IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 26 June 2024, accepted 29 August 2024, date of publication 5 September 2024, date of current version 16 September 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3454509

RESEARCH ARTICLE

Food Texture Prediction Method Using Multiple Measurement and Template Data

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This work was supported by the Japan Society for the Promotion of Science (JSPS) KAKENHI under Grant JP20K12026.

This work involved human subjects in its research. Approval of all ethical and experimental procedures and protocols was granted by the Ethics Committee of Kobe University Graduate School of System Informatics under Application No. R02-01, and performed in line with the Helsinki Declaration.

ABSTRACT Food texture is an essential factor in the perception of chewing. Compared to taste and aroma, food texture is dominant in the palatability of solid and semi-solid foods. Hence, food development processes require a method for evaluating broad food textures. This study proposes a prediction method for food texture using multiple measurements and template data. First, a measurement system recorded the force, vibration, and sound pressure data during food compression. The moisture rate of food was also measured by a moisture meter. Second, many template data are automatically determined from the outline waveforms of measurement data. Third, the dynamic time warping calculates distance vectors between measurement and template data. Finally, the Gaussian process regression algorithm determines the relationship between the distance vectors and sensory evaluation data. The advantage of using template data is that there is no need to extract specific features from measurement data. The effectiveness of the proposed method was validated through sensory evaluation and measurement experiments. The proposed method was able to predict food texture value with low errors through the experiment with nine textures and 21 samples.

INDEX TERMS Food texture, machine learning, measurement, sensory evaluation.

I. INTRODUCTION

Food texture is an essential factor for the perception of chewing. Compared to taste and aroma, food texture is dominant in the palatability of solid and semi-solid foods [1], [2]. Hence, food companies develop new products with the preferred food textures for consumers. A method that evaluates various food textures is required in the food development process.

Sensory evaluation is a major method for measuring the quality and intensity of texture through human perception [3]. Evaluation results that directly reflect human perceptions are obtained. However, human subjects have individual differences in their perceptions, which gives variance to the results. Hence, trained subjects are required to minimize the variance [4]. An appropriate environment should also be prepared for subjects. So, the sensory evaluation needs a lot of costs and time.

Instrumental measurements are suitable for quantitatively evaluating the physical characteristics of food in laboratories. Texture profile analysis (TPA) uses a motion and measurement device that compresses a bite-size food sample twice in reciprocating motion [1], [5]. A sensor measures the force in the compressions and outputs a force-time curve. TPA extracts texture parameters from the curve. Texture parameters, such as hardness, adhesiveness, and so on, quantify the physical characteristics and are important to assess food texture. Because the measurement data are objective, other measuring instruments were also applied for food texture evaluation. Chauvin et al. evaluated crispness and crunchiness from the acoustic data of dry and wet foods in compression [6]. Taniwaki et al. measured acoustic data of potato chips and evaluated their texture by analyzing the data in the frequency domain [7]. Shibata et al.

The associate editor coordinating the review of this manuscript and approving it for publication was Siddhartha Bhattacharyya.

evaluated the doughnut's texture using a sheet-type pressure distribution sensor and teeth and tongue mechanical parts [8]. Kohyama investigated the effectiveness of a balloon-type pressure sensor for the texture evaluation of tongue-crushable foods [9]. These studies picked up a specific texture or physical parameter and proposed methods for precisely evaluating specific textures.

According to the definition by the International Organization for Standardization, texture is defined as "all the mechanical, geometrical, and surface attributes of a product perceptible by means of mechanical, tactile and, where appropriate, visual and auditory receptors [10]." Food texture is the perception of multisensory integration. Hence, it is reasonable to use an instrument with multiple sensors to evaluate food textures [11]. Vickers measured the acoustic and force data of potato chips and analyzed the relationship between sensory and measurement values [12]. Varela et al. also investigated the combination of acoustic and force data for the crispness of almonds [13]. Çarşanba et al. analyzed the acoustic and force data of wafer products [14]. Nakamoto et al. measured the force, vibration, and acoustic data to evaluate snack foods' textures [15]. In addition, multiple reports measured the sound and force, e.g., [16], [17]. It is expected that detailed data related to texture can be obtained by combining sophisticated sensor devices. However, the relationship between the physical characteristics of food and the texture perception by humans has been discussed insufficiently. This matter makes it difficult for texture evaluation using measurement data.

To determine the relationship between food texture and measurement data, recently, machine learning methods have been used [18]. Simon and Uma used a deep learning model to classify the food texture [19]. Khan et al. discussed the output of artificial neural networks can provide information about various mechanical properties based on the information in food drying [20]. If machine learning is used, it is expected to predict the intensity of food texture as perceived by humans, rather than distinguishing food texture or predicting physical properties. Kato et al. used the neural network to evaluate the level of textures such as crispness and crunchiness in the range (0,1) [21]. Nakamoto et al. predicted five food textures of ten snack samples by a logistic regression model [22]. They proposed methods to quantitatively predict food texture from measurement data, but the range of textures and foods was limited such as crispness and potato chips. To expand the range of food textures and foods, a method that predicts food textures from a variety of measurement data that are not limited to specific textures and food is needed. Texture prediction using measurement data has the potential to be an alternative to sensory evaluation. A method for texture prediction for a wide variety of foods is needed for application in food development.

This study proposes a method to predict food texture using four measurement data: force, vibration, sound pressure, and moisture rate. This method uses the distance between measurement data and template data as feature values instead of using separately selected features depending on the texture. A machine learning algorithm predicts an evaluation value along a food texture descriptor from the distances. The advantage of this method is that it can be applied to a variety of food textures. This study validated the effectiveness of the method through a prediction demonstration of nine food textures for 21 samples.

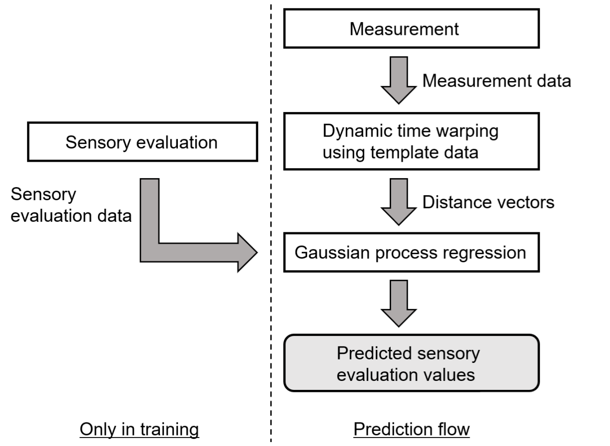

FIGURE 1. Flow of food texture prediction.

