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Food texture evaluation using logistic regression model and magnetic food texture sensor

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Abstract

A food texture evaluation method using a magnetic food texture sensor is proposed for the visualization of food texture. The food texture sensor measures two time-series waves, one of force and one of vibration, during fracture of a food sample. Twenty profiles were extracted from the two waves. The evaluation method selected the profiles to use in the logistic model and determined the coefficients of the model based on the results of sensory tests. Laboratory experiments confirmed that the logistic model evaluated the food textures as radar charts. In addition, the model can potentially evaluate the food textures of unknown foods.

1. Introduction

Humans mainly perceive taste, savor, and food texture in mastication. These perceptions are essential for our health, and enjoyable meals and are an important factor in food production. Regarding the measurement of taste and savor, the literature includes several advanced studies (Etoh et al. 2008; Rock et al. 2008; Uchida et al. 2001). Electronic tongue and measurement instruments are already commercially available (Tahara and Toko 2013). They are effectively used for objective evaluation of taste and savor. In addition, some food texture instruments are also used for texture measurement (Chen and Opara 2013). These instruments mainly comprise a load cell, a motorized slider, and analysis software. The load cell is attached to a plunger that touches and presses a food item and measures the reaction force during fracture. The instrument collects time-series reaction force data and extracts the features from these data via texture profile analysis (TPA) (Friedman, Whitney, and Szczesniak 1963). TPA is a standard method for evaluating food textures; it enables the measurement of textural profiles of mechanical properties such as hardness, cohesiveness, and elasticity, among others. However, the TPA is not effective for quantifying fine textures that humans perceive. A novel combination of a sensor and an analysis method capable of evaluating the details of food textures is required by advanced food manufacturers.

Some researchers have used measurement methods involving acoustic signals to evaluate the details of food textures (Saeleaw and Schleining 2011; Taniwaki and Kohyama 2012; Varela et al. 2006). Verela et al. combined acoustic and mechanical measurements to evaluate the crispness of roasted almonds (Varela et al. 2006), and Taniwaki et al. analyzed the crispness of potato chips using force and sound pressure (Taniwaki and Kohyama 2012). Thus, acoustic signals are useful for evaluating crispness. Furthermore, the literature contains reports detailing the use of different sensors. Taniwaki et al. used a piezoelectric sensor to detect vibration during the fracture of samples (Taniwaki, Hanada, and Sakurai 2006). Iwatani et al. proposed a food-texture evaluation method involving an accelerometer (Iwatani, Akimoto, and Sakurai 2013). These studies demonstrate that different signals in fractures provide details about the texture of food. Actually, humans have mechanoreceptors in the periodontal membrane under their teeth. These receptors have different adaptive characteristics that play an important role in detecting food texture (Dong et al. 1993). Hence, the different sensing elements combined with an appropriate analysis method can potentially be used to determine details of the texture of food.

In this study, we propose a food texture evaluation method based on a magnetic food texture sensor. The food texture sensor has two different sensing elements that acquire time-series force and vibration data during fracture. Feature quantities are subsequently derived from the measured waves. The feature quantities are used to evaluate food textures via logistic regression models. The logistic regression models evaluate five food textures through laboratory experiments. The results presented herein confirm that the proposed evaluation method is effective for visualizing food textures using radar charts.

2. Materials and methods

The structure of the magnetic food texture sensor is shown in Fig. 1. The structure is designed to mimic a human tooth. The upper part of the food texture sensor comprises a contactor, an elastic membrane, and a base, which correspond to a tooth, a periodontal membrane, and an alveolar bone, respectively. They are assembled and fixed on the sensor board. The contactor contains a permanent magnet. When a food sample touches the contactor, the contactor deforms the elastic membrane and moves closer to the base. The magnetic field between the magnet and the sensor board is changed by the movement of the contactor. Two sensor elements on the sensor board detect the change of the magnetic field. One of the sensors is a magnetic resistance element, which responds to the strength of the magnetic field. The force from the food to the contactor is determined on the basis of the outputs of eight magnetic resistance elements. The other sensor is an inductor, which generates an induced voltage in response to the change of the magnetic field, in accordance with Faraday's law of induction. The induced voltage especially changes when the change of the magnetic field is rapid. Hence, the inductor detects the vibration in the fracture. The food texture sensor is attached to a motorized stage that presses the sensor against a food sample as shown in Fig. 2. The outputs of the magnetic resistance elements and the inductor are amplified by an amplifier circuit and are recorded by a personal computer via an A–D conversion board.

