Pressure Distribution-Based Texture Sensing by Using a Simple Artificial Mastication System

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***Abstract*— This paper proposes a novel texture sensing method for nursing-care gel by using an artificial mastication system, in which not only mechanical characteristics but also geometrical ones are objectively and quantitatively evaluated. When human masticates gel food, she or he perceives the changes of the shape and contact force simultaneously. Based on the impressions, they evaluate the texture. For reproducing such a procedure, the pressure distribution of gel is measured in the simple artificial mastication, and the information associated to both the geometrical and mechanical characteristics is simultaneously acquired. The relationship between the value of sensory evaluation (i.e. impression human perceives), and the pressure distribution data is numerically modeled by applying the image texture analysis. Experimental results show that the proposed method succeeds in estimating the values of sensory evaluation of nine kinds of gel with the coefficient of determination greater than 0.93.**

I. INTRODUCTION

Nursing-care gel food for nutritional support and rehabilitation is developed for elders with oral difficulties. Such gel is soft, and can be fractured by using tongue without teeth. For nursing-care gel foods, it is desired that deliciousness coexists with safety in masticating and swallowing, from the viewpoint of quality of life [1]. The deliciousness depends not only on chemical properties such as taste or aroma, but also strongly on texture attributed to physical properties of food.

The texture can be generally categorized into the mechanical characteristics (*elasticity*, *stickiness*, *fragility*, etc.) and geometrical characteristics (*smoothness*, *granularity*, etc.) of food [2], and it is assessed by sensory evaluation by human. Therefore, it needs tremendous labor hours for collecting reliable and objective evaluation data. For achieving a more efficient and systematic evaluation, the instrumental evaluation method that quantitatively assesses the texture by physical measurement has been developed. In the texture profile analysis (TPA), the texture is evaluated based on the force response curve obtained by compression [3]. Also, there have been works applying techniques of robotics and sensing for evaluating the texture [4][5]. These works have treated to recognize the force or torque response-based texture, namely the mechanical characteristics. On the other hand, vision system and image analysis have been utilized to recognize the geometrical condition of food bolus during or after mastication [6][7]. However, there is no established instrumental method that can evaluate the geometrical characteristics of the texture associated to delicate impressions during the mastication.

This paper proposes a texture sensing method for gels by using a simple artificial mastication, in which the geometrical characteristics of texture as well as the mechanical ones can be evaluated. When human compresses and fractures a gel with tongue and palate, she or he perceives the changes of food shape and contact force simultaneously. Based on the impressions, they evaluate the texture (Fig. 1(a)). For reproducing such a basic principle artificially, the proposed texture sensing method is composed of pressure distribution measurement and image texture analysis. Using simple artificial mastication, the pressure distribution of the gel during compression and fracture is measured, so that the information associated to both the geometrical and mechanical characteristics is simultaneously acquired (Fig. 1(b)). By the image texture analysis, the relationship between the value of sensory evaluation and the pressure distribution is numerically modeled (Fig. 1(c)). The proposed modeling is verified by experiments with nine different kinds of gel and four texture terms. It is shown that the values of sensory evaluation can be appropriately estimated.

II. OUTLINE OF PROPOSED TEXTURE SENSING

Fig. 1 shows the overview of the proposed method that evaluates the texture of gel. As evaluation index of texture, value of sensory evaluation by human shown in Fig. 1(a) is utilized. Let n_i denote the value of sensory evaluation in the texture term i, e.g. *smoothness*, where n_i is defined in the range of 0–100. In preparation, the values of sensory evaluation of various kinds of gel, which are handled as the reference data, are obtained by using panelists.

We obtain the model for estimating the value of sensory evaluation of gel by the following procedure.

Pressure distribution measurement in artificial mastication: To artificially reproduce the mastication process, a simple mastication apparatus is constructed, as shown in Fig. 1(b). The part for compressing and fracturing a gel is composed of an upper plate and a base. A pressure distribution sensor is implemented in the base. The pressure distribution of the gel in the compression and fracture processes is recorded as time-series data, which can be processed as image frames. The pressure distribution data of gels with different values of sensory evaluation are collected.