II. METHODOLOGY

A. FLOW OF FOOD TEXTURE PREDICTION

This study proposes a prediction method of food texture from measurement data as shown in Fig. 1. Measurement data that reflects the characteristics of texture can be time series, sequential data, or one piece of data. Multiple template data are determined based on the range of the measurement data. Next, dynamic time warping (DTW) calculates the DTW distance [23], which represents the similarity between the measurement data and template data. The method uses the DTW distance as a feature value to construct a distance vector. A model of the relationship between distance vectors and human food texture perception evaluation values is determined using Gaussian process regression. The human texture evaluation value uses intensity along texture descriptors, which is easier to understand intuitively than physical quantities. On the left side of Fig. 1, although the texture evaluation value is obtained by sensory evaluation, this is only conducted when determining the model. In the texture prediction, the vertical flow from measurement to prediction on the right side of Fig. 1 is used. One of the advantages of this method is the usage of template data. By using multiple comprehensively created templates, it is expected to perform evaluations that are independent of the waveform characteristics of specific measurement data. Furthermore, even if a measuring instrument is added in the training stage, the method is able to predict texture using the

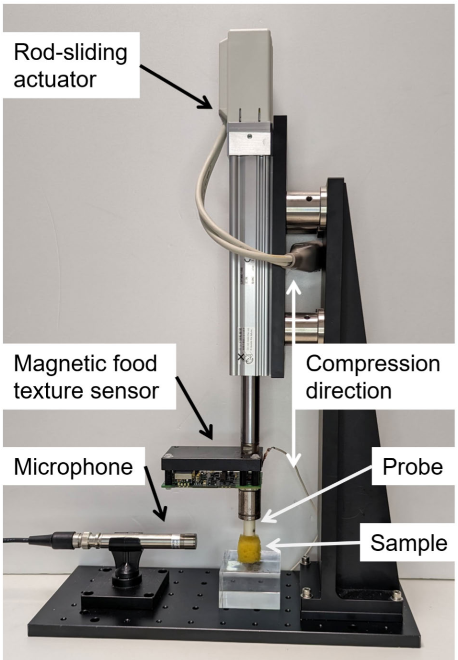

FIGURE 2. **Measurement system.**

same flow by adding templates based on the measurement data by the instrument.

B. MEASUREMENT

A measurement system that obtains force, vibration, and sound pressure data during the compression of a food sample is shown in Fig. 2. This system has a rod-sliding mechanism (LEY16DA, SMC Co. Ltd., Japan) using a step motor and compresses a food sample by vertical motion [24]. A magnetic food texture sensor equipped on the tip of the rod measures force and vibration simultaneously during the two-time compression [25]. The probe of the texture sensor is cylinder-shaped and 10 mm in diameter to simulate the shape of the molar. The compression velocity is 10 mm/s, and the compression length from the point where the probe touches the sample is 80% of the sample height. The sampling frequency of the texture sensor is 10 kHz. A microphone is placed horizontally to a sample with a 35-mm distance. The microphone (MI-1271M12, Ono Sokki Co. Ltd., Japan) starts and stops to record sound pressure synchronously with the measurement of the texture sensor. The sampling frequency of the microphone is 51.2 kHz. The measurement time is 8 s. The sample size is 10.

This study also measures the moisture rate of samples. The moisture rate on a wet basis is determined using a moisture meter (MX-50, A&D Co., Ltd., Japan) that measures the weight of moisture evaporated by the radiant heat of the halogen lamp from the weight of the sample at a sampling frequency of 1 Hz. The change of moisture weight is recorded as time series data of the evaporation rate of a food. It includes information on the microscopic structure of the sample that affects its texture. The measurement of the moisture rate was conducted separately from the measurement of the force, vibration, and sound pressure. The sample size is 3.

C. SIGNAL PROCESSING

The measurement data are processed by the following procedures.

1) FORCE DATA

A lowpass filter is applied to the force data for noise reduction. The force data mainly have two peaks by two-time compression and sometimes include small drops on the peaks by sample fracture. The cut-off frequency was determined as 54 Hz through preliminary trials to retain the small drops on the peaks in the force data. The 8th-order Butterworth filter was used. In addition, the filtered force data is resampled at 1 kHz to reduce the calculation time for DTW. Therefore, the length of the force data is 8000 after this process.

2) VIBRATION DATA

The vibration data is the voltage change proportional to the probe velocity and has spike waveforms in both plus and minus directions with 0 V as the baseline. The vibration data has a stationary noise derived from an amplifier circuit. To remove the noise, the standard deviation of the noise is calculated from 50 data without vibration, and the data within the three times the standard deviation are set to 0 V. After that, a moving average filter is applied to their absolute values to transform the spike waveforms into smooth waveforms based on the height and number of waves. The length of averaging data is 50. The smoothed vibration data is resampled at 1 kHz to reduce the calculation time for DTW. The length of the smoothed vibration data is 8000.

3) SOUND PRESSURE DATA

Regarding the sound pressure data, in the same manner as the vibration data, the stationary noise of sound pressure data is removed. The sound pressure data are characterized by amplitude and frequency. Hence, a-weighted 1/3 octave spectra from 0.02 to 20 kHz are calculated [26]. The range from 0.02 to 20 kHz almost coincides with the frequency range of human hearing except for the very low range. The length of the spectra data is 31.

4) MOISTURE RATE

Time-series moisture rate data tends to be recorded without variance by using samples of the same size. Hence, average time-series moisture rate data are calculated from three-time measurement data. The length of the data depends on the sample. To fix the data length, the length of the moisture rate data is set to 8000 to match the length of the force data, and the trailing part with no data is filled with zeros.

D. DTW AND GENERATION OF TEMPLATE DATA

DTW is a pattern-matching algorithm that minimizes the sum of distances between elements of two sequential data using

TABLE 1. Key points of outline form of force data.

Key Point	PF1 (t_{f1}, p_{f1})	PF2 (t_{f2}, p_{f2})	PF3 (t_{f3}, p_{f3})	PF4 (t_{f4}, p_{f4})	PF5 (t_{f5}, p_{f5})	PF6 (t_{f6}, p_{f6})	PF7 (t_{f7}, p_{f7})	PF8 (t_{f8}, p_{f8})	PF9 (t_{f9}, p_{f9})	PF10 (t_{f10}, p_{f10})
Time and force range	(0, 0)	$(0.05T$, 0–101)	$(0.10T$, 0–101)	$(0.15T$, 0–101)	$(0.25T$, -8–0)	$(0.30T, 0)$	$(0.50T, 0)$	$(0.60T$, 0–101)	$(0.70T, 0)$	$(T, 0)$

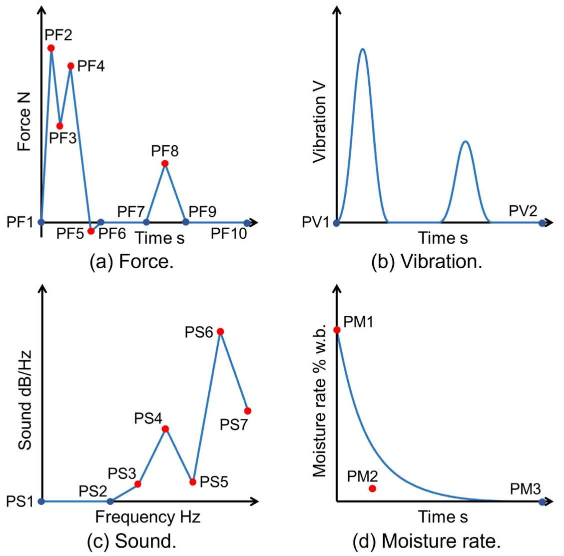

FIGURE 3. Outline waveforms and parameters of template data.

