Application of a Neural Network to Human Tasting

Akira SUGANUMA, Masato KATAOKA*, and Keijo ARAKI

Department of Computer Science and Communication Engineering
Kyushu University
Hakozaki, Higashi, Fukuoka 812 Japan

1 Introduction

Computers were invented as tools for calculation, and were used as only calculators in the beginning. Many people think the main use of them is to calculate numerical values. Since computers have progressed quite remarkably in recent years, they are applied to various fields such as databases, natural language processing, and so on. In China, a computer is named "电脑" (electric brain). It might be intended that a computer should simulate the human brain. It is claimed that calculating capacity of computers has surpassed that of human.

On the other hand, the recognition of human, which is a very important function of the brain, is still a weak point of computers. Nowadays, the pattern recognitions, such as character recognition, visual recognition for the sense of sight and phoneme recognition for hearing, have been widely studied. However, those studies have many problems to be solved. The human recognition is superior in ability to that of computers.

We are interested in the study of recognition by computers. We try to solve the problem of the recognition with an artificial neural network (ANN). We are interested particularly in sense of taste, because the sense of human taste is influenced by temperature, atmosphere, emotion and so on. A human taste is determined by interactions five basic tastes. A taste sensor has been developed recently. Though the taste sensor responds to various taste substances, it is very difficult to map the responses to a concentration of each substance. This paper describes the attempt to recognize the sensor responses and map them to the concentration of the substances. When an analytical approach was applied to this problem, it did not bring about a desired effect. Using an artificial neural network, however, it is not hard to estimate the strength of the five basic tastes by the sensor responses.

Abstract

This paper describes applying an artificial neural network to human tasting. In food industry, it is a very important problem to take an objective view of the human taste, because the sense of human taste is influenced by temperature, atmosphere, emotion and so on. A human taste is determined by interactions five basic tastes. A taste sensor has been developed recently. Though the taste sensor responds to various taste substances, it is very difficult to map the responses to a concentration of each substance. This paper describes the attempt to recognize the sensor responses and map them to the concentration of the substances. When a analytical approach was applied to this problem, it did not bring about a desired effect. Using an artificial neural network, however, it is not hard to estimate the strength of the five basic tastes by the sensor responses.

The transducer responds to taste substances and returns electric signals as its output. In this paper, we describe an experiment to apply the method of an ANN to simulating human tasting.

Taste substances are classified into five basic tastes, namely saltiness, sourness, sweetness, bitterness and umami. Lipid membranes of a taste transducer, however, can not respond to each taste substance selectively. Thus, it is necessary to recognize the output patterns of the sensor and map them into the strengths of the five basic tastes. If we can estimate it only by the responses of the sensor, it follows that we can take an objective view of a taste. In food industry, this is a very important problem.

We intend to establish the way how to represent the sense of taste, and also present the model of the human sense of taste in a computer. In this paper, we discuss mainly the former issue. In Section 2, we describe the taste sensor briefly. Section 3 presents an experiment of estimating the strength of each taste substance from the responses of the sensor. In Section 4, we present the results of an experiment with an ANN. Concluding remarks are given in section 5.

2 Taste Sensor

Taste substances are classified into five basic tastes, namely saltiness, sourness, sweetness, bitterness and umami. The output signal of a gustatory bud expresses interactions between these taste substances.

Sensors for the sense of sight, hearing and touch have been developed, because these sensors can measure a single physical quantity, e.g., light for the sense of sight, sound for hearing and pressure for touch. A taste sensor, however, can measure a lot of chemicals, such as the five basic tastes. A taste is also influenced by a temperature, an atmosphere, emotion and so on. Thus a taste sensor has not been developed for a long time, because it is very difficult to analyze these interrelated factors.

Tokyo-Yamafuji group, however, have developed a multichannel taste sensor. The taste sensor consists of eight kinds of lipid membranes which can respond to taste substances. These membranes convert

*Currently, TOYOTA Motor Corporation, Toyota-chou, Toyota, Aichi 471, Japan

The typical taste substance for umami is a monosodium glutamate. A soup stock of kelp tastes umami. There is not an English word equivalent to umami.
the strength of taste into an electric potential, and respond to different taste quality by unique patterns of output signals. The membranes, however, are not able to respond to each taste substance selectively. They developed the taste sensor using the property of the membranes. The multichannel sensor responds to five basic taste substances in five different ways. In this study, we used the responses of the multichannel sensor they measured.