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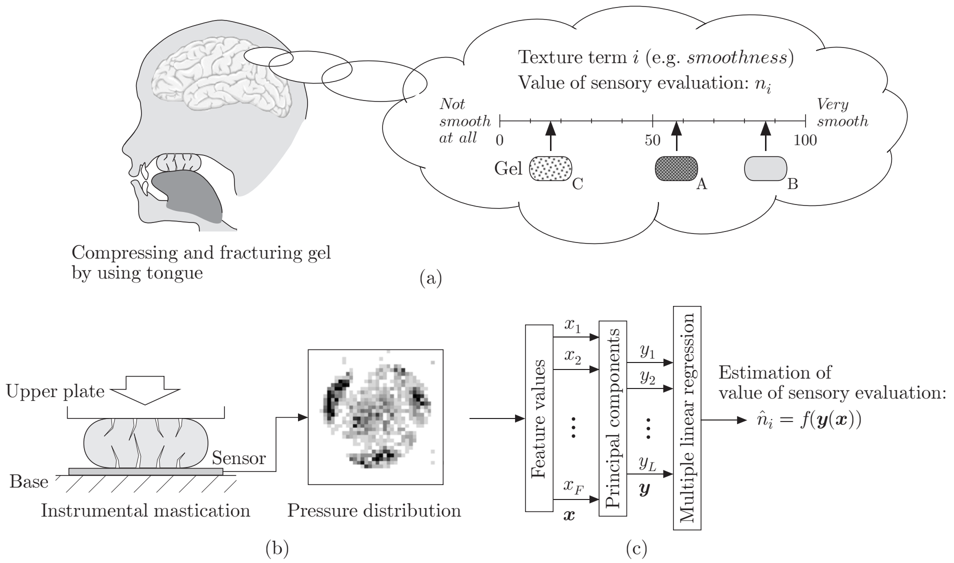

Fig. 1. The overview of the proposed method. (a) In preparation, reference values of sensory evaluation of gels are obtained from panelists. (b) The pressure distribution of the gel is measured through the artificial mastication. (c) The relationship between the pressure distribution and the value of sensory evaluation is modeled based on the image texture analysis, and the equation for estimating the value of sensory evaluation is derived.

Modeling and estimating the value of sensory evaluation by image texture analysis: The relationship between the pressure distribution and the value of sensory evaluation is modeled, as shown in Fig. 1(c). Firstly the feature vector $\boldsymbol{x}$ is extracted from the pressure distribution data by the image texture analysis of the Spatial Gray Level Dependence Method (SGLDM) [8]. Then, the principal component vector $\boldsymbol{y}$ is calculated. Finally, a multiple linear regression analysis is carried out. The equation for estimating the value of sensory evaluation $\hat{n}_i = f(\boldsymbol{y}(\boldsymbol{x}))$ is derived by constructing the multiple linear regression model, that has the principal component vector $\boldsymbol{y}$ as its predictor variable and the value of sensory evaluation n_i as its response variable. This modeling is done at each texture term i. By substituting the pressure distribution of an unknown gel in the equation for estimation, the value of sensory evaluation can be estimated.

The details of the above procedure are described from the next section, together with experimental data.

III. PRESSURE DISTRIBUTION MEASUREMENT

A. *Artificial Mastication Model*

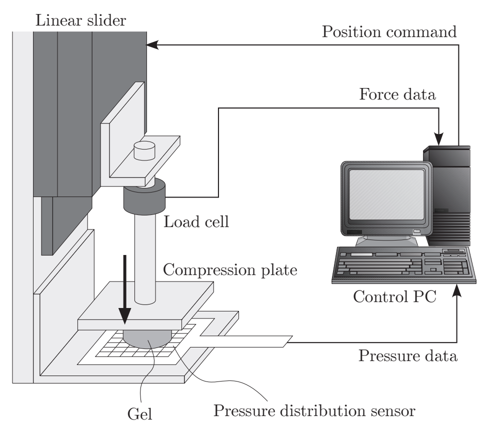

Fig. 2. Experimental setup.

Fig. 2 shows the overview of experimental system of the artificial mastication. While the upper compression plate is driven by a linear slider controlled by a PC, the lower plate is fixed at the base. Tested gels have cylindrical shape with the diameter of 20 mm and the height of 10 mm. A tested gel is compressed and fractured by moving down the upper plate. The pressure distribution sensor (I-SCAN40, Nitta Corp.: measurement range 44 mm $\times$ 44 mm, spatial resolution 1 mm, temporal resolution 10 ms, pressure resolution 0.08 kPa) is installed on the surface of the lower plate. When the gel is compressed and fractured, the pressure distribution is recorded as a time-series data. At the same time, the force response is also measured by a load cell placed between the linear slider and the upper plate. In the initial condition, the upper plate locates at the height of 10 mm from the surface of the pressure distribution sensor. For compressing the gel, the plate moves down with the distance of 9 mm at the velocity of 2 mm/s, and then stops. Considering the individual error in the height of gel and the roughness of its surface, the time of the initial contact between the upper plate and the specimen is judged by the output of the load cell.

B. *Pressure Distribution*

Fig. 3(a) shows an example of the force response measured by the load cell, when a gel is tested. In Fig. 3(a), as the plate compresses the gel, the force increases. Later, the gel begins being fractured at 2.3 s. At this moment, the force begins to decrease. The period between the initial contact and the start of fracture is defined as compression phase. After the force once decreases, it increases again until the plate stops, as the gel continues being compressed. The period between the start of the gel's fracture and the end of plate motion is defined as fracture phase.

