Sensory Descriptive Texture Analyses of Cooked Rice and Its Correlation to Instrumental Parameters Using an Extrusion Cell

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ABSTRACT

Sensory characteristics of cooked rice texture for three cultivars were evaluated using both descriptive sensory methods and an instrumental extrusion cell. Nine sensory textural characteristics were evaluated and five instrumental parameters were used to establish predictive models for the sensory characteristics evaluated. Multiple regression models with R^2 ranging from 0.22 to 0.70 were obtained for seven of nine sensory attributes studied. Sensory characteristics most effectively predicted were hardness (R^2 =0.62) and toothpack (R^2 =0.70). Predictive models of textural sensory characteristics of cooked rice were also evaluated using partial least square regression techniques. Best results were obtained for hardness (relative ability of prediction [RAP] = 0.52), cohesiveness of mass (RAP = 0.60), toothpull (RAP = 0.73), and toothpack (RAP = 0.54).

One of the greatest challenges that the rice industry faces is to control the overall quality of rice. An important aspect of cooked rice quality lies in its textural characteristics, creating a need to develop instrumental methods capable of accurately predict the sensory perception of texture in cooked rice.

"Texture is defined as the sensory manifestation of the structure of a food and the manner in which that structure reacts to applied force" (Szczesniak 1968). This definition implies that texture is a multidimensional sensory quality. Texture is also an important attribute of food acceptance by consumers (Moskowitz and Drake 1972), and as such, a critical step in quality assessment. Rice texture is affected by factors such as rice variety, amylose content, gelatinization temperature (Juliano and Perez 1983, Del Mundo et al 1989), and processing factors (Perez and Juliano 1979, 1981; Okabe 1979; Chrastil 1990; Rousset et al 1995). Hardness and stickiness govern palatability of cooked rice in Asian markets (Okabe 1979), with hardness being the most important parameter.

Sensory evaluation techniques have been used by several researchers to evaluate the effects of storage (Perez and Juliano 1979, 1981; Okabe 1979; Chrastil 1990), processing (Rousset et al 1995), and variety (Juliano et al 1984, Damardjati et al 1986, Kumari and Padmavathi 1991, Perez et al 1993) on end-use quality of rice. However, descriptive analysis has not often been among the techniques used to describe texture differences in cooked rice.

Sensory profiling or descriptive analysis methods consist of formal procedures for assessing, in a reproducible manner, specific attributes of a sample and rating intensity on a suitable scale. These methods can be used for evaluating aroma, flavor, appearance, and texture, separately or in combination (ISO 1994). As such, descriptive sensory profiling is the most sophisticated sensory tool available to the sensory professional (Stone and Sidel 1993). Results from descriptive analysis provide a complete sensory description of an array of products and can provide a basis for distinguishing those sensory attributes that are important for acceptance by consumers (Stone and Sidel 1993).

Apart from the use of sensory techniques, an alternative approach to the evaluation of texture properties involves the use of instruments specifically designed for the evaluation of the physical characteristics of foods. The instrumental evaluation of cooked rice hardness has been studied by many researchers and several instrumental methods have been examined (Bourne 1978, Perez and Juliano 1981, Juliano and Perez 1983, Del Mundo et al 1989, Champagne et al 1996). One of the most popular methods of instrumental evaluation (Perez and Juliano 1981, Del Mundo et al 1989) involves the use of an Ottawa Texture Measuring System extrusion cell. With this empirical method, the maximum force during the extrusion process is recorded and generally correlates with the sensory perception of hardness (Del Mundo et al 1989). However, the instrumental methods promoting the extraction of a single instrumental parameter ignore the multidimensional aspect of texture and prevent the prediction of multiple sensory attributes. A novel approach to correlating instrumental measurements to the perception of sensory texture attributes utilizes the realization that multiple instrumental parameters may be necessary to explain a single sensory attribute, or vice versa (Szczesniak 1987).

The objectives of this study were to: 1) evaluate correlations between descriptive sensory attributes and instrumental parameters extracted from the force-deformation curves; 2) evaluate predictive models for textural sensory characteristics of rice using multiple instrumental parameters as predictors.

MATERIALS AND METHODS

Postharvest Treatments

Two long-grain rice varieties (Kaybonnet and Cypress) and one medium-grain rice variety (Bengal) were harvested from the University of Arkansas Rice Research and Extension Center in Stuttgart, AR, in September 1996 with harvest moisture contents of 19.1, 16.5, and 17.5% (wb), respectively. The rice was brought immediately to the Biological and Agricultural Engineering laboratory and cleaned using a dockage tester (Carter-Day Co., Minneapolis, MN). It was then placed in plastic, airtight buckets and stored at –10°C for approximately one month. The rice was then dried using a parameter control generator unit in a laboratory-scale dryer at 43.3°C and 38.2% rh for 75 min. After drying, samples of Cypress, Kaybonnet, and Bengal were separated into three lots to be equilibrated to final moisture contents of 10, 12, and 14%. Equilibration occurred in wooden-framed wire-mesh trays (rice layer 0.5 in. deep) in air-controlled chambers until reaching the target moisture content. Samples of each variety (Kaybonnet, Cypress, and Bengal) at each moisture content (10, 12, and 14%) were again divided into thirds, placed in airtight plastic buckets, and stored at 4, 21, or 38°C (27 treatments). Samples were stored for 24 weeks before evaluation using instrumental texture and sensory texture profiling.