TABLE 2. Parameters of outline form of vibration data.

Parameter	a_{v1}	a_{v2}	v_v
Range	0–0.215	0–0.215	0–20

a warping function [23]. The measurement data includes a variance based on the sample's individual differences. It occurs in the directions of both time and value (e.g., force). DTW optimizes the correspondence relation between elements of two sequential data and minimizes the data variance in the time direction. The sum of distances between elements is called a DTW distance that becomes a small value if the two sequential data are similar. For force, vibration, and moisture rate, this study uses the DTW distance as a distance value between two sequential data; one of the two sequential data is measurement data, and the other is template data. For sound data, the Euclidean distance is calculated from measurement and template data because the sound data are transformed into the 1/3 octave frequency band.

The measurement system compresses a food sample two times and measures force, vibration, and sound simultaneously. Although the time-series waveforms of measurement data depend on the physical characteristics of the sample, a possible waveform can be determined as an outline form of measurement data. Hence, this study determines the outline waveform as shown in Fig. 3 and generates multiple template data from the outline.

A force's outline waveform has 10 key points from PF1(t_{f1}, p_{f1}) to PF10(t_{f10}, p_{f10}) as shown in Fig. 3(a). Because the measurement system compresss a sample with a constant compression velocity, the time of each point is almost constant. Their times are determined as listed in Table 1. T is a measurement time and is 8 s in the experiment as mentioned in II-B. The maximums of force in Table 1 were also determined based on all force data. Force template data are generated by dividing the force maximums of p_{f2}, p_{f3}, p_{f4}, p_{f5}, and p_{f8} equally down to zero. The number of the dividing step is 4, and the number of force template data is 1024. The length of template data is 8000, which corresponds to 1 kHz sampling. The data between key points are generated by linear interpolation as shown in Fig. 3(a).

Vibration data have information on the magnitude and frequency of the probe's vibration and are processed in the smooth waveform shown by a moving average. As shown in Fig. 3(b), the outline waveform of the vibration data consists of two waves expressed by an exponential function. The waveform functions $v(t)$ are as follows:

$$v_e(t, t_c, v_v) = exp(-\frac{(t-t_c)^2}{v_v}) \tag{1}$$

$$v(t) = \begin{cases} a_{v1}v_e(t, \frac{T}{8}, v_v) & (0 \leq t < \frac{T}{2}) \\ a_{v2}v_e(t, \frac{5T}{8}, v_v) & (\frac{T}{2} \leq t \leq T) \end{cases} \tag{2}$$

The peak values and width of the two waves that are defined by a_{v1}, a_{v2}, and v_v, are listed in Table 2. a_{v1} and a_{v2} are devided into 16 steps down to zero and v_v is also devided into 4 steps. The number of vibration template data is 1024. As in the case with force, the length of template data is 8000.

Sound data, which are transformed into the frequency domain data have an outline waveform as shown in Fig. 3(c). Except for sound pressure levels from 20 to 200 Hz that were almost zero, the sound data has seven key points from PS1(f_{s1}, p_{s1}) to PS7(f_{s7}, p_{s7}). f_{s1} and f_{s7} are determined by the frequency range of the microphone and f_{s4}, f_{s5}, and f_{s6} are determined by the equal logarithmic interval frequency between f_{s3} and f_{s7} in the frequency domain listed on Table 3. Regarding the sound pressure level, in the same manner as the force data, the maximums of p_{s3} to p_{s7} were determined based on all sound data, and sound template data are generated by dividing the maximums equally down to zero. The number of sound template data is 1024. Because the number of the center frequency in 1/3 octave is 31, the length of template data also is 31. The data between key points are generated by linear interpolation.

TABLE 3. Key points of outline form of sound data.

Key Point	PS1 (f_{s1}, p_{s1})	PS2 (f_{s2}, p_{s2})	PS3 (f_{s3}, p_{s3})	PS4 (f_{s4}, p_{s4})	PS5 (f_{s5}, p_{s5})	PS6 (f_{s6}, p_{s6})	PS7 (f_{s7}, p_{s7})
Frequnecy and spectrum range	(20, 0)	(200, 0)	(500, 0–40)	(1250, 0–40)	(3150, 0–40)	(8000, 0–40)	(20000, 0–40)

TABLE 4. Key points of outline form of moisture data.

Key Point	PM1 (t_{m1}, p_{m1})	PM2 (t_{m2}, p_{m2})	PM3 (t_{m3}, p_{m3})
Time and moisture rate range	(0, 0–100)	$(0\text{–}\frac{11}{12}T_M, 0\text{–}p_{m2})$	$(T_M, 0)$

Moisture rate starts at the highest peak and decreases to zero over time. The study assumes the decreasing curve is expressed with a Bezier curve as shown in Fig. 3(d). The equation is as follows:

$$t(u) = m_1(u)t_{m1} + m_2(u)t_{m2} + m_3(u)t_{m3},$$
$$p(u) = m_1(u)p_{m1} + m_2(u)p_{m2} + m_3(u)p_{m3}, \qquad (3)$$

where $0 \leq u \leq 1$, and

$$m_1(u) = (1-u)^2, \quad m_2(u) = 2(1-u)u, \quad m_3(u) = u^2. \quad (4)$$

Three key points in Fig. 3(d) are PM1(t_{m1}, p_{m1}), PM2(t_{m2}, p_{m2}), and PM3(t_{m3}, p_{m3}). The maximum of p_{m2} is calculated from p_{m1}, t_{m2} and t_{m3} as follows:

$$p_{m2} = (-\frac{t_{m2}}{t_{m3}} + 1)p_{m1}. \qquad (5)$$

The maximums of p_{m1} and t_{m2} were also determined as listed in Table 4. The template data of water content are generated by dividing the maximums equally down to zero. The dividing steps of p_{m1}, p_{m2} and t_{m2} are 20, 11 and 5, respectively. The number of moisture template data is 1100. The maximum measurement time is $T_M = 8000$ s. The length of template data is 8000, which corresponds to 1 Hz sampling.

E. PREDICTION OF FOOD TEXTURE

To predict food texture evaluation values, this study uses Gaussian process regression (GPR), one of the machine learning methods with a nonlinear model. GPR needs a dataset of explanatory variables and an objective variable in the learning process. The explanatory variables are vectors consisting of the DTW distances between force, vibration, and moisture rate data and their template data, and the Euclidean distances between the sound data and the template data. Since the sample size of each sample is 10, the number of distance vectors calculated from force, vibration, and sound data is also 10. The moisture rate is average data, hence, its DTW distance is added as a common value for the sample to the other 10 distance vectors. The objective variable is an average of sensory values evaluated by human subjects. One GPR model predicts an evaluation value of one food texture from the vector of DTW distances. Hence, the number of GPR models corresponds to the number of food textures. In prediction calculation, the kernel function in the GPR model is a squared exponential kernel. The average function is constant. The hyperparameters of the kernel function are optimized using one of the general methods, the quasi-Newton algorithm. The prediction performance is evaluated by mean absolute error (MAE) between the target and prediction values through 10-fold cross-validation. In the learning and prediction process, the calculation was conducted by MATLAB (R2023b, Mathworks, Inc, USA) and Python (ver. 3.11, Python Software Foundation, USA).

