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Title

Sum of variance for quantifying the variation of multiple sequential data for the crispness evaluation of chicken nugget

(Short running title: Instrumental crispness measurement)

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Abstract

Crispness is one of the words most frequently used to describe the texture of fried or dried food in addition to being a key to the determination of freshness for many non-fried foods. In this study, a new feature value called the sum of variance was assessed for its contribution to the estimation of crispness. Dynamic time warping and its averaging algorithms were employed to determine the sum of variance from a set of sequential force data measured using an instrument. The sum of variance is a feature value that expresses the variance of multiple sequential data. In an experiment, seven chicken nugget samples were prepared, and five panels evaluated their texture according to six Japanese word descriptors. An instrument experiment determined the six feature values, including the sum of variance from the measurement data, whereas multiple linear regression was applied to determine the relationship between the sensory values and feature values. For three of the six textures, the sum of variance reduced the error between the sensory values and their estimated values by up to 50%, confirming that this feature contributes to the textural estimation of food crispness.

Keywords

Food texture, Crispness, Sum of variance, Multiple linear regression

1. Introduction

Crispness is an important attribute of texture often used to describe fried or dried food in addition to being a key to the determination of freshness for many non-fried foods (Tunick et al., 2013). In the United States, Szczesniak (1971) revealed in a survey of 150 individuals (with a good balance of gender, area, age, and economic status) the terms crispness and crunchy being the most frequently used descriptors of food texture. Similarly, in Austria, Rohm (1990) reported that out of the 105 texture words identified, crispness was the most often used by the 208 college students surveyed when asked to describe the texture of 50 different types of food. Recently, in North America, Luckett and Seo (2015) asked 337 participants to enumerate the first three words they would use to describe 32 different types of food grouped according to the attributes of texture, flavor, and aroma, among others. Under texture, the top pick for the pool of words/adjectives was crunch/crunchy, followed by crisp/crispy. Vickers (1983) indicated that crispness contributes to the enjoyment felt from food consumption. Hence, some researchers reported the improvement of the crispness of various foods (Link, Tribuzi, de Moraes, & Laurindo, 2018; Monteiro, Link, Tribuzi, Carciofi, & Laurindo, 2018; Assis et al., 2019; Barreto, Tribuzi, Marsaioli, Carciofi, & Laurindo, 2019). Crispness is a widely popular texture descriptor across many areas and ages and also has a longstanding primacy in the texture attributes for a long time.

Crispness and crunchiness are well defined in many research works. In their list of definitions, Saeleaw and Schleining (2011) indicated the difficulty in defining crispness when ascribed only to the established generalized concept. Dijksterhuis et al. (2007) presented a vocabulary describing crisp and crunchy foods. Yoshikawa et al. (1970) revealed that the Japanese people have used more textural words, a total of 406, compared with the 78 words used mainly in the United States. Hayakawa et al. (2005) reinvestigated the texture words often used in four areas in Japan, which consequently totaled 445 words. In general, the Japanese people describe specific textures of crispness and crunchiness using many onomatopoeic words, i.e., *pari-pari*, *kari-kari*, *saku-saku*, and *gari-gari*, which do not have corresponding equivalents to the words used in the United States. This indicates that the textural meaning of crispness and crunchiness has a varied and wide range.

Different methods have been proposed to evaluate food texture in terms of crispness (Tunick et al., 2013), focusing mainly on using the sound impression when the food is compressed. Christensen and Vickers (1981) investigated the relationship between the biting sounds and crispness. Duizer et al. (1998) measured the acoustic levels of the sounds of 12 samples of extruded corn puffs and observed the high correlations between the sensory characteristics of crispness and the fractal dimensions of the acoustic signatures. Chauvin et al. (2008) recorded the chewing or biting sounds of panels and analyzed their scales via a multidimensional scaling test. Taniwaki et al. (2006) developed a measurement system to obtain acoustic vibration by a piezoelectric sensor. They also proposed and measured the characteristic, called texture index, of four potato chips (Taniwaki, Sakurai, & Kato, 2010). Zadeike et al. (2018) investigated mechanical and acoustic parameters relating to the evaluation of bread dough texture and bread crust crispness. Some researches employed texture profile analysis (TPA) to measure the force (Szczesniak, 1963; Bourne, 2002) or both the force and acoustic sound. Saklar et al. (1999) compared the instrumental characteristics determined from the force data with the sensory crispness and crunchiness of hazelnuts. Salvador et al. (2009) simultaneously measured the force and the sound in a fracture of six samples of potato chips and demonstrated that the numbers of force and sound peaks contribute to the evaluation of the hardness and crispness of the potato chips. Mohamed et al. (1982) and Varela et al. (2006) reported that using the combination of force and sound is effective in evaluating the crispness of, respectively, friable foods and roasted almonds. Recently, machine learning algorithms contribute to the evaluation of crispness. Gouyo et al. (2020) proposed a method estimating the sensory characteristics, including the crispness of French fries, based on force and acoustic data by random forest. Although machine learning algorithms typically require a large data set, they possess the potential to quantify crispness by learning.