The measured pressure values, ranged from 0 to 80 kPa, are converted into 16 levels. The converted pressure

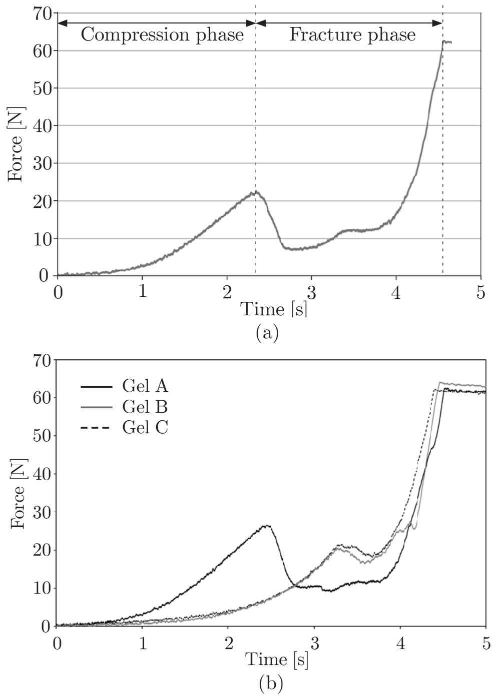

Fig. 3. Force responses of Gels A, B, and C.

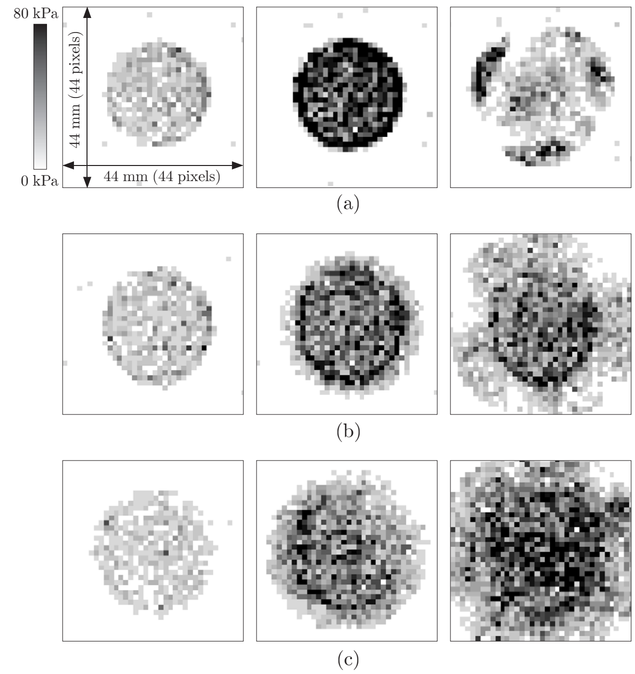

Fig. 4. Pressure distributions. (a) Gel A, (b) Gel B, and (c) Gel C. From left, initial contact, compression, and fracture.

distribution data is processed as a series of image frames with 44×44 pixel and the gray level of $N = 16$. As examples of the pressure distribution, Fig. 4(a), (b), and (c) show the images of the pressure distribution data of three different kinds of gel, Gels A, B, and C, respectively. In Fig. 4(a)-(c), characteristic frames are shown (from left, after the beginning of the compression, during the compression phase, and during the fracture phase). In each image, a pixel with darker color indicates a greater value of pressure. In each of Fig. 4(a)-(c), it can be seen that for the first one or two images from the left, the pressure of the gel increases while keeping the circular shape of the gel's bottom. After this, as shown in the third image, the gel is fractured and the differences in both geometrical and mechanical conditions are observed. By comparing Fig. 4(a)-(c), it is seen that the pressure distribution of Gel A has a clear difference from Gels B and C. However, it is difficult to tell difference between the pressure distributions of Gel B and Gel C, by visual inspection.

Fig. 3(b) shows the force responses measured by the load cell, where the solid, gray, and dotted lines show the force responses with Gels A, B, and C, respectively. From Fig. 3(b), it is seen that, based on the force responses, Gel A can be easily recognized from the other two kinds of gel. However, it is difficult to discriminate between Gel B and Gel C. In other words, it is difficult for the conventional methods depending on the force response, to make clear difference in the texture between them.

