XVII[th] 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

MELON SOLUBLE SOLIDS CONTENT MEASUREMENT USING VIS/NIR DIFFUSE REFLECTANCE SPECTROSCOPY

H.S. SHIN[1], S.R. SUH[1]*, K.H. LEE[1], S.H. YU[1]

[1] Dept. of Rural and Biosystems Engineering, Chonnam National University, Gwangju, Korea * Corresponding author, srsuh@jnu.ac.kr

CSBE10174 – Presented at Section VI: Postharvest Technology, Food and Process Engineering Conference

ABSTRACT Visible/near-infrared diffuse reflectance spectroscopy for assessment of fruit quality is in intermediate level between simple reflection and transmittance spectroscopy in term of travel length of light. This study was aimed to assess the soluble solids content of muskmelon fruits using VIS/NIR reflectance spectroscopy. Muskmelon samples of the same cultivar were taken at the same growing area but in different seasons. Calibration models were built using partial least square regressions with nine pre-processed spectral data and raw spectral data. The calibration models from the spectral data collected using the diffuse reflectance spectroscopic technique showed good performance for assessment of melon SSC (R_c^2 > 0.969). But the models were unstable depending on the experiments that were conducted with the melon samples of different seasons. This can be a critical problem for practical application of the technique. New models were built with the mixed spectral data sets. In general, the performance of the models from the mixed data was improved. The coefficients of determination of prediction (R_p^2) of the model was in a range of 0.666~0.916 with the standard error of prediction as 0.58~0.80^{o}Brix. The result shows that 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.

Keywords: muskmelon, soluble solids content, diffuse reflectance, VIS/NIR spectroscopy

INTRODUCTION Muskmelon is one of income raising fruit vegetables for farmers in Korea and it is more profitable to farmers if melon could be sorted by internal qualities non-destructively. Since melon is covered with thick peel, it would be difficult to measure the internal qualities of the fruit non-destructively.

Soluble solids content (SSC) of fruit is the very important factor to assess internal quality of fruits, and various techniques have been developed 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 (Lee et al., 2004; Subedi et al., 2007).

In application of the VIS/NIR spectroscopy to a fruit, three lighting methods can be used: simple reflection, diffuse reflectance and transmittance (Lee et al., 2004; Ruiz-Altisent and Ortiz-Canavate, 2005). Among the three, diffuse reflectance and transmittance are better to measure internal quality of fruit, because light travelled inside the fruit could be collected by the methods. Internal quality of fruit measured by transmittance can be more representative than quality measured by diffuse reflectance, because the area travelled by light in the transmittance is larger than that in diffuse reflectance (Lu et al., 2000). However, energy required for light travel in fruit in the transmittance is much more and generate more problems than that in the diffuse reflectance (Nicolai et al., 2007). The problem is more serious for a fruit of thick peel like muskmelon. This study was aimed to assess the SSC of muskmelon fruits by a way of consuming less energy using VIS/NIR diffuse reflectance spectroscopy. A series of experiment using melon samples of different season was performed to ensure performance of the spectroscopic technique for the assessment.

A model to predict SSC for a lot of fruit could be used only for the lot naturally. This means that each prediction model has to be developed for calibration for every lot of fruit. Such calibration is cumbersome and impractical for many lots of small number of fruits. To reduce the troublesome, several prediction models using mixed spectral data collected from different lots of melons were developed, and performance of the models was evaluated and discussed.

MATERALS AND METHOD

Materials

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

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

Experiment #	Diameter (cm)	Weight (kg)	SSC (°Brix)
11	14.6 ±0.7	1.6 ±0.3	10.2 ±1.3
12	15.9 ±0.6	2.0 ±0.2	9.3 ±2.1
13	-	1.7 ±0.3	10.2 ±1.7

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 as shown in Figure 1.