The above studies have suggested various methods for quantifying crispness. Some studies measured force and/or acoustic data in the fracture of samples and analyzed these data one by one. However, in the case of fried food typically characterized by uneven and different outer skins, i.e., chicken, potato, onion, and other snacks, have different outer skin or shape. If an instrument measures force in compression of them, there are variations in the data. Figure 1 presents the typical data of chicken nuggets obtained from a TPA test, for five sequential force data with two-time compression. Because an instrument compressed the same central part of nuggets, the second peaks were lower than their first peaks. In a TPA profile, the height of the first peaks determines the hardness. The variance of hardness can be calculated to evaluate the unevenness of the samples. However, because the difference between the force data is not only at the peaks, but also in the whole force data in the first and second compressions, a novel variance of the sequential force data is introduced in this paper to evaluate such a difference. In this paper, the unevenness of the outer surface is assumed to contribute to the crispness of the fried food. Based on this assumption, a new feature value called *the sum of variance* was developed to evaluate the degree of variation of the measured data. To calculate the sum of variance, this study employs a dynamic time warping (DTW) and DTW barycenter averaging. The DTW, one of the algorithms used to calculate the distance between sequential data, determines an optimal match between the elements of two sequential data (Sakoe & Chiba, 1978). When the data show a difference in peak times, the DTW fits these peak times by partial expansion and contraction of the sequence data. The iterative algorithm of DTW barycenter averaging (DBA) then determines the average sequential data (Petitjean, Ketterlin, & Gançarski, 2011), following this procedure. First, the initial average sequence data are determined. Second, DTW is applied to find the optimal match between the average sequential data and one of the sequence data. The DBA then stacks the correspondence between an element of the average data and the elements of the sequence data and updates the average data based on the stack. Moreover, the DBA iterates the second process until the update of the average data stops. In an experiment, deep-fried chicken nuggets are used as food samples. Six kinds of nuggets are designed. The effect of the sum of variance on food crispness is validated via a multiple regression analysis through a sensory evaluation and a measurement experiment.

2. Materials and methods

2.1 Sum of variance

The DBA algorithm produces the data set of an element of the average data and elements of the sequence data. It could be seen in Fig. 2 that the i-th element of the average data matched three elements, two from Sequence data #1 and one from Sequence data #2. Hence, the variance of the elements of the sequence data tied to the element of the average data can be calculated using the formula:

$$\sigma_i^2 = \frac{1}{N_i}\sum_{j=1}^{N_i}\left(m_{ij} - \overline{m}_i\right)^2 , \tag{1}$$

where m_{ij} is the j-th matched element of the sequence data with the i-th element of the average data, $\overline{m}_i$ is a value of the i-th element of the average data, and N_i and σ_i^2 are the number and variance of the matched elements m_{ij}, respectively. Note that the variance σ_i^2 of the matched elements is a partial variance of the sequential data. Hence, the sum of variance can be represented by the equation.

$$\sigma^2 = \sum_{i=1}^{N} \sigma_i^2 , \qquad (2)$$

where N is the number of elements of the average data. Because this equation interprets the sum of the element variances of the sequential data concerning each element of the average data, the sum of variance is also the total variance of the sequence data. On one hand, the TPA obtains the physical properties from one sequence data, such as hardness. On the other hand, the sum of variance is calculated from a set of sequence data and is a common property for the data. Even if devices for the TPA analysis have low sampling frequency, the sum of variance expresses the unevenness of the samples from a set of sequence data. In this study, N is constant in an experiment and is the same as the number of elements of the measurement data. When the numbers of elements are different, the average of variance divided by N can be calculated.

2.2 Food texture for crispness

The Japanese language is rich in textural vocabulary and uses many onomatopoeic words (Bourne, 2002). The textural vocabulary is sensitive to subtle nuances in textures. To evaluate the difference in subtle nuances, six textural onomatopoeic words, *saku-saku*, *sakut*, *zaku-zaku*, *kari-kari*, *karit*, and *gari-gari*, were selected to describe chicken nuggets in the running experiment. All words, as defined in Table 1, refer to mechanical attributes related to crispness and crunchiness. The differences between saku-saku and sakut and between kari-kari and karit are in fracture method with the molars or incisors. They are often used to describe the typical food listed by Hayakawa et al. (2013).

