Prediction of Cooked Rice Texture Using Extrusion and Compression Tests in Conjunction with Spectral Stress Strain Analysis

Chanintorn Sitakalin and Jean-Francois C. Meullenet[1]

Cereal Chem. 77(4):501–506

ABSTRACT

Sensory texture attributes of cooked rice from two cultivars (Bengal and Cypress) harvested in 1997 (56 samples) were predicted using extrusion and compression tests along with spectral stress strain analysis. Predictive models for each of nine sensory texture attributes studied were evaluated using force values from the instrumental tests in conjunction with partial least squares regression. All sensory attributes were well predicted using both the extrusion and compression tests (relative ability of prediction > 0.70). However, the extrusion test consistently provided more accurate and discriminative predicted models (root mean square error of prediction < 0.55, S_{tot}/RMSEP > 2.0). Spectral stress strain analysis predictive models for adhesiveness to lips and hardness were explained.

Texture is an extremely important attribute of cooked rice and has been used as an indicator for consumer acceptance. Chemical characterization methods (e.g., amylose content and gel consistency value), sensory evaluation, and instrumental methods have been used for assessing rice quality. However, rices with similar chemical properties are not always similar with respect to texture properties (Del Mundo et al 1989). Instrumental extrusion and compression tests have been successfully used in assessing cooked rice texture attributes. Extrusion tests are normally performed using different instruments including the Ottawa texture measuring system (OTMS) in conjunction with a universal testing machine (Instron) (Perez and Juliano 1979, 1981; Juliano et al 1981; Rousset et al 1995; Del Mundo et al 1989) and a back extrusion cell in conjunction with a texture analyzer (Meullenet et al 1998, 1999). Compression tests have been performed with instruments and methods such as double compression in texture profile analysis (TPA) using a cylindrical plunger in conjunction with a texture analyzer (Champagne et al 1998), and single compression using a plunger in conjunction with a tensile testing machine (Juliano et al 1981). Extrusion tests are commonly performed on bulk samples while compression tests are usually performed on a few kernels. Tests performed on bulk samples yield more consistent results (Juliano et al 1981). However, compression tests present the main advantage of requiring smaller sample sizes than extrusion tests.

Empirically, single parameters (e.g., maximum load) have been extracted from force-deformation curves and correlated to sensory attributes. However, the prediction of the multidimensional aspect of texture from a single instrumental parameter is often unsuccessful. Meullenet et al (1998) proposed the use of additional parameters extracted from the force-deformation curve and used them for developing multiple regression predictive models. Their results showed that using several parameters did improve the predictive ability of the models for attributes such as hardness and toothpack (Meullenet et al 1998). Spectral stress strain analysis (SSSA) is a novel approach that considers the force-deformation curve generated from any instrumental test as a spectrum. In this method, individual stress or force values rather than preselected parameters are used to predict sensory attributes (Meullenet et al 1999). Each measured force at a given deformation can be regarded as an individual variable and have the same chance of influencing the prediction of a given sensory texture characteristic. This new method, if successfully developed, would provide the rice industry with the tools necessary to rapidly and accurately assess texture characteristics of cooked rice.

[1] Corresponding author. Department of Food Science, University of Arkansas, 272 Young Avenue, Fayetteville, AR 72704. Phone: (501) 575 6822, Fax: (501) 575 6936, E-mail: jfmeull@comp.uark.edu

Publication no. C-2000-0606-05R.
© 2000 American Association of Cereal Chemists, Inc.

The objectives of this study were to 1) to confirm the potential of SSSA in combination with either an extrusion test or a compression test for predicting cooked rice texture, and 2) compare the performances of the extrusion and compression tests.

MATERIALS AND METHODS

Samples

One long-grain (Cypress) and one medium-grain (Bengal) rice cultivar were acquired from a rice farm in Dewitt, AR, in 1997. For both cultivars, on-farm partially dried rice and wet rice were collected and brought to the University of Arkansas Rice Processing Laboratories and then cleaned using a Carter-Day dockage tester. Samples were stored in airtight plastic buckets. Drying conditions for on-farm dried and laboratory dried final moisture contents and storage temperatures are given in Fig. 1. Samples were pulled after five different storage durations: 0, 12, 28, and 52 weeks. These samples were part of a series of studies designed to evaluate the effects of drying and storage conditions on rice sensory quality.

Stored samples were allowed to equilibrate to room temperature before hull and bran removal. A McGill sample sheller (husker) and a McGill No. 2 mill were used to remove hull and bran, respectively. Samples were milled to a constant degree of milling (DOM = 90). A Satake milling meter MM-1B was used for measuring the DOM.