Samples were allowed to equilibrate to room temperature. A McGill sample sheller (husker) was used to remove the hulls and a McGill No. 2 mill was used to remove the bran. Samples were milled to a constant degree of milling (DOM) of 90. The DOM was measured using a Satake milling meter MM-1B.

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Sensory Methodology

Nine professionally trained panelists (Sensory Spectrum, Chatham, NJ), employed by the Institute of Food Science and Engineering at the University of Arkansas, developed a sensory profile of cooked rice samples. During panel orientation (three sessions of 3 hr), nine textural attributes were identified by the panelists as adequately describing the texture profile of cooked rice. These were adhesiveness to lips, hardness, cohesiveness of mass after three chews, cohesiveness of mass after eight chews, roughness of mass, toothpull, particle size, toothpack, and loose particles. Attribute definitions and techniques are provided in Table I. All samples were evaluated under white lights in a sensory testing laboratory featuring individual booths and positive pressure. Intensities of each of the nine attributes evaluated were quantified on a 0–15 continuous scale (Meilgaard et al 1991). Panelists used paper ballots and intensified each sensory attribute using a number between 0 and 15 with one significant digit. The intensities of texture attributes were assessed by comparison with carefully chosen references for each attribute having assigned intensities. A list of the references and their intensities is provided in Table I.

Samples were cooked for 20 min in household steam rice cookers (model SR-W10FN, National) at a 1:2 (v/v) rice-to-water ratio without prior rinsing or soaking. Cooked samples were mixed and fluffed in the rice cooker using a plastic fork to ensure homogeneity, and immediately dipped using a plastic spoon and presented to the panel. Samples were presented at 71 ± 1°C in preheated glass bowls insulated with plastic cups and covered with watch glasses. Panelists were instructed to monitor temperature during the test using digital thermometers and to complete the evaluation before the temperature of the sample reached 60 ± 2°C. Panelists were allowed a 10-min break between each sample evaluation and were instructed to rinse their palate with unsalted saltine crackers and water. The order of sample presentation was randomized across treatments (across three sessions of 3 hr), but not randomized across panelists because of limited sample availability and the importance of serving temperature. Each treatment was evaluated twice by each of the nine panelists. A reference rice sample (Cypress, stored at 4°C at 10% mc) was presented as a warm-up sample at the beginning of each session so that panel repeatability could be evauated. Panel performance was monitored for repeatability, use of scales, and discrimination using the macro GRAPES (SAS Institute, Cary, NC) (Schlich 1994) (data not shown).

Sample Preparation for Instrumental Texture Analysis

A 100-g rice sample was added to 946 mL of boiling water and cooked for 20 min after the water returned to boiling. Okabe (1979) reported that cooked rice texture changes rapidly after cooking. Preliminary experiments conducted in our laboratory also showed that repeatability of instrumental measurements was poor when conducted on warm rice. Consequently, the rice samples were sifted immediately after cooking and rinsed for 5 min under cold water. Samples were then spread on plastic trays and covered with aluminum foil. Samples were stored at 4°C until testing (2–3 hr). Samples were allowed to equilibrate to room temperature for 30 min before analysis.

The two different cooking methods used for the instrumental and sensory evaluation methods do not represent the ideal testing conditions for the purpose of correlating instrumental data with sensory perception. However, the instrumental data needed to be generated using the cooking method described to obtain reproducible instrumental results. Furthermore, the focus of this study was to develop an instrumental method capable of predicting the sensory perception of textural attributes. Our intention was not to necessarily develop an imitative test reproducing the actual testing conditions of cooked rice using sensory methods.

Extrusion Test

A cylindrical extrusion cell (40 mm diameter, 70 mm deep) was used in conjunction with a texture analyzer (model TAXT2, Texture Technologies, Scarsdale, NY). Perez et al (1993) reported that an extrusion plate with holes of 3.2–4.8 mm in diameter best discriminated among U.S. long-grain and U.S. medium-grain commercial rice varieties. In addition, preliminary studies (data not shown) in our laboratory demonstrated the effectiveness of an extrusion cell featuring holes of 3.2 mm diameter.

The texture analyzer (model TAXT2) was calibrated at the beginning of each testing session using a 5-kg weight and procedures outlined in the data acquisition software (X-Trad Version 3.7). Rice (35 g) was placed in the extrusion cell for each test repetition. A 20-kg maximum-load load cell was used and the cross-head speed was set to 5 mm/sec for a total travel of 60 mm. Data acquisition was initiated using a 10-g contact force. Data were acquired using the X-Trad software (version 3.7). Force (kg) required to extrude the sample was recorded as a function of time and eight test replicates were performed on each of the samples tested.