3 Test with a Computer

3.1 Restriction

Our final goal is to probe a relation between five basic tastes. This relation is, however, so complex that we decided to choose saltiness and sourness from the five basic tastes, and investigated a relation between the two basic tastes.

Toko-Yamafuji group used two chemicals typical of the two basic taste substances, NaCl for saltiness and tartaric acid for sourness. They sampled seven different concentrations of solutions of each chemicals, which covers the whole area of human taste. These samples could stand at regular intervals on logarithmic scale of concentration. They prepared 49 (= 7²) samples mixing two solutions and measured electric potential responses of the taste sensor to those samples.

We normalized each concentration of these taste substances to integers 0 to 6, as shown in Figure 1. In the graphs, the x-axis, which was drawn from center to right, denotes the strength of sourness (0 to 6) in the sample, y-axis, which was drawn from center to left, denotes the strength of saltiness (0 to 6), and z-axis denotes the electric potential response of the each lipid membrane.

3.2 Application of the Analytical Approach

We must estimate the strength of basic taste by the electric potential responses of the sensor. At first, we tried to set up a simple equation,

$$V_i = f_i(x,y)$$

where $$V_i$$ denotes the electric potential of i-th lipid membrane in the sensor (i = 1, 2, · · · , 8), x and y denote the strength of saltiness and sourness; $$f_i$$ denotes the unknown function. If the surface of the electric potential approximates a plane, it follows that the function $$f_i$$ is a linear function on x and y. In that case, we could find the x and y by $$V_i$$ to solve simultaneous equations of the first degree. This means we are able to calculate the strength of saltiness and sourness with the electric potential of the sensor. In Figure 1, however, the surfaces are curved very much and do not approximate to a plane. Therefore the assumption is not good enough for this problem.

We then decided to calculate x and y given $$V_i$$ (i = 1, 2, · · · , 8). In other words, we must find the following function F and G:

$$x = F(V_1, V_2, · · · , V_8)$$
$$y = G(V_1, V_2, · · · , V_8)$$.  

It is very difficult to find the functions F and G, even if the surface approximates to a quadric curve surface. It may be too difficult to apply this method to the case of more than two basic tastes. Thus we gave up the analytical approach.

3.3 Artificial Neural Networks

We adopted the method to estimate the strength of each taste substance with an ANN. It is difficult to estimate it with the analytical approach as above. This is because the 49 points of electric potentials of each channel do not form a plane. Thus we gave up to set up an equation, and decided to train an ANN to the shape of the surface.

The ANN used in our experiment consists of maximum 28 neurons. The input values to the ANN were real numbers between 0 and 1, which were translated from the outputs of the sensor channels. Each neuron returns a value between 0 and 1 as its output. The output of the ANN as a whole also falls in that range. The final results were obtained by magnifying the ANN output by six.

We adopted a layered network for the ANN. The ANN has three layers: an input layer, a hidden layer, and an output layer. The input layer has eight neurons for eight types of lipid membrane in the multichannel sensor. Each neuron at the input layer and each sensor channel is in a one-to-one ratio. Each neuron is given a real numbers translated from the output of the sensor channel. The output layer has two neurons for the two taste substances, NaCl and tartaric acid, because we handled the solution of only saltiness and sourness in this experiment. We prepared fifteen ANNs whose hidden layer consists of two to sixteen neurons.

The output of the ANN is calculated by the equations:

$$n_l(l) = \sum_{j=1}^{N_{l-1}} W_{ij}(l)O_j(l-1) + \theta_i(l)$$
$$O_l(l) = f(n_l(l))$$

where $$n_l(l)$$, $$O_l(l)$$, and $$\theta_i(l)$$ denote the net input, output, and bias of the i-th neuron at the l-th layer (l = 0, 1, 2), respectively. $$W_{ij}(l)$$ denotes the weight value of the interaction between the i-th neuron at the l-th layer and the j-th neuron at the (l - 1)-th layer. $$N_l$$ denotes the number of neurons at the l-th layer. f is the nonlinear activation function defined by $$f(x) = \frac{1}{1 + e^{-x}}$$.

