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Food Texture Estimation Using Robotic Mastication Simulator Equipped with Teeth and Tongue

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In this paper, we propose a food texture estimation system using a robotic mastication simulator equipped with teeth and a tongue. On the basis of the human oral function, we first introduce the mastication robot with which we can measure biting force and tongue pressure simultaneously during artificial mastication. We then develop a texture estimation system that estimates the value of human sensory evaluation from feature values of measured data. Finally, we describe an experiment where textures of doughnuts are estimated. The experimental results suggest that the proposed method can accurately estimate the value of human sensory evaluation when using both the biting force and the tongue pressure.

1. Introduction

In the food industry, technologies for the quantification of deliciousness are gathering attention.(1,2) Deliciousness depends on texture based on the physical properties of food as well as chemical properties such as taste or aroma.(3,4) Human mastication includes a fracture mode in which teeth are used and a compress mode involving the tongue. A food bolus is formed by alternating the two modes. During such a process, a person evaluates the texture based on the biting force at the teeth and the pressure distribution on the tongue.(5) While objective and quantitative data of the texture are strongly required for the research and development, the sensory evaluation test by humans requires a tremendous number of labor hours. To cope with this issue, texture evaluation methods using physical quantity measurement devices have been developed. They can be categorized into two groups: the teeth type employing a rigid end effector and the tongue type employing a soft end effector. Regarding teeth-type methods, the texture analyzer(6) is a popular commercial device by which the texture is evaluated from the force response curve measured in the compression test of a food sample (texture profile analysis(7)). There have been studies on applying robotics techniques to the evaluation of the texture. Sun *et al*. developed a chewing robot that can measure the three-dimensional force during the mastication of a food sample.(8) Xu *et al*. developed a robot that reproduces the

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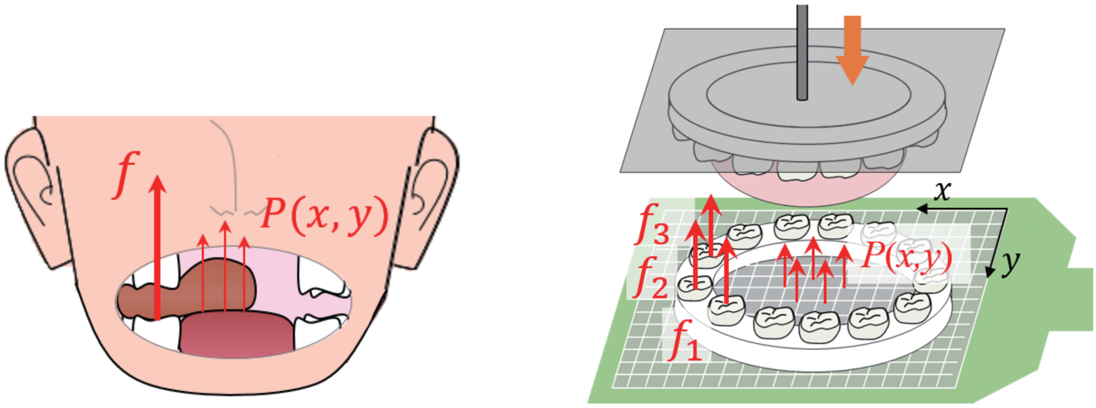
lower jaw motion and evaluated a torque of the actuator needed for chewing a food sample.(9) Meullenet and Gandhapuneni developed a robot with teeth and evaluated the stiffness of food samples from the jaw force measured in mastication.(10) Arvisenet *et al*. developed a mastication device equipped with teeth and investigated the relationship between the particle size of a crunched apple and the compression motion.(11) Nakamoto *et al*. developed a magnetic force sensor based on the structure of a tooth, whereby the high-frequency vibration of the tooth as well as the biting force can be detected.(12) On the other hand, few studies regarding tongue-type methods have been reported. Ishihara *et al*. employed an imitation tongue made of silicone in a compression test of gel-like food. They investigated the relationship between the stiffness of silicone and the fracture of the food sample.(13) Shibata *et al*. developed a texture-sensing system equipped with an imitation tongue with a variable elasticity mechanism. The tongue pressure distribution is used to estimate the texture of gel-like food.(14) Furthermore, Salles *et al*. developed a mastication device equipped with both teeth and tongue to evaluate fragrance generated in the chewing process.(15) However, the tongue was made of hard synthetic resin and had no soft tongue function. As far as we know, there have been no mastication devices employing both imitation teeth and tongue for evaluating delicate food texture.

We propose a texture estimation system using a robotic mastication simulator equipped with both imitation teeth and tongue. From the biting force and tongue pressure, the system estimates the value of human sensory evaluation of texture. By abstracting the human oral function, we first design an end effector of the robotic simulator, including rigid teeth and a soft tongue. With a pressure distribution sensor, the biting force at the teeth and the pressure distribution at the tongue can be simultaneously measured during artificial mastication. We then propose the texture estimation system in which the value of human sensory evaluation is estimated from feature values extracted from the biting force and tongue pressure. Finally, we describe an experiment where the textures of six types of doughnut are accurately estimated using the proposed system. The experimental result suggests the superiority of the proposed system capable of measuring both the biting force and the tongue pressure.

This paper is organized as follows. In Sect. 2, the basic concept of the mastication robot is shown. In Sect. 3, an overview of the texture estimation system is explained. In Sects. 4 and 5, the experimental method and results are described, respectively. Finally, in Sect. 6, the conclusions of this work are described.