TABLE I
Vocabulary for Sensory Texture Attributes of Cooked Rice

Sensory Attribute	Definition	Technique	Reference
Surface			
Adhesiveness to lips	Degree to which sample adheres to lips	Compress sample between lips, release, and evaluate	Cherry tomato, 0.0; nougat, 4.0; breadstick, 7.5; pretzel rod, 10.0
First bite			
Hardness	Force required to compress sample	Compress or bite through sample with molars	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; Life Savers, 14.5
Chewdown			
Cohesiveness of mass after 3 or 8 chews	Amount chewed sample holds together	Chew sample with molars 3 or 8 times and evaluate	Licorice, 0.0; carrot, 2.0; mushroom 4.0; hot dog, 7.5; American cheese, 9.0; brownie, 13.0
Roughness of mass	Amount of roughness perceived in chewed sample	Chew sample with molars 8 times and evaluate	Jello, 0.0; orange peel, 3.0; cooked, oatmeal 6.5
Toothpull	Force required to separate jaws during mastication	Chew 3 times and evaluate	Clam, 3.5; caramel, 5.0; Jujubes, 15.0
Particle size	Amount of space particle fills in mouth	Place sample in mouth and evaluate	Rice grain, 0.5; Tic Tac, 2.5; M&M, 4.0; Mike&Ikes, 6.0; Cherry Bite, 11.0
Toothpack	Amount of product packed into crowns of teeth after mastication	Chew sample 8 times, expectorate, and feel surface of crowns of teeth with tongue	Captain Crunch, 5.0; Heath Bar, 10.0
Loose particles	Amount of particles remaining in and on surface of mouth after swallowing	Chew sample 8 times with molars, swallow, and evaluate	Carrot, 10.0

Force-Deformation Curves Analysis

Five instrumental parameters, initial slope (S_{init}, kg/sec), maximum slope (S_{max}, kg/sec), maximum load (H, kg), average load (H_{avg}, kg), and area under the curve (A, kg/sec), were extracted from each force/deformation curve using the X-Trad software (Fig. 1). S_{init} was calculated as the average slope (kg/sec) during the first second of the compression (i.e., after a travel of 5 mm). S_{max} was calculated as the average slope between cross-head travel distances of 30 and 50 mm. The maximum load was estimated as the absolute maximum force measured during the compression. The average load was calculated as the average load between cross-head travel distances of 50 and 60 mm. The area under the curve was estimated from cross-head travel distances of 0–60 mm.

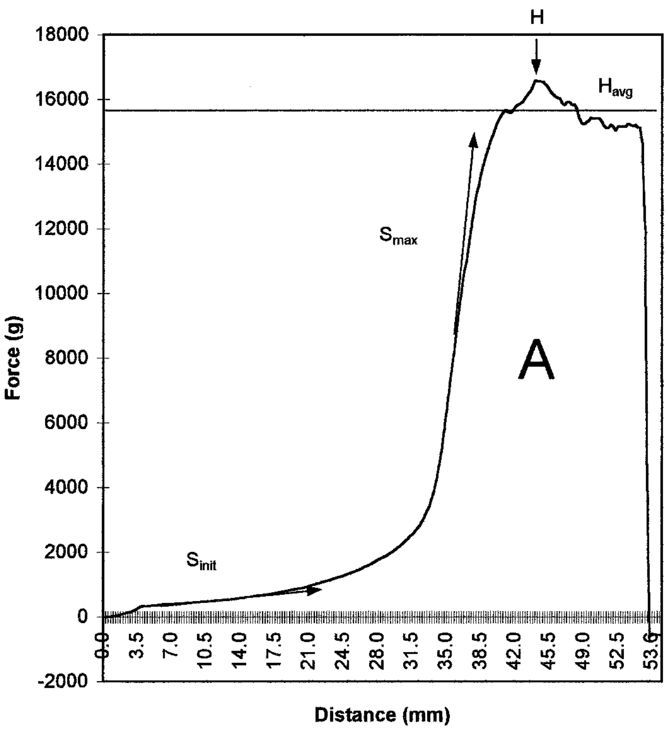

Fig. 1. Sample force and deformation curve. Instrumental parameters extracted: initial slope (S_{init}), maximum slope (S_{max}), maximum load recorded during extrusion (H), average load across the flattened part of the curve (H_{avg}), area under the curve or total work during the extrusion test (A).