2.3 Sample preparation

To express the six textures of crispness and crunchiness in Table 1, seven kinds of chicken nuggets were used as samples, with ground leg meat as the main ingredient. A food processor was used to obtain the meat paste from the chicken leg meat, which were then applied with a mixed seasoning. The same meat paste was used for all the nuggets. The paste was placed in molds to create a uniformly elliptical cylinder nugget shape and then rapidly frozen. Each mold-shaped nugget had a size of 95 × 70 × 12 mm (in the long and short axes, and the thickness) and weighs 28 g. Some researchers investigated mixtures of batter and breader (Tamsen, Shekarchizadeh, & Soltanizadeh, 2018; Pongsawatmanit, Ketjarut, Choosuk, & Hanucharoenkul, 2018; Tapia-Hernandez et al., 2018). Deep-fried battered and breaded coatings affect sensory crispness (Voong, Norton-Welch, Mills, & & Norton, 2019). Seven mixtures of a batter coating from the main flour were coated to the frozen meat. Three of the seven nugget samples were coated with breading. Table 2 presents the materials of the batter coating and the breader. The samples are termed from S1 to S7. The batter and breader coating process are as follows: The frozen meat was soaked into the batter in a bowl and immediately was picked out. The amount of the batter for one sample was 12-13 g measured by decrease the weight of the bowl. If the meat with the batter needs the breader, the breader was covered to the whole of the meat with the batter. Immediately, the samples were put into vegetable oil. In the case of the nuggets without breader, the samples were fried after coating the batter. All samples were fried in vegetable oil at 180 °C for 5 min. A measurement instrument measured the samples after a waiting period of 5 min on a cooling rack at room temperature of 20 ℃. Table 3 presents the mean and standard deviation of the thickness of the coating (n=12).

2.4 Sensory evaluation

Five expert panels with over three-year experience associated with the manufacture of edible oils in a private company conducted a sensory evaluation in the descriptive analysis. It was ascertained that each panel has understood in advance the common nuances in Table 1 before testing the samples. Besides, each panel evaluated the textures in Table 1 using snack samples and reduced the individual difference of the evaluation values through a preliminary test. The tests were repeated three times, however, one panel had missing values for five samples in one of these instances.

2.5 Instrumental measurement

The texture of the nugget samples was measured using the instrument JSV-TEX-100N (Japan Instrumentation System, Japan) by applying two-time compression. Each sample was measured five times. The probe used was HOP-F4 (Japan Instrumentation System, Japan) having a 9-mm-wide wedge shape. The wedge probe was 9 mm in diameter. The tip part of the wedge was an isosceles triangle with an angle of 90 °. After the probe touched the center of a sample elliptical surface, the instrument compressed the sample with a 15 mm distance. The conditions of the compression speed and sampling frequencies were 2 mm/s and 10 Hz, respectively. The time between the first and second compressions was 15 s. The software SOP-TEX (Japan Instrumentation System, Japan) was used to calculate the hardness, brittleness, and springiness of the samples based on the measurement data. Here, hardness was defined as the maximum force of the first compression, brittleness as the momentary dropping force in the compression, and springiness as the ratio of the maximum force of the second compression to that of the first compression. The ratios of moisture and oil of coating were also measured as follows: a fried nugget sample was separated into meat paste and coating. Regarding the moisture, we measured the weight change of the coating before and after 135 °C air drying of 2 hours. Oil content was measured by the JOCS (Japan Oil Chemists' Society) standard methods as follows: First, weigh accurately 10 g of the ground sample into a thimble and cover lightly with absorbent cotton. Second, dry in the oven at 105±3 °C for 1 h (preliminary drying). Third, place a filter paper into the Soxhlet extractor assembled with a tared extraction flask, and extract with 100 - 150 mL of diethyl ether on the water bath for 8 h. Heat in the water bath to allow the solvent to drop from the condenser on the center of the filter paper at the circulation rate of about 15 times/h. Forth, take out the filter paper from the extractor and recover the solvent in the extraction flask, then dry the flask in the vacuum oven at 60 for 1 h. Finally, weigh the flask after cooling in a desiccator for 30 min and calculate the percentage of the weight of extracted oil to the weight of the ground. Besides, the sum of variance, a partial sum of variance, and the variance of the hardness from the measurement data were calculated. Also note that the partial sum of variance was defined herein as the sum of variance until the maximal peak of the first compression.