F. FOOD SAMPLE

Food samples are listed in Table 5. They are easily available in Japan. They have different structures and various physical characteristics. The samples S1 to S9 have relatively crispy textures made by baking or frying. The samples S10 to S12 have high water contents and have some viscoelasticities. S13 is relatively soft of gummy candies. S14 is a Japanese traditional food with dense and soft textures. S15 is a soft and small cheese. The samples S16 to S21 are baked or steamed foods made from mainly flour. The measurement condition in Table 5 indicates the size of the sample in measurement. For samples with a large volume, such as konjac S10 and white bread S16, the center part was cut out and used for measurement. Although some samples have low height, the compression rate by the measurement system is 80% and this rate is constant for all samples.

G. TEXTURE DESCRIPTOR

Nine texture descriptors with significantly different physical properties were selected to represent the texture of each food. Their definitions are listed in Table 6. Participants for sensory evaluation discussed these descriptors and their definitions in advance and determined them.

H. SENSORY EVALUATION

Ten participants in the sensory evaluation perceived and recorded the food texture of the sample after two times of chewing. The average age of the participants was 23.5 ± 1.72, mean ± standard deviation and the male-to-female ratio was 9:1. Each participant conducted three-time evaluations of 21 samples shown in Table 5. The samples on a spoon were provided to participants in random order, and the participants chewed them with the molars. The participants had their prior eating experiences with the samples. The room temperature was approximately 20 °C. This study was approved by the Ethics Committee of Kobe University Graduate School of System Informatics (No. R02-01) in accordance with the Helsinki Declaration.

TABLE 5. Samples.

Index	Measurement Condition [a]	Sample	Product name and company
S1	A	Biscuit	Moonlight, Morinaga Co., Ltd.
S2	A	Cylindrical rice cracker	Peanuts age, Bonchi Co., Ltd.
S3	A	Thick rice cracker	Parinko, Sanko Seika Co., Ltd.
S4	B	Potato chip	Pure potato, Koike-ya Inc.
S5	B	Thin and hard rice cracker	Kameda usuyaki, Kameda Seika Co., Ltd.
S6	B	Thin rice cracker	Petit jakottoume, Bourbon Co.
S7	A	Deep-fried dough	Shiro karinto, Aeon Co., Ltd.
S8	B	Pretzel stick	Super karikari pretz, Ezaki Clico Co., Ltd.
S9	B	Fried stick of sweet potato	Imokenpi, Nangoku Seika Co., Ltd.
S10	C	Konjac	Kuro konjac, Wakakusa Co., Ltd.
S11	C	Jelly	Konnyaku batake, Mannanlife Co., Ltd.
S12	C	Fish cake	Senzaki kamaboko, Fujimitsu Co.
S13	A	Gummy candy	Kajyu gummy, Meiji Holdings Co., Ltd.
S14	C	Red bean jelly	Hitokuchi yokan, Yamazaki Baking Co., Ltd.
S15	C	Cylindrical cheese	Candy cheese, Lawson, Inc.
S16	C	Sliced white bread	Choujuku, Pasco Shikishima Co.
S17	C	Steamed bread	Hokkaido cheese mushi cake, Yamazaki Baking Co., Ltd.
S18	C	Baumkuchen	Atsugiri baumkuchen, Aeon Co., Ltd.
S19	C	Sponge cake	Castella, Imuraya Co., Ltd.
S20	A	Financier	Butter Financier, Fujiya Co., Ltd.
S21	C	Rice flour roll bread	Komeko roll, Pasco Shikishima Co.

[a] Measurement conditions are indicated as follows. A: Cut into 15 mm^2 and used less than 15 mm height, B: Cut into 15 mm^2 and stack to 5 mm height, C: Cut into 15 mm^3.

TABLE 6. Texture descriptors.

Descriptor	Definition [b]	Typical food [b]
Sakusaku	Easily broken by biting with a weak force	Cookie, apple
Paripari	Breaking thin foods with a relatively high-frequency sound	Potato chips, sliced cucumber
Karikari	Short fracture with a relatively strong force in mastication	Roasted nuts, unripe plum
Purupuru	Soft elastic and slightly wobby	Jelly, custard pudding
Gunyagunya	Flexible, elastic, bends or warps easily under pressure	Konjac gel, gummy jelly
Guchagucha	Mushy; having lost its original shape in mastication, a little sticky	Rice porridge in thick broth, rice gruel
Fuwafuwa	Soft and fluffy, compression with slight pressure	Sponge cake, marshmallow
Shittori	Moist and soft, cohesiveness in a mastication	Sponge cake, steamed bread
Mochimochi	Sticky, elastic and chewy	Bread, udon (wheat noodles)

[b] Definitions and typical foods are determined by referring to the paper [27].

In recording the intensity of textures in Table 6, the participants made a vertical mark at the position representing the intensity on a 150-mm horizontal line in a check card. The horizontal line had two-word anchors at 15 mm from both terminals. The left and right terminals corresponded to “no feel” and “strong feel”. After checking, the distance from the left anchor to the position of the vertical mark was measured and converted into numerical data with intensity ranging from 0 to 10.

III. RESULTS AND DISCUSSION

A. SENSORY EVALUATION

The results of the sensory evaluation are summarized in Table 7, which include also significant differences between the samples regarding food textures ($p<0.01$) by Tukey’s honestly significant difference test. Samples with high sensory evaluation values differ depending on the texture; e.g., S1 to S3 are sakusaku, S4 to S6 are paripari, and S7 to S9 are karikari. Some samples had a high value in only one texture, such as S1 and S13, and some had high values in two or more, such as S17 to S19.

B. MEASUREMENT EXPERIMENT

Typical measurement data are shown in Fig. 4. The samples S1 to S9 have physical properties with fractures, and the data shows that vibration and sound pressure are generated, and the force peaks synchronize with the other peaks. The samples S10 to S12 had high moisture rates and were low force, and S13 to S15 had middle or low moisture rates. The samples from S16 to S21 were low force, as typified by S16 (white bread), and had a relatively low moisture rate. Furthermore, almost no vibrations or sounds were observed from S10 to S21. The samples with high moisture rates required time to dry. There were differences in drying speed, such as between S17 and S21, and some, such as S20, had a low drying speed due to their dense structure even if the moisture rate was low.