Statistical Analysis

Means for each sample evaluated were calculated for all sensory attributes (n = 18, nine panelists and two replicates) as well as for instrumental parameters (n = 16, eight test replicates and two cooking replicates) using PROC MEANS (SAS). Mean values were used to evaluate correlations (PROC CORR) between sensory and instrumental data. Principal components analysis (PCA) was performed on both sensory and instrumental data using Unscrambler (Camo, version 6.1b). Reduced multiple regression models were evaluated using PROC STEPWISE (stepwise option), including all significant variables ($P < 0.1$). Previous research in our laboratory has shown that the use of psychophysical models to predict sensory characteristics of foods had great potential (Meullenet et al 1997). Psychophysical models were originally intended to relate a single sensory attribute to a single instrumental measurement (Stevens 1953). The assumption was that the instrumental measurement was a direct measure of the corresponding sensory modality. Unfortunately, the perception of texture is multidimensional and very complex. It is doubtful that any of the modern instrumental tests used today to evaluate texture directly measure particular sensory characteristics and even more doubtful that a single instrumental parameter extracted from a force-deformation curve is an accurate predictor of a given sensory attribute. As a result, we feel that including several instrumental parameters in predictive models is not a violation of psychophysical principals. Partial least square regression (PLSR) was also used (Unscrambler, version 6.1b) to develop predictive models of sensory characteristics using instrumental parameters. The Unscrambler option PSL2 was used to determine predictive models simultaneously for all sensory attributes. The random cross-validation method was used on centered data. Each variable was weighted by its respective standard deviation so that each variable was given the same chance to influence the predictive models. RAP values, indicators of the quality of predictive models, which take into account the unexplained variation in the sensory data, were calculated as described by Martens and Martens (1986) and Windham et al (1997).

RESULTS AND DISCUSSION

Correlations Among Sensory Attributes

Adhesion to lips was significantly correlated to cohesiveness of mass after eight chews ($r = 0.57$, $P < 0.005$), toothpull ($r = 0.57$,

TABLE II
Pearson's Correlation Coefficients Between Instrumental and Sensory Attributes[a]

	S_{init}	S_{max}	H_{avg}	H	A	Adhes	Hard	Com1	Com2	Rough	Tpull	Parz	Tpack	Loose
Instrumental parameters[b]														
Initial slope (S_{init})	1.0	0.76	0.86	0.85	0.89	ns[c]	0.60	ns	ns	0.44	ns	0.40	ns	ns
Maximum slope (S_{max})		1.0	0.79	0.85	0.79	ns	0.60	ns	–0.52	ns	ns	0.53	–0.43	ns
Average load (H_{avg})			1.0	0.98	0.98	ns	0.49	ns	ns	ns	ns	0.42	ns	ns
Maximum load (H)				1.0	0.95	ns	0.60	ns	ns	0.39	ns	0.47	ns	ns
Area under curve (A)					1.0	ns	0.52	ns	ns	ns	ns	0.45	ns	ns
Sensory attributes[d]														
Adhesion to lips (Adhes)						1.0	ns	ns	0.57	ns	0.57	ns	0.54	ns
Hardness (Hard)							1.0	ns	–0.49	0.66	ns	0.59	–0.49	0.39
Cohesiveness of mass after 3 chews (Com1)								1.0	0.65	ns	0.56	ns	ns	ns
Cohesiveness of mass after 8 chews (Com2)									1.0	ns	0.65	–0.57	0.42	ns
Roughness of mass (Rough)										1.0	n.s	ns	ns	0.76
Toothpull (Tpull)											1.0	n.s	0.59	ns
Particle size (Parz)												1.0	n.s	ns
Toothpack (Tpack)													1.0	ns
Loose particles (Loose)														1.0

[a] Total number of observations, N = 27.
[b] Definitions for instrumental parameters are provided in Fig. 1.
[c] Correlation not significant ($P > 0.05$).
[d] Definitions for sensory attributes are provided in Table 1.

$P < 0.005$), and toothpack ($r = 0.54$, $P < 0.005$) (Table II). Assuming that adhesion to lips is a measure of rice stickiness, its correlation with toothpull and toothpack is appropriate. It is also expected that a rice exhibiting higher stickiness will exhibit a higher cohesiveness of mass. Hardness was most highly correlated with roughness of mass ($r = 0.66$, $P < 0.001$) and particle size ($r = 0.59$, $P < 0.005$). It is likely that samples exhibiting higher hardness sustained shearing and compression strains applied during chewing, and ultimately also yielded higher intensities for roughness of mass and particle size. This observation is supported by the negative correlation reported between hardness and cohesiveness of mass after eight chews ($r = -0.49$, $P < 0.01$). Cohesiveness of mass after three and eight chews were both correlated with toothpull ($r = 0.56$, $P < 0.005$; $r = 0.65$, $P < 0.001$). Previous study showed that the more sticky the sample, the better the mass holds together (higher cohesiveness of mass). It is then expected that samples with higher cohesiveness of mass (i.e., also stickier) will yield higher values for toothpull (force required to separate the jaws during mastication). Roughness of mass was most highly correlated with loose particles ($r = 0.76$, $P < 0.0001$). Particles not reduced to a paste during chewing were perceived as roughness in the chewed sample and as loose particles after swallowing.