IV. MODELING AND ESTIMATION

A. Image Texture Analysis for Extracting Feature Values

The texture feature values of the image frame representing the pressure distribution are extracted by using SGLDM [8]. This method computes the statistical values based on the gray level distribution within an image, which are the space-dependent functions expressing the characteristics of image texture. A brief explanation of the method is as follows: Firstly the Gray Level Co-occurrence Matrix (GLCM) is computed from the image frame. Let $g(x, y)$ denote the gray level at pixel (x, y), while d and θ represent the scanning distance and direction, respectively. It is supposed that a pair of pixels (x_1, y_1) and (x_2, y_2) whose relative position is given by (d, θ) in the image. If their gray levels are given by $g(x_1, y_1) = p$ and $g(x_2, y_2) = q$, respectively, then the element (p, q) of GLCM $\boldsymbol{S}_{(d,\theta)}$ is incremented by 1, where $p = \{0, \dots, N-1\}$, $q = \{0, \dots, N-1\}$ and N is the number of gray levels. GLCM $\boldsymbol{S}_{(d,\theta)} \in \Re^{N \times N}$ representing the frequency of existing gray level pairs (p, q), is determined by carrying out a scanning with respect to (d, θ) for all the pixels within the image. Here, twenty GLCMs $\boldsymbol{S}_{(d,\theta)}$ are calculated for each frame, by the combinations of $d = \{1, 2, 4, 8, 16\}$ pixel and $\theta = \{0, 45, 90, 135\}°$. Each of the elements $S_{(d,\theta)}(p, q)$ of $\boldsymbol{S}_{(d,\theta)}$ are converted to the probability value $P_{(d,\theta)}(p, q)$, as follows,

$$P_{(d,\theta)}(p, q) = \frac{S_{(d,\theta)}(p, q)}{\sum_{p=0}^{N-1} \sum_{q=0}^{N-1} S_{(d,\theta)}(p, q)} \,. \tag{1}$$

By substituting the matrix $\boldsymbol{P}_{(d,\theta)} \in \Re^{N \times N}$ in (2)–(6), five feature values, energy E, entropy H, inertia I, correlation C, and local homogeneity L are calculated.

$$E(\boldsymbol{P}_{(d,\theta)}) = \sum_{p=0}^{N-1} \sum_{q=0}^{N-1} \left\{P_{(d,\theta)}(p, q)\right\}^2 \tag{2}$$

$$H(\boldsymbol{P}_{(d,\theta)}) = -\sum_{p=0}^{N-1}\sum_{q=0}^{N-1} P_{(d,\theta)}(p,q)\log P_{(d,\theta)}(p,q) \quad (3)$$

$$I(\boldsymbol{P}_{(d,\theta)}) = \sum_{p=0}^{N-1}\sum_{q=0}^{N-1} (p-q)^2 P_{(d,\theta)}(p,q) \quad (4)$$

$$C(\boldsymbol{P}_{(d,\theta)}) = \frac{\sum_{p=0}^{N-1}\sum_{q=0}^{N-1} pqP_{(d,\theta)}(p,q) - E_xE_y}{D_xD_y} \quad (5)$$

$$L(\boldsymbol{P}_{(d,\theta)}) = \sum_{p=0}^{N-1}\sum_{q=0}^{N-1} \frac{P_{(d,\theta)}(p,q)}{1+(p-q)^2}\ . \quad (6)$$

In (5), E_x, E_y, D_x, and D_y are given by

$$E_x = \sum_{p=0}^{N-1}\left\{p\sum_{q=0}^{N-1} P_{(d,\theta)}(p,q)\right\} \quad (7)$$

$$E_y = \sum_{q=0}^{N-1}\left\{q\sum_{p=0}^{N-1} P_{(d,\theta)}(p,q)\right\} \quad (8)$$

$$D_x^2 = \sum_{p=0}^{N-1}\left\{(p-E_x)^2\sum_{j=0}^{N-1} P_{(d,\theta)}(p,q)\right\} \quad (9)$$

$$D_y^2 = \sum_{q=0}^{N-1}\left\{(q-E_y)^2\sum_{i=0}^{N-1} P_{(d,\theta)}(p,q)\right\}\ . \quad (10)$$

For each frame, 5 feature values $\times$ 20 GLSMs = 100 feature values are calculated. Fig. 5 shows examples of the five feature values, (a) energy, (b) entropy, (c) inertia, (d) correlation, and (e) local homogeneity with $d = 1$ pixel and $\theta = 0°$, with respect to the frame number (the frame rate is 100 fps), where the left one is in the compression phase and the right one is in the fracture phase. The solid, gray, and dotted lines indicate Gels A, B, and C, respectively. In Fig. 5, it can be seen that the feature values change with frame number. Also, the tendency in the compression phase and that in the fracture phase are different. It is supposed that by human some texture is evaluated based on a feel in the compression phase and the other texture is done in the fracture phase. Considering the above, we calculate five statistical values, the mean, standard deviation, range, maximum, and minimum, for each phase. As a result, 100 feature values $\times$ 2 phases $\times$ 5 statistical values = 1000 feature values are calculated. Adding the number of frames in the compression phase and the number of frames in the fracture phase, finally the feature vector $\boldsymbol{x} \in \Re^F$ with the dimension of $F = 1002$, is obtained for the pressure distribution data of one gel.