The relationship between sensory evaluation value and measurement data is confirmed. Sakusaku was high in samples S1 to S3, and the force data showed that they were fractured by low force. Paripari was high in S4 to S6, and the sound pressure occurred for about 0.5 s, as defined by breaking with sound. In particular, S4 had low force and high sound data, and it can be considered that sound has

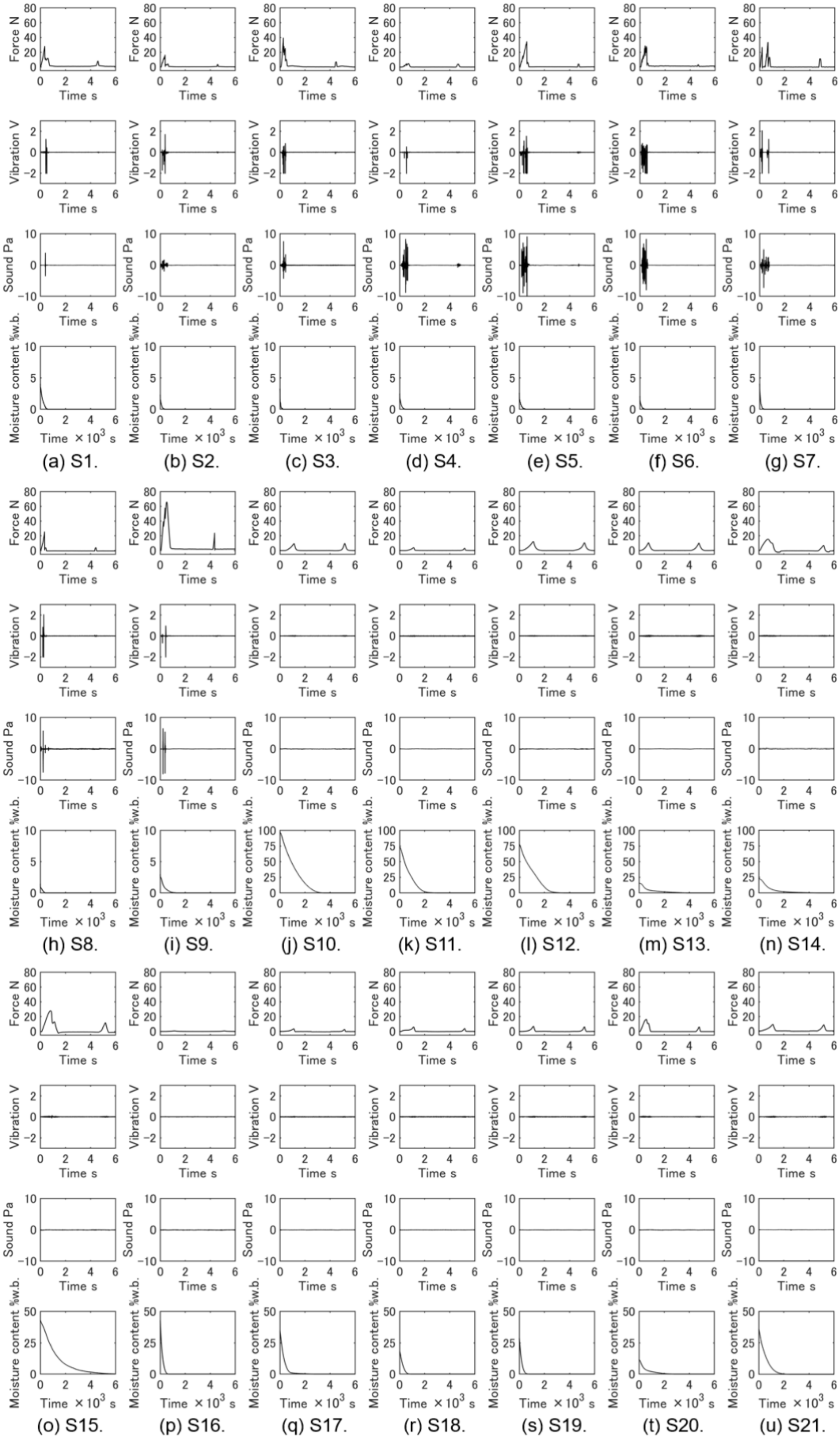

FIGURE 4. Typical measurement data of 21 samples. The horizontal axis is limited to 6000 s for moisture rate and 6 s for the other measurement data. The ranges of the vertical axis of moisture rate differ depending on the initial moisture rate of the sample.

TABLE 7. Result of sensory evaluation.

Sample index	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12
Sakusaku	8.5 ± 1.4^{a}	8.5 ± 0.9^{a}	8.2 ± 1.2^{a}	4.8 ± 2.1^{b}	3.7 ± 2.1^{b}	3.6 ± 2.0^{b}	4.5 ± 2.1^{b}	3.8 ± 2.2^{b}	1.6 ± 1.4^{ce}	0.0 ± 0.0^{de}	0.0 ± 0.0^{de}	0.0 ± 0.0^{de}
Paripari	1.0 ± 1.6^{abg}	2.0 ± 2.2^{abg}	4.5 ± 2.1^{cf}	8.5 ± 1.1^{d}	9.2 ± 0.6^{d}	9.1 ± 0.8^{d}	3.0 ± 2.3^{bef}	3.4 ± 2.9^{cef}	2.9 ± 2.2^{bef}	0.0 ± 0.0^{ag}	0.0 ± 0.0^{ag}	0.0 ± 0.0^{ag}
Karikari	1.2 ± 1.7^{ab}	2.2 ± 1.8^{abc}	2.0 ± 1.6^{abc}	3.1 ± 2.0^{bcd}	3.8 ± 2.4^{cd}	4.3 ± 2.3^{cd}	8.2 ± 1.5^{e}	8.3 ± 1.4^{e}	9.2 ± 0.7^{e}	0.0 ± 0.0^{f}	0.0 ± 0.0^{f}	0.0 ± 0.0^{f}
Purupuru	0.0 ± 0.0^{a}	0.0 ± 0.0^{a}	0.0 ± 0.0^{a}	0.0 ± 0.0^{a}	0.0 ± 0.0^{a}	0.0 ± 0.0^{a}	0.0 ± 0.0^{a}	0.0 ± 0.1^{a}	0.0 ± 0.0^{a}	6.5 ± 2.9^{b}	9.2 ± 0.8^{c}	3.6 ± 2.0^{d}
Gunyagunya	0.0 ± 0.0^{ahi}	0.0 ± 0.0^{ahi}	0.0 ± 0.0^{ahi}	0.0 ± 0.0^{ahi}	0.0 ± 0.0^{ahi}	0.0 ± 0.0^{ahi}	0.0 ± 0.0^{ahi}	0.0 ± 0.1^{ahi}	0.0 ± 0.0^{ahi}	6.8 ± 2.7^{bd}	4.6 ± 2.1^{c}	7.6 ± 1.5^{bde}
Guchagucha	0.2 ± 0.4^{abceg}	0.0 ± 0.0^{abce}	0.0 ± 0.1^{abce}	0.0 ± 0.0^{abce}	0.0 ± 0.0^{abce}	0.0 ± 0.0^{abceg}	0.1 ± 0.2^{abce}	0.0 ± 0.0^{abce}	0.0 ± 0.0^{abce}	1.2 ± 1.3^{abcdeg}	0.7 ± 0.8^{abcdeg}	2.2 ± 2.7^{cdegh}
Fuwafuwa	0.5 ± 1.7^{abg}	0.0 ± 0.1^{ab}	0.1 ± 0.4^{ab}	0.0 ± 0.2^{ab}	0.0 ± 0.0^{ab}	0.0 ± 0.0^{ab}	0.0 ± 0.1^{ab}	0.0 ± 0.0^{ab}	0.0 ± 0.0^{ab}	0.0 ± 0.1^{ab}	0.1 ± 0.2^{ab}	0.3 ± 0.6^{ab}
Shittori	0.8 ± 1.3^{abd}	0.0 ± 0.2^{ab}	0.1 ± 0.3^{ab}	0.0 ± 0.0^{ab}	0.0 ± 0.0^{ab}	0.0 ± 0.0^{ab}	0.0 ± 0.0^{ab}	0.0 ± 0.0^{ab}	0.0 ± 0.0^{ab}	0.4 ± 1.1^{ab}	0.4 ± 0.9^{ab}	0.7 ± 1.5^{abd}
Mochimochi	0.0 ± 0.1^{abf}	0.1 ± 0.3^{abef}	0.0 ± 0.1^{abf}	0.0 ± 0.0^{abf}	0.0 ± 0.0^{abf}	0.0 ± 0.0^{abf}	0.0 ± 0.0^{abf}	0.0 ± 0.0^{abf}	0.0 ± 0.0^{abf}	0.3 ± 0.9^{abef}	0.2 ± 0.4^{abef}	0.4 ± 0.6^{abef}