Sensory Evaluation

Sample preparation. Rice samples were cooked in household rice cookers (National, model SR-W10FN) for 20–21 min with a constant rice-to-water ratio of 1:2 (v/v) and immediately mixed using a plastic rice dipper before presentation to panelists at 75 ± 2°C. Samples were presented in preheated glass bowls insulated with Styrofoam cups and covered with watch glasses labeled with random three-digit codes. Panelists were instructed to monitor temperature closely during the tests using digital thermometers and to taste rice samples before the temperature of samples reached 60°C. Water and soda crackers were provided to individual panelists to clean their palate between each sample. Serving orders were randomized across treatment but not across panelists due to sample availability and the importance of sample temperature. Samples were unimodally presented to the panelists, who sat in individual booths featuring incandescent lighting and positive pressure. Seven to eight samples were presented to panelists for evaluation at each of the testing sessions. Each sample was evaluated twice by panelists on the same testing day. At the beginning of each session a reference rice sample (Riceland extra long-grain, Riceland Foods, Inc., Stuttgart, AR) was presented as a warm-up sample.

Sensory methodology. Nine panelists with three years of experience and trained in descriptive analysis techniques according to the Spectrum methodology (Sensory Spectrum, Chatham, NJ) evaluated eight texture attributes of cooked rice. Four 3-hr orientation sessions were held for the panelists to develop the rice lexicon and the test technique for each attribute evaluated. Attributes evaluated and definitions are described in Fig. 2. Eight texture attributes were evaluated during four evaluation stages. The first attribute evaluated was adhesiveness to lips as a surface characteristic by compressing the sample between the lips and evaluating the degree to which it adhered to the lips. The next attribute evaluated in this stage was particle size, which was assessed by placing the sample on the center of the tongue and evaluating the amount of space the particle filled in the mouth. Hardness was evaluated during the first bite by biting through the sample between molars and evaluating the force required to bite through. Cohesiveness of mass after three and eight chews, roughness of mass, and toothpull were evaluated during the chew down stage. Cohesiveness of mass was assessed by chewing the samples with the molars and evaluating the degree to which the chewed sample held together after the third and eighth chew. Roughness of mass was evaluated by chewing the samples with the molars eight times and evaluating the degree of roughness perceived. Toothpull was determined from the force required to separate the jaws after chewing the samples three times. Toothpack and loose particles were evaluated last in the residual stage after expectoration. Toothpack was evaluated from the amount of the samples packed into the crowns. Loose particles were assessed from the amount of particles remaining on the surface of the mouth after swallowing.

Panelists used paper ballots and sensory scores of 0–15 (Meilgaard et al 1991). References were provided to panelists to use as anchors for specific attributes. A list of references used is provided in Fig. 2.

Instrumental Texture Analysis

Extrusion cell test. Rice samples were cooked in excess water. Milled rice (100 g) was added to four cups of boiling water and cooked for 20 min. Then water was drained from the samples through a strainer and rice samples were rinsed with cold water for 5 min to stop cooking. Samples were spread on plastic trays and covered with aluminum foil. Samples were stored in a refrigerator at 4°C overnight until testing. Samples were allowed to equilibrate to room temperature for 30 min before testing.

The two different cooking methods used for the instrumental and sensory evaluation methods might not represent the ideal testing conditions for the purpose of correlating instrumental data with sensory perception. However, logistical problems prevented instrumental evaluation from being conducted concurrently with sensory evaluation. Furthermore, limited sample availability and the difficulties associated with maintaining sample temperature during instrumental testing prevented the use of identical cooking procedures.

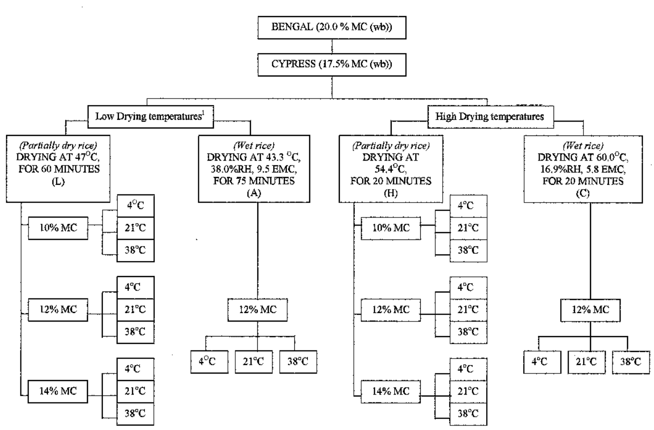

Fig. 1. Processing conditions for rice samples. Partially dried rice was dried on-farm (conditions H and L). Wet rice was dried in a thin-layer laboratory-scale drier (conditions A and C). MC = moisture content.

However, the focus of this study was to develop an instrumental method capable of predicting the sensory perception of texture attributes. Our intention was not to develop an imitative test reproducing the actual testing conditions of cooked rice using sensory methods.

Cooked rice (35 g) was weighed into a cylindrical back extrusion cell (40 mm diameter and 70 mm deep with 3.2-mm diameter holes extrusion plate). A texture analyzer (model TA-XT2, Texture Technologies Corp., Scarsdale, NY) was used to perform the extrusion test. A 25-kg maximum-load load cell was used and the cross-head speed was set to 5.0 mm/sec for a total travel of 55 mm as previously reported by Meullenet et al (1999). Data were collected using the X-TRAD software (version 3.70) (Stable Microsystems, Surrey, England). The force in Newton (N) required to extrude the sample was recorded as a function of time. Six repeated measures were performed on each sample.