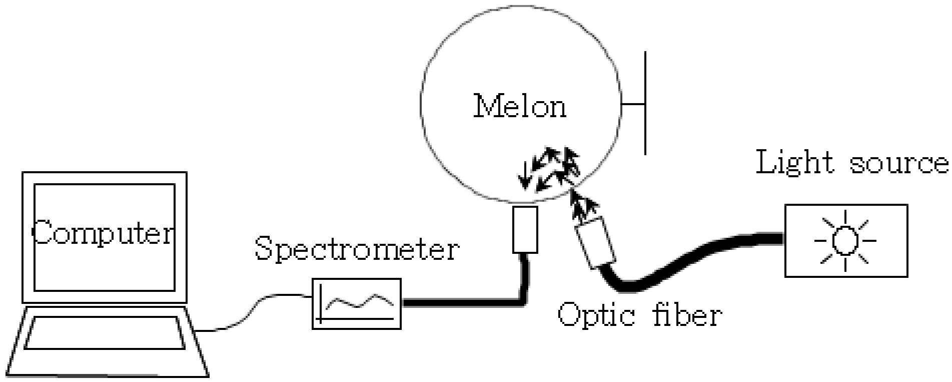

Figure 1. Schematic of the VIS/NIR spectral data acquisition system.

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

Acquisition of spectral data: Spectral data were collected from evenly distributed 6 points in the equator line of a melon. At the points, the collecting part of light guide line was placed close to the point.

Measurement of SSC of melon: To measure SSC of melon**,** doughnut shaped fruit flesh of melon was cut from middle part along with equator line of melon with a thickness of 20 mm. On the surface of the flesh cut, 6 points where the spectral data were collected were pointed on a center circle of fruit flesh. From the measuring points, juice of melon flesh was collected and the SSC of the juice was measured with a portable refractometer (PR-32, Atago, Japan).

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 SSC of melon.

The calibration was performed on the three sets of experimental data. Besides of this, samples of the experiment #13 sized about double of the experiments #11 and #12 were divided into two evenly; each for the modeling and validation of the model. Coefficients of determination of calibration (R_c^2) and the standard error of calibration (SEC) were noted to compare performance of the developed prediction models. All the developed models were tested by cross-validation and the coefficients of determination of cross-validation (R^2_{cv}) and the standard error of 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 SSC of melon

The indices of performance, R^2_c and R^2_{cv}, 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^2_c are 0.281~0.991, 0.879~0.969 and 0.745 ~0.978, and the ranges of R^2_{cv} are 0.0~0.405, 0.370 ~0.906 and 0.324~0.723 for the experimental data of #11, #12 and #13, respectively.

A model showing the highest R^2_c and R^2_{cv} in each experiment was selected and performance of the selected PLSR models is shown in Table 2. The preprocessors resulted in the highest R^2_c and R^2_{cv} in each experiment are listed. The preprocessors of the highest R^2_c and R^2_{cv} are the same in the experiment #11 and #12, but in the experiment #13, the preprocessors of the highest R^2_c and R^2_{cv} are different as shown. 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 models of the highest R^2_c and R^2_{cv} to predict SSC of melon in each experiment.

Experiment	Preprocessor	Calibration		Cross Validation	
		R^2_c	SEC(°Brix)	R^2_{cv}	SECV(°Brix)
#11	Raw data	0.991	0.12	0.405	1.06
#12	Normalization-range	0.969	0.37	0.906	0.65
#13	Savitzky-Golay-1st deriv.	**0.978**	0.25	0.559	1.13
#13	SNV	0.790	0.76	**0.723**	0.88

The table shows that the highest R^2_c and the corresponding SEC of model in each experiment are higher than 0.969 and lower than 0.37°Brix, respectively. The result means that the selected calibration models for prediction of SSC of melon are precise enough and the VIS/NIR spectroscopic technique has a very high potential for the prediction of SSC in a practical sorting process even though peel of the fruit is so thick.

But R^2_{cv} and SECV of the highest R^2_c model in each experiment resulted in a range of variation as 0.405~0.906 and 0.65~1.13 °Brix, respectively. The performance is not good enough for practical applications. A study on robustness of the models is needed to check performance of the models with the spectral data of melons of different lots like a test of validation (Zude et al, 2007). The test was carried out on the models of the highest R^2_c and R^2_{cv}, in each experiment to evaluate the robustness of the models. The test results were presented by a coefficient of determination of the test (R^2_p) and a standard erroe of prediction (SEP).