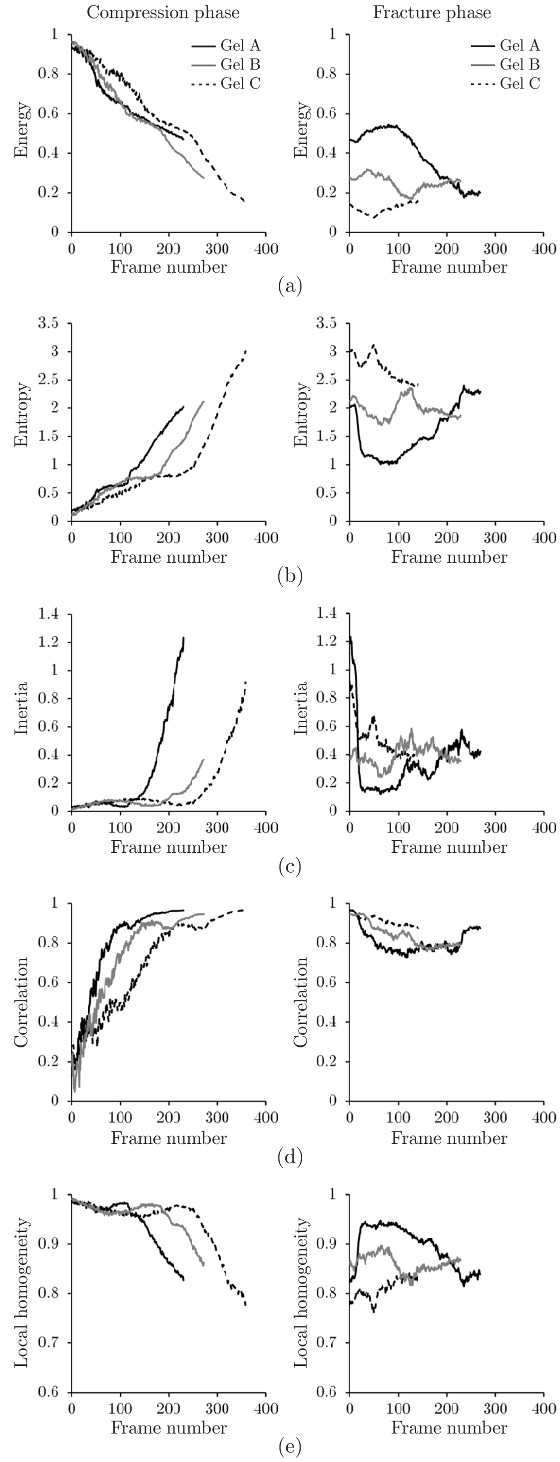

Fig. 5. Feature values with respect to frame number. (a) Energy, (b) Entropy, (c) Inertia, (d) Correlation, and (e) Local homogeneity.

B. Multiple Linear Regression Model for Estimating Value of Sensory Evaluation

In order to eliminate redundant information among feature values, the principal component analysis is carried out. Let $\boldsymbol{y}$ be the principal component vector obtained from the feature value vector $\boldsymbol{x}$. Then, the multiple linear regression model is constructed using the principal component vector $\boldsymbol{y}$ as the predictor variable and the value of sensory evaluation n_i at the texture term i as the response variable, and as a result, the equation for estimating the value of sensory evaluation is obtained. The relationship between the principal component vector $\boldsymbol{y}$ and the value of sensory evaluation n_i is obtained by the following linear regression equation

$$n_i = \boldsymbol{a}_i^{\mathrm{T}}\left[1, \boldsymbol{y}^{\mathrm{T}}\right]^{\mathrm{T}} \quad (11)$$

$$\boldsymbol{a}_i = \left[a_{i0}, a_{i1}, \ldots, a_{iL}\right]^{\mathrm{T}} \in \Re^{L+1}\ , \quad (12)$$

where a_{i0} is the constant term, and a_{il} $(l = 1, 2, \ldots, L)$ is the partial regression coefficient corresponding to each principal component. The estimated values of the constant term and the partial regression coefficients $\hat{\boldsymbol{a}}_i$ are calculated by the least squares method by using all principle component vectors $\boldsymbol{y}$ and the values of sensory evaluation n_i. Moreover, we carry out the null hypothesis test for the constant term and the partial regression coefficient $a_l = 0$. If there are partial regression coefficient with a significance level over 5%, the coefficients are given up and the multiple linear regression is carried out again. This procedure is repeated until all the partial regression coefficients and the constant term have a significance level less than 5%, then the final equation for estimating the value of sensory evaluation, $\hat{n}_i = \hat{\boldsymbol{a}}_i^{\mathrm{T}} \left[1, \boldsymbol{y}^{\mathrm{T}}\right]^{\mathrm{T}}$, is determined.

