A Study on Classification of Food Texture with Recurrent Neural Network

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Abstract. This study constructs a food texture evaluation system using a food texture sensor having sensor elements of 2 types. Characteristics of food are digitized by using the food texture sensor in imitation of the structure of the human tooth. Classification of foods is carried out by the recurrent neural network. The recurrent neural network receives the time-series outputs from the food texture sensor, and outputs classification signals. In the experiment, 3 kinds of food are classified by the recurrent neural network.

Keywords: Food texture · Recurrent neural network, RNN · Back propagation through time, BPTT · Classification of food texture

1 Introduction

Food texture greatly affects the taste that a human feels. In addition, it depends on the texture, whether it is the food which an infant and an elderly person are easy to take in. Methods to evaluate the food texture are mainly a sensory evaluation and an evaluation using the food texture measuring equipment now. The sensory evaluation is a method that large number of subjects eat food. However, this method includes individual difference and subject's preferences and needs much time and cost. In addition, it is difficult to quantify the food texture. On the other hand, Fig. 1 shows the food texture sensor which is generally used.

This sensor analyzes a time-series force in food structure. This evaluation method improves the problems of the sensory evaluation. However, the measured value is only the force, and it is difficult to express an index of the food texture in only it [2]. Therefore, a new method to quantify food texture is required. This study built food texture evaluation system which used a food texture sensor which has a sensor device with different kind. In the food texture evaluation system, firstly, the food texture sensor outputs the characteristics of the food as a numerical value. Secondly, the value is inputted to a network designed on a model of living nerve circuitry called the recurrent neural network. Finally, food is classified by the output of the recurrent neural network.

N. Kubota et al. (Eds.): ICIRA 2016, Part I, LNAI 9834, pp. 247–256, 2016.
DOI: 10.1007/978-3-319-43506-0_21

Fig. 1. Creep meter (JSV-H1000) [1].

2 Food Texture Measurement System

2.1 Human Receptors in Periodontal Membrane

There is periodontal membrane in the structure of the human tooth. It fixes a tooth and reduces load to depend on a tooth. Furthermore, it has perception receptors. These receptors have a slowly adapting and a quickly adapting. Therefore the food texture is perceived by the receptors in the periodontal membrane. When a human bites food, he senses a texture by letting a teeth vibrate. A tooth is displaced by stretching the periodontal membrane between a tooth and alveolar bones. The alveolar bone is a bone supporting the root of the tooth.

2.2 Measurement Principle

Figure 2 shows the structure of food texture sensor.

The food texture sensor used in this study has a plunger, a base, an elastomer layer. These correspond to the tooth, the alveolar bone, the periodontal membrane each. The plunger has a magnet. It is a columnar forms of 6 mm in diameter and the magnetizing force is 2070G/207mT. When the sensor touched food, a plunger is displaced. The board of the electronic circuit is glued on the lower part of the base. The board has GMR (Giant Magneto Resistive) elements and an inductor for coil element. The GMR elements and the inductor play a part in the slowly adapting and quickly adapting. The GMR element uses giant magneto resistive effect. When force increased to the plunger, the elastomer layer stretches and the plunger is displaced. The output of GMR elements changes by

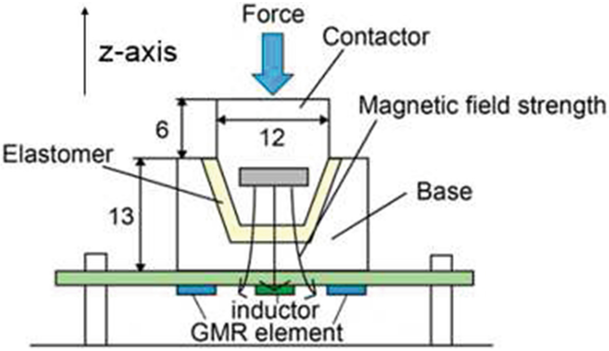

Fig. 2. Structure of food texture sensor.

increasing force for food. The output voltage of the inductor changes by changing a magnetic field when the magnet in the plunger is displaced. The inductor expresses the vibration when the human chewed food.