Correlation Between Sensory Attributes and Instrumental Parameters

No significant correlations ($P < 0.05$) between sensory attributes and instrumental parameters were reported for adhesion to lips, cohesiveness of mass after three chews, toothpull, and loose particles (Table II). Hardness was most highly correlated with initial slope (S_{init}, $r = 0.60$, $P < 0.001$), maximum slope (S_{max}, $r = 0.60$, $P < 0.001$), and maximum load (H, $r = 0.60$, $P < 0.001$). Hardness was correlated to a lesser degree to average load (H_{avg}, $r = 0.49$, $P < 0.05$) and area under the curve (A, $r = 0.52$, $P < 0.01$). Cohesiveness of mass after eight chews was negatively correlated with maximum slope ($r = -0.52$, $P < 0.01$). Roughness of mass was correlated with initial slope ($r = 0.44$, $P < 0.05$) and maximum load ($r = 0.39$, $P < 0.05$). Particle size was significantly correlated ($P < 0.05$) with all five instrumental parameters and most highly correlated with maximum slope ($r = 0.53$, $P < 0.01$). Finally, toothpack was negatively correlated with maximum slope ($r = -0.43$, $P < 0.05$).

PCA Loadings for Sensory and Instrumental Attributes

The first and second principal components explained 37 and 23%, respectively, of the variation in the data. Figure 2 (PC1 vs. PC2) is a plot of principal component loadings of sensory and instrumental parameters on the first and second principal components. Adhesion to lips, cohesiveness of mass (Com_1, Com_2), toothpull, and toothpack loaded similarly on both PC1 and PC2. This indicates that the stickier rice samples were more cohesive, required more force to separate the jaws, and resulted in more of the sample packed into the crowns. Maximum slope loaded similarly to hardness, roughness of mass, loose particles, and particle size on the first two principal components. These results suggest that harder rice samples also exhibited a rougher sample mass, a larger particle size, and more loose particles. All the other instrumental parameters, area under the curve, average load, initial slope, and peak load, loaded similarly on the first two principal components.

Predictive Models for Sensory Attributes Using Instrumental Parameters and Multiple Regression

Predictive models are reported for seven of the nine sensory attributes evaluated since no significant ($P < 0.05$) models could be evaluated for cohesiveness of mass evaluated after three chews and loose particles (Table III). Adhesion to lips was best predicted by a semilogarithmic model ($R^2 = 0.47$) using maximum slope (S_{max}) and area under the curve (A) as predictors. All three models (linear, semilogarithmic, and power models) employed S_{max} and A as predictors. No other instrumental parameters were significant ($P < 0.15$). Hardness was equally well predicted by the semilogarithmic and the power models using S_{init}, H_{avg}, and H (maxi-