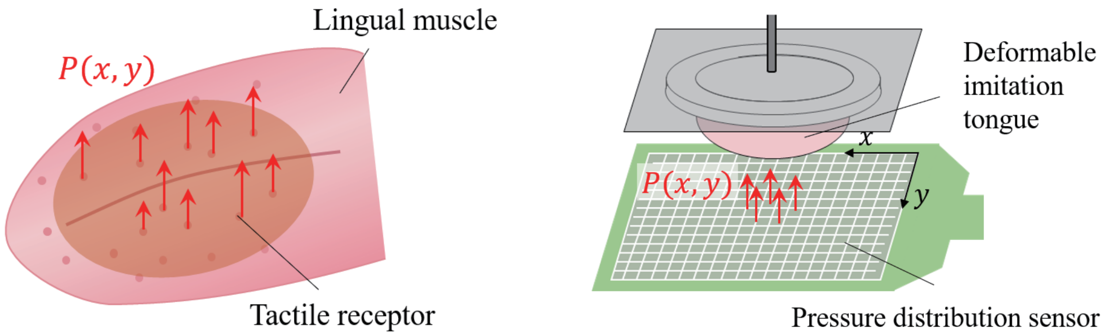
2. Basic Concept of Mastication Robot with Both Teeth and Tongue

In this section, the basic concept of the proposed mastication robot is described by focusing on its end effector. Humans perceive the biting force at a tooth and the pressure distribution on the tongue simultaneously, as shown in Fig. 1(a). To reproduce this human function, we adopt the concept of a mastication robot equipped with both imitation teeth and a tongue, as shown in Fig. 1(b). Figure 2(a) shows a simplified structure of the human tongue, which is mainly made of muscle and can be regarded as an elastic body. Humans perceive interaction between such an elastic body and a food bolus by sensing the pressure distribution through tactile receptors on



(a) (b)

Fig. 1. (Color online) Basic concept of the proposed approach. (a) Human oral processing. (b) End effector of the mastication robot equipped with imitation teeth and tongue.



(a) (b)

Fig. 2. (Color online) Sensing of tongue pressure distribution.

the tongue. To reproduce such characteristics of the human tongue, we adopt a combination of an elastic imitation tongue and a pressure distribution sensor, as shown in Fig. 2(b), which were introduced in our previous work.(14) On the other hand, Fig. 3(a) shows a simplified structure of a human tooth, which consists of a rigid enamel body, a rigid alveolar bone, and a thin and soft periodontal membrane. When biting a bolus, the periodontal membrane is elastically deformed, and humans perceive an interaction between the tooth and the bolus by sensing the biting force via tactile receptors in the periodontal membrane. To reproduce such characteristics of the human tooth, we introduce a tooth button composed of a rigid imitation tooth, an elastic body, rigid walls, and a base, as shown in the upper part of Fig. 3(b). The aforementioned pressure distribution sensor is used as a tactile receptor. When a biting force acts on the tooth button, the imitation tooth moves downward slightly and the resultant pressure is measured by the sensor. Multiple tooth buttons are arranged on the sensor, as shown in the lower part of Fig. 3(b). By computing pressure values corresponding to the respective tooth button, we can acquire the

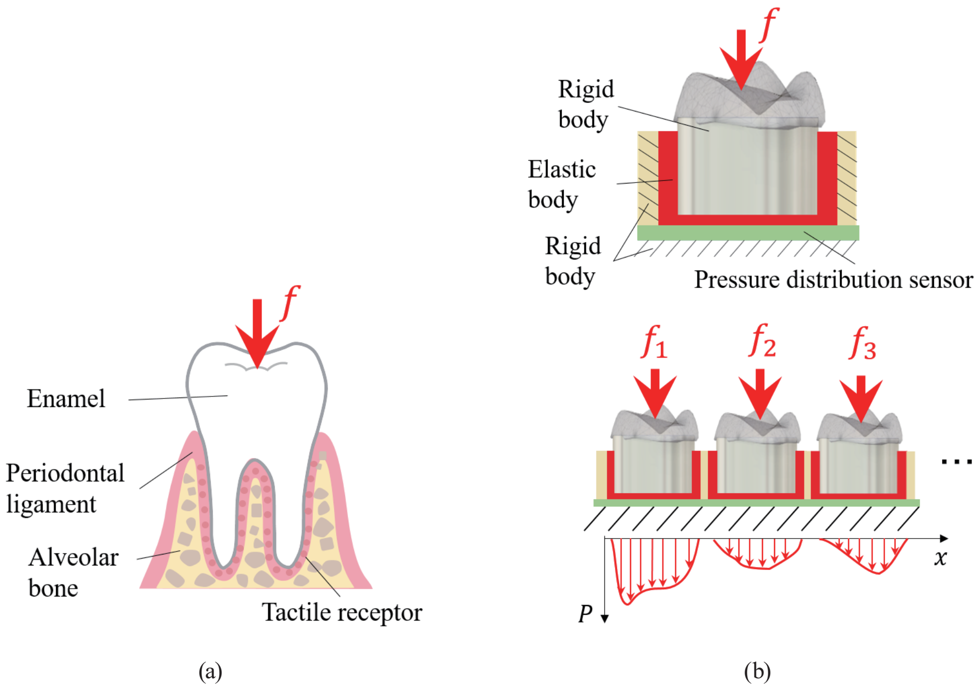


Fig. 3. (Color online) Sensing of biting force.

biting force acting on each tooth button. The above imitation oral function is integrated as shown in Fig. 1(b). The tooth buttons and pressure distribution sensor are installed in the lower jaw. The tongue is installed in the upper jaw. In addition, fixed imitation teeth without the sensing function are installed in the upper jaw. Artificial mastication is performed by controlling the upward and downward motions of the upper jaw. The biting force f_k and tongue pressure distribution $P(x, y)$ are simultaneously measured via the pressure distribution sensor.