The magnetic food texture sensor acquires two time-series data sets of force and vibration during fracture of food specimens. Twenty feature quantities are subsequently extracted from the two time-series data sets. The feature quantities of force are maximum, average, standard deviation, variance, skewness, and kurtosis. The features of vibration are maximum, minimum, average of positive pulses, standard deviation of positive pulses, variance of positive pulses, skewness of positive pulses, kurtosis of positive pulses, effective value, number of high positive pulses, number of middle positive pulses, number of low positive pulses, average gap between positive pulses, maximum gap of positive pulses, and number of negative pulses. The thresholds between the low and middle positive pulses and between the middle and high pulses are 0.2 and 1.0 V, respectively. In experiments, the food texture sensor was used to measure 10 food samples: biscuit (CHOICE, manufactured by Morinaga Co. Ltd, Tokyo, Japan), cookie (MOON LIGHT, manufactured by Morinaga Co. Ltd., Tokyo, Japan), potato snack A (Jagarico, manufactured by Calbee Co. Ltd., Tokyo, Japan), potato snack B (Jagabee, manufactured by Calbee Co. Ltd., Tokyo, Japan), corn snack (Karl, manufactured by Meiji Co. Ltd., Tokyo, Japan), wafer (Vanilla wafers, manufactured by Miura Seika Co. Ltd., Aichi, Japan), potato chip A (chipstar, manufactured by Yamazaki Biscuits Co. Ltd., Tokyo, Japan), potato chip B (Pringles, manufactured by Kellogg Co., Michigan, US), thick rice cracker (Curry Sen, manufactured by Kameda Seika Co. Ltd., Niigata, Japan), and thin rice cracker (Usuyaki, manufactured by Kameda

Seika Co. Ltd., Niigata, Japan). The textural parameters and moisture of the samples are shown in Table 1. The parameters were measured by an instrument (JSV-H1000, Japan Instrumentation System Co., Ltd) and were the average values of 10 times data. These samples were shaped to 7.5 mm in height. Thin foods such as potato chip were stacked up to 7.5 mm. Since the area of the food texture sensor's contactor is 12 mm in diameter, the size of samples was cut in 20 × 20 × 7.5 mm. The food texture sensor pressed these samples 6.0 mm at a velocity of 1.0 mm/s. Each sample was pressed once.

The food texture was quantified from the features via a logistic regression model, which allows any real input Z and takes values between zero and one as an output (Walker and Duncan 1967). Using input Z, we define the logistic regression function as

$$p(Z) = \frac{1}{1 + e^{-Z}}.$$

Let us assume that Z is a linear function of multiple explanatory variables $\boldsymbol{x} = (x_1, x_2, \cdots, x_r)$. Z is expressed as

$$Z = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_r x_r.$$

The multiple explanatory variables are the feature quantities determined from the time-series data. Hence, the food texture is interpretable as a conditional probability $p(Z)$ under the condition $\boldsymbol{x}$. In this study, response variables that indicate the food textures as binary variables are obtained by sensory evaluation. The parameters $\boldsymbol{\beta} = (\beta_0, \beta_1, \cdots, \beta_r)$ are determined by the maximum likelihood estimation. If Z includes too many feature quantities, the generalizing capability of $p(Z)$ might be lost. It is not suitable for $p(Z)$ to depend on a specific time-series data. Hence, the stepwise regression selects appropriate feature quantities based on the Akaike information criterion (Hocking 1976). In this study, after $\boldsymbol{\beta}$ is determined, the logistic model expressed by the equation $p(Z)$ is used to evaluate the food texture as a probability.

3. Results

Examples of force and vibration during pressing are shown in Fig. 3. In each figure, the bold line shows a time-series force and the dashed line shows a time-series vibration. The sensory evaluation results are shown Table 2. The numbers are the total of the subjects who perceived the food texture. The numbers in parentheses indicate whether the results met the significance level of 5%, where a "1" indicates that the food has the food texture. The numbers in parentheses were used for the logistic regression analysis.

To determine the coefficient $\boldsymbol{\beta}$ for each food texture, the logistic regression analysis uses the experimental and sensory results for the biscuit, potato snack A, corn snack, potato chip A, thick rice cracker, and the thin rice cracker. Tables 3–6 show the analytic results for selected features, coefficients, odds ratios, and P-values. In addition, Fig. 4 shows the results of the logistic regression using the selected features and the coefficients.

The logistic regression model determined by the analysis demonstrated the evaluation of food texture. Fig. 5 shows the results for each food. The solid line and the dashed line show the results of the sensory evaluation and the evaluation by the logistic model, respectively. Each radar chart has five axes showing the degree of the food texture. The degrees of the sensory evaluation are the ratios of the subjects who perceived the food texture. The degrees by the logistic model are the averages of the $p(Z)$ calculated according to equation (1). The ten measurement data were averaged.

4. Discussion

The biscuit and the cookie exhibited high force without vibration. The force of the cookie was higher than that of the biscuit at the moment of fracture. Potato snacks A and B exhibited frequent high vibrations during fracture, where potato snack B had higher force. The corn snack and the wafer exhibited low force and frequent low vibration. Potato chips A and B also exhibited low force; the vibration pulses were sparse and of intermediate amplitude. The thick and thin rice crackers exhibited high force and intense pulses.

The food texture sensor showed the differences in food texture among the food samples via the two wave forms. The force and the vibration reflected slow and rapid changes during fracture, respectively. The center frequencies of the force and the vibration differ; hence, the food texture sensor measured more details of the fracture compared with instruments that use a load cell.

As shown in Table 2, each food texture had a high point for a certain food. These results show that the different foods were strongly correlated with a specific food texture. However, potato snacks A and B did not exhibit a one-to-one relation with a specific texture. They have a hard outer skin and an inside structure with a high void ratio. Hence, the human subjects selected multiple food textures for these foods. The test at a significance level of 5% classified the sensory evaluation results as positive (1), negative (0), or undetermined (-). The logistic model allows only a binary value for response variables. In the present study, to evaluate the majority of food texture detection, the combinations of food texture and food sample determined as (-) were not used for the determination of $\boldsymbol{\beta}$. Actually, the undetermined results can possibly be used to evaluate a minority of the food textures.