2.3 Prototype Sensor and Measurement System

Figures 3, 4 and 5 show the food texture sensor, the board of the electronic circuit using for the food texture sensor, and appliances used for the experiment in the measurement system for this study.

8 GMR elements are in a circle and at regular intervals. An inductor is the center of the circle. The texture sensor fractures food by moving the motorized

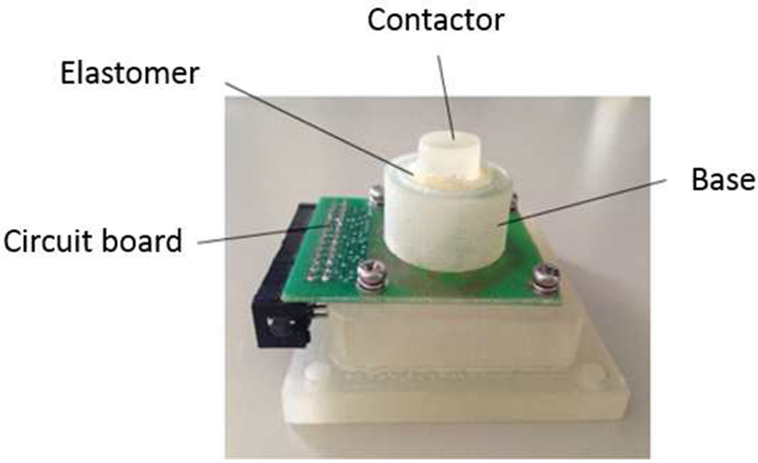

Fig. 3. Food texture sensor.

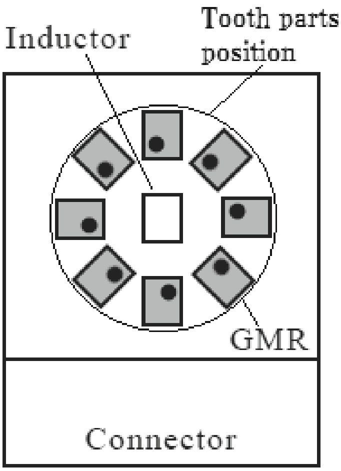

Fig. 4. Sensor circuit.

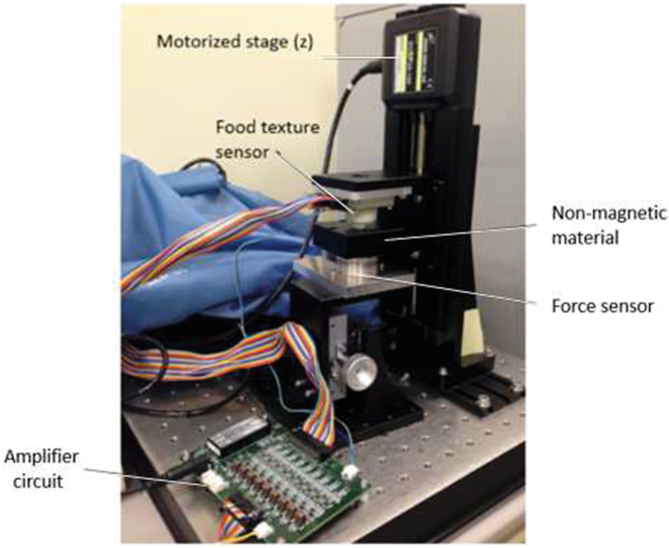

Fig. 5. Instrument for experiment.

stage. In this time, the output of the GMR element and the output voltage of the inductor are amplified it to 32 times and 10,000 times each by an amplifier circuit. After that, a PC obtains them using A/D converter. Finally, the PC calculates force based on the GMR's outputs.

3 Classification Using Recurrent Neural Network

3.1 Recurrent Neural Network

The recurrent neural network expands neural network in imitation of the structure of the human brain [3]. The recurrent neural network is easier to input time-series data than a neural network [4]. This study uses fully connected the recurrent neural network, which is a kind of the recurrent neural network (Fig. 6).

The way of learning is used back propagation through time (BPTT) which is a supervised learning [5]. At this time, it is assumed that the structure of fully connected recurrent neural networks becomes the laminar perceptron (Fig. 7) [6].

T is a maximum time.