3. Overview of Texture Estimation System

Here, we describe the texture estimation system using the mastication robot shown in the previous section. In the system, the value of sensory evaluation by humans is estimated from the biting force and tongue pressure distribution measured during artificial mastication. Figure 4 shows an outline of the proposed system, which consists of three components.

Preparation of value of sensory evaluation: The values of human sensory evaluation of various types of target food, which are used as teaching data, are obtained from panelists, as shown in Fig. 4(a). Let n_i denote the value of the sensory evaluation of texture i [e.g., *crispiness* (i = 1), *crumbliness* (i = 2)].

Artificial mastication and force/pressure measurement: A food sample is compressed and fractured by the end effector of the mastication robot described in the previous section, as shown in Fig. 4(b). The biting force and tongue pressure distribution are recorded as time-series data.

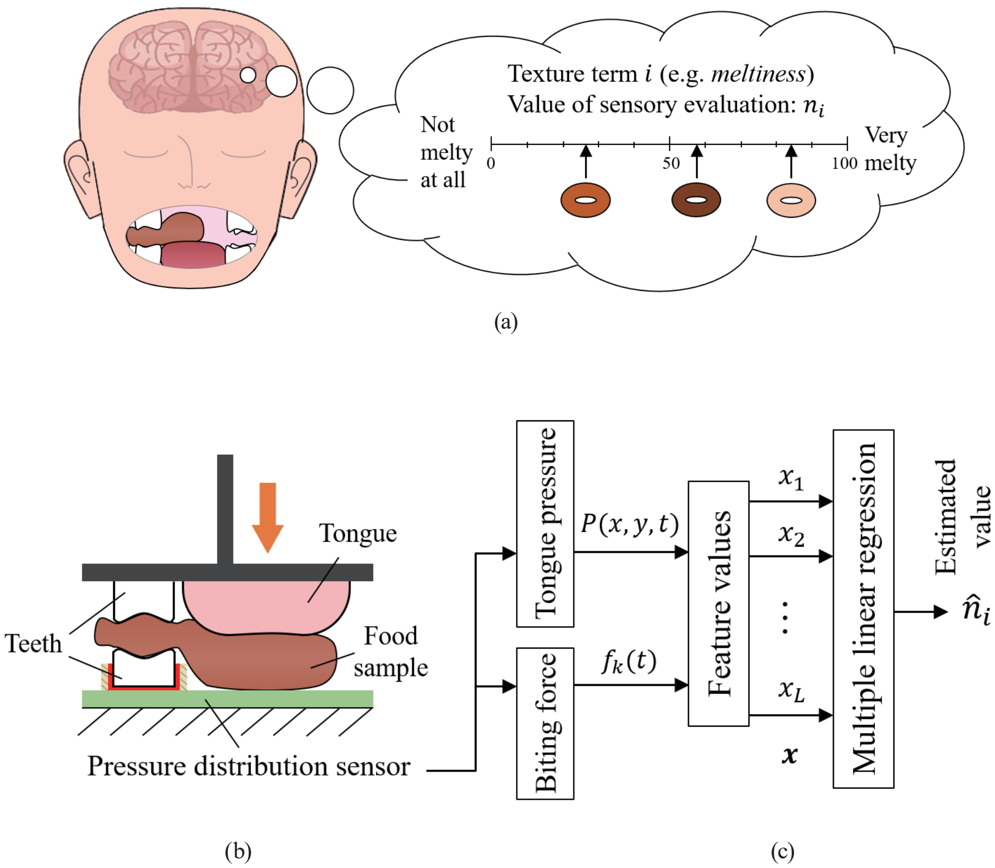


Fig. 4. (Color online) Outline of texture estimation system. (a) Preparation of value of sensory evaluation. (b) Artifical mastication and force/pressure measurement. (c) Texture estimation processing.

Texture estimation processing: As shown in Fig. 4(c), the relationship between the measured data and the value of sensory evaluation is mathematically modeled. First, feature vector $\boldsymbol{x} = [x_1, \cdots, x_L]^{\mathrm{T}}$ is extracted from the biting force and tongue pressure distribution. Next, the equation for estimating the value of sensory evaluation, $\hat{n}_i = F(\boldsymbol{x})$, is derived via multiple linear regression analysis with the feature vector $\boldsymbol{x}$ as its predictor variable and the value of sensory evaluation, $\hat{n}_i$, as its response variable. By substituting the feature vector of an unknown food sample into the obtained equation, we can estimate the value of sensory evaluation.