2.6 Multiple linear regression

Multiple linear regression was performed using MATLAB R2017b (MathWorks, USA) to analyze the relationship between the sensory evaluation values and the feature values. The models were first-degree polynomial equations, which utilize some of the feature values as explanatory variables and estimate the sensory evaluation values as the objective variables. For the six food textures, the analysis determined six corresponding models and their standardized partial regression coefficients. In one cycle, the analysis determined the coefficients of the model based on 21 of the 35 measurement data of all samples and estimated the sensory evaluation values using the other 14. The 1000 cycles of the analysis were repeated by changing the data set without the same combination. The common feature values were hardness, brittleness, and springiness, and the conditions having common values, as well as one of the sum of variance, the partial sum of variance, and the variance of hardness, were analyzed in comparison with the condition of the only common values.

2.7 Data analysis

The statistical analysis of the results was carried out using MATLAB R2017b (MathWorks, USA) (ANOVA) and R programs (AIC). The ANOVA procedure at a significance level at 0.05 and the Tukey test were applied to assess significant differences between the investigated parameters.

3. Results and discussion

3.1 Sensory evaluation

Table 4 presents the average scores and standard deviations of the textural descriptors against the samples. The evaluation values of S1 and S5 were below 4, suggesting less texture of crispness. S2 and S3 showed median values of less than 5, indicating relative crispness. S4, S6, and S7 showed the highest values exceeding 6, implying much crispness. This was mainly because although the nuggets were made from the same meat paste, they were also different in the mixture of batter, and with/without breading, hence, they were expected to differ in crispness.

3.2 Instrumental measurement

All these feature values are presented in Table 5, and correlation coefficients among the feature values in Table 6, suggesting that the sum of variance is not correlated with the hardness, brittleness, springiness, and variance of hardness. Moreover, the relationship between the sum and partial sum of variance is similar, but not the same. This resulted in the sum of variance expressing a different feature of the measurement data, which the TPA could not obtain. The sum of variance and the partial sum of variance revealed the same tendency, but with the former showing a weak correlation with the variance of hardness. Further, the feature values of TPA evaluated the partial feature of the measurement data, whereas the sum of variance evaluated the whole feature of the measurement data.

3.3 Multiple linear regression

Figure 3 and Table 7 present the relationship between the sensory evaluation values and the estimated values and the root mean squared error (RMSE) between these values, respectively, by the multiple linear regression. Table 8 presents the Akaike information criterion (AIC) in each condition. Moreover, the standardized partial regression coefficients determined by the regression analysis are presented in Table 9. If the standardized partial regression coefficient was high, then its explanatory variable would contribute to the estimation of a sensory evaluation value.

Using the multiple linear regression to estimate the six textures, the case with the explanatory variables with the sum of variance produced a relatively small error in the estimation of the sensory evaluation values of *kari-kari*, *karit*, and *gari-gari*, as shown by the respective RMSEs of 0.85, 0.70, and 1.13, respectively, in Table 7, which, when compared with the condition with only hardness, brittleness, springiness, were reduced from 31% to 50%. In Table 8, the AICs of them with the sum of variance were smaller than the condition without the sum of variance. The standardized partial regression coefficients of the sum of variance in Table 9 were also relatively high. Accordingly, the sum of variance contributed to the estimation of the sensory evaluation values, and although the partial sum of variance and the variance of hardness also contributed to the same estimation, the RMSEs of the sum of variance were lower than those of the partial sum of variance. The sun of variance might have been able to capture the significant variation of the time-series force in mastications to estimate *kari-kari*, *karit*, and *gari-gari*. Contrarily, *saku-saku*, *sakut*, and *zaku-zaku* showed large errors, as in the case of S6, between the sensory evaluation values and the estimated values; hence, their RMSEs were not affected by the sum of variance. *Saku-saku*, *sakut*, and *zaku-zaku* had sensory scores with relatively small variation between the samples in the sensory evaluation compared to the other three textures in Table 4. The variances of the mean scores for *saku-saku*, *sakut*, *zaku-zaku*, *kari-kari*, *karit*, *gari-gari* are 1.19, 1.41, 2.81, 5.40, 5.88, 5.23, respectively. It was considered that the regression did not positively determine the coefficients of the linear equation to fit a high value such as S6 shown in Fig. 3. This is also reflected in the standardized partial regression coefficients in Table 9, and the coefficients of *saku-saku* and *sakut* are relatively small. From this, we considered that the samples were not particularly suitable for evaluating the effectiveness of the sum of variances for *saku-saku* and *sakut*.