As shown in Table 3, the maximum of vibration was significant for the food texture "sakusaku." The "sakusaku" texture was evaluated by the sensor's signal without high vibration. In Table 4, the variance of force, skewness of positive pulses, and effective value of vibration were significant for the "paripari." food texture. In particular, the effective value of vibration had a high odds ratio. As shown in Table 4, the "paripari" texture was evaluated mainly by the continuous vibration. The "baribari" food texture depended on the maximum of force, as shown in Table 5. Hard foods have a tendency to be evaluated as having "baribari" texture. The skewness of force was significant for “karikari,” as shown in Table 6. A large force with low frequency was evaluated as “karikari.” Table 7 shows that, although the effective value of vibration was significant for “garigari,” the two other variables also had low P-values. Actually, “garigari” was evaluated by three feature quantities. As shown in Fig. 4, the logistic models successfully evaluated the positive (1) and negative (0) of each food texture. The selected feature quantities were effective for evaluating five food textures. However, the “sakusaku” texture had a biased selection. We speculate that greater variation of the food samples is required to decrease the bias.

As shown in Fig. 5, in the case of the biscuit, potato snack A, corn snack, cookie, and the wafer, the evaluations of the logistic model correspond to the sensory evaluation. In particular, even though the cookie and wafer were not used for the determination of the logistic model, they fit well with the sensory evaluation results. These results confirm that the proposed method is effective for evaluating the textures of the aforementioned food samples. However, clear differences are observed between the sensory and the logistic model's evaluations in the case of the other five foods. The major cause is less variation among the food samples. As shown in Table 2, “baribari,” “karikari,” and “garigari” had only one positive food. Hence, “garigari” had differences for potato chip A, the thin rice cracker, and potato chip B. We speculate that the generalization of the logistic model would require greater variation of the food samples.

5. Conclusion

The magnetic food texture sensor was used to measure two time-series waves during fracture, and features were extracted from the waves. Regarding the five food textures, the effective features for the logistic regression model are selected to have agreement with the results of the sensory test. Even if the samples were unknown foods, the logistic model evaluated the food textures as corresponding to the sensory tests.

In this paper, only the six foods were used for the selection of the features and the determination of the beta coefficients. Various foods should be used to decrease the difference between the results obtained with the logistic model and those obtained from sensory tests. This work contributes additional logistic models for other food textures and expands the variation of the food textures for evaluation.

Acknowledgement

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References

Chen, Lan, and Umezuruike Linus Opara. 2013. “Texture Measurement Approaches in Fresh and Processed Foods - A Review.” *Food Research International* 51(2): 823–35.

http://dx.doi.org/10.1016/j.foodres.2013.01.046.

Dong, W K, T Shiwaku, Y Kawakami, and E H Chudler. 1993. “Static and Dynamic Responses of Periodontal Ligament Mechanoreceptors and Intradental Mechanoreceptors.” *Journal of neurophysiology* 69(5): 1567–82. http://www.ncbi.nlm.nih.gov/pubmed/8389830.

Etoh, Shinichi, Lingyan Feng, Kenichi Nakashi, and Kenshi Hayashi. 2008. “Taste Sensor Chip for Portable Taste Sensor System.” 20(4): 151–60.

Friedman, Herman H., James E. Whitney, and Alina Surmacka Szczesniak. 1963. “The Texturometer-A New Instrument for Objective Texture Measurement.” *Journal of Food Science* 28(4): 390–96.

Hocking, R R. 1976. “A Biometrics Invited Paper. The Analysis and Selection of Variables in Linear Regression.” *Biometrics* 32(1): 1–49. http://www.jstor.org/stable/2529336.

Iwatani, Shin Ichiro, Hidemi Akimoto, and Naoki Sakurai. 2013. “Acoustic Vibration Method for Food Texture Evaluation Using an Accelerometer Sensor.” *Journal of Food Engineering* 115(1): 26–32. http://dx.doi.org/10.1016/j.jfoodeng.2012.09.015.

Rock, F et al. 2008. “Electronic Nose: Current Status and Future Trends.” *Chemical Reviews* 108(2): 705–25. http://pubs3.acs.org/acs/journals/doilookup?in_doi=10.1021/cr068121q%5Cnpapers://316bc3e6-3d1b-427b-a4e3-80bd1b4d480e/Paper/p1578.

Saeleaw, Mayyawadee, and Gerhard Schleining. 2011. “A Review: Crispness in Dry Foods and Quality Measurements Based on Acoustic-Mechanical Destructive Techniques.” *Journal of Food Engineering* 105(3): 387–99. http://dx.doi.org/10.1016/j.jfoodeng.2011.03.012.

Tahara, Yusuke, and Kiyoshi Toko. 2013. “Electronic Tongues-a Review.” *IEEE Sensors Journal* 13(8): 3001–11.

Taniwaki, Mitsuru, Takanori Hanada, and Naoki Sakurai. 2006. “Device for Acoustic Measurement of Food Texture Using a Piezoelectric Sensor.” *Food Research International* 39(10): 1099–1105.

Taniwaki, Mitsuru, and Kaoru Kohyama. 2012. “Mechanical and Acoustic Evaluation of Potato Chip Crispness Using a Versatile Texture Analyzer.” *Journal of Food Engineering* 112(4): 268–73. http://dx.doi.org/10.1016/j.jfoodeng.2012.05.015.