4. Materials and Methods

4.1 Food samples and sensory evaluation

Six different types of commercially available old-fashioned doughnut, A–F, were tested. Four texture terms, *crispiness* (i = 1), *crumbliness* (i = 2), *gooeyness* (i = 3), and *meltiness* (i = 4), were considered. *Crispiness* is the impression that the bolus touches the teeth. *Crumbliness* is the impression that the bolus collapses. *Gooeyness* is the impression that the bolus clings to the mouth. *Meltiness* is the impression that the bolus mixes with saliva and quickly disappears from the mouth. We chose them as representative texture terms for evaluating doughnuts. Five trained panelists participated in this experiment. A sensory evaluation test based on the descriptive analysis (DA) [16] was carried out. In this method, panelists eat a mouthful of the food sample and evaluate it for each texture term. The mean values from the panelists were used as the teaching data n_i for the modeling process. Table 1 shows n_i ($0 \le n_i \le 100$) for doughnuts A–F. Note that, in human mastication, the state of the food bolus changes as mastication proceeds. Taking the change into account, we divided the human mastication process into four periods: preparation period ($0 \le t \le 5$ s), mastication period I ($5 \le t \le 20$ s), mastication period II ($20 \le t \le 35$ s), and mastication period III ($35 \le t \le 50$ s). In this experiment, we used artificial food boluses I–III (Bolus I–III), which reproduced the state of the bolus during mastication periods I–III, respectively. They were produced as follows. Bolus I was prepared by cutting a doughnut into 8.0 g pieces, which is one mouthful. Bolus II was prepared by adding 1.2 ml water to Bolus I, chopping for 0.5 s in a food processor (Crush Millser, Iwatani Corp., Japan), and forming it into a ball. Bolus III was prepared by adding 1.2 ml water to Bolus II, chopping for 0.5 s in the food processor, and forming it into a ball. Figure 5 shows Boluses I, II, and III of six types of doughnut.

4.2 Experimental setup

4.2.1 Experimental system

Figure 6(a) shows the prototype of the developed end effector. Figure 6(b) shows the overview of the experimental system. The lower jaw has three tooth buttons made of ABS plastic. The tooth has the 3D shape of the left mandibular first molar.[17] Each tooth is inserted into a hole of the ring-shaped bone part, and elastic adhesive is used as the elastic mediating element between them. A rubber sheet is attached as the elastic mediating element at the

Table 1
Values of sensory evaluation.

	n_1	n_2	n_3	n_4
A	56.2	65.9	30.3	64.0
B	62.0	67.6	21.5	65.3
C	37.5	50.2	5.25	52.1
D	70.4	53.1	27.7	42.7
E	24.2	35.5	71.8	25.5
F	68.5	61.9	2.45	71.7
Mean	53.1	55.7	38.1	53.6
S.D.	16.9	11.0	18.1	15.7

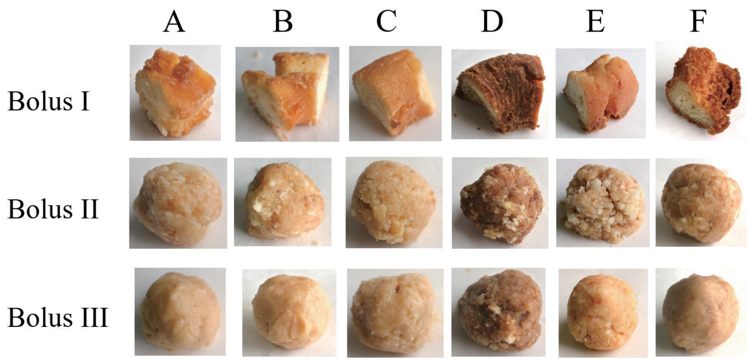
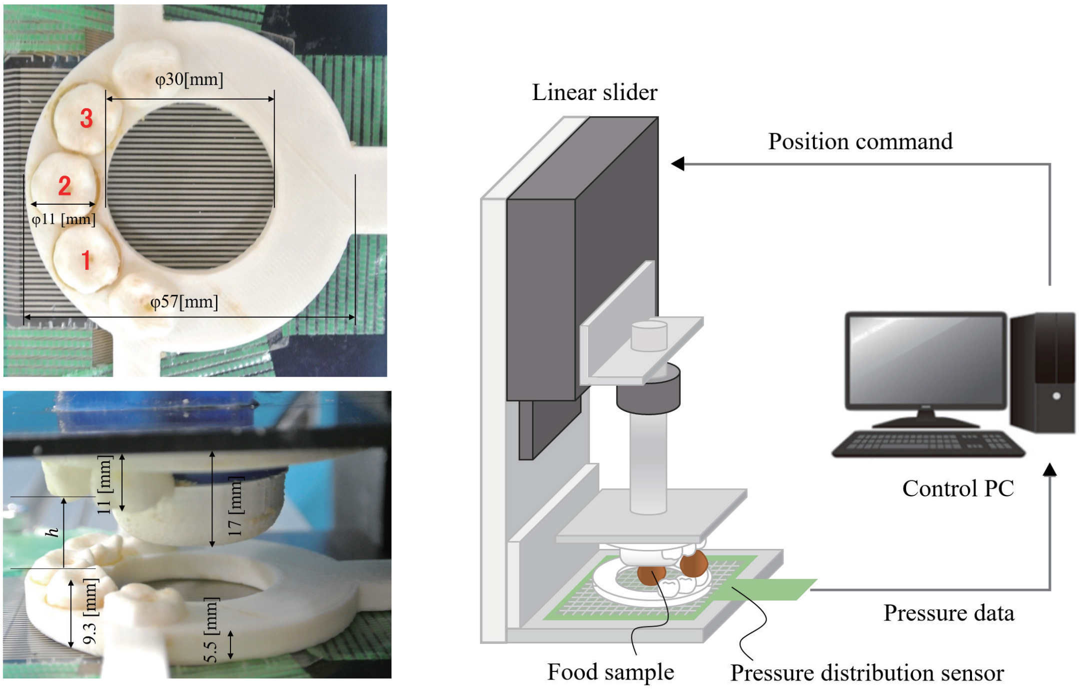


Fig. 5. (Color online) Artificial boluses.