The number of measurements for each sample (five in total) is the limitation of this study. Although there were 1000 cycles calculated and summarized via the multiple regression analysis avoiding the same data set, the number of measurements should be more. The sum of variance might contribute to estimation with non-linear models. Further analysis with non-linear models is required. The instrumental measurement employed only the wedge-shaped probe. A cylindrical probe should be also used to discuss the estimate values of six texture descriptors with two probes. The sum of variance imitates repetitive mastication. In the case of human mastication with the molars, saliva is added to the bolus and affects the food texture. The calculation of the sum of variance should refer to the change of food texture in mastication.

4. Conclusion

In this study, the sum of variance was proposed for the evaluation of the texture of food crispness. It was calculated from multiple measurement data through the DTW and DBA algorithms. The feature values of TPA explained the partial features of the measurement data, whereas the sum of variance expressed the whole data feature. Sensory evaluation and measurement experiments were conducted using the chicken nuggets and the multiple regression analysis. Based on the results, the sum of variance contributed to the effective estimation of crispness of *kari-kari*, *karit*, and *gari-gari* and reduced the estimation errors by as high as 50%. The future direction of this research is geared toward improving the estimation of the texture values using an instrument having a high resolution and a high sampling frequency.

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Author contributions

Hiroyuki Nakamoto: Conceptualization, methodology, experiment, data analysis, discussion, writing. Takeaki Yasuda: Methodology, experiment, data analysis, discussion. Futoshi Kobayashi: Methodology, discussion. Yuya Nagahata: Methodology, experiment, discussion, sample preparation. Rina Shimizu: Methodology, experiment, discussion, sample preparation. Ko Kimura: Methodology, experiment, discussion, sample preparation.

Ethical statement

Conflict of Interest: The authors declare that they do not have any conflict of interest.

Ethical Review: To perform the sensory evaluation, we followed the declaration of Helsinki.

Informed Consent: Written informed consent was obtained from all study participants.

Data Availability Statement: The data that support the findings of this study are available, upon reasonable request.

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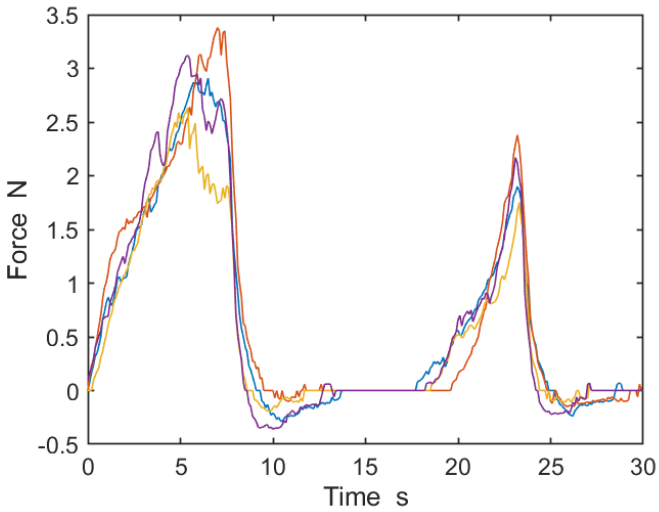
Figure Caption

Fig. 1 Typical force data in two-time compression. The second peak is smaller than the first one due to compressing the same part of a sample.

Fig. 2 Relationship between the i-th element of the average data and the three matched elements of the sequence data in the DBA algorithm. Sequence data #1 and #2 show measurement data. The variance of the three matched elements is calculated as the variance of the i-th element of the average data. The sum of variance is determined by the summation of the variances of all elements of the average data.

Fig. 3 Relationship between the sensory evaluation values and those estimated by multiple linear regression. The bars and error bars indicate the mean and the range of standard deviation, respectively. The common feature values include hardness, brittleness, and springiness. The sum of variance refers to the data set of the common values and the sum of variance, which is also true for the partial sum of variance and the variance of hardness.