Uchida, T et al. 2001. “A New Method for Evaluating the Bitterness of Medicines by Semi-Continuous Measurement of Adsorption Using a Taste Sensor.” *Chemical & pharmaceutical bulletin* 49(10): 1336–39.

Varela, P., J. Chen, S. Fiszman, and M. J. W. Povey. 2006. “Crispness Assessment of Roasted Almonds by an Integrated Approach to Texture Description: Texture, Acoustics, Sensory and Structure.” *Journal of Chemometrics* 20(6–7): 311–20. http://doi.wiley.com/10.1002/cem.1029 (May 9, 2017).

Walker, Strother H, and David B Duncan. 1967. “Biometrika Trust Estimation of the Probability of an Event as a Function of Several Independent Variables.” *Source: Biometrika Biometrika Trust* 54(12): 167–79. http://www.jstor.org/stable/2333860.

Table 1 Textural parameters and moisture of food samples.

	Hardness (N/m2)	Adhesiveness (J/m3)	Cohesiveness (%)	Springiness (%)	Moisture (%)
Biscuit	49.07	0.00	2.8	87.9	0.7
Cookie	60.01	0.00	1.4	63.4	0.5
Potato snack A	67.02	0.06	14.3	19.5	4.5
Potato snack B	36.06	0.00	5.1	65.6	4.1
Corn snack	44.24	0.00	22.4	43.5	3.1
Wafer	47.70	0.00	19.6	35.8	7.1
Potato chip A	24.17	0.00	32.9	38.8	1.0
Potato chip B	57.49	0.00	31.8	41.5	1.4
Thick rice cracker	89.33	0.07	10.6	24.9	2.0
Thin rice cracker	40.61	0.00	13.7	17.3	2.2

Table 2 Results of sensory evaluation. The numbers in parentheses indicate whether the test at a significance level of 5% classified the results as positive (1), negative (0), or undetermined (-).

	Sakusaku	Paripari	Baribari	Karikari	Garigari
Biscuit	9 (1)	0 (0)	1 (0)	1 (0)	1 (0)
Cookie	10 (1)	0 (0)	1 (0)	0 (0)	0 (0)
Potato snack A	1 (0)	1 (0)	1 (0)	9 (1)	10 (1)
Potato snack B	6 (-)	1 (0)	1 (0)	4 (-)	5 (-)
Corn snack	10 (1)	0 (0)	0 (0)	1 (0)	0 (0)
Wafer	9 (1)	3 (-)	0 (0)	0 (0)	0 (0)
Potato chip A	5 (-)	10 (1)	3 (-)	2 (-)	0 (0)
Potato chip B	4 (-)	10 (1)	4 (-)	3 (-)	0 (0)
Thick rice cracker	1 (0)	5 (-)	9 (1)	2 (-)	1 (0)
Thin rice cracker	0 (0)	9 (1)	6 (-)	3 (-)	1 (0)

Table 3 Variables and analytic results for texture “sakusaku”

Variable	β	Odds ratio	P-value
Intercept	25.47		
Maximum of vibration	−5.28	0.000009	0.0323

Table 4 Variables and analytic results for texture “paripari”

Variable	β	Odds ratio	P-value
Intercept	−5225		
Variance of force	−0.03	0.01	0.0436
Skewness of force	−2.531	0.1127	0.1076
Number of small positive pulses	−0.017	0.0027	0.0517
Skewness of positive pulses	0.112	28.19	0.0418
Effective value of vibration	1758	176.9	0.0188

Table 5 Variables and analytic results for texture “baribari”

Variable	β	Odds ratio	P-value
Intercept	−19.03		
Minimum of vibration	2.387	3.3704	0.2808
Mean distance between positive pulses	−0.138	0.0242	0.091
Skewness of positive pulses	0.125	1.1136	0.102
Maximum of force	0.352	1100	0.0431
Number of medium positive pulses	−0.073	0.1045	0.3045

Table 6 Variables and analytic results for texture “karikari”

Variable	β	Odds ratio	P-value
Intercept	2.114		
Skewness of force	9.35	1469	0.0193
Mean distance between positive pulses	−0.078	0.0866	0.3805

Table 7 Variables and analytic results for texture “garigari”

Variable	β	Odds ratio	P-value
Intercept	4354		
Standard deviation of force	−0.4426	0.0606	0.0882
Number of medium positive pulses	0.1801	692.8	0.0646
Effective value of vibration	−1466	0.0141	0.0307

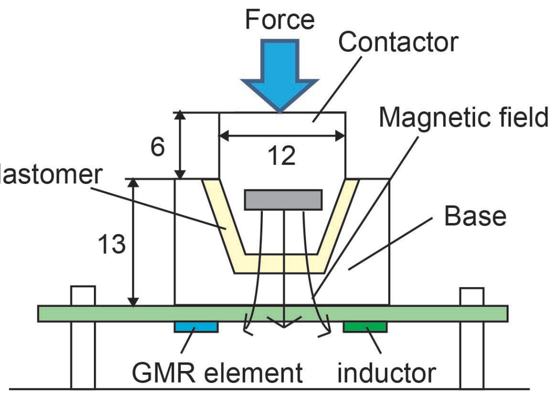


Fig. 1　Structure of the magnetic food texture sensor.