(a) (b)

Fig. 6. (Color online) Experimental system. (a) Prototype of end effector. (b) Overview of the system.

bottom of the tooth. A pressure distribution sensor (I-SCAN40, Nitta Corp.; measurement area 44 × 44 mm², spatial resolution 1 mm, and temporal resolution 10 ms) is installed between the surface of the rigid base and the tooth buttons. The end effector has three tooth buttons 1–3. The biting force of the k-th tooth (k = 1, 2, 3) is measured by the following procedure. First, the integrated value of the pressure corresponding to tooth k is computed as

$$f_{k0} = \sum_{m=1}^{M_k} A_C P_{km}, \tag{1}$$

where A_C = 1 mm^2 is the area of a single cell of the pressure distribution sensor and P_{km} (m = 1, ..., M_k) is the pressure value of the m-th cell in contact with the bottom of tooth k (M_k is the number of corresponding cells). Since the biting force is partially dissipated via the elastic element of the side of the tooth, f_{k0} is smaller than the actual biting force. Therefore, we computed the biting force f_k as

$$f_k = b_{k1} f_{k0}^2 + b_{k2} f_{k0}. \tag{2}$$

Table 2 shows the values of coefficient parameters b_{k1} and b_{k2} for each tooth. They were obtained from a calibration experiment. The inside area of the ring-shaped bone is where the

Table 2
Coefficients of calibration.

Tooth k	b_{k1}	b_{k2}
1	0.028	2.4
2	0.035	2.5
3	0.019	2.1

tongue pressure distribution $P(x, y)$ is measured. As time series data, the biting force $f_k(t)$ and tongue pressure distribution $P(x, y, t)$ are recorded in a PC. In the lower jaw, two fixed teeth are additionally installed. The upper jaw has five fixed teeth and a silicone tongue (Young's modulus $E = 3.7 \times 10^5$ Pa) attached to a linear slider so that the position can be controlled by the PC. The position is measured with a linear encoder.

4.2.2 Artificial mastication

An artificial bolus was divided into two parts: one part was respectively placed at the center of tooth 2 and the other at the center of the tongue pressure measurement area. Considering the human mastication motion, a sinusoidal-based position trajectory was employed for the linear slider as:

$$h(t) = \alpha\left(1 + \cos 2\pi f t\right) + h_0, \tag{3}$$

where h is the distance between the upper and lower teeth, α is the amplitude, f is the frequency, and h_0 is the offset value. In this experiment, $f = 1$ Hz, $\alpha = 15$ mm $[0 \le t \le 1/(2f)]$ and 5 mm $[1/(2f) \le t \le T_s]$, and $h_0 = 0.3$ mm were given. The time for masticating a bolus was $T_S = 10$ s, and the biting force and tongue pressure distribution during this period were measured. In this experiment, the artificial mastication was carried out for fifteen samples for each of the six types of doughnuts, namely, the total number of samples was $N = 90$. The total biting force of the three teeth was given as

$$f_B(t) = \sum_k f_k(t). \tag{4}$$

Hereafter, we simply refer to f_B as the biting force and it was used for texture estimation. Furthermore, the tongue force given as

$$f_T(t) = \sum_x \sum_y A_C P(x, y, t) \tag{5}$$

was computed and used for texture estimation. Figure 7(a) shows the distance between the upper and lower teeth, h, while Fig. 7(b) shows examples of the biting force f_B and tongue force $f_T(t)$. As shown in Fig. 7(a), the actual trajectory did not follow the reference trajectory at approximately $h = 0$ mm because of the performance of the linear slider (maximum force: 82 N).

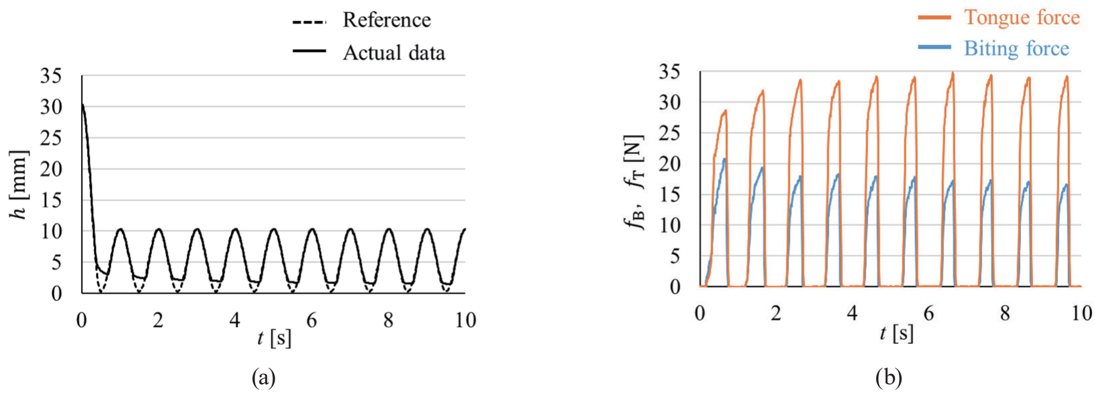


Fig. 7. (Color online) Example of experimental data. (a) Distance between the upper and lower teeth. (b) Biting force and tongue force.

As shown in Fig. 7(b), the biting force and tongue force changed during the mastication process. Note that, when the sensor sheet was not pressed by the tooth button, the sensor sheet output an invalid value because of slight floating and bending. On the basis of the position and moving direction of the upper jaw, we removed the above invalid values from output waves.