V. EXPERIMENTAL VALIDATION

A. Tested Gels and Sensory Evaluation

Nine different kinds of gel, Gels A–I, are tested. In preparation, the sensory evaluation for the gels was carried out by using eight panelists. Four texture terms, *elasticity* ($i = 1$), *stickiness* ($i = 2$), *smoothness* ($i = 3$), and *granularity* ($i = 4$) were tested. While *elasticity* and *stickiness* belong to the mechanical characteristics, *smoothness* and *granularity* are the geometrical characteristics [2]. Visual Analog Scale Method [9], as shown in Fig. 1(a), was employed. In this method, a scale with a length of 100 mm is set with a texture term description. The left end represents none and the right one indicates the maximum feel about the texture term. The panelist marks on the line the point that represents the perception of feel in masticating. The value of sensory evaluation is determined by measuring in millimetres from the left end of the line to the point that the panelist marks. The statistical results of the sensory evaluation for four texture terms are shown in the second and third columns in TABLEs I–IV. As the reference value of sensory evaluation n_i provided to the modeling process, the mean value is used as shown in the fourth column in TABLEs I–IV.

TABLE I
VALUES OF SENSORY EVALUATION n_1 AND ESTIMATED VALUES $\hat{n}_1$.

Gel	Sensory evaluation		n_1	$\hat{n}_1$	
	Mean ± S.D.	Range		Mean ± S.D.	Range
A	11.3 ± 5.1	4–18	11.3	11.1 ± 5.6	1.2–18.8
B	73.9 ± 10.3	57–86	73.9	74.9 ± 5.4	67.2–89.3
C	84.9 ± 9.0	70–95	84.9	84.7 ± 4.3	74.5–91.0
D	16.3 ± 4.3	10–23	16.3	16.6 ± 3.9	10.9–24.4
E	11.0 ± 4.1	5–16	11.0	10.8 ± 3.6	3.9–18.2
F	23.6 ± 8.9	10–34	23.6	24.0 ± 3.7	17.4–29.2
G	53.5 ± 11.4	36–76	53.5	50.5 ± 3.2	44.8–57.2
H	9.3 ± 6.3	4–22	9.3	12.0 ± 3.4	8.3–21.7
I	75.8 ± 7.8	65–88	75.8	74.9 ± 4.9	65.1–84.8

TABLE II
VALUES OF SENSORY EVALUATION n_2 AND ESTIMATED VALUES $\hat{n}_2$.

Gel	Sensory evaluation		n_2	$\hat{n}_2$	
	Mean ± S.D.	Range		Mean ± S.D.	Range
A	5.3 ± 3.8	2–11	5.3	6.9 ± 5.3	0–18.3
B	57.5 ± 14.5	38–80	57.5	56.7 ± 5.0	50.4–70.4
C	89.1 ± 11.5	70–98	89.1	88.4 ± 3.7	81.3–95.1
D	9.1 ± 2.6	6–14	9.1	12.7 ± 3.5	3.6–18.3
E	15.1 ± 4.1	11–22	15.1	10.8 ± 3.0	4.4–16.9
F	21.8 ± 8.8	5–32	21.8	24.0 ± 4.1	16.8–31.1
G	15.4 ± 7.9	5–26	15.4	18.1 ± 3.3	12.3–24.0
H	6.5 ± 5.5	1–17	6.5	5.5 ± 2.8	0–11.5
I	83.8 ± 9.5	68–98	83.8	82.6 ± 5.7	69.5–93.9

TABLE III
VALUES OF SENSORY EVALUATION n_3 AND ESTIMATED VALUES $\hat{n}_3$.

Gel	Sensory evaluation		n_3	$\hat{n}_3$	
	Mean ± S.D.	Range		Mean ± S.D.	Range
A	62.3 ± 13.2	44–82	62.3	63.9 ± 6.8	53.4–73.8
B	83.6 ± 8.9	67–93	83.6	78.8 ± 5.5	63.2–86.4
C	13.3 ± 7.7	5–26	13.3	15.3 ± 7.1	0.8–27.9
D	78.3 ± 6.6	65–87	78.3	75.1 ± 2.6	71.9–79.4
E	71.1 ± 19.4	31–94	71.1	76.4 ± 3.4	70.5–82.4
F	74.4 ± 9.8	60–92	74.4	71.6 ± 3.1	67.1–79.0
G	62.9 ± 14.7	49–90	62.9	65.9 ± 4.4	58.1–73.9
H	77.0 ± 15.2	51–95	77.0	74.5 ± 4.3	63.3–80.9
I	40.0 ± 14.7	21–57	40.0	41.4 ± 4.1	31.4–48.9

TABLE IV
VALUES OF SENSORY EVALUATION n_4 AND ESTIMATED VALUES $\hat{n}_4$.