Sample index	S13	S14	S15	S16	S17	S18	S19	S20	S21
Sakusaku	0.0 ± 0.0^{de}	0.0 ± 0.0^{de}	0.0 ± 0.0^{de}	0.0 ± 0.0^{de}	0.0 ± 0.0^{de}	0.0 ± 0.1^{de}	0.0 ± 0.0^{de}	0.5 ± 0.7^{cde}	0.0 ± 0.0^{de}
Paripari	0.0 ± 0.0^{ag}	0.0 ± 0.0^{ag}	0.0 ± 0.0^{ag}	0.0 ± 0.0^{ag}	0.0 ± 0.0^{ag}	0.0 ± 0.0^{ag}	0.0 ± 0.0^{ag}	0.0 ± 0.0^{ag}	0.0 ± 0.0^{ag}
Kaikari	0.0 ± 0.0^{f}	0.0 ± 0.0^{f}	0.0 ± 0.0^{f}	0.0 ± 0.0^{f}	0.0 ± 0.0^{f}	0.0 ± 0.0^{f}	0.0 ± 0.0^{f}	0.0 ± 0.0^{f}	0.0 ± 0.0^{f}
Purupuru	3.2 ± 2.4^{d}	0.4 ± 0.8^{a}	0.4 ± 1.0^{a}	0.0 ± 0.1^{a}	0.0 ± 0.0^{a}	0.0 ± 0.1^{a}	0.0 ± 0.0^{a}	0.0 ± 0.0^{a}	0.0 ± 0.0^{a}
Gunyagunya	8.9 ± 0.9^{de}	1.6 ± 1.4^{fghj}	2.6 ± 3.0^{fgj}	0.3 ± 0.9^{afhij}	0.1 ± 0.2^{ahij}	0.1 ± 0.3^{ahij}	0.1 ± 0.3^{ahij}	0.1 ± 0.3^{ahij}	1.4 ± 2.0^{fghij}
Guchagucha	1.5 ± 2.0^{abcdeg}	8.8 ± 0.9^{f}	7.8 ± 1.9^{f}	1.3 ± 2.1^{abcdeg}	1.8 ± 2.3^{cdegh}	1.6 ± 1.9^{acdegh}	1.3 ± 1.8^{abcdeg}	3.1 ± 2.7^{dgh}	1.2 ± 2.0^{abcdeg}
Fuwafuwa	0.0 ± 0.1^{ab}	0.1 ± 0.2^{ab}	0.0 ± 0.0^{ab}	8.5 ± 1.5^{cdf}	7.8 ± 1.9^{cdef}	6.9 ± 2.3^{def}	7.5 ± 1.8^{cdef}	1.6 ± 1.9^{ag}	3.8 ± 2.4^{h}
Shittori	0.4 ± 0.7^{ab}	2.9 ± 2.2^{cdeg}	1.9 ± 2.1^{acd}	3.8 ± 1.9^{ceg}	6.9 ± 2.3^{f}	7.1 ± 1.8^{f}	6.3 ± 2.6^{f}	7.6 ± 1.9^{f}	4.2 ± 2.0^{ceg}
Mochimochi	2.0 ± 2.2^{cef}	0.2 ± 0.4^{abef}	0.3 ± 0.7^{abef}	4.1 ± 2.9^{d}	1.2 ± 1.8^{bcef}	1.0 ± 1.1^{abcef}	0.9 ± 1.2^{abef}	0.4 ± 0.7^{abef}	8.6 ± 1.7^{g}

Average±standard deviation. The results with different alphabet combinations have significant differences ($p<0.01$).

a role for Paripari. Karikari was high in samples S7 to S9. Since they were fractured at once with high force, the force and sound data of S8 and S9 had one peak. S7 had two peaks because it was broken twice on one surface and the opposite surface of the cylindrical sample shape. The two peaks were also observed in the vibration data. Purupuru was high in S11, and the second highest in S10, and the measurement data showed that the force was low and the first and second peaks of the force data were almost the same height. In addition, they had no vibration or sound and high moisture rates. Gunyagunya was high in S13 and had low force and low moisture rate. Guchagucha was high in S14 and S15 and was characterized by a difference in the height of the peaks of the first and second peaks of force. It also had adhesive characteristics, indicating a force in the tensile direction after compression. Fuwafuwa had a high evaluation value for S16 to S19, which are soft and porous foods. It had the characteristics of low force and drying in a short time regardless of the initial moisture rate. Sittori was high in S17 to S20, and the measurement data showed that the samples had a moisture rate of about 25% in addition to the low force. Mochimochi was high in S21. The heights of the first and second force peaks were almost the same, indicating elasticity. The relatively long drying time indicates difficulty in evaporating moisture.

Since the samples have different physical properties, even if it is only the force data, there were differences between samples when looked at in detail. Furthermore, it is possible to confirm these differences in more detail by measuring force, vibration, sound pressure, and moisture rate as in this experiment. However, these differences can be confirmed through comparison, and it isn't easy to quantify individual characteristics for each sample. Hence, the proposed method characterizes them using template data and predicts their food texture.