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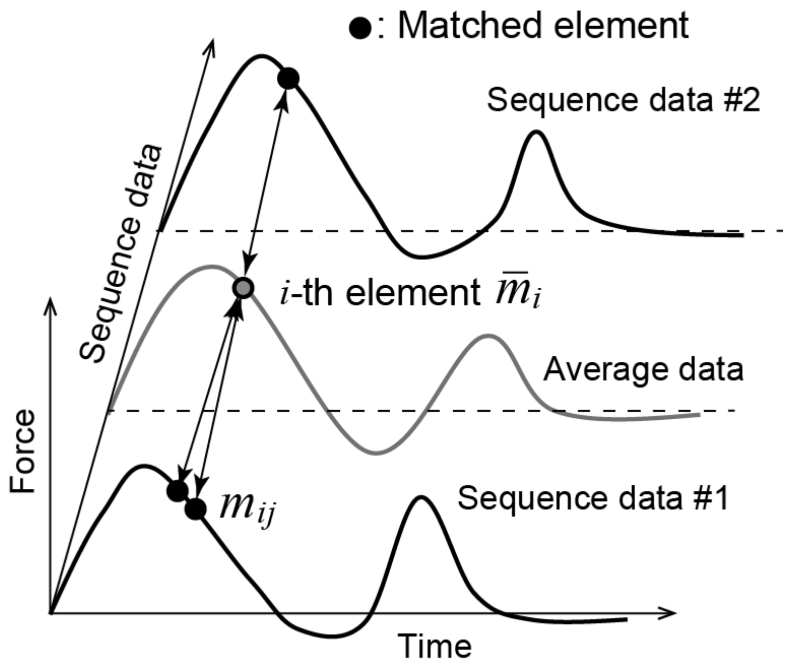

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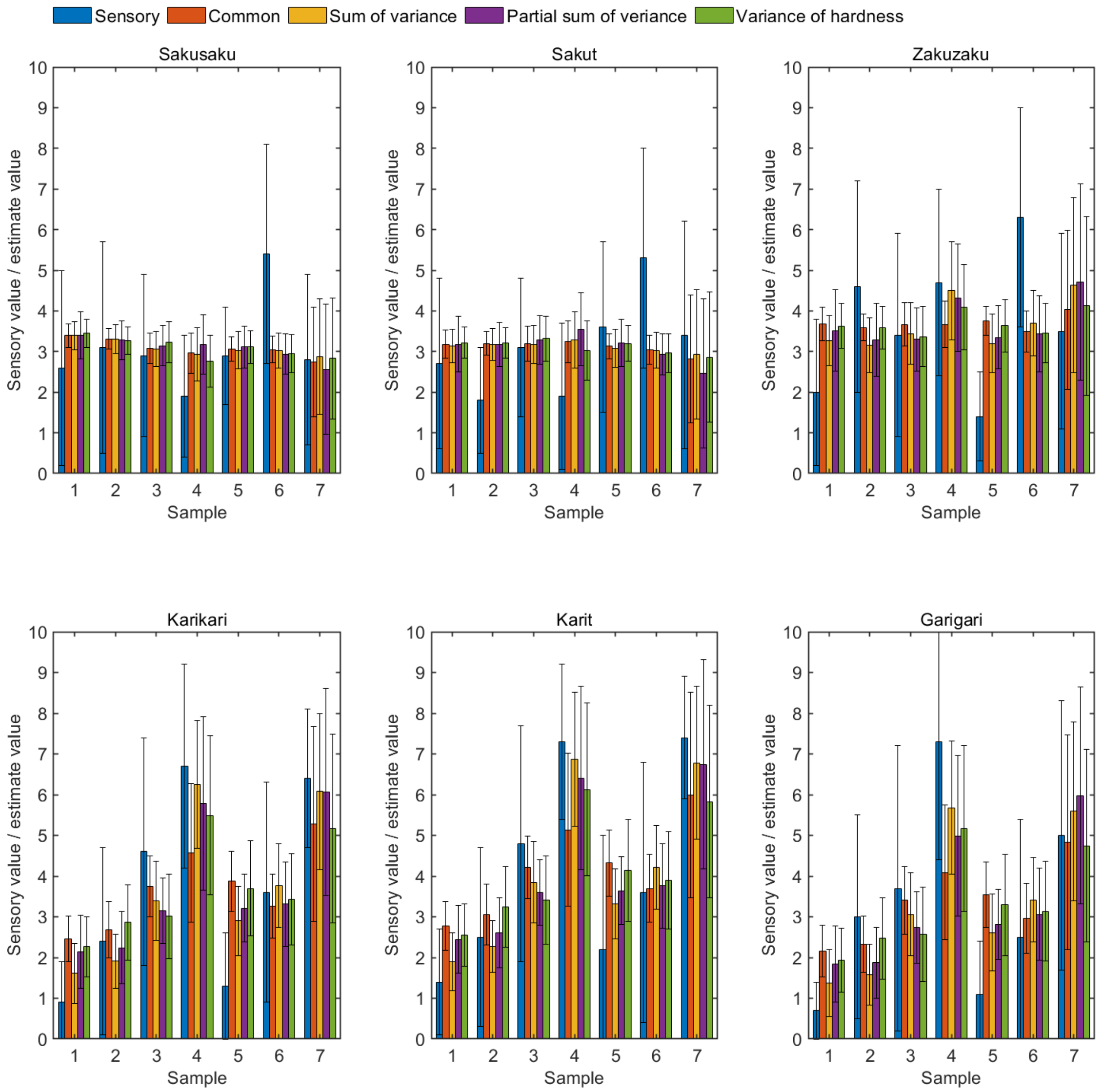

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Table 1 Texture words, their definitions for chicken nuggets in the experiment in this study, and the typical food they describe. The panels matched the force strength of each other's senses.