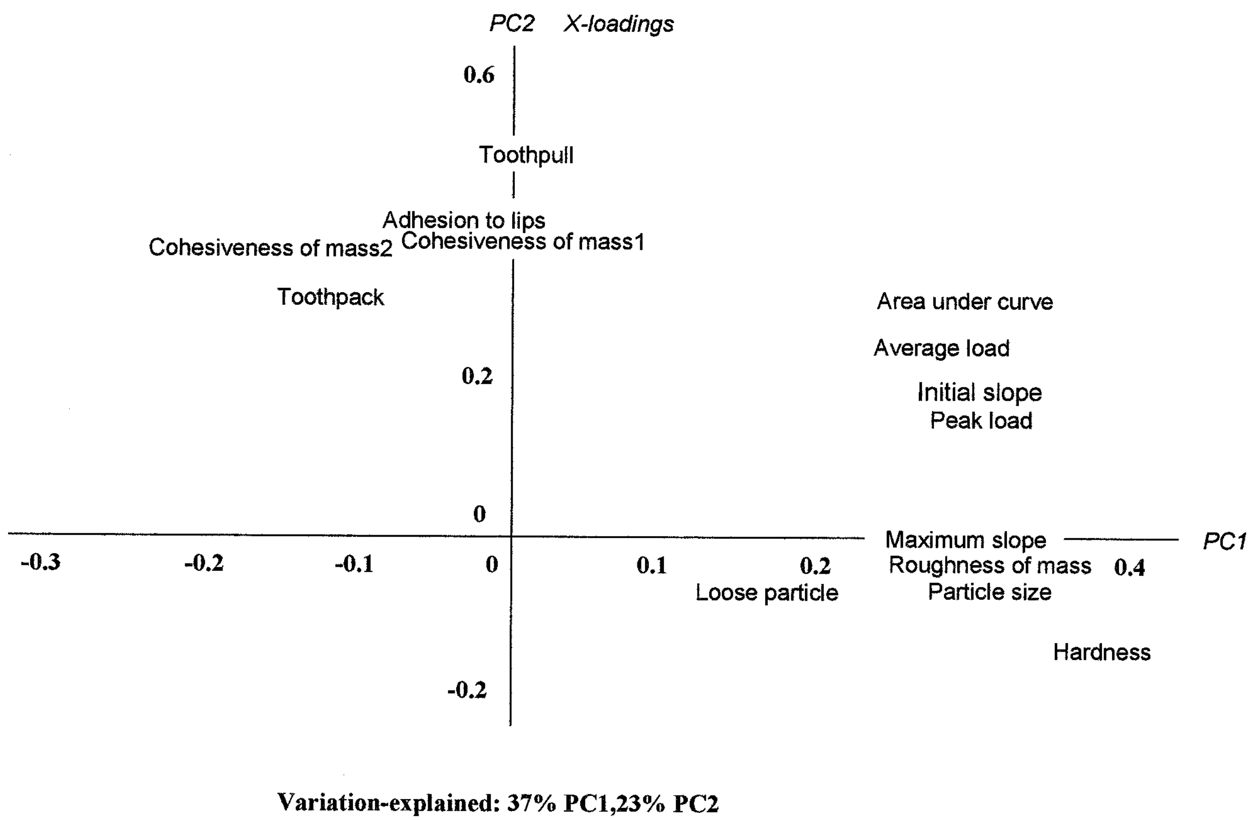

Fig. 2. Relationship of sensory texture profile attributes and instrumental texture parameters evaluated by principal components analysis: PC1 vs. PC2 loadings.

mum load) as predictors. The weights attributed to the predictors (regression coefficients) were of different signs. An increase in S_{init} and H contributed to an increase in the perceived hardness prediction, while an increase in H_{avg} tended to decrease predicted hardness values. The opposite effect that H and H_{avg} have on the prediction of hardness, and the similar weights that both parameters carry, suggest that the ratio of H to H_{avg} may be an important predictor of cooked rice perceived hardness. Meullenet et al (1997) also reported that S_{min} and H were important instrumental parameters for the prediction of food hardness. Intensities reported by the panel for the cohesiveness of mass evaluated after three chews (Com_1) were not predictable from the instrumental parameters obtained with the extrusion cell. However, the initial and maximum slopes were useful in determining predictive models of cohesiveness of mass evaluated after eight chews (Com_2). The best model developed was of the power type (R^2 = 0.48). Increasing values of S_{max} contributed to a decrease in the predicted values of Com_2, while increasing values of S_{init} contributed to an increase in predicted scores of Com_2. The exponents associated with both S_{init} and S_{max} were almost identical (0.31, –0.32) but of different signs. This result suggests that the ratio of S_{init} to S_{max} may be a reasonably good predictor of cohesiveness of mass (evaluated after eight chews). Roughness of mass was poorly predicted by a power model (R^2 = 0.22) including S_{init} as a single predictor. Toothpull was described best by a linear model (R^2 = 0.42) including S_{max} and A (area under the curve) as predictors. Particle size was poorly predicted by a linear model (R^2 = 0.28) including S_{max} as a sole predictor. Toothpack was predicted with moderate accuracy by a semilogarithmic model (R^2 = 0.70) comprising S_{max}, S_{init}, H_{avg}, and H. No significant models were reported for the sensory attri-

TABLE III
Predictive Models for Sensory Parameters Using Instrumental Parameters[a]

Sensory Attribute[b]	Model Type	R^2	Model[c]
Adhesion to lips (Adhes)	Linear	0.42	$\text{Adhes} = 10.75 - 0.29S_{max} + 0.06A$
	Semilogarithmic	0.47	$\text{Adhes} = 3.15 - 3.29\log(S_{max}) + 3.93\log(A)$
	Power	0.46	$\text{Adhes} = 50.4(S_{max})^{-0.29}(A)^{0.36}$
Hardness (Hard)	Linear	0.36	$\text{Hard} = 3.42 + 0.07S_{max}$
	Semilogarithmic	0.62	$\text{Hard} = 3.38 + 0.92\log(S_{init}) - 3.25\log(H_{avg}) + 3.38\log(H)$
	Power	0.62	$\text{Hard} = 16.43(S_{init})^{0.22}(H_{avg})^{-0.79}(H)^{0.83}$
Cohesiveness of mass after 3 chews (Com1)	Linear	…	ns
	Semilogarithmic	…	ns
	Power	…	ns
Cohesiveness of mass after 8 chews (Com2)	Linear	0.45	$\text{Com2} = 4.84 - 0.14S_{max} + 1.19S_{init}$
	Semilogarithmic	0.47	$\text{Com2} = 8.01 - 1.49\log(S_{max}) + 1.43\log(S_{init})$
	Power	0.48	$\text{Com2} = 180.71(S_{max})^{-0.32}(S_{init})^{0.31}$
Roughness of mass (Rough)	Linear	0.19	$\text{Rough} = 5.19 + 0.68S_{init}$
	Semilogarithmic	0.21	$\text{Rough} = 5.87 + 0.79\log(S_{init})$
	Power	0.22	$\text{Rough} = 58.88(S_{init})^{0.13}$
Toothpull (Tpull)	Linear	0.42	$\text{Tpull} = 1.37 - 0.08S_{max} + 0.02A$
	Semilogarithmic	…	ns
	Power	…	ns
Particle size (Parz)	Linear	0.28	$\text{Parz} = 0.80 + 0.02S_{max}$
	Semilogarithmic	0.24	$\text{Parz} = 0.59 + 0.18\log(S_{max})$
	Power	0.23	$\text{Parz} = 0.39(S_{max})^{0.18}$
Toothpack (Tpack)	Linear	0.63	$\text{Tpack} = 1.42 - 0.04S_{max} - 0.39S_{init} + 0.21H_{avg} - 0.14H$
	Semilogarithmic	0.70	$\text{Tpack} = 0.79 - 0.45\log(S_{max}) - 0.42\log(S_{init}) + 2.86\log(H_{avg}) - 2.18\log(H)$
	Power	0.63	$\text{Tpack} = 2.43(S_{max})^{-0.46}(H_{avg})^{2.18}(H)^{-1.77}$
Loose particles (Loose)	Linear	…	ns
	Semilogarithmic	…	ns
	Power	…	ns