Robustness of the developed prediction models

Results of the robustness test on the models of the highest R_c^2 and R_{cv}^2 in each experiment are summarized in Table 3. The model developed from the experiment #11 showed higher R_p^2 (Table 3-a) than R_{cv}^2 shown in Table 2, but the models from the experiment #12 and #13 resulted in lower value of R_p^2 to the melons of the experiment #11 as low as 0.238~0.313. Hence, it is concluded that robustness of the tested models is not good in general, and any possible approach to enhance the robustness should be sought in order to use the technique in the practical sorting process of melon. Since the three sets of experimental data showed such precise calibration results, development of a prediction model with mixed data of different lots of melon might be a solution to solve the problems of practical use of the spectroscopic technique (Lu and Bailey, 2005).

Table 3. Results of the robustness test on the best model of each experimental data set.

(a) The best model from the data set of #11

Exp. #12		Exp. #13	
R_p^2	SEP(°Brix)	R_p^2	SEP(°Brix)
0.642	1.32	0.673	0.96

(b) The best model from the data set of #12

Exp. #11		Exp. #13	
R_p^2	SEP(°Brix)	R_p^2	SEP(°Brix)
0.242	1.49	0.511	1.21

(c) The model of the highest R_c^2 from the data set of #13

Exp. #11		Exp. #12	
R_p^2	SEP(°Brix)	R_p^2	SEP(°Brix)
0.238	1.19	0.833	0.89

(d) The model of the highest R_{cv}^2 from the data set of #13

Exp. #11		Exp. #12	
R_p^2	SEP(°Brix)	R_p^2	SEP(°Brix)
0.313	1.24	0.637	1.29

Performance of a prediction model of mixed data

For the investigation of mixing experimental data, samples of the experiment #13 were randomly divided into two, named as '#13-a' and '13-b', in order to have two sets of sample (n=52), which have the similar size of the sample of the experiment #11(n=48) and #12 (n=45). Models for prediction of SSC from the two experimental data sets were developed as the same procedure as before. Models of the highest R_c^2 and R_{cv}^2 in the experimental data sets of #13-a and #13-b were selected and listed in Table 4.

Table 4. Preprocessors and performance of models of the highest R_c^2 and R_{cv}^2 to predict SSC of melon developed from the experimental data #13-a and #13-b.

Experimental data	Preprocessor	Calibration		Cross Validation	
		R_c^2	SEC(°Brix)	R_{cv}^2	SECV(°Brix)
#13-a	Savitzky-Golay-1st deriv.	**0.968**	0.31	0.674	0.99
#13-a	SNV	0.882	0.59	**0.771**	0.83
#13-b	Savitzky-Golay-1st deriv.	**0.997**	0.08	0.600	1.03
#13-b	Normalization-range	0.829	0.67	**0.659**	0.96

It was noted that performance of the models developed from the experimental data #13-a and #13-b wase similar to that of the experimental data #13 shown in Table 2. The results indicated that a sample size of about 50 was roughly enough to develop an effective model to predict SSC of melon. It was also noted that the models developed from the experimental data #13-a and 13-b had each different model of the highest R_c^2 and R_{cv}^2.

All of the spectral data of the experiment #11, #12 and one half of the data of the experiment #13 were mixed and two sets of mixed experimental data were prepared. Models for prediction of SSC of melon were developed using the 9 preprocessors. Performance of the developed models was evaluated as the same way as before. Models of the highest R_c^2 and R_{cv}^2 were selected and listed in Table 5.

Table 5 Results of calibration and cross-validation of the best models developed from the mixed data of the experiment #11+#12+#13-a and #11+#12+#13-b.

Experimental data	Preprocessor	Calibration		Cross Validation	
		R_c^2	SEC (°Brix)	R_{cv}^2	SECV (°Brix)
#11+#12+#13-a	Savitzky-Golay-1st	**0.938**	0.44	0.553	1.22
	Raw	0.814	0.77	**0.703**	0.98
#11+#12+#13-b	Norris Gap-1st	**0.973**	0.29	0.605	1.11
	Raw	0.875	0.61	**0.708**	0.95

Robustness test was performed on the selected two models in each mixed experimental set with the experimental data of the experiment #11, #12, #13-a and 13-b. Among the selected models of the highest R_c^2 and R_{cv}^2, models of the highest R_{cv}^2 showed higher performance than the models of the highest R_c^2 in the robustness test on the two sets of mixed data. Results of the test on the models of the highest R_{cv}^2 are summarized in Table 6.