Texture word	Definition	Typical food[†]
Saku-saku	Continuous crispness with a small force in mastications	Cookie, apple
Sakut	Short crispness with a small force in the first-bite fracture	
Zaku-zaku	Repetitive crunchiness with a small force by molar teeth	Shaved ice, cornflakes
Kari-kari	Continuous crispness with a relatively strong force in mastications	Roasted nuts, unripe plum
Karit	Short crispness with a relatively strong force in the first-bite fracture	
Gari-gari	Repetitive crunchiness with a relatively strong force by molar teeth	Ice lolly, ice

[†]Extract from (Hayakawa et al., 2013). *Saku-saku* and *sakut* have the same typical food, as well as *kari-kari* and *karit*.

Table 2 Materials of batter mix and breader mix. The unit is g.

Materials of batter mix	S1	S2	S3	S4	S5	S6	S7
Wheat flour	70	80	40	20	80	80	10
Acetylated oxidized starch	30	10	25	0	20	20	0
Acid treated starch	0	0	0	20	0	0	0
Oxidized starch	0	0	0	30	0	0	30
Pregelatinized cornstarch	0	0	0	0	0	0	20
Distarch phosphate	0	0	35	30	0	0	40
Dextrin	0	10	0	0	0	0	0
Paprika pigment	0.4	0.4	0.4	0.4	0.4	0.4	1
Leavening agent	0	0	0	0	0.3	0.3	0
Xanthan gum	0	0	0	0	0	0	0.1
Cold water	120	120	100	100	140	140	140
Materials of breader mix	**S1**	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**
Wheat flour	90	60	-	-	-	0	-
Pregelatinized cornstarch	0	20	-	-	-	100	-
Distarch phosphate	0	20	-	-	-	0	-
Fat powder	10	0	-	-	-	0	-
Leavening agent	0.2	0	-	-	-	0	-

Table 3 Mean and standard deviation of thickness of fried nuggets' coating (n=12).

	S1	S2	S3	S4	S5	S6	S7
Thickness mm	1.6 ± 0.4^{a}	2.6 ± 1.0^{b}	1.7 ± 0.6^{a}	1.5 ± 0.7^{a}	1.7 ± 0.6^{a}	2.5 ± 0.5^{b}	1.7 ± 0.4^{a}

Different letters (a, b) indicate significant differences ($p < .05$) among the samples.

Table 4 Average scores and standard deviations of the sensory evaluation between the texture descriptors and the samples.

Sample	*Saku-saku*	*Sakut*	*Zaku-zaku*	*Kari-kari*	*Karit*	*Gari-gari*
S1	2.6 ± 2.4^{a}	2.7 ± 2.1^{a}	2.0 ± 1.8^{ab}	0.9 ± 1.0^{ab}	1.4 ± 1.3^{ab}	0.7 ± 0.7^{b}
S2	3.1 ± 2.6^{ab}	1.8 ± 1.3^{b}	4.6 ± 2.6^{a}	2.4 ± 2.3^{ab}	2.5 ± 2.2^{ab}	3.0 ± 2.5^{ab}
S3	2.9 ± 2.0^{a}	3.1 ± 1.7^{a}	3.4 ± 2.5^{a}	4.6 ± 2.8^{a}	4.8 ± 2.9^{a}	3.7 ± 3.5^{a}
S4	1.9 ± 1.5^{c}	1.9 ± 1.8^{c}	4.7 ± 2.3^{b}	6.7 ± 2.5^{ab}	7.3 ± 1.9^{a}	7.3 ± 2.9^{a}
S5	2.9 ± 1.2^{ab}	3.6 ± 2.1^{a}	1.4 ± 1.1^{b}	1.3 ± 1.3^{b}	2.2 ± 2.8^{ab}	1.1 ± 1.3^{b}
S6	5.4 ± 2.7^{ab}	5.3 ± 2.7^{ab}	6.3 ± 2.7^{a}	3.6 ± 2.7^{ab}	3.6 ± 3.2^{ab}	2.5 ± 2.9^{b}
S7	2.8 ± 2.1^{b}	3.4 ± 2.8^{b}	3.5 ± 2.4^{b}	6.4 ± 1.7^{a}	7.4 ± 1.5^{a}	5.0 ± 3.3^{ab}

Different letters (a–c) in the same column indicate significant differences ($p < .05$) among the samples.