Gel	Sensory evaluation		n_4	$\hat{n}_4$	
	Mean ± S.D.	Range		Mean ± S.D.	Range
A	63.1 ± 16.9	26–79	63.1	63.0 ± 6.1	51.0–75.8
B	26.3 ± 12.2	9–44	26.3	28.3 ± 3.4	21.5–33.3
C	56.8 ± 12.3	36–74	56.8	56.7 ± 5.3	43.8–64.8
D	15.3 ± 6.5	4–26	15.3	21.3 ± 3.4	17.1–29.1
E	23.6 ± 7.0	16–32	23.6	20.0 ± 4.8	12.4–30.2
F	14.4 ± 7.1	5–29	14.4	17.3 ± 2.6	12.6–24.1
G	61.9 ± 9.0	50–72	61.9	60.7 ± 6.3	49.0–71.8
H	73.0 ± 12.7	57–98	73.0	69.3 ± 7.5	53.6–77.3
I	8.9 ± 6.1	2–19	8.9	7.6 ± 3.4	2.3–13.6

B. Estimation Results

The pressure distribution data of 153 specimens (= 9 kinds of gel A–I × 17 specimens each) were measured in the artificial mastication. The dimension of resultant principle component vector was $L = 25$. For *elasticity* ($i = 1$), *stickiness* ($i = 2$), *smoothness* ($i = 3$), and *granularity* ($i = 4$), the equations for estimating the values of sensory evaluation were prepared. Here, the Leave One Out Cross Validation [10] was employed. Figs. 6 and 7 show the relationships between the true values of sensory evaluation n_i and the estimated values $\hat{n}_i$ by the proposed method in *elasticity* ($i = 1$) and *stickiness* ($i = 2$), respectively. The numerical data of the estimated values $\hat{n}_i$ are shown in the fifth and sixth columns in TABLEs I and II. As shown in Figs. 6 and 7, the values of sensory evaluation in the nine kinds of gel were accurately estimated with the coefficient of determination of $R^2 = 0.98$, in the mechanical characteristics. In the same way, Figs. 8 and 9 show the relationships between the true values of sensory evaluation n_i and the estimated values $\hat{n}_i$ in *smoothness* ($i = 3$) and *granularity* ($i = 4$), respectively. The numerical data of the estimated values $\hat{n}_i$ are shown in TABLEs III and IV. Figs. 8 and 9 show that the proposed method appropriately estimated the values of sensory evaluation with $R^2 \geq 0.93$ in the geometrical characteristics.

In addition, Fig. 6 shows that the proposed method can discriminate Gel A from Gels B and C with the mechanical characteristics of *elasticity*. This can be also done by the conventional methods depending on the total force response, as shown in Fig. 3(b). On the other hand, Fig. 8 shows that the proposed method can completely discriminate between Gel B and Gel C by focusing on the geometrical character-

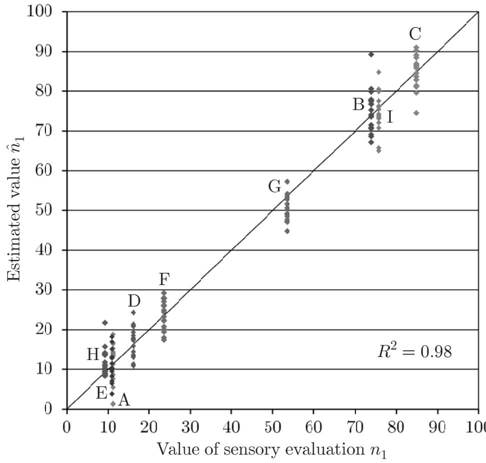

Fig. 6. Relationship between values of sensory evaluation n_1 and estimated values $\hat{n}_1$ in *elasticity* $(i = 1)$.

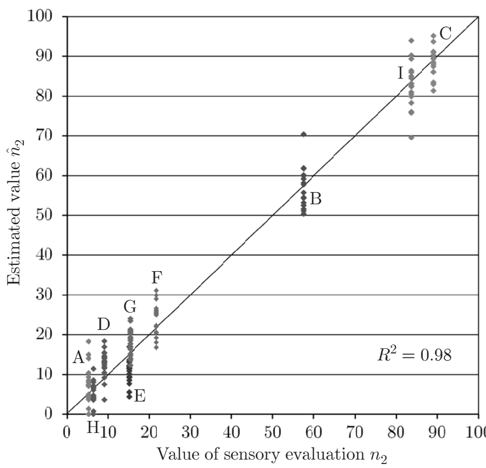

Fig. 7. Relationship between values of sensory evaluation n_2 and estimated values $\hat{n}_2$ in *stickness* $(i = 2)$.