Flat plate compression test. Rice samples were collected during sensory testing and the tests were performed on the same day on rice samples at room temperature. Five intact rice kernels were randomly selected and placed on the base. The clearance between the flat compression plate (51 mm diameter) and the base was set at 5.4 mm. The same texture analyzer was used to perform the compression test. The compression plate traveled 5.0 mm at a test speed of 0.5 mm/sec. Data were collected using the X-TRAD software (version 3.70). The force in Newton (N) required to compress the sample was recorded as a function of time. Six repeated measures were performed on each sample.

Data Analysis

Means for all sensory texture attributes for each sample were calculated using PROC MEANS (version 7.0, SAS Institute, Cary, NC). The average force-deformation curve for each sample was exported to a spreadsheet software (Microsoft Excel 97). A multivariate analysis software, Unscrambler (version 6.11a, Camo, Throndheim, Norway), was used to determine predictive models of texture attributes. Means for sensory data and force-deformation

TERM	DEFINITION	TECHNIQUE	REFERENCES	
SURFACE:				
Adhesiveness to lips	The degree to which the sample adheres to the lips.	Compress sample between lips, release, and evaluate.	Tomato	0.0
			Nougat	4.0
			Breadstick	7.5
			Pretzel Rod	10.0
			Rice Krispies	15.0
Particle size	The amount of space the particle fills in your mouth.	Place sample in center of mouth and evaluate.	Rice grain	0.5
			Tic Tac	2.5
			M & M (plain)	4.0
			Mike & Ikes	6.0
			Cherry Bite	11.0
			Spearmint Leaf	13.0
			Peppermint Patties	20.0
FIRST CHEW:				
Hardness	The force required to compress the sample.	Compress or bite through sample with molars or incisors.	Cream cheese	1.0
			Egg white	2.5
			American cheese	4.5
			Hot dog	5.5
			Olive	7.0
			Peanut	9.5
			Almond	11.0
			Carrot	11.0
			Life Savers	14.5
CHEWDOWN:				
Cohesiveness of mass	The degree in which the chewed sample holds together.	Chew sample with molar teeth up to 3 times and evaluate.	Licorice	0.0
			Carrot	2.0
			Mushrooms	4.0
			Hot dog	7.5
			American cheese	9.0
			Brownie	13.0
			Dough	15.0
Roughness of mass	The amount of roughness perceived in the chewed sample.	Chew sample with molar teeth 8 times and evaluate.	Unchewed Jell-O	0.0
			Orange peel	3.0
			Cooked oatmeal	6.5
Toothpull	The force required to separate the jaws during mastication.	Chew sample up to 3 times and evaluate.	Clam	3.5
			Caramel	5.0
			Jujubes	15.0
RESIDUAL:				
Toothpack	The amount of product packed into the crowns of your teeth after mastication.	Chew samples up to 8 times, expectorate, and feel the surface of the crowns of the teeth with tongue.	Captain Crunch	5.0
			Heath Bars	10.0
Loose particles	The amount of particles remaining in and on the surface of the mouth after swallowing.	Chew sample up to 8 times with molars, swallow and evaluate.	Carrot	10.0

Fig. 2. Vocabulary for sensory texture attributes of cooked rice.

curves were exported to the Unscrambler software. Points extracted from the force-deformation curve (217 points for the extrusion test and 251 points for the compression test) were used as variables in a regression model to predict each sensory attribute, thus the name given to the method, spectral stress strain analysis (SSSA).

Data was fitted by partial least squares regression using the PLS1 option of the Unscrambler. With the PLS regression method, both X (instrumental variables) and Y (sensory attributes) matrices are evaluated simultaneously to find the latent variables in X that would best predict the latent variable in Y. Instrumental data were weighted by standard deviation so that each instrumental variable was given the same chance to influence the predictive models. A validation method (full cross-validation) was used on centered data to determine how well the model would predict texture characteristics of samples not included in the calibration data set. The validation method is based on estimating the uncertainty on future predictions. With the full cross-validation method, the same samples are used for both model estimation and testing. A sample from the calibration data set was omitted. The model was then calibrated on the remaining data points and used to predict omitted samples. The process was repeated until all samples have been omitted once. Weighted regression coefficients assisted in identifying the variables (stages from force-deformation curve) important to the relationship between Y and all the X variables. Large absolute values indicated large importance, while small values (close to 0) indicated unimportant variables. The coefficient value indicated the average increase in Y when the corresponding X variables was increased by one unit, while maintaining all other variables constant.