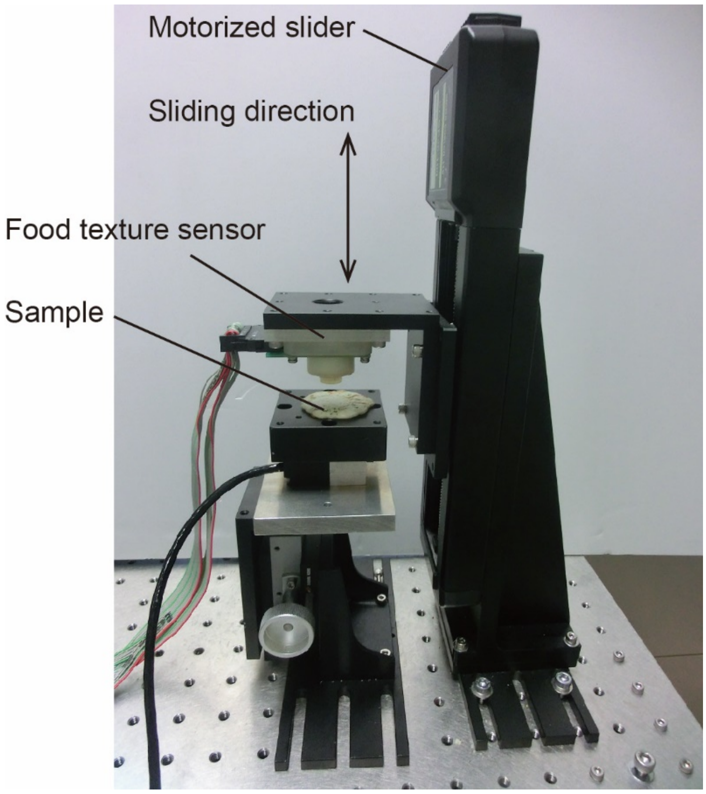
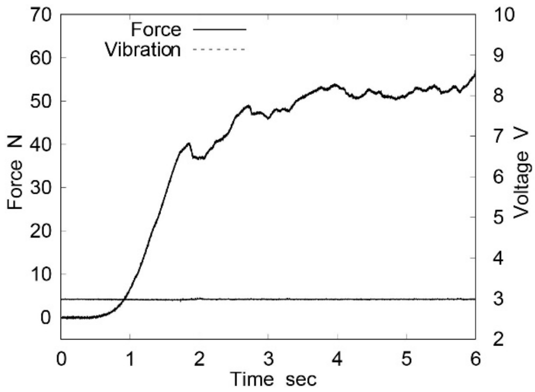
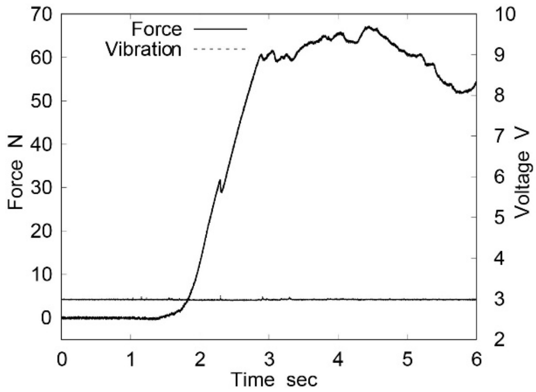


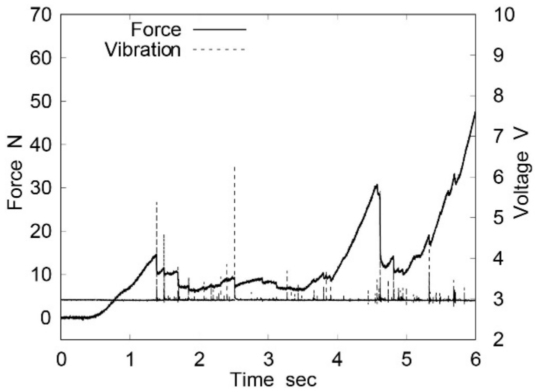
Fig. 2　The motorized stage and food texture sensor.



