	S N V	0.759	2.3	0.653	2.8
#13	Raw data	0.719	2.2	0.439	3.2

The table shows that prediction of firmness of melon by the VIS/NIR spectroscopic technique is possible up to levels of R_c^2 of 0.759 and R_{cv}^2 of 0.653, even though peel of fruit is so thick. But the best performance in each experiment, especially R_{cv}^2, shows a significant variation even with the 3 lots of melon samples produced in a same area but in different seasons. Hence, a conclusion can be drawn that, even though the spectroscopic technique is feasible to predict firmness of melon, the technique has a serious drawback of performance variation from lot to lot of melon which should be overcome for practical application.

Performance of a prediction model was investigated using the spectral data of melons of different lots like the test of validation as a test for multi-use. Among the prediction models developed in this study, SNV preprocessed model in the experiment #12 that resulted in the highest values of R_c^2 and R_{cv}^2 was selected for the investigation. The model resulted in a coefficient of determination of the test (R_t^2) and the standard error of prediction (SEP) as 0.08 and 4.6 N, respectively, for the spectral data of the experiment #11, and 0.0 and 6.7 N, respectively, for the spectral data of the experiment #13. The results mean that a prediction model for a lot of melon cannot be used for the other lots of melon, and so each prediction model has to be developed for calibration for every lot of melon. Such calibration procedure is annoying and sometimes impractical, especially for many lots of small number of melons. Hence, any possible approach to reduce the troublesome should be sought in order to use the technique in the practical sorting process of melon.

Performance of a prediction model of mixed data

Development of a prediction model with mixed spectral data of different lots of melon might be a solution to relieve the mentioned drawbacks of the spectroscopic technique (Lu and Bailey, 2005). As a trial of this, all of the spectral data of the experiment #11 and #12 were mixed and prediction models were developed using the 9 preprocessors. Performance of the developed models was evaluated as the same way as before, and a model of the 2nd derivative of Norris Gap preprocessors, resulting in the highest R_c^2, was selected.

To test the multi-use of the models, all of the spectral data of the experiment #11 and #12 were used, and the spectral data of 50 samples of the experiment #13 were tried also. Results of the tests are shown in Table 3.

Table 3. Results of calibration and the test for multi-use of the developed models using the mixed spectral data of the experiment #11 and #12.

a) Calibration and cross validation

Preprocessor	Calibration		Cross Validation	
	R_c^2	SEC (N)	R_{cv}^2	SECV (N)
Norris Gap-2nd derivative	0.976	1.1	0.378	5.5

b) Test for multi-use

Exp. #11		Exp. #12		Exp. #13	
R_t^2	SEP (N)	R_t^2	SEP(N)	R_t^2	SEP (N)
0.912	1.1	0.954	1.0	0.178	4.6

The model of the 2nd derivative of Norris Gap resulted in high levels of R_t^2 to both of the spectral data of the experiment #11 and #12, and any reasonable interpretation was not possible for the results. The model gave low value of R_t^2 and high SEP to the spectral data of the experiment #13, which were not included in the development of the models, as expected.

As a second trial of the mixing data, all the spectral data of the experiment #12 and the data of 50 samples of the experiment #13 were mixed and prediction models were developed and evaluated their performance as the same way as before. Among the models of the mixed data, a model of the SNV preprocessors was selected as a model of the highest R_c^2. To test the multi-use of the models, the spectral data of the experiment #12, #13 and #11 were used. Results of the test are shown in Table 4.

Table 4. Results of calibration and the test for multi-use of the developed models using the mixed spectral data of the experiment #12 and #13.

a) Calibration and cross validation

Preprocessor	Calibration		Cross Validation	
	R_c^2	SEC (N)	R_{cv}^2	SECV (N)
S N V	0.586	2.8	0.417	3.4

b) Test for multi-use

Exp. #12		Exp. #13		Exp. #11	
R_t^2	SEP (N)	R_t^2	SEP(N)	R_t^2	SEP (N)
0.692	2.6	0.450	3.0	0.110	3.6

The model gave R_t^2 to the spectral data of the experiment #12 and #13 as 0.692 and 0.450, respectively, which are about the same level as R_{cv}^2 of the experiments as explained in Table 2. To the spectral data of the experiment #11, which were not participated in the development of the models, the model gave low value of R_t^2 and high SEP as the same as above.

The three sets of spectral data of experiment #11, #12 and #13 (data of 50 samples) were mixed and used to develop a prediction model using the 9 preprocessors, and performance of the developed model was evaluated. Among the models of various preprocessors using the mixed data, a model of the 2nd derivative of Norris Gap preprocessors was selected as a model of the highest performance. To test the multi-use of the model, the spectral data of the experiment #11, #12 and #13 were used, and the results are summarized in Table 5.

Table 5 Results of calibration and the test for multi-use of the developed models using the mixed spectral data of the experiment #11, #12 and #13.

a) Calibration and cross validation

Preprocessor	Calibration		Cross Validation	
	R_c^2	SEC (N)	R_{cv}^2	SECV (N)

Norris Gap-2nd derivative	0.876	2.2	0.390	5.0

b) Test for multi-use

Exp. #11		Exp. #12		Exp. #13	
R_t^2	SEP (N)	R_t^2	SEP(N)	R_t^2	SEP (N)
0.539	2.4	0.794	2.2	0.752	2.0

The drawback of performance variation of the spectroscopic technique was considerably dissolved by the data mixing method. As shown in Table 2, R_{cv}^2 values in each experiment are in a range of 0.094~0.653, while R_t^2 values in Table 5 are in a range of 0.539~0.794.

As shown in Table 5, the R_t^2 evaluated by the each experimental data are higher than the R_{cv}^2 of each experiment showed in Table 2, and the SEP of the mixed data are lower than the SECV of each experiment in Table 2. The result is almost the same for the 2 cases of mixed data as explained before. The results mean that the data mixing has a good potential to improve performance of the model to predict firmness of melon. Since the model showed improved performance to all of the 3 experimental data, the result exemplified a possibility of the multi-use of the model, and the possibility could be expanded to a possibility of multi-season use of the model, if a model is developed using spectral data of melon of various seasons.

CONCLUSIONS

VIS/NIR spectroscopic technique of diffuse reflectance and PLSR with 9 preprocessors were applied to measure firmness of muskmelon. Three lots of melon cultivated in the same area but different season were used to estimate feasibility of the firmness measurement and the following conclusions were drawn:

- Prediction of firmness of melon by the VIS/NIR spectroscopic technique was potentially feasible. The highest R^2 values of calibration and cross-validation were 0.759 and 0.653. But the technique had a critical drawback of performance variation from lot to lot of melon which should be overcome for practical application.

- The drawback of performance variation of the spectroscopic technique was considerably dissolved by mixing data collected from several lots of melon produced in a same area but in different seasons.

- Data mixing has a good potential to improve performance of the model to predict firmness of melon, and the model of mixed data has a possibility of multi-season use, if the model was developed using spectral data of melon of various seasons.

Since the results were derived from a limited number of experiments, a further study is needed to verify them. More number of melon lots with a larger number of melon samples is essential for the study.

Acknowledgements: "This work was supported by the Korea Research Foundation Grant funded by the Korean Government (MOEHRD)." (KRF-2007-314-D00343)

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