Root mean square error of prediction (RMSEP) was used to express the predictive ability of each model. RMSEP measures the average difference between predicted and measured response values. RMSEP was expressed in the same units as the original response variable (sensory score). Relative ability of prediction (RAP) was also calculated and used as an indicator of the quality of the predictive models. RAP was calculated as described by Martens and Martens (1986) and Windham et al (1997). A value close to 1 indicated an accurate predictive model. Unlike R^2, RAP takes into account the unexplained variation in sensory data. RAP is defined as:

$$\mathrm{RAP} = (S^2_{\mathrm{tot}} - \mathrm{RMSEP}^2)/(S^2_{\mathrm{tot}} - S^2_{\mathrm{ref}})$$

where S_{tot} is the standard deviation of a sensory attribute and S_{ref} is a measure of the uncertainty of the analysis due to panelists. S_{ref} is defined for each sensory characteristic as:

$$S_{\mathrm{ref}} = (\mathrm{MSE}/[P \times R])^{1/2}$$

where MSE is the mean square error derived from two-way analysis of variance with samples and panelists as class-variables and P and R were the number of sensory panelists and replicates, respectively.

Besides RAP and RMSEP values, ratio of root mean square error of prediction and root mean square error of calibration (RMSEP/RMSEC) was used as an indication of model robustness. A ratio close to 1 indicated a robust model. In addition, ratio of the standard deviation of a sensory attribute (S_{tot}) and RMSEP were calculated to indicate model discrimination ability. Models with a large ratio (≥ 2) were considered to be discriminative.

TABLE I
Model Statistics[a] for Prediction of Texture Attributes of Cooked Rice Using an Extrusion Test[b]

Sensory Attributes	Intensity Range	PC[c]	R_p	RMSEP	R_c	RMSEC	RMSEP/ RMSEC	S_{tot} /RMSEP	S_{ref}	RAP
Adhesiveness to lips	8.1–12.7	5	0.85	0.54	0.91	0.41	1.32	3.16	0.24	0.92
Hardness	3.0–5.7	4	0.86	0.36	0.89	0.32	1.13	2.48	0.12	0.85
Cohesiveness of mass (after three chews)	3.5–8.3	3	0.61	0.39	0.69	0.35	1.11	3.57	0.14	0.93
Cohesiveness of mass (after eight chews)	3.1–6.4	1	0.89	0.32	0.91	0.30	1.07	4.63	0.15	0.96
Roughness of mass	5.5–7.0	4	0.81	0.19	0.86	0.16	1.19	6.34	0.11	0.98
Toothpull	1.3–3.6	4	0.69	0.31	0.77	0.26	1.19	2.78	0.11	0.89
Particle size	0.8–1.3	3	0.64	0.08	0.72	0.07	1.14	4.09	0.04	0.96
Toothpack	0.9–2.8	2	0.70	0.32	0.74	0.30	1.07	3.10	0.11	0.91
Loose particles	1.9–4.7	5	0.74	0.45	0.82	0.39	1.15	3.16	0.14	0.91

[a] R_p = correlation for the validation model; RMSEP = root mean square error of prediction; R_c = correlation for the calibration model; RMSEC = root mean square error of calibration; S_{tot} = ratio of the standard deviation of a sensory attribute; S_{ref} = measure of the uncertainty of the analysis due to panelists = $(\mathrm{MSE}/[P \times R])^{1/2}$; RAP = relativive ability of prediction.
[b] Total number of observations = 56, minimum and maximum sensory mean values.
[c] Number of principle components chosen in the regression model explains most of the variation in sensory attributes.

TABLE II
Model Statistics[a] for Prediction of Texture Attributes of Cooked Rice Using a Compression Test[b]

Sensory Attribute	PC[c]	R_p	RMSEP	R_c	RMSEC	RMSEP/ RMSEC	S_{tot} /RMSEP	S_{ref}	RAP
Adhesiveness to lips	2	0.62	0.82	0.74	0.68	1.21	2.07	0.24	0.78
Hardness	5	0.79	0.47	0.91	0.29	1.62	1.92	0.12	0.74
Cohesiveness of mass (after three chews)	4	0.74	0.33	0.86	0.24	1.38	4.15	0.14	0.95
Cohesiveness of mass (after eight chews)	3	0.83	0.41	0.90	0.31	1.32	3.63	0.15	0.93
Roughness of mass	5	0.64	0.26	0.87	0.15	1.73	4.63	0.11	0.96
Toothpull	5	0.73	0.32	0.91	0.17	1.88	2.68	0.11	0.88
Particle size	4	0.57	0.08	0.79	0.06	1.33	3.77	0.04	0.95
Toothpack	1	0.49	0.39	0.58	0.36	1.08	2.52	0.11	0.85
Loose particles	4	0.73	0.47	0.86	0.35	1.34	3.09	0.14	0.90

[a] R_p = correlation for the validation model; RMSEP = root mean square error of prediction; R_c = correlation for the calibration model; RMSEC = root mean square error of calibration; S_{tot} = ratio of the standard deviation of a sensory attribute; S_{ref} = measure of the uncertainty of the analysis due to panelists = $(\mathrm{MSE}/[P \times R])^{1/2}$; RAP = relativive ability of prediction.
[b] Total number of observations = 56.
[c] Number of principle components chosen in the regression model explains most of the variation in sensory attributes.