[a] Models were evaluated using PROC STEPWISE (SAS Institute).
[b] Definitions for instrumental parameters are provided in Fig. 1.
[c] Definitions for sensory attributes are provided in Table 1. Only instrumental predictors with $P < 0.15$ were included in the models.

TABLE IV
Prediction Models and Relative Ability of Prediction (RAP) Values for Textural Sensory Attributes of Cooked Rice

	Regression Coefficient[b]					
Sensory Attribute[a]	S_{init}	S_{max}	H_{avg}	H	A	**RAP[c]**
Adhesion to lips	–1.11	–0.17	0.34	–0.41	0.08	0.21
Hardness	0.98	0.003	–0.10	0.18	–2.43	0.52
Cohesiveness of mass after 3 chews	…	…	…	…	…	ns
Cohesiveness of mass after 8 chews	0.63	–0.12	0.08	–0.13	2.19	0.60
Roughness of mass	…	…	…	…	…	ns
Toothpull	–0.04	–0.05	0.10	–0.13	2.57	0.73
Particle size	–0.03	0.02	0.001	0.001	2.04	0.19
Toothpack	–0.60	–0.05	0.09	–0.10	2.21	0.54
Loose particles	…	…	…	…	…	ns

[a] Definitions for sensory attributes are provided in Table 1.
[b] Definitions for instrumental parameters are provided in Fig. 1.
[c] Estimated RAP values were ≤0. RAP is defined for a specific sensory characteristic as: $RAP = (S^2_{tot} - RMSEP^2)/(S^2_{tot} - S^2_{ref})$, where S_{tot} is the standard deviation of the sensory intensities for a particular attribute across all samples, RMSEP is the root mean square error of prediction calculated from the validation segment in partial least squares regression and is a measure of the prediction error expressed in the same units as the original response variable, and S_{ref} is a measure of the uncertainty of the analysis due to inherent variation between panelists. S_{ref} is defined for each sensory characteristic as: $S_{ref} = \sqrt{MSE/P \cdot R}$, where MSE is the mean square error derived from a two-way analysis of variance using samples and panelists as class variables, and P and R are the number of panelists ($P = 9$) and test replications ($R = 2$), respectively.

bute loose particles. In general, the R^2 values, calculated for the models in Table III, are lower than those reported by Meullenet et al (1997). However, it should be considered that the models evaluated by Meullenet et al. (1997) used a wide variety of foods representing a wide spectrum of intensities on the sensory scales. In the present study, the spectrum of sensory intensities was very narrow (≈2 points on the 15 point universal scales), explaining the relatively low R^2 values reported.

Predictive Models for Sensory Attributes Using Instrumental Parameters and PLSR

Table IV presents regression coefficients and RAP values for the predictive models developed for each of the sensory attributes studied, while Fig. 3 is a plot of the weighted regression coefficients (B_w). B_w indicates the relative importance of each of the predictors present in the model, and as a result, are important in identifying those instrumental parameters most important in the prediction of a particular sensory attribute.

Cohesiveness of mass evaluated after three chews, roughness of mass, and loose particles could not be predicted using PSLR (Table IV). H_{avg}, H, and A were the instrumental parameters most important in predicting adhesiveness to lips (Fig. 3). However, the RAP value (0.21) was low, demonstrating that the extrusion test used is not appropriate to predict rice stickiness. Hardness was not extremely well predicted (RAP = 0.52) using PLSR techniques. Increasing S_{init} and H values contributed to higher predicted hardness scores, while increasing values for H_{avg} and A tended to decrease predicted hardness (Fig. 3). Cohesiveness of mass after eight chews (Com_2) was somewhat well predicted (RAP = 0.60), all five instrumental parameters contributing significantly to the prediction of Com_2. Toothpull was reasonably well predicted (RAP = 0.73) by a predictive model in which S_{max}, H_{avg}, H, and A were the instrumental parameters contributing the most to the prediction. The instrumental parameters extracted from the force deformation curve poorly predicted the residual particle size (RAP = 0.19) as perceived by the descriptive panel. All five instrumental parameters were important in the prediction of toothpack (RAP = 0.54), with H_{avg}, H, and A being most important.