Fully connected recurrent neural networks is defined as

$$s_i^{t+1} = \sum_{j=1}^{n} w_{ij} y_i^t, \tag{1}$$

$$y_i^t = f(s_i^t) \qquad (m+1 \leq i \leq n), \tag{2}$$

$$y_i^t = x_i^t \qquad (1 \leq i \leq m), \tag{3}$$

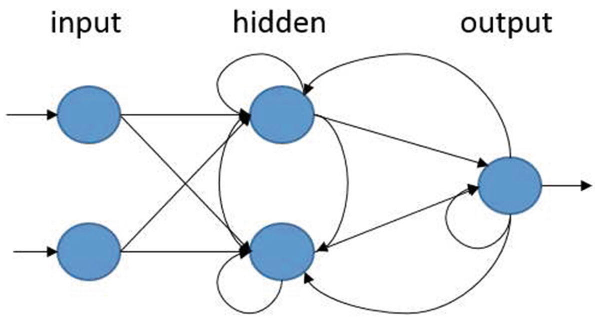

Fig. 6. Structure of recurrent neural networks

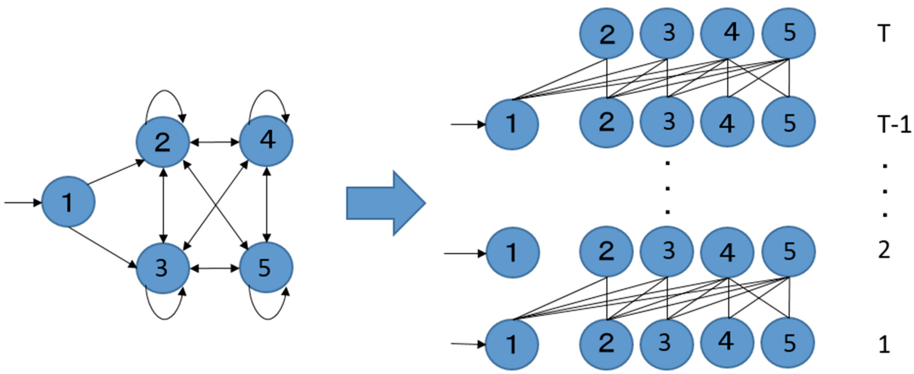

Fig. 7. Hierarchical structure

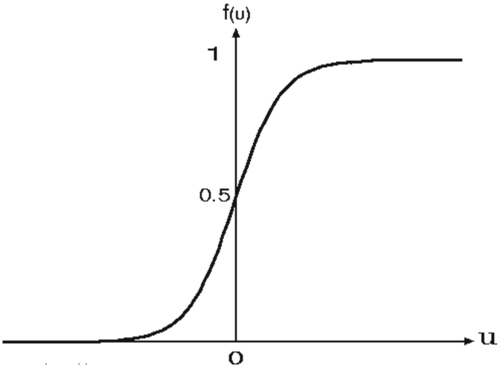

Fig. 8. Sigmoid function

where y_i^t the output of hidden layer and output layer, x_i^t is the input from outside, s_i^t is the internal state of the neuron, w_{ij} is a weight from the j-th neuron to the i-th neuron, n is the number of neurons, m is the number of input layer's neurons. The output function is used a sigmoid function (Fig. 8).

The BPTT learn by decreasing an error of outputs and teaching signals. It is defined as

$$\frac{1}{2}\sum_{k=m+1}^{n} \mu_k(t)[y_k^t - d_k(t)]^2, \tag{4}$$

where $d_k(t)$ is the teaching signal k-th neuron at time t, $\mu(t)$ is a mask function which decides relation between outputs and errors. The error from the T-th layer to the t-th layer is E^t, it is as follows:

$$E^t = E^{t+1} + \frac{1}{2}\sum_{k=m+1}^{n} \mu_k(t)[y_k^t - d_k(t)]^2. \tag{5}$$

Equation (5) is differentiated in s_k^t with a chain rule. The case of $T = t$ is

$$\frac{\partial E^T}{\partial s_k^T} = \mu_k(T)[y_k^T - d_k(T)]f'(s_k^T). \tag{6}$$