RESULTS AND DISCUSSION

The compression test used represented a method requiring small amounts of sample, while the extrusion test, a usually more reproducible method, required larger amounts of sample. A comparison between these two mechanical instrumental tests would help define the optimal method capable of accurately predicting cooked rice texture. Overall, all sensory attributes were well predicted using both extrusion (Table I) and compression tests (Table II) (RAP > 0.7, RMSEP < 1, S_{tot} / RMSEP > 2). However, RMSEP values, the average error of prediction expressed in the same unit as the sensory scores, were lower in most of the models calculated from the extrusion data.

Adhesiveness to lips was accurately predicted using SSSA (Tables I and II). However, this attribute was better predicted using the extrusion test (RAP_e = 0.92) than the compression test (RAP_c = 0.78). Furthermore, RMSEP for the extrusion test ($RMSEP_e$ = 0.54) was lower than the value from the compression test ($RMSEP_c$ = 0.82). The RMSEP value from the extrusion test was improved by 34.2% compared with the value acquired from the compression test. The predicted model using the extrusion data (S_{tot} / $RMSEP_e$ = 3.16) was more discriminative than that obtained from the compression data (S_{tot} / $RMSEP_c$ = 2.07). The result presented here is in agreement with previous findings by Juliano et al (1981), who reported that data acquired from the instrumental test performed on bulk samples were more reproducible and representative of sensory characteristics than data acquired from instrumental tests performed on individual grains. The RAP from the extrusion data (RAP_e = 0.92) was much higher than the value (RAP = 0.21) previously reported by Meullenet et al (1998). The results presented here showed SSSA provided additional information not accounted for in conventional data analysis techniques. In addition, samples used in the previous study were from harvest year 1996 with a total number of observations of only 27, while samples used in the present study were from harvest year 1997 with a total number of observations of 56. Differences in harvest year, number of samples, and panel performance might also have contributed to the improvement in the prediction of adhesiveness to lips.

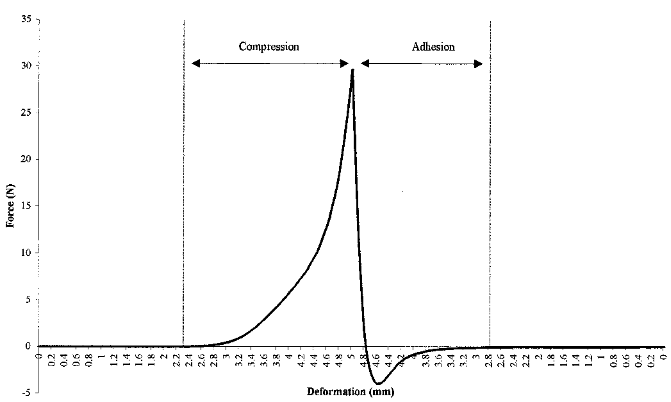

Fig. 3. Sample force-deformation curve for the compression test. Compression and adhesion phases were identified and used for regression model description.

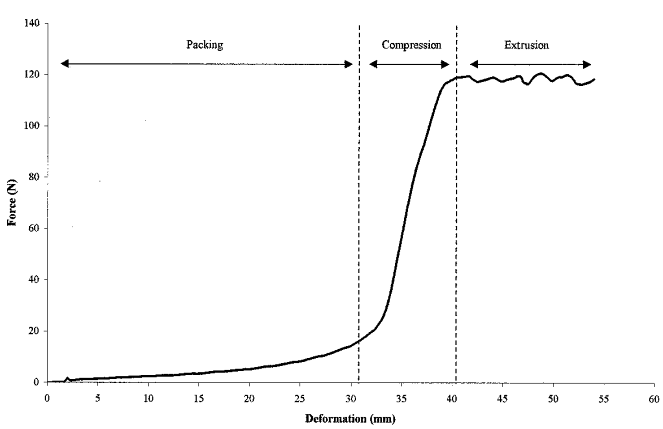

Fig. 4. Sample force-deformation curve for the extrusion test. Packing, compression and extrusion phase were identified and used for regression model description

Hardness was also well predicted using both the extrusion and the compression tests with RAP values of 0.85 (Table I) and 0.74 (Table II), respectively. The RMSEP value from the extrusion data ($RMSEP_e$ = 0.36) was slightly lower than the value from the compression data ($RMSEP_c$ = 0.47), which represented an improvement of 23.4% in favor of the model defined using extrusion data. The RMSEP values from both instrumental tests were small, demonstrating the potential of SSSA to provide reliable prediction of cooked rice hardness. As with the predicted models for adhesiveness to lips, the predictive model from the extrusion data (S_{tot} / $RMSEP_e$ = 2.48) was more discriminative than that from the compression data (S_{tot} / $RMSEP_c$ = 1.92). The model yielded from the extrusion data ($RMSEP_e$ / $RMSEC_e$ = 1.13) was also more robust than that determined from the compression data ($RMSEP_c$ / $RMSEC_c$ = 1.62).