4.3 Texture estimation

4.3.1 Feature values

From the biting force, tongue force, and tongue pressure distribution, we extracted feature values for texture estimation. With respect to the biting force, three feature values were defined as

$$x_1 = f_{B1},\ x_2 = \frac{f_{B2}}{f_{B1}},\ x_3 = \frac{f_{B10}}{f_{B1}}, \tag{6}$$

where f_{Bu} denotes the maximum biting force in the u-th stroke. With respect to the tongue pressure distribution, seven feature values were defined as

$$\begin{gathered} x_4 = f_{T1},\ x_5 = \frac{f_{T2}}{f_{T1}},\ x_6 = \frac{f_{T10}}{f_{T1}}, \\ x_7 = A_1,\ x_8 = \frac{A_{10}}{A_1},\ x_9 = S_1,\ x_{10} = \frac{S_{10}}{S_1}, \end{gathered} \tag{7}$$

where f_{Tu} denotes the maximum tongue force in the u-th stroke. A_u and S_u denote the area of cells where pressure was detected and the standard deviation of pressure values, respectively, at the time of occurrence of f_{Tu}.

Bolus I–III were produced from one sample of doughnut and artificially masticated by the robot. From the measured data of Bolus I, ten feature values $x_1^{\mathrm{I}}, \ldots, x_{10}^{\mathrm{I}}$ were obtained. In the same way, $x_1^{\mathrm{II}}, \ldots, x_{10}^{\mathrm{II}}$ and $x_1^{\mathrm{III}}, \ldots, x_{10}^{\mathrm{III}}$ were obtained from the measured data of Bolus II and Bolus III, respectively. Therefore, thirty feature values were obtained from one sample of doughnut.

4.3.2 Multiple regression model

For each texture term i (i = 1–4), the equation for estimating the value of human sensory evaluation was derived by constructing a multiple linear regression model wherein the feature values $x_1^{\mathrm{I}} - x_{10}^{\mathrm{I}}$, $x_1^{\mathrm{II}} - x_{10}^{\mathrm{II}}$, and $x_1^{\mathrm{III}} - x_{10}^{\mathrm{III}}$ are the predictor variables and the value of sensory evaluation n_i is the response variable. The equation for estimation is

$$\hat{n}_i = a_{i0} + a_{i1}^{\mathrm{I}} x_1^{\mathrm{I}} + \cdots + a_{i10}^{\mathrm{I}} x_{10}^{\mathrm{I}} + a_{i1}^{\mathrm{II}} x_1^{\mathrm{II}} + \cdots + a_{i10}^{\mathrm{II}} x_{10}^{\mathrm{II}} + a_{i1}^{\mathrm{III}} x_1^{\mathrm{III}} + \cdots + a_{i10}^{\mathrm{III}} x_{10}^{\mathrm{III}}, \tag{8}$$

where a_{i0} is a constant and $a_{i1}^{\mathrm{I}}, \ldots, a_{i10}^{\mathrm{III}}$ are partial regression coefficients. We tested for the null hypothesis for the partial regression coefficient a_{il}^{j} = 0 (j = I, II, III, l = 1, ..., 10). When there was any partial regression coefficient with a significance greater than 5%, the feature value with the highest significance was removed, and then the multiple regression model was derived again. This procedure was repeated until all the partial regression coefficients have a significance less than 5%. Furthermore, we employed the leave-one-out cross validation(18) to confirm the validity of the modeling method.

5. Results and Discussion

5.1 Biting force and tongue pressure distribution

Figures 8(a) and 8(b) show the biting force and tongue force, respectively, for doughnuts A–F and Boluses I–III, respectively. Note that the average force of fifteen samples for each type of doughnut is shown. From Fig. 8, we can see that the temporal changes in the biting and tongue forces varied depending on the type of doughnut. Bolus II and Bolus III had high liquidity, because they were made with fragments of the food sample and water. They were spread and lower biting force and tongue force than Bolus I through the mastication process. Therefore, the biting force and tongue force were detected only when the distance between the upper and lower teeth was small. Thus, Bolus II and Bolus III exhibited narrower waves than Bolus I. Figure 9 shows the tongue pressure distribution for Bolus I (from the left: pressure distribution images at the first, second, and tenth strokes). From Fig. 9, we can see the difference in tongue pressure distribution depending on the type of doughnut.