C. FOOD TEXTURE PREDICTION

Prediction values calculated by GPR through 10-fold cross-validation are shown in Fig. 5, and MAEs between sensory and prediction values are listed in Table 8. The samples with high values in the sensory evaluation, e.g., samples S1 to S3 for sakusaku, had high prediction values. Even if only one of the samples had a high sensory value such as mochimochi, GPR could predict it. Sakusaku, paripari, and karikari are categorized into crispy textures and have relatively similar textures in the textures of this study. GPR predicted them even for the small difference of samples with a similar texture tendency. Focused on low evaluation values, gunyagunya, fuwafuwa, and shittori had errors within 1.0, e.g., samples S4 to S7 for gunyagunya. The sensory value of some samples was outside of the error bar of prediction. It might be difficult for GPR to predict a low evaluation value because there is a wide variation of physical characteristics without a certain texture. For example, samples S1 to S15 have different physical characteristics, but their prediction values of fuwafuwa are all expected to be close to zero.

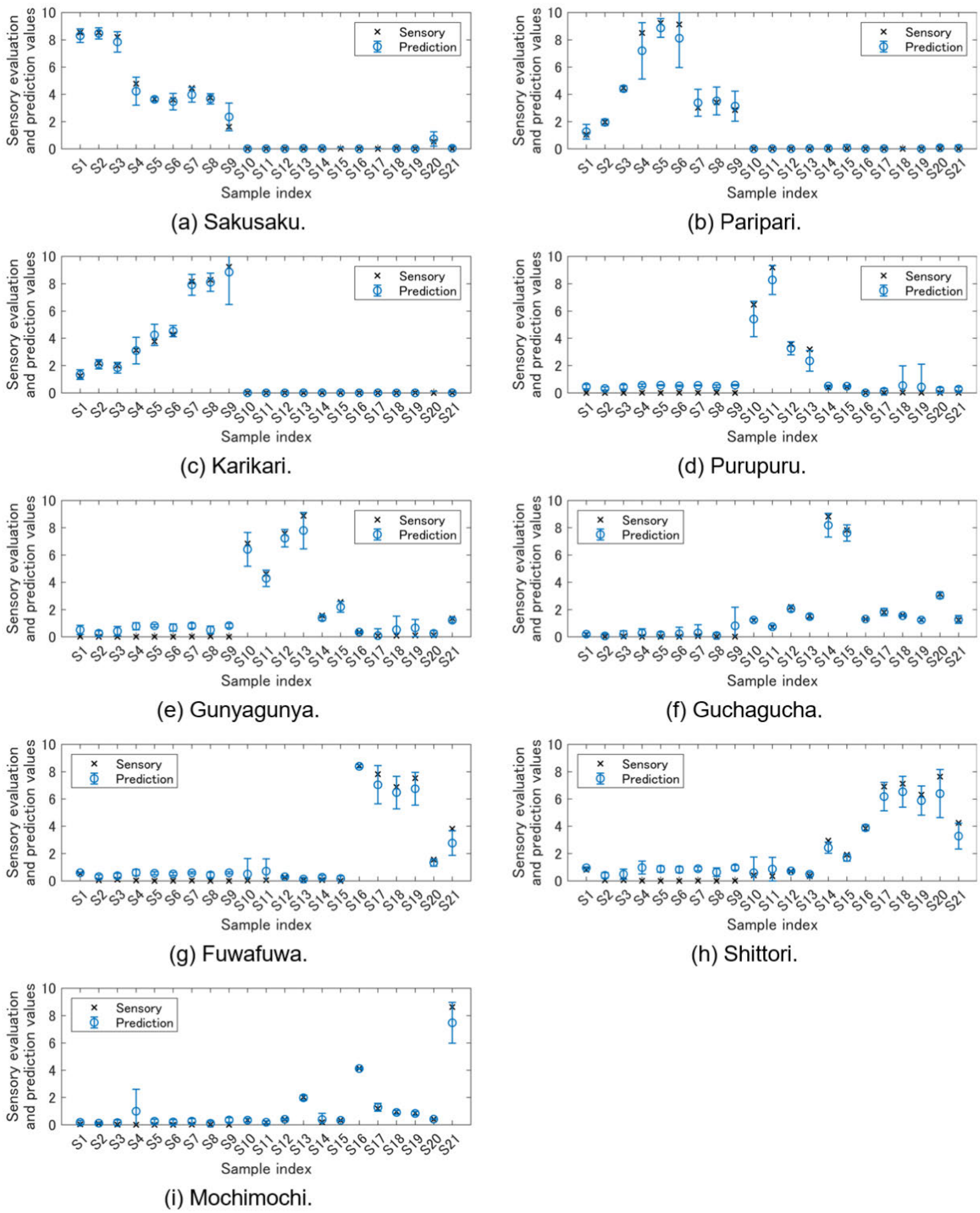

FIGURE 5. Relationship between sensory and prediction values.

TABLE 8. MAE between sensory and prediction values.

Descriptor	Sakusaku	Paripari	Karikari	Purupuru	Gunyagunya	Guchagucha	Fuwafuwa	Shittori	Mochimochi
MAE	0.26	0.43	0.26	0.51	0.54	0.23	0.56	0.65	0.24

Regarding Table 8, all MAEs were within 0.7. Because the range of sensory values was from 0 to 10, GPR was able to predict sensory values with an accuracy within 10%. Five of nine textures were less than 5%. The previous study also predicted the crispy textures from the feature values of force, vibration, and sound data [15]. The MAEs of sakusaku, paripari, and karikari which were corrected for the range of sensory evaluation were 0.35, 0.50, and 0.50, respectively. These MAEs were higher than those predicted by the method using template data in Table 8. The proposed method also used moisture rate data. However, despite the expansion of the variety of textures, the proposed method predicted them with low errors. Due to using template data and being demonstrated on various textures and samples, it is confirmed that the proposed method is more effective for food texture prediction.

The limitations of this study are as follows: The outline waveform and its parameters to generate template data were determined from all measurement data of food samples used in this study. Hence, the outline waveforms depend on the measurement data, and their ranges are limited. Because the standard GPR model was used to predict texture, variations in kernel functions and hyperparameters were not compared. The prediction accuracy could change depending on their optimization. This study used 21 samples and nine food texture descriptors. Because the Japanese language has 445 food texture descriptors, the texture descriptors in this study are just a few. The same goes for the food samples.

IV. CONCLUSION

This study proposed the food texture prediction method using the distance vector between the measurement data of force, vibration, sound pressure, and moisture rate and the template data. The template data are generated from the outline of measurement waveforms. GPR determines the relationship between the distance vectors and a sensory evaluation and then predicts a sensory evaluation value from the distance vector. In the experiment, the measurement system and the moisture meter measured 21 food samples (solid and semi-solid samples), and 10 participants evaluated the samples' food texture along nine descriptors. GPR predicted relatively high sensory evaluation values with high accuracy. The key findings of this study are as follows:

- The proposed method was able to predict the food textures using the same procedure regardless of whether the food was solid or semi-solid.
- Whether the target texture is crispy or elastic, the proposed method was capable of predicting it with an MAE of 10% or less.