Cohesiveness of mass evaluated after three chews was successfully predicted using the extrusion (RAP_e = 0.93, $RMSEP_e$ = 0.39) and the compression (RAP_c = 0.95, $RMSEP_c$ = 0.33) tests. The results obtained in the present study do not agree with those of Meullenet et al (1998, 1999). Cohesiveness of mass evaluated after three chews was not successfully predicted in previous studies using either conventional method of data analysis or SSSA (RAP = 0.16, RMSEP = 1.19) (Meullenet et al 1999). Once again, harvest year or panel performance may account for the discrepancy of the present results with previous studies (Meullenet et al 1998, 1999). Cohesiveness of mass evaluated after eight chews was successfully predicted using either extrusion (RAP_e = 0.96, $RMSEP_e$ = 0.32) or compression (RAP_c = 0.93, $RMSEP_c$ = 0.41) tests. The RAP value from the extrusion test using SSSA was

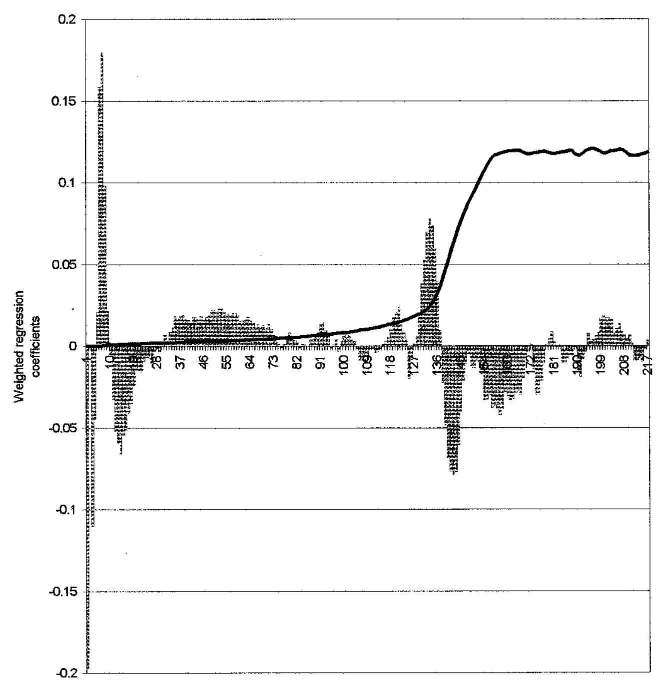

Fig. 5. Weighted regression coefficients and sample extrusion force-deformation curve for predicting adhesiveness to lips from an extrusion test. Weighted regression coefficients and force-deformation curves are not on the same scale

significantly higher than the value (RAP = 0.60) reported by Meullenet et al (1998) using five instrumental parameters or SSSA (RAP = 0.57) (Meullenet et al 1999) performed on three rice cultivars harvested in 1996. The predictive model evaluated using extrusion data was more robust and discriminative ($RMSEP_e$ / $RMSEC_e$ = 1.07, S_{tot} / $RMSEP_e$ = 4.63) than using compression data ($RMSEP_c$ / $RMSEC_c$ = 1.32, S_{tot} / $RMSEP_c$ = 3.63).

In a previous study by Meullenet et al (1998), roughness of mass could not be predicted using multiple instrumental parameters along with PLS regression. However, roughness of mass was satisfactorily predicted using SSSA in conjunction with either the extrusion (RAP_e = 0.98) or compression (RAP_c = 0.96) tests. The model calculated from the extrusion data ($RMSEP_e$ / $RMSEC_e$ = 1.19, S_{tot} / $RMSEP_e$ = 6.34) was much more robust and discriminative than that from the compression data ($RMSEP_c$ / $RMSEC_c$ = 1.73, S_{tot} / $RMSEP_c$ = 4.63). Moreover, the RMSEP values for models obtained from extrusion ($RMSEP_e$ = 0.19) and compression ($RMSEP_c$ = 0.26) data were very low. The RMSEP values decreased by 27.0% when using the extrusion data over the compression data. Toothpull was successfully predicted using SSSA for either the extrusion (RAP_e = 0.89) or compression (RAP_c = 0.88) data. Meullenet et al (1999) reported that SSSA poorly predicted toothpull (RAP = 0.12). Differences in rice samples harvested in different years and panel performance such as discrimination ability may have contributed to this marked improvement.

Particle size was effectively predicted using either the extrusion (RAP_e = 0.96) or compression (RAP_c = 0.95) tests along with SSSA. The predictive model from the extrusion test ($RMSEP_e$ / $RMSEC_e$ = 1.14, S_{tot} / $RMSEP_e$ = 4.09) was slightly more robust and discriminative than that from the compression test ($RMSEP_c$ / $RMSEC_c$ = 1.33, S_{tot} / $RMSEP_c$ = 3.77). The average error of prediction values or RMSEP for predicting particle size from both instrumental tests were low (RMSEP = 0.08). Small differences in kernel size (sensory score range 0.5–2.3) might have resulted in low RMSEP values. Toothpack was better predicted using the extrusion data (RAP_e = 0.91) than the compression data (RAP_c = 0.85). The predictive model from the extrusion data (S_{tot} / $RMSEP_e$ = 3.10) was also slightly more discriminative than that from the compression data (S_{tot} / $RMSEP_c$ = 2.52). Both the extrusion (RAP_e = 0.91) and the compression (RAP_c = 0.90) tests, along with SSSA, were successfully used in predicting loose particles. The RMSEP values for both tests were low ($RMSEP_e$ = 0.45, $RMSEP_c$ = 0.47). As with other sensory attributes, the predictive model was slightly more robust and discriminative for the extrusion test ($RMSEP_e$ / $RMSEC_e$ = 1.15, S_{tot} / $RMSEP_e$ = 3.16) than that for the compression test ($RMSEP_c$ / $RMSEC_c$ = 1.34, S_{tot} / $RMSEP_c$ = 3.09).