We used the back-propagation algorithm[5][6] to change $$W_{ij}$$ and $$\theta_i$$ to reduce the squared error E.
Figure 1: Electric Potentials of the Taste Sensor for 7$^3$ Samples
The Number of the neurons at the Hidden Layer

![Graph showing the interval estimation of the error of the ANN output.](image)

**Figure 2:** The Interval Estimation of the Error of the ANN Output

We investigated the effect caused by the modification of the number of neurons at the hidden layer. After training the ANN, we made the ANN calculate the estimators of the strength of saltiness and sourness for every sample data. We found the error of each substance defined by \((O_i - t_i)\) for \(7^2\) samples. We calculated the average \((\mu)\) and the standard deviation \((\sigma)\) of the \(7^2 \times 2\) errors. Varying the number of neurons at the hidden layer from two to sixteen, we calculated the average and the standard deviations. The error is expected to obey the normal distribution. We made the interval estimation of the error.

Figure 2 shows the interval of the error. In Figure 2, the horizontal axis denotes the number of neurons at the hidden layer, and the vertical axis denotes the error of the ANN. In the figure, vertical segments represent confidence intervals of the errors. The interval is defined by \((\mu \pm 2\sigma)\). As shown in the graph, the error decreases as the number of the neurons at the hidden layer increases. This feature is conspicuous when the hidden layer has less than seven neurons. For more than seven neurons, the segments are of the approximately same length.

We used the ANN whose the hidden layer consisting of sixteen neurons in the following experiment. Figures 3 and 4 show the net output and the absolute error defined by \(|O_i - O_t|\), where \(t_i\) and \(O_i\) are defined in the same as the previous experiment. In the graphs, the x-axis, which was drawn from center to right, denotes the strength of sourness \((0 - 6)\) in the samples, the y-axis, which was drawn from center to left, denotes the strength of saltiness \((0 - 6)\), and z-axis denotes the net output or the error.

In Figure 3, the surface is visualized using squares. z-coordinate of the four vertices of the squares were the values of the net output. An ideal surface is a plane \(z = y\) for saltiness (A) and \(z = x\) for sourness (B). Though these two surfaces do not make a perfect plane, they approximately conformed to a plane. In Figure 4, each bar in the bar charts denotes the absolute error for each sample. As shown in these bar

\[
E = \frac{1}{2} \sum_{i=1}^{2} (t_i - O_i)^2
\]
For the next test, we trained the ANN with 40 samples in the above $7^2$ samples. At the training, we did not use the 9 sample whose both values of the strength of saltiness and sourness are odd numbers. We tested that ANN with the response of sensor at $7^2$ sample points. Figures 5 and 6 show the results.

In Figure 5, the surfaces of the net output also conform approximately to a plane. Although, in Figure 6, the absolute errors are not very large. The absolute errors of the 9 sample points which we did not use in the training also are not very large. At some of the 9 samples, the absolute error is even smaller than that of the other samples. The maximum error is about 0.25 and the minimum error is about 0.003. These values are not inferior to the previous results. Hence it is possible to estimate the strength of each taste substance for the unknown solution, which is not used for the training of the ANN.

5 Conclusion
We analyzed the output pattern of a taste sensor, to map it into the strength of saltiness and sourness. The analytical approach is not suitable for this problem, because it is difficult to set up equations for the surfaces of electric potential responses of the taste sensor. It is, however, possible to train an ANN to the shape of these surfaces. We found that it is possible to estimate the strength of saltiness and sourness with an ANN even in an unknown solution.

There are some problems left in this method. Though the ANN approach in this paper assumes no external interference, the actual measurement was influenced by the temperature of the solution and the air. To avoid the undesirable effects of the external interferences, there are two approaches:

1) Maintain the environment of measurement constant;
Train the ANN using the environmental factors, such as temperature.

The second approach is better for extending the application of the proposed method.

In this paper, we focused on two basic tastes, saltiness and sourness. Future work will be adding an additional basic taste, because human being senses the five basic tastes. We must examine if the method with an ANN can analyze more than three basic tastes.

Acknowledgments
We would like to give our sincere thanks to Prof. K. Yamafuji, Prof. K. Toko, Dr. K. Hayashi and T. Murata of Kyushu University, who supplied valuable data of sensor output. We also thank Dr. H. Amano for his valuable comments to make the final paper.

References