Otherwise, it is

$$\begin{aligned}\frac{\partial E^t}{\partial s_k^t} &= \sum_{l=m+1}^{n} \frac{\partial E^{t+1}}{\partial s_l^{t+1}}\frac{\partial s_l^{t+1}}{\partial s_k^t} + \mu_k(t)[y_k^t - d_k(t)] \\ &= \sum_{l=m+1}^{n} \frac{\partial E^{t+1}}{\partial s_l^{t+1}} w_{lk} f'(s_k^t) + \mu_k(t)[y_k^t - d_k(t)]f'(s_k^t) \\ &= f'(s_k^t)(\sum_{l=m+1}^{n} w_{lk}\frac{\partial E^{t+1}}{\partial s_l^t} + \mu_k(t)[y_k^t - d_k(t)]).\end{aligned} \tag{7}$$

Therefore, the weight is updated as follows:

$$\begin{aligned}\Delta w_{ij} &= -\alpha \sum_{t=1}^{T} \frac{\partial E^t}{\partial w_{kl}} \\ &= -\alpha \sum_{t=1}^{T} \sum_{k=m+1}^{n} \frac{\partial E^t}{\partial s_k^t} \frac{\partial s_k^t}{\partial w_{ij}} \\ &= -\alpha \sum_{t=1}^{T} \frac{\partial E^t}{\partial s_i^t} \frac{\partial s_i^t}{\partial w_{ij}} \\ &= -\alpha \sum_{t=1}^{T} \frac{\partial E^t}{\partial s_i^t} y_j^{t-1}, \end{aligned} \tag{8}$$

$$w_{ij} = w_{ij} + \Delta w_{ij}. \tag{9}$$

Δw_{ij} is update amounts of the weight.

3.2 Classification

The classification of the food is carried out by the recurrent neural network. When a measured food texture data is input into the recurrent neural network, it learns the weight using 3 expressions. The teacher signal is set for each input. After learning, the weight is decided, and a new food texture data is input into recurrent neural networks using the weight. A food is classified by comparing the teacher signal with the output.

4 Experiment

4.1 Measurement of Food Textures

The sample to use for this experiment is cookies, gummy candies, corn snacks. These foods are put on the stage of the texture sensor, and the output force of GMR and the output voltage of the inductor of these foods is measured when they are fractured by the food texture sensor. They are measured for 6 s and the output voltage of the inductor is 10 KHz. They are measured by ten times per 1 food. Figures 9, 10 and 11 show the results of measurement of force and inducted voltage.

The characteristic of the biscuit is to significantly change the force from 3 to 6 s. The characteristic of the gummy candy isn't to change both the force and the inducted voltage from first to last. The characteristic of the corn snack is to significantly change the inducted voltage from 3 to 6 s.

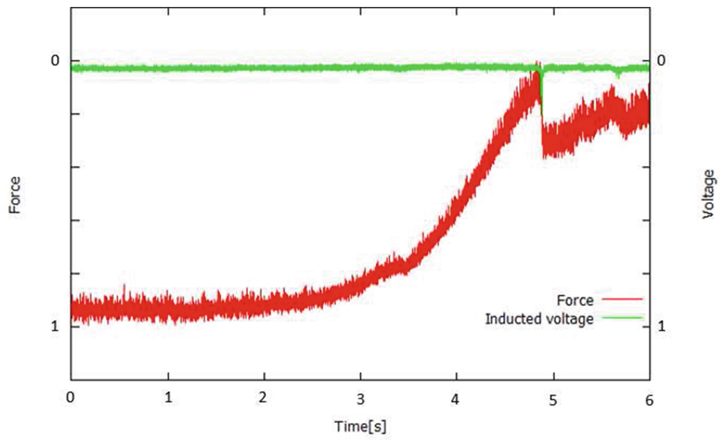

Fig. 9. Force and inducted voltage of biscuits.