In this study, we hypothesized that the force-deformation curve from the instrumental tests could be regarded as a spectrum, and each measured force was used as an individual variable in the predictive models. Weighted regression coefficients were calculated and used to identify the most important variables for predicting particular sensory attributes. Force-deformation curves for each instrumental test were divided into several stages. For the compression test, two stages were identified: compression and adhesion (Fig. 3). The compression stage was defined as the stage where the flat plate compression contacted rice kernels and traveled until it reached the maximum distance. The adhesion stage was defined as the stage from the point the flat plate started to travel back until it reached the point where it first contacted rice kernels. For the extrusion test, the force-deformation curve was divided into three phases: packing, compression, and extrusion (Fig. 4). The packing phase started from the original position of the piston until it contacted the rice sample and packed it in the extrusion cell.

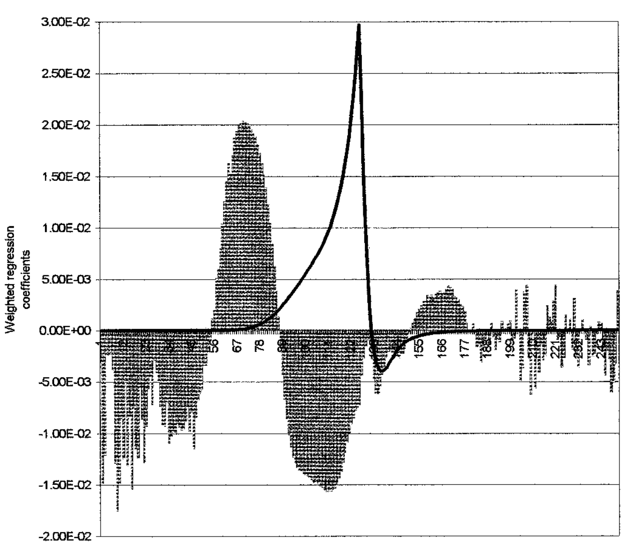

Fig. 6. Weighted regression coefficients and sample compression force-deformation curve for predicting adhesiveness to lips from a compression test. Weighted regression coefficients and force-deformation curves are not on the same scale.

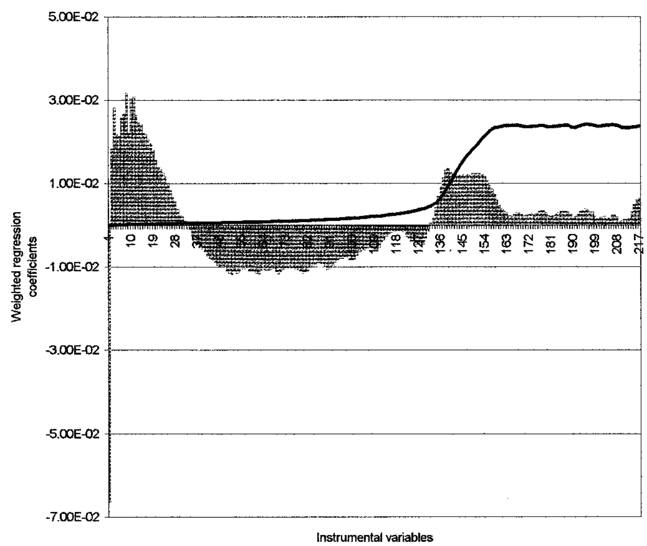

Fig. 7. Weighted regression coefficients and sample extrusion force-deformation curve for predicting hardness from extrusion test. Weighted regression coefficients and force-deformation curves are not on the same scale.

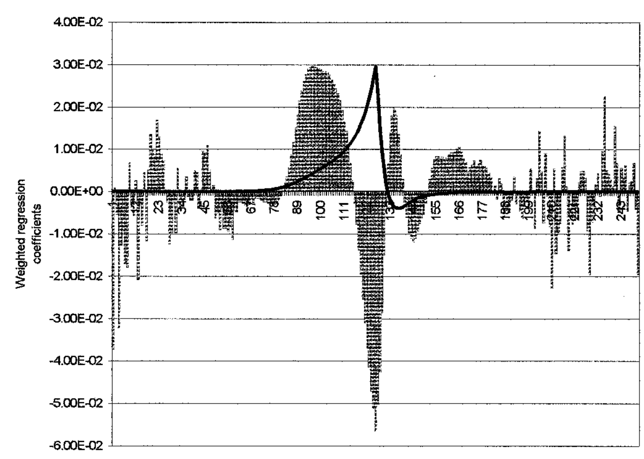

Fig. 8. Weighted regression coefficients and sample compression force-deformation curve for predicting hardness from a compression test. Weighted regression coefficients and force-deformation curves are not on the same scale.