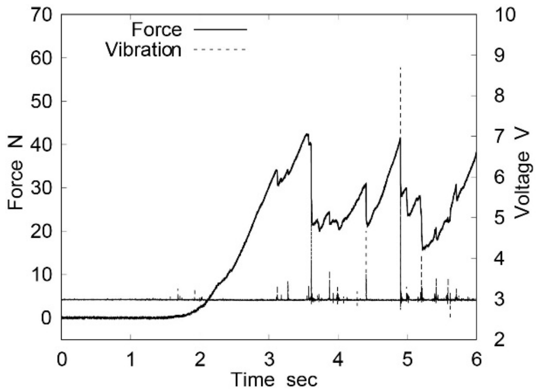
(a) Biscuit



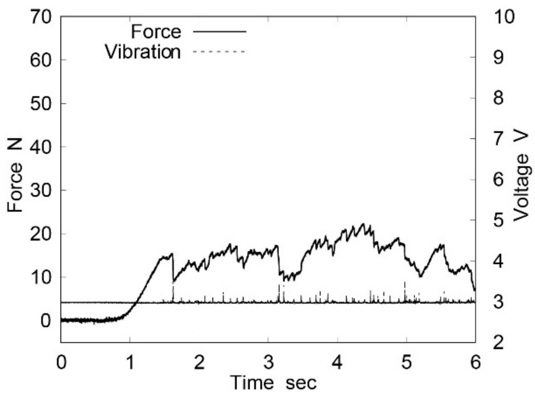
(b) Cookie



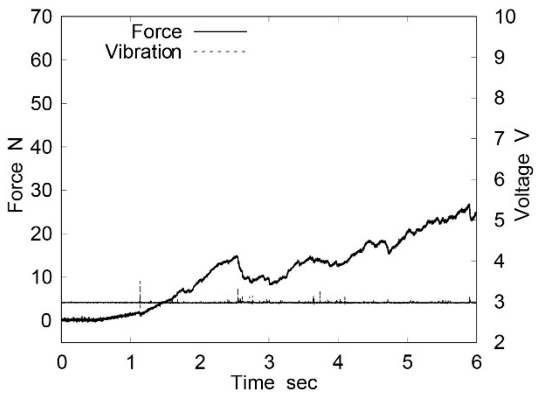
(c) Potato snack A



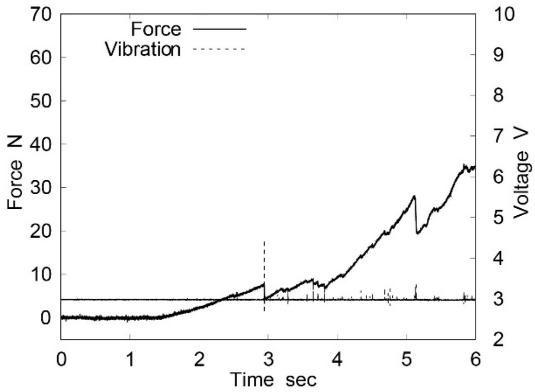
(b) Potato snack B



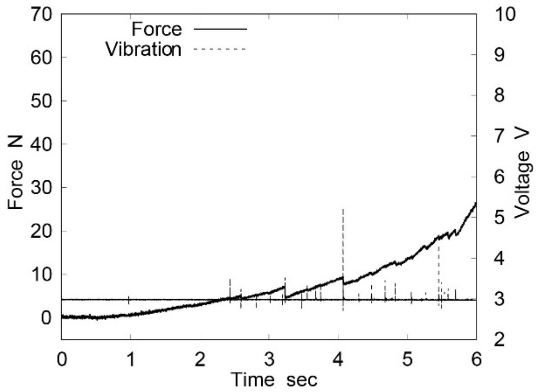
(e) Corn snack



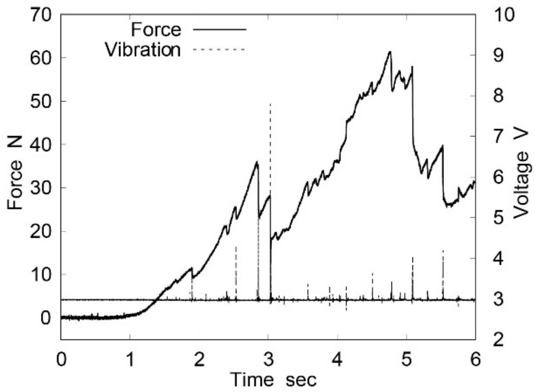
(f) Wafer



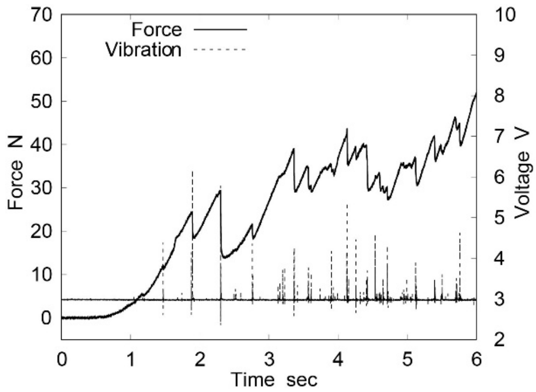
(g) Potato chip A



(h) Potato chip B

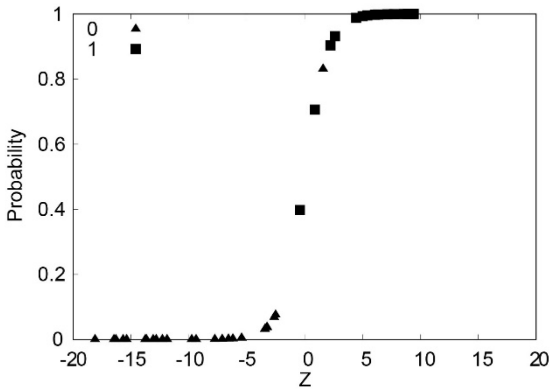


(i) Thick rice cracker

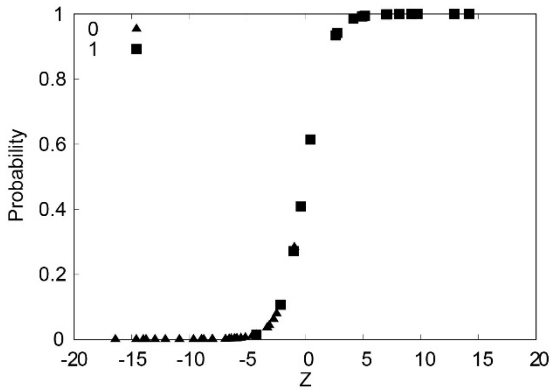