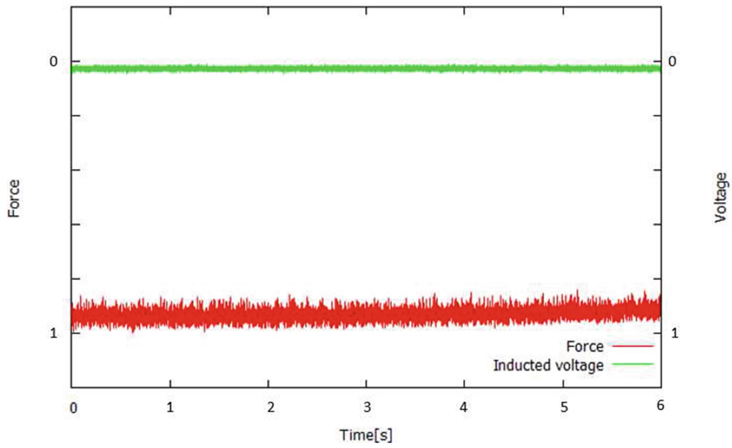

Fig. 10. Force and inducted voltage of gummy candy.

4.2 Classification

In the experiment, the training data is 1 and the test data are 9 out of measured data of 10 times. The test data are replaced with the training data, 10 times by classifications in total are carried out. The number of the inputs is 60000 because of one data in 6 s, but they are reduced to 1000 by 3 conditions, because neural network is easy to learn a little number of the inputs.

Condition 1, Measured data are averaged for every 60.
Condition 2, Measured data from 5 to 6 s are averaged for every 10.
Condition 3, The input is the data between 5.5 s and 5.6 s.

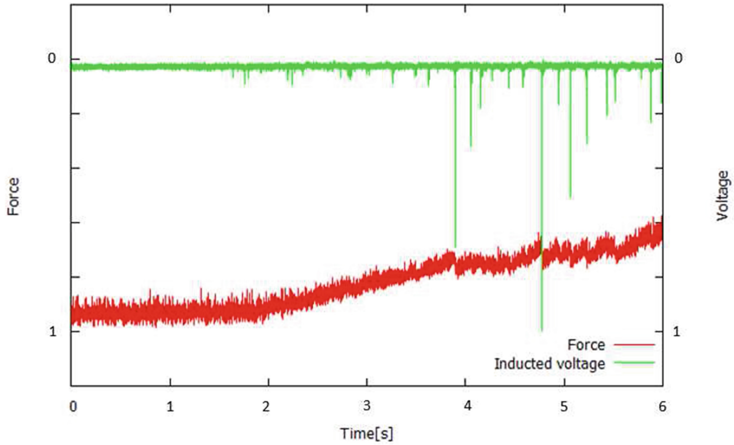

Fig. 11. Force and inducted voltage of corn snack.

Table 1. Parameters of the recurrent neural network

Time T	Number of learning	Number of neuron in hidden layer	Learning constant α
1000	10000	40	0.1

Table 2. Result of condition 1

	Biscuits	Gummy candy	Corn snack
Correct answer rate	70 %	62 %	54 %

Table 3. Result of condition 2

	Biscuits	Gummy candy	Corn snack
Correct answer rate	90 %	94 %	43 %

Table 4. Result of condition 3

	Biscuits	Gummy candy	Corn snack
Correct answer rate	100 %	96 %	76 %

The parameter of the recurrent neural network is set like Table 1. Tables 2, 3 and 4 show the result of the classification.

4.3 Discussion

Condition 3 was the best result in the three conditions. The reasons are as follows. First, the character of the food was reflected directly by not averaging measured data. Second, the change of training data and test data is about the same. In condition 1, the change became smaller by averaging it. Therefore, the classification of all foods was difficult. In condition 2, the change of corn snack of training data didn't get right with that of test data, so the classification was difficult. This study used the parameters in Table 1, but they aren't always the most suitable parameters. Therefore, it is necessary for conducting the experiment while changing the parameters.

5 Summary

This study proposed the food texture sensor based on the receptors that the human had and the food texture evaluation system using the recurrent neural networks. In the experiment, first, the food texture sensor measured the food texture of 3 foods. Second, those data were compressed by 3 conditions. Third, they were input into recurrent neural networks. Finally, the classification of the food texture was carried out by comparing the output of recurrent neural networks with the teacher signal. As a future work, this study will propose a method compressing measured data without reducing food characteristics and improve the correct answer rate of the classification.

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