The compression phase was defined as the phase during which the sample was compressed before being extruded. The extrusion phase was defined as the time during which the sample was being extruded through the extrusion plate holes before the piston traveled back to its original position.

Predictive models for adhesiveness to lips were mostly influenced by the variables included in compression phase of the extrusion test (Fig. 5), while compression and adhesion stages of the compression test both influenced its prediction (Fig. 6). For hardness, packing and compression stages of the extrusion test (Fig. 7) contributed most to predicting scores whereas the compression stage of the compression test contributed most to its prediction (Fig. 8). This result indicated that the use of the maximum load for predicting rice hardness, a common practice in instrumental measurements, may not be suitable. Moreover, this result is also in partial agreement with a previous study, where Meullenet et al (1998) extracted five parameters (initial slope, maximum slope, maximum load, average load, and area under the curve) from the force-deformation curve and evaluated prediction models using these five parameters. In their study, initial slope and area under the force-deformation curve most influenced sensory hardness scores.

CONCLUSIONS

The use of a novel approach, spectral stress strain analysis (SSSA), for relating the sensory perception of cooked rice texture to instrumental measurements (extrusion and compression tests) was successful. All sensory attributes evaluated, except for cohesiveness of mass evaluated after three chews, were effectively predicted using SSSA in conjunction with both the extrusion and compression tests. However, the predictive models calculated from the extrusion data offered a lower average error of prediction and were more robust and discriminative than those from compression data. However, differences in rice cooking methods for the two instrumental tests prevent a direct comparison between compression and extrusion tests. SSSA in conjunction with the extrusion test showed the greatest potential for use as an accurate method for predicting rice sensory texture characteristics. However, the extrusion method required a large amount of sample (100 g of milled rice). This limitation may render the extrusion test useless in applications such as breeding programs where sample availability is limited. Thus, rice breeders may find the compression test more applicable to their field.

LITERATURE CITED

Champagne, E. T., Lyon, B. G., Min, B. K., Vinyard, B. T., Bett, K. L., Barton, F. E., II, Webb, B. D., McClung, A. M., Moldenhauer, K. A., Linscombe, S., McKenzie, K. S., and Kohlwey, D. E. 1998. Effects of postharvest processing on texture profile analysis of cooked rice. J. Cereal Chem. 75:181-186.

Del Mundo, A. M., Kosco, D. A., Juliano, B. O., Siscar, J. J. H., and Perez, C. M. 1989. Sensory and instrumental evaluation of texture of cooked and raw milled rices with similar starch properties. J. Texture Stud. 20:97-110.

Juliano, B. O., Perez, C. M., Barber, S., Blakenet, A. B., Iwasaki, T., Shibuya, N., Keneaster, K. K., Chung, S., Laignelet, B., Launay, B., Del Mundo, A. M., Suzuki, H., Shiki, J., Tsuji, S., Tokoyama, J., Tatsumi, K., and Webb, B. D. 1981. International cooperative comparison of instrumental methods for cooked rice. J. Texture Stud. 12:17-38.

Martens, M., and Martens, H. 1986. Near-infrared reflectance determination of sensory quality of peas. Appl. Spectroscopy 40:303-310.

Meilgaard, M., Civille, G. V., and Carr, B. T. 1991. Descriptive analysis techniques. Pages 187-199 in: Sensory Evaluation Techniques, 2nd ed. CRC Press: Boca Raton, FL.

Meullenet, J.-F., Gross, J., Marks, B. P., and Daniels, M. 1998. Sensory descriptive texture analyses of cooked rice and its correlation to instrumental parameters using an extrusion cell. Cereal Chem. 75:714-720.

Meullenet, J.-F., Sitakalin, C., and Marks, B. P. 1999. Prediction of rice texture by spectral stress strain analysis: A novel technique for treating instrumental extrusion data used for predicting sensory texture profile. J. Texture Stud. 30:435-450.

Perez, C. M., and Juliano, B. O. 1979. Indicators of eating quality for non-waxy rices. Food Chem. 4:185-195.

Perez, C. M., and Juliano, B. O. 1981. Texture changes and storage of rice. J. Texture Stud. 12:321-333.

Rousset, S., Pons, B., and Pilandon, C. 1995. Sensory texture profile, grain physico-chemical characteristics and instrumental measurements of cooked rice. J. Texture Stud. 26:119-135.

Windham, W. R., Lyon, B. G., Champagne, E. T., Barton, F. E., II, Webb, B. D., McClung, A. M., Moldenhauer, K. A., Linscombe, S., and McKenzie, K. S. 1997. Prediction of cooked rice texture quality using near-infrared reflectance analysis of whole-grain milled samples. Cereal Chem. 74:626-632.

[Received November 15, 1999. Accepted April 12, 2000.]