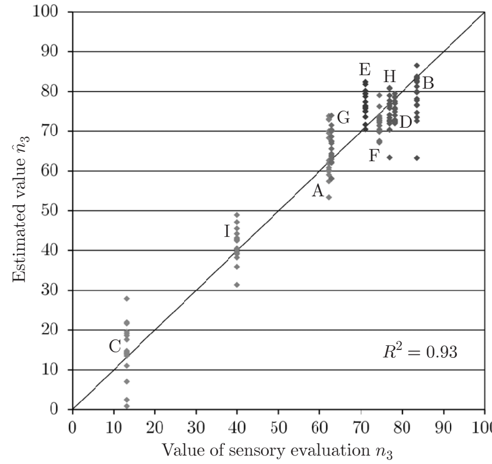

Fig. 8. Relationship between values of sensory evaluation n_3 and estimated values $\hat{n}_3$ in *smoothness* $(i = 3)$.

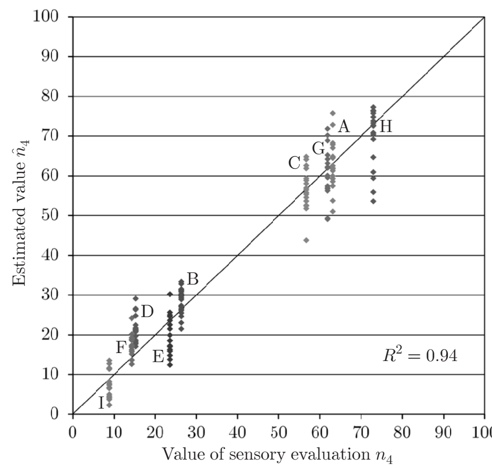

Fig. 9. Relationship between values of sensory evaluation n_4 and estimated values $\hat{n}_4$ in *granularity* $(i = 4)$.

istics of *smoothness*. Since their force responses are similar to each other, the difference between Gel B and Gel C is not easy to be observed by conventional methods. This result strongly supports the advantage of the proposed method.

VI. CONCLUSION

This paper proposed the texture sensing method for gels by using the simple artificial mastication system. The relationship between the value of sensory evaluation and the pressure distribution of gel during mastication was modeled. In experiments, the values of sensory evaluation in the geometrical characteristics as well as the mechanical ones were accurately estimated. The proposed method can contribute to developing new nursing-care gels, by evaluating texture of gel with new material and/or composition. In the future, the components of the proposed method should be investigated, for example, periodic masticating motion, time-dependent feature value, and non-linear modeling.

REFERENCES

[1] K. Nishinari: "Texture and Rheology in Food and Health. Food Science and Technology Research," vol.15, pp.99–106, 2009.
[2] A.S. Szczesniak: "Texture is a Sensory Property," Food Quality and Preference, vol.13, pp.215–225, 2002.
[3] M.C. Bourne: "Food Texture and Viscosity, Second Edition: Concept and Measurement," Academic Press, 2002.
[4] H. Iwata, H. Yano, T. Uemura, and T. Moriya: "Food Texture Display," Proc. of the 12th Int. Symp. on Haptic Interfaces for Virtual Environment and Teleoperator Systems, pp.310–315, 2004.
[5] W.L. Xu, J.D. Torrance, B.Q. Chen, J. Potgieter, J.E. Bronlund, J.-S. Pap: "Kinematics and Experiments of a Life-Sized Masticatory Robot for Characterizing Food Texture," IEEE Trans. on Industrial Electronics, Vol.55, Issue 5, pp.2121–2132, 2008.
[6] H. Dan, T. Azuma, and K. Kohyama: "Characterization of Spatiotemporal Stress Distribution During Food Fracture by Image Texture Analysis Methods," Journal of Food Engineering, vol.81, no.4, pp.429–436, 2007.
[7] C. Tournier, M. Grass, D. Zope, C. Salles, and D. Bertrand: "Characterization of Bread Breakdown During Mastication by Image Texture Analysis," Journal of Food Engineering, vol.113, no.4, pp.615–622, 2012.
[8] R.M. Haralick, K. Shanmugam, and I. Dinstein: "Textural Features for Image Classification," IEEE Trans. on Systems, Man and Cybernetics, vol.SMC-3, no.6, pp.610–621, 1973.
[9] M.E. Wewers and N.K. Lowe: "A Critical Review of Visual Analogue Scales in the Measurement of Clinical Phenomena," Research in Nursing and Health, vol.13, pp.227–236, 1990.
[10] S. Arlot: "A Survey of Cross-Validation Procedures for Model Selection," Statistics Surveys, vol.4, pp.40–79, 2010.