(j) Thin rice cracker

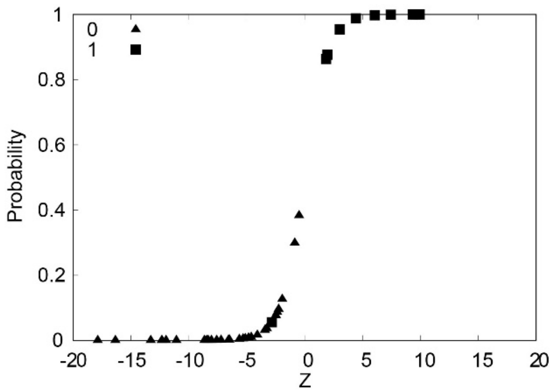
Fig. 3 Time-series force and voltage data collected during fracture experiments.



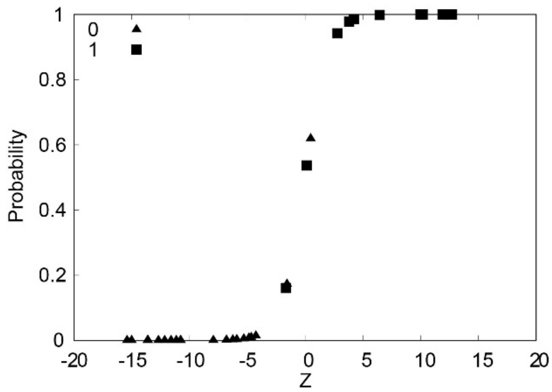
(a) Sakusaku



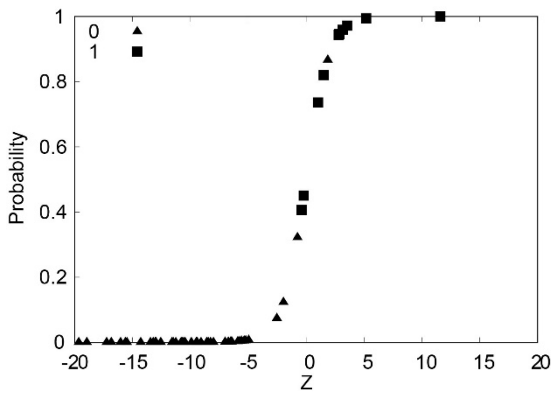
(b) Paripari



(c) Baribari

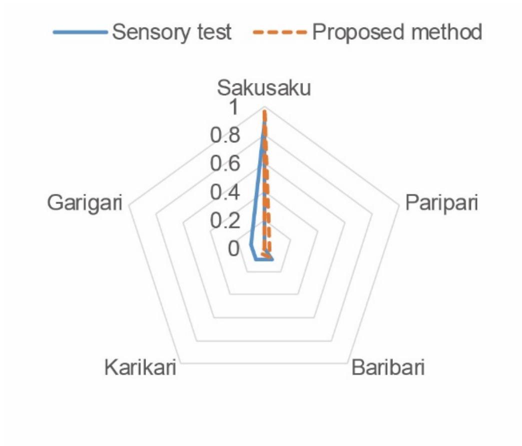


(d) Karikari

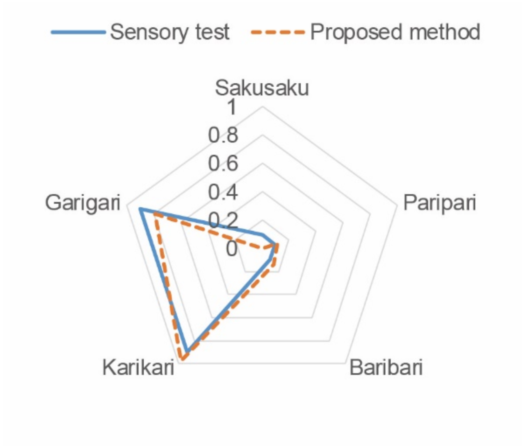


(e) Garigari

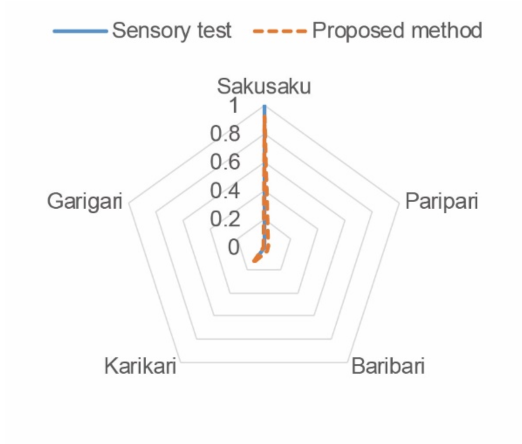
Fig. 4 Food textures evaluated by the logistic regression model.