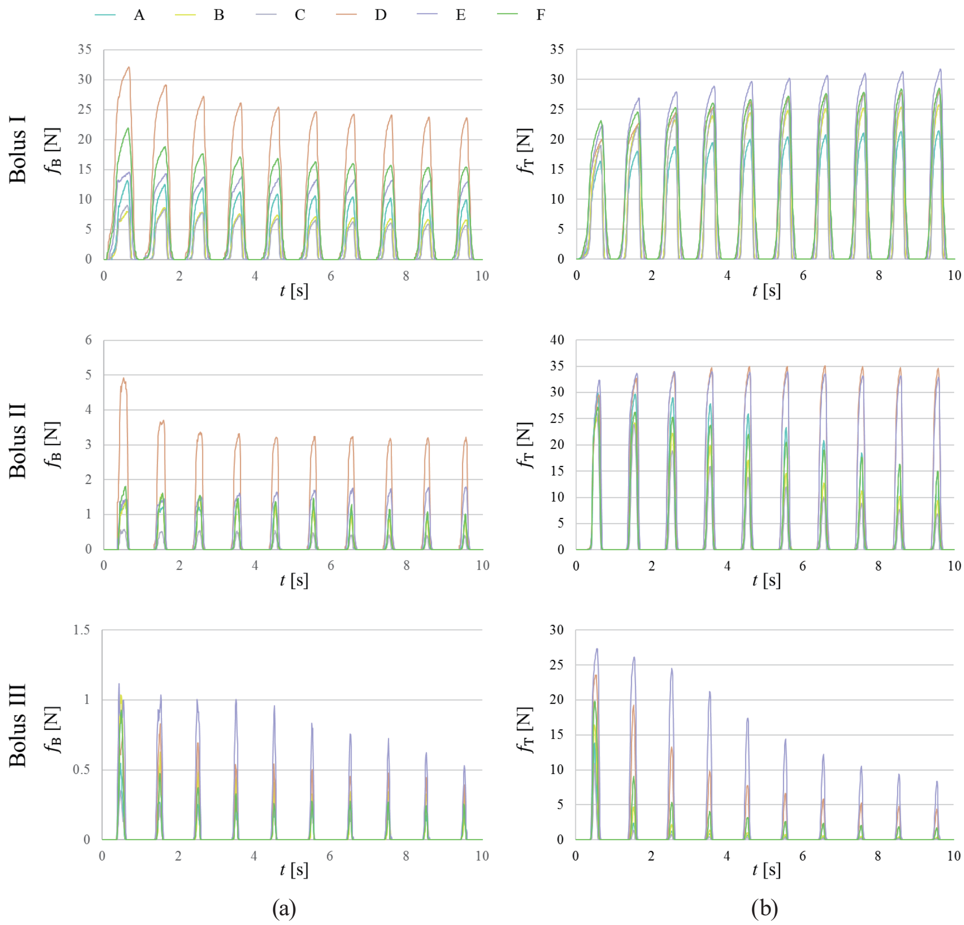


Fig. 8. (Color online) Experimental results. (a) Biting force. (b) Tongue force.

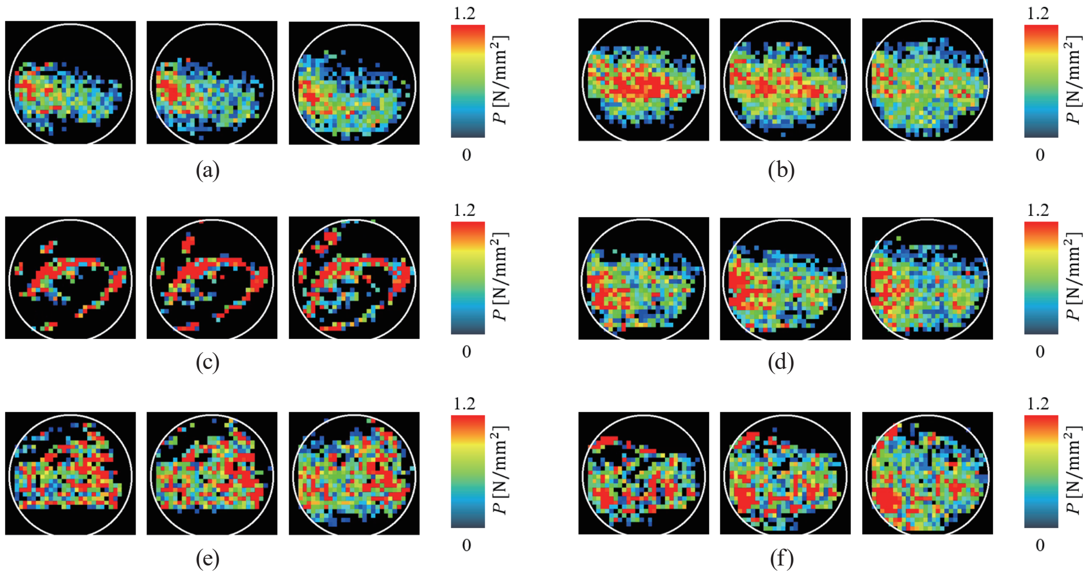


Fig. 9. (Color online) Tongue pressure distribution for Bolus I of doughnuts (a) A, (b) B, (c) C, (d) D, (e) E, and (f) F.

5.2 Texture estimation

Figure 10 shows the texture estimation results for the relationship between the value of human sensory evaluation, n_i, and the value estimated by the proposed system, $\hat{n}_i$. The accuracy of the texture estimation is evaluated from the coefficient of determination, R^2, and the root mean square error (RMSE). From Fig. 10, we can see variation in fifteen estimated values for each type of doughnut ($0.56 \le R^2 \le 0.70$ and $RMSE \le 11.8$). This is presumed to be caused by individual differences and measurement error. However, the average value of the fifteen estimated values, shown by squares, is highly accurate ($0.87 \le R^2 \le 0.92$ and $RMSE \le 6.3$). This suggests that at least fifteen samples are needed to appropriately evaluate the texture using the proposed system. To confirm the effectiveness of the proposed system, the texture estimations using only biting force data or only tongue pressure distribution data were also conducted. Figure 11 shows the coefficients of determination of the estimation models for four texture terms. For all texture terms, the coefficient of determination for the estimation model using both the biting force and the tongue pressure is the largest. This result confirms the validity of the proposed system equipped with teeth and tongue.