Table 5 Feature values calculated from the measurement data, as reflected in the averages of the value of hardness, brittleness, springiness, moisture, and oil of coating. The sum of variance, the partial sum of variance, and variance of hardness are calculated from five measurement data for each sample.

Sample	Hardness N	Brittleness N	Springiness	Moisture of coating %	Oil of coating %	Sum of variance	Partial sum of variance	Variance of hardness
S1	3.05±0.29[a]	0.19±0.21[a]	0.78±0.17[a]	28.4	20.8	0.37	0.12	0.08
S2	3.24±0.42[a]	0.25±0.17[a]	0.83±0.18[a]	23.2	21.6	0.52	0.20	0.17
S3	3.92±0.32[ab]	0.19±0.09[a]	0.94±0.18[a]	22.9	20.4	0.82	0.21	0.10
S4	4.68±1.13[b]	0.30±0.10[a]	0.89±0.27[a]	16.6	30.9	2.26	0.70	1.27
S5	4.15±0.49[ab]	0.26±0.13[a]	0.86±0.15[a]	22.3	30.7	0.75	0.24	0.24
S6	3.60±0.52[ab]	0.23±0.11[a]	0.87±0.28[a]	21.2	27.8	1.57	0.41	0.27
S7	4.67±1.03[b]	1.51±1.20[b]	1.83±1.72[a]	22.7	27.6	4.30	2.01	1.06

Different letters (a, b) in the columns of hardness and brittleness indicate significant differences ($p < .05$) among the samples.

Table 6 Correlation coefficients among the feature values.

Feature value	Hardness	Brittleness	Springiness	Sum of variance	Partial sum of variance	Variance of hardness
Hardness	1.00	0.41	0.12	0.56	0.50	0.61
Brittleness		1.00	0.68	0.66	0.71	0.44
Springiness			1.00	0.44	0.47	0.28
Sum of variance				1.00	0.98	0.83
Partial sum of variance					1.00	0.75
Variance of hardness						1.00

Table 7 Root mean squared errors between the sensory evaluation values and the estimated values.

Condition	*Saku-saku*	*Sakut*	*Zaku-zaku*	*Kari-kari*	*Karit*	*Gari-gari*
Common	1.03	1.17	1.63	1.50	1.40	1.66
Sum of variance	1.03	1.17	1.47	0.85	0.70	1.13
Partial sum of variance	1.10	1.28	1.59	1.09	0.92	1.37
Variance of hardness	1.04	1.16	1.58	1.38	1.28	1.36

Table 8　AICs in the four conditions for six texture words.

Condition	*Saku-saku*	*Sakut*	*Zaku-zaku*	*Kari-kari*	*Karit*	*Gari-gari*
Common	107	115	140	145	144	148
Sum of variance	106	114	139	121	112	114
Partial sum of variance	109	117	138	122	114	138
Variance of hardness	110	118	141	133	126	143

Table 9 Standardized partial regression coefficients determined by multiple linear regression.

Condition	*Saku-saku*	*Sakut*	*Zaku-zaku*	*Kari-kari*	*Karit*	*Gari-gari*
Common						
Hardness	-0.26	-0.04	0.07	0.55	0.57	0.56
Brittleness	0.04	0.20	-0.07	0.13	0.12	0.04
Springiness	-0.03	-0.11	0.05	0.10	0.14	0.04
Sum of variance						
Hardness	-0.25	-0.05	-0.28	0.07	0.11	0.10
Brittleness	0.00	0.16	-0.13	0.09	0.09	0.01
Springiness	0.01	-0.10	-0.11	-0.16	-0.12	-0.21
Sum of variance	-0.01	0.05	0.65	0.91	0.90	0.88
Partial sum of variance						
Hardness	-0.14	0.10	-0.15	0.25	0.28	0.21
Brittleness	0.01	0.18	-0.10	0.14	0.14	0.05
Springiness	-0.09	-0.21	-0.07	-0.10	-0.06	-0.10
Partial sum of variance	-0.12	-0.12	0.51	0.70	0.69	0.73
Variance of hardness						
Hardness	-0.14	0.07	-0.08	0.30	0.32	0.26
Brittleness	-0.01	0.16	-0.06	0.18	0.18	0.10
Springiness	0.04	-0.06	-0.03	-0.08	-0.05	-0.15
Variance of hardness	-0.23	-0.19	0.33	0.59	0.62	0.68