Table 6 Results of the robustness test on the models of the highest R_{cv}^2 developed from the mixed data of the #11+#12+#13-a and #11+#12+#13-b.

(a) The model from the data set of #11+#12+#13-a

Exp. #11		Exp. #12		Exp. #13-a	
R_p^2	SEP (°Brix)	R_p^2	SEP(°Brix)	R_p^2	SEP (°Brix)
0.666	0.76	0.869	0.80	0.826	0.72

(b) The model from the data set of #11+#12+#13-b

Exp. #11		Exp. #12		Exp. #13-b	
R_p^2	SEP (°Brix)	R_p^2	SEP(°Brix)	R_p^2	SEP (°Brix)
0.804	0.58	0.916	0.64	0.857	0.62

In summary, the model from the data set of #11+#12+#13-a resulted in R_p^2 in a range of 0.666~0.869 and SEPs less than 0.80°Brix, and the model from the data set of #11+#12+#13-b resulted in R_p^2 in a range of 0.804 ~0.916 and SEPs less than 0.64°Brix. The models from the data set of #11+#12+#13-a and #11+#12+#13-b were tested with the experimental data of #13-b and #13-a, respectively, which was not included in the results explained above. The tests resulted in R_p^2 as 0.716 and 0.734 and SEP as 0.87 and 0.89°Brix, respectively.

The performance of the models is very much encouraging because the data mixing improves performance of the model to predict SSC of melon considerably. The indices of the performance, R_p^2 and SEPs, show much more stable with the experimental data sets tested and higher than those of the other models explained before. Therefore, the model from the mixed data is expected as a model of having a good potential to be used in practical sorting process of melon. This is because melons are sorted into only two or three grades of SSC in practical sorting process and the model from the mixed data is expected to sort melons at high ratio of correct classification in the sorting process.

The result also 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 was applied to measure SSC of musk melon. Three lots of melon of the same cultivar cultivated in the same area but different season were used to estimate feasibility of the measurement and the following conclusions were drawn:

VIS/NIR diffuse reflectance spectroscopic technique showed high potential for assessment of melon SSC with good calibration results (R_c^2 > 0.969). But the performance of the models in cross validation and validation with the data sets that were not used to build the models was not good as the calibration and varied based on lots of melon samples harvested in different seasons.

This can be a critical problem for practical application of the technique. The spectral data sets collected from different lots of melon samples were mixed and new models were built with the mixed spectral data sets. In general, the performance of the models from the mixed data was improved. The R_p^2 values of the models were in a range of 0.666~0.916 with the standard error of prediction as 0.58~0.80^{o}Brix. The R_p^2 of the models for the data sets that was not included in making the models were higher than 0.716 and the SEP were lower than 0.89°Brix. These results present that mixing of the spectral data collected in different seasons has a great potential to improve performance of a model for the assessment of SSC and enhance a model more stable. And the results imply that the model of mixed data has a possibility of multi-season use.

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)

REFERENCES

Lee, K., S. Kang, K. Choi. 2004. Nondestructive quality measurement of fruits and vegetables using near-infrared spectroscopy. Food Engineering Progress. 8(3):158-169.

Lu, R., B. B. Bailey. 2005. NIR measurement of apple fruit soluble solid content and firmness as affected by postharvest storage. An ASAE Meeting Presentation Paper Number: 056070.

Nicolai, B. M., K. Beullens, E. Bobelyn, A. Peirs, W. Saeys, K. Theron, J. Lammertyn. 2007. Nondestructive measurement of fruit and vegetable quality by means of NIR spectroscopy: A review. Postharvest Biology and Technology. 46(2007):99-118.

Ruiz-Altisent M. and J. Ortiz-Canavate. 2005. Instrumentation and procedures for commercial non-destructive determination of firmness of various fruits. An ASAE Meeting Presentation Paper Number: 056176.

Subedi, P. P., K. B. Walsh, G. Owens. 2007. Prediction of mango eating quality at harvest using short-wave near infrared spectrometry. Postharvest Biology and Technology. 43(2007):326-334.

Zude, M. I. Birlouez-Aragon, P. Paschold, D. N. Rutledge. 2007. Non-invasive spectrophotometric sensing of carrot quality from harvest to consumption. Postharvest Biology and Technology. 45(2007):30-37.