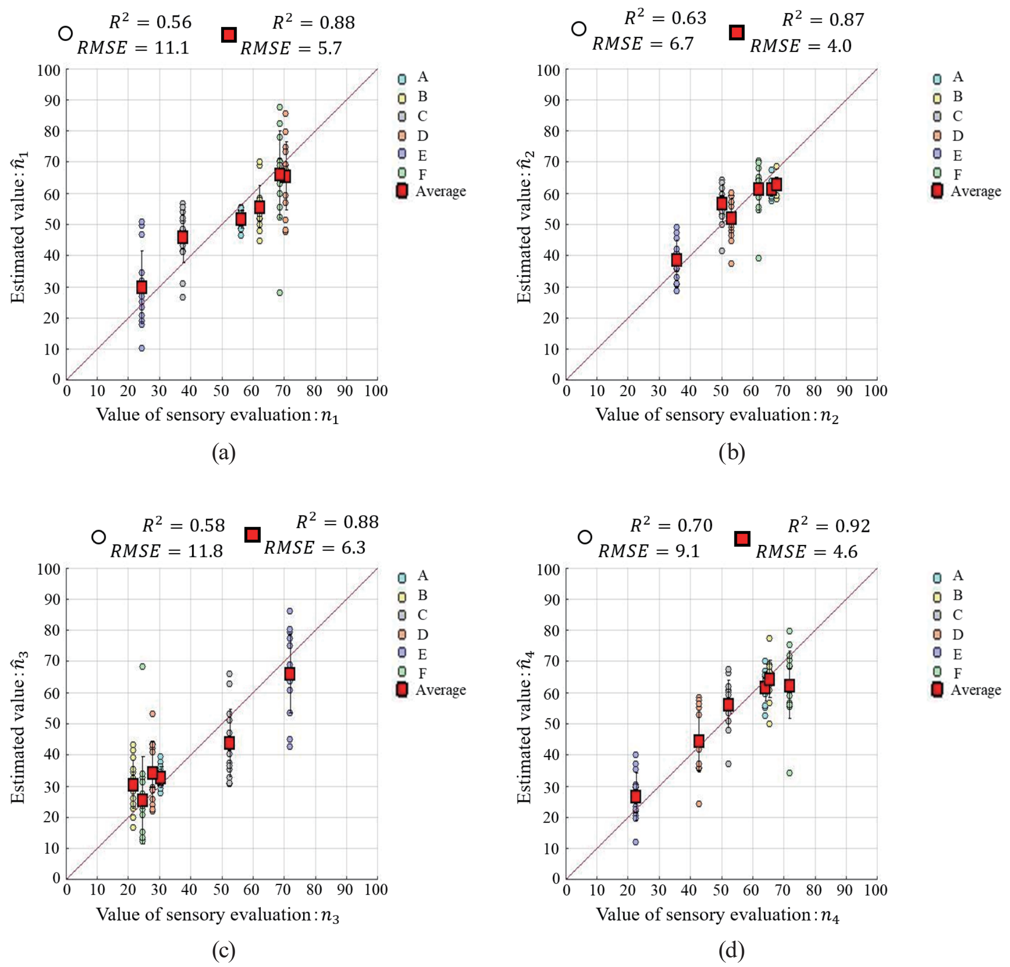


Fig. 10. (Color online) Estimation results. (a) Crispiness. (b) Crumbliness. (c) Gooeyness. (d) Meltiness.

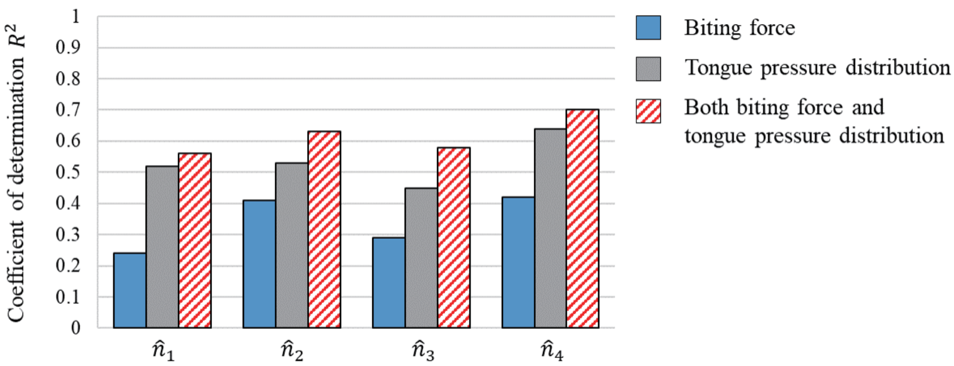


Fig. 11. (Color online) Accuracy of estimation.

6. Conclusions

We presented a texture estimation system in which a robotic mastication simulator is used. The main results are summarized as follows.

- To artificially reproduce human mastication, we developed an end effector of the robotic simulator that includes rigid teeth and a soft tongue. With the use of a pressure distribution sensor, the biting force and tongue pressure distribution can be simultaneously measured during artificial mastication.
- We proposed a texture estimation system in which the value of human sensory evaluation is estimated from the biting force and tongue pressure distribution.
- We described the experiment where the textures of six types of doughnut were accurately estimated using the proposed system. The results indicated the validity of the proposed system capable of measuring both the biting force and the tongue pressure.

One important future task is to develop a robotic simulator system that can form a food bolus. If the robot itself can form a food bolus and measure spatiotemporal data during such a forming process, it may be possible to estimate more delicate textures and increase the accuracy of estimation. Toward the development of such a system, future issues include the increase in the degree of freedom of jaw and tongue motions as well as the optimization of feature values of measured data.

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