CONCLUSIONS

It has been shown that accurate predictive models can be derived from instrumental tests when textural properties of foods vary greatly and obvious differences can be reported (Juliano et al 1984, Del Mundo et al 1989, Perez et al 1993, Meullenet et al 1997). In the present study, the objective was to attempt the prediction of sensory attributes using a set of rice samples exhibiting small differences. The relatively low R^2 values reported are most probably due to the small spread of the data. Overall, the prediction of sensory attributes in cooked rice from an instrumental test was a difficult task. Various statistical procedures, such as multiple regression and PLSR, showed potential for predicting textural characteristics of cooked rice as perceived by a descriptive panel. In particular, hardness was reasonably well predicted (R2 = 0.62) using a nonlinear model and several instrumental parameters. However, the accurate prediction of sensory hardness has not been satisfactorily demonstrated, and the predicted values are merely estimates. Toothpack was predicted well (R^2 = 0.70) using a nonlinear model and multiple regression techniques. This result was anticipated because the mechanism of action of the extrusion cell used in this experiment is imitative of tooth packing during mastication. As for the other sensory attributes evaluated, the quality of the predictive models evaluated varied from poor to average. We also foresee that an attempt to use similar cooking procedures to prepare samples for both instrumental and sensory testing might improve the statistical models presented here. The use of PLSR did not drastically improve upon the models evaluated using psychophysical concepts. However, the use of multivariate analysis

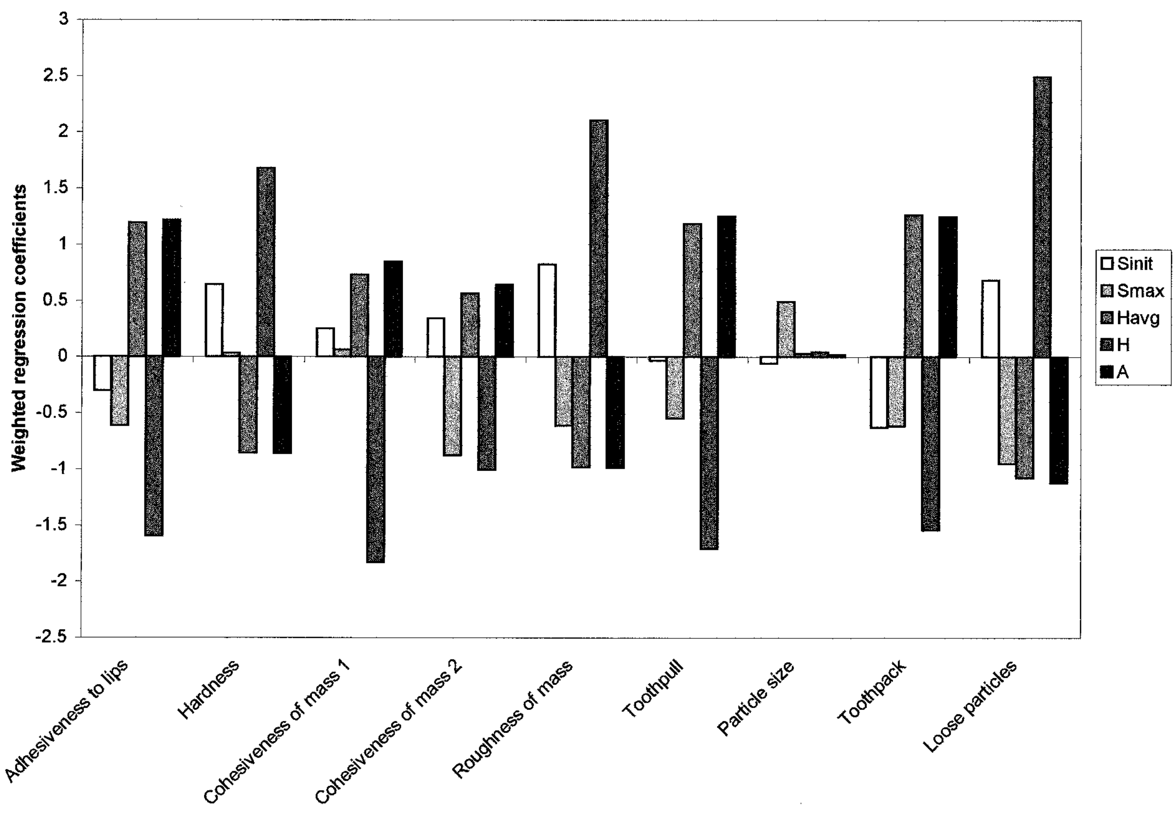

Fig. 3. Weighted regression coefficients for predictive models of textural sensory attributes of cooked rice as determined using partial least square regression. Instrumental parameters extracted: initial slope (S_{init}), maximum slope (S_{max}), maximum load recorded during extrusion (H), average load across the flattened part of the curve (H_{avg}), area under the curve or total work during the extrusion test (A).

methods is becoming a standard in research and further use could provide valuable information for developing reliable instrumental techniques. In addition, RAP values take into account the accuracy of the sensory methodology used, and provide a more accurate evaluation of the quality of the predictive models calculated. Obviously, more research is needed to develop accurate predictive models of textural sensory characteristics for food products, such as cooked rice, exhibiting small differences. However, the use of novel data analysis such as PLSR should allow the development of reliable instrumental tests designed to accurately predict sensory characteristics of cooked rice and other food products.

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