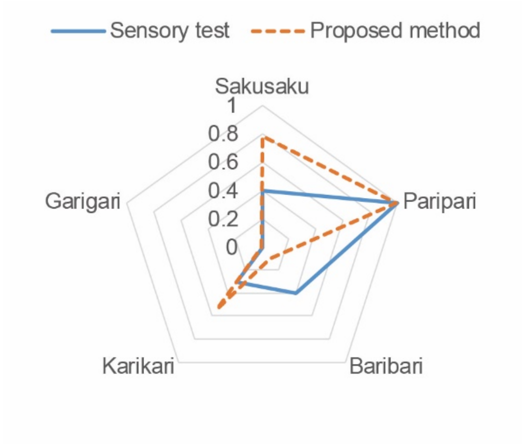
(a) Biscuit



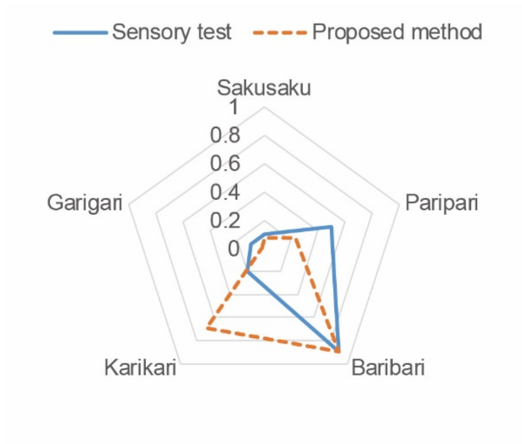
(b) Potato snack A



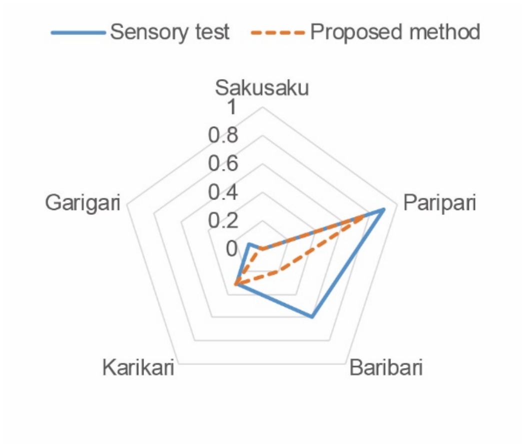
(c) Corn snack



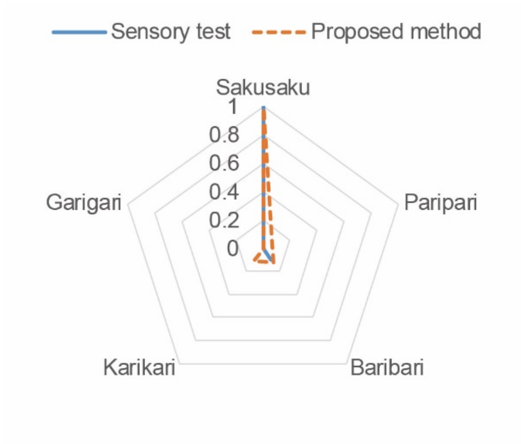
(d) Potato chip A



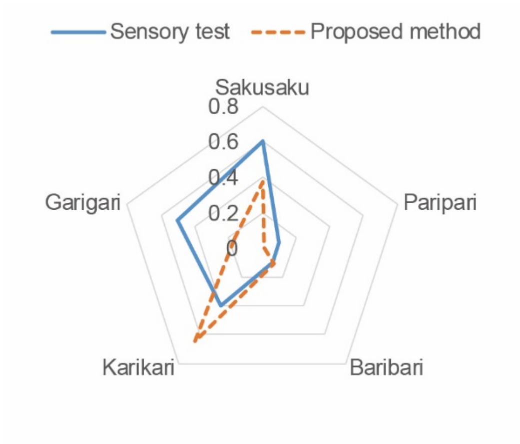
(e) Thick rice cracker



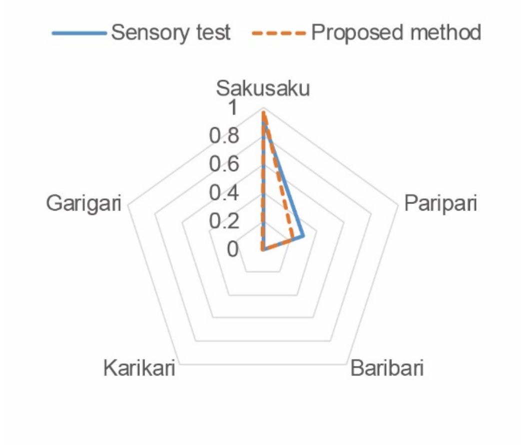
(f) Thin rice cracker



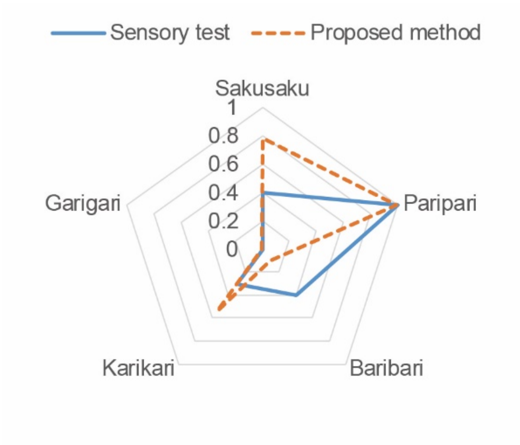
(g) Cookie



(h) Potato snack B



(i) Wafer



(j) Potato chip B

Fig. 5 Comparison between the results of sensory tests and the proposed method for five food textures.