The advantage of the proposed method is that it summarizes the measurement data into a distance vector. Even if new measurement data is obtained by adding measurement devices, the proposed method can be expanded to use those data.

In future works, we will verify the effectiveness of the proposed method using more broad types of textures and samples. Increasing the data set of sensory evaluation and measurement data is expected to not only improve the accuracy of prediction but also identify the measurement data that are the principal factors on a certain texture. This will clarify the relationship between the physical properties of food and texture, and it is expected that this relationship will greatly contribute to food development in food companies.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

REFERENCES

[1] A. S. Szczesniak, "Texture is a sensory property," *Food Quality Preference*, vol. 13, no. 4, pp. 215–225, Jun. 2002.
[2] M. C. Bourne, "Texture, viscosity, and food," in *Food Texture and Viscosity*, 2nd ed., New York, NY, USA: Academic, 1982, pp. 1–23.
[3] H. T. Lawless and H. Heymann, "Texture evaluation," in *Sensory Evaluation of Food*, 2nd ed., New York, NY, USA: Springer, 1999, pp. 379–405.
[4] M. C. Bourne, "Sensory methods of texture and viscosity measurement," in *Food Texture and Viscosity*, 2nd ed., New York, NY, USA: Academic, 1982, pp. 247–279.
[5] H. H. Friedman, J. E. Whitney, and A. S. Szczesniak, "The texturometer—A new instrument for objective texture measurement," *J. Food Sci.*, vol. 28, no. 4, pp. 390–396, Jul. 1963.
[6] M. A. Chauvin, F. Younce, C. Ross, and B. Swanson, "Standard scales for crispness, crackliness and crunchiness in dry and wet foods: Relationship with acoustical determinations," *J. Texture Stud.*, vol. 39, no. 4, pp. 345–368, Aug. 2008.
[7] M. Taniwaki, N. Sakurai, and H. Kato, "Texture measurement of potato chips using a novel analysis technique for acoustic vibration measurements," *Food Res. Int.*, vol. 43, no. 3, pp. 814–818, Apr. 2010.
[8] A. Shibata, R. Takahashi, Y. Nagahata, K. Kimura, R. Shimizu, M. Hotta, M. Inoue, and M. Higashimori, "Food texture estimation using robotic mastication simulator equipped with teeth and tongue," *Sensors Mater.*, vol. 31, no. 7, p. 2367, Jul. 2019.
[9] K. Kohyama, "Application of a balloon-type pressure sensor in texture evaluation of tongue-crushable foods," *J. Texture Stud.*, vol. 53, no. 3, pp. 357–365, Jun. 2022.
[10] (2020). *Texture, ISO 11036:2020(En)*. [Online]. Available: https://www.iso.org/obp/ui#iso:std:iso:11036:ed-2:v1:en:term:3.1
[11] J. O. de Moraes, P. Andreani, B. H. P. Murta, J. V. Link, G. Tribuzi, J. B. Laurindo, S. Paul, and B. A. M. Carciofi, "Mechanical-acoustical measurements to assess the crispness of dehydrated bananas at different water activities," *LWT*, vol. 154, Jan. 2022, Art. no. 112822.
[12] Z. M. Vickers, "Sensory, acoustical, and force-deformation measurements of potato chip crispness," *J. Food Sci.*, vol. 52, no. 1, pp. 138–140, Jan. 1987.
[13] P. Varela, J. Chen, S. Fiszman, and M. J. W. Povey, "Crispness assessment of roasted almonds by an integrated approach to texture description: Texture, acoustics, sensory and structure," *J. Chemometrics*, vol. 20, nos. 6–7, pp. 311–320, Jun. 2006.
[14] E. Çarşanba, K. Duerrschmid, and G. Schleining, "Assessment of acoustic-mechanical measurements for crispness of wafer products," *J. Food Eng.*, vol. 229, pp. 93–101, Jul. 2018.
[15] H. Nakamoto, R. Nishimura, and F. Kobayashi, "Effects of sensory combination on crispness and prediction of sensory evaluation value by Gaussian process regression," *PLoS ONE*, vol. 19, no. 2, Feb. 2024, Art. no. e0297620.
[16] A. Salvador, P. Varela, T. Sanz, and S. M. Fiszman, "Understanding potato chips crispy texture by simultaneous fracture and acoustic measurements, and sensory analysis," *LWT Food Sci. Technol.*, vol. 42, no. 3, pp. 763–767, Apr. 2009.
[17] M. Taniwaki and K. Kohyama, "Mechanical and acoustic evaluation of potato chip crispness using a versatile texture analyzer," *J. Food Eng.*, vol. 112, no. 4, pp. 268–273, Oct. 2012.
[18] M. I. H. Khan, S. S. Sablani, R. Nayak, and Y. Gu, "Machine learning-based modeling in food processing applications: State of the art," *Comprehensive Rev. Food Sci. Food Saf.*, vol. 21, no. 2, pp. 1409–1438, Feb. 2022.
[19] P. Simon and V. Uma, "Integrating InceptionResNetv2 model and machine learning classifiers for food texture classification," in *Proc. Int. Conf. Commun. Cyber Phys. Eng.* Singapore: Springer, 2023, pp. 531–539.

[20] M. I. H. Khan, S. S. Sablani, M. U. H. Joardder, and M. A. Karim, "Application of machine learning-based approach in food drying: Opportunities and challenges," *Drying Technol.*, vol. 40, no. 6, pp. 1051–1067, May 2022.
[21] S. Kato, N. Wada, R. Ito, T. Shiozaki, Y. Nishiyama, and T. Kagawa, "Snack texture estimation system using a simple equipment and neural network model," *Future Internet*, vol. 11, no. 3, p. 68, Mar. 2019.
[22] H. Nakamoto, D. Nishikubo, and F. Kobayashi, "Food texture evaluation using logistic regression model and magnetic food texture sensor," *J. Food Eng.*, vol. 222, pp. 20–28, Apr. 2018.
[23] H. Sakoe and S. Chiba, "Dynamic programming algorithm optimization for spoken word recognition," *IEEE Trans. Acoust., Speech, Signal Process.*, vol. ASSP-26, no. 1, pp. 43–49, Feb. 1978.
[24] H. Nakamoto, Y. Nagahata, and F. Kobayashi, "Food texture measurement system using rod type actuator for imitation of human mastication," *Int. J. Autom. Technol.*, vol. 16, no. 4, pp. 421–426, Jul. 2022.
[25] H. Nakamoto, Y. Nagahata, and F. Kobayashi, "A magnetic food texture sensor and comparison of the measurement data of chicken nuggets," *Sensors*, vol. 21, no. 10, p. 3310, May 2021.
[26] *Design Response of Weighting Networks for Acoustical Measurements*, Standard ANSI S1.42, 2001.
[27] F. Hayakawa, Y. Kazami, K. Nishinari, K. Ioku, S. Akuzawa, Y. Yamano, Y. Baba, and K. Kohyama, "Classification of Japanese texture terms," *J. Texture Stud.*, vol. 44, no. 2, pp. 140–159, Apr. 2013.

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