Recognition of Material Temperature Response Using Curve Fitting and Fuzzy Neural Network

Young-Jae Ryoo, Seong-Hwan Kim, Young-Hak Chang, Young-Cheol Lim, Eui-Sun Kim, and Jin-Kyu Park

Abstract: This paper describes a system that can be used to recognize an unknown material regardless of the change of ambient temperature using temperature response curve fitting and fuzzy neural network(FNN). There are some problems to realize the recognition system using temperature response. It requires too many memories to store the vast temperature response data and it has to be filtered to remove noise which occurs in experiment. And the temperature response is influenced by the change of ambient temperature. So, this paper proposes a practical method using curve fitting to remove above problems of memories and noise. And FNN is proposed to overcome the problem caused by the change of ambient temperature. Using the FNN which is learned by temperature responses on fixed ambient temperature and known thermal conductivity, the thermal conductivity of the material can be inferred on various ambient temperature. So the material can be recognized by the thermal conductivity.

Keywords: material recognition, temperature response, curve fitting, fuzzy neural network

I. Introduction

Robots which can sense, think and act like man are required. Various sensors were studied to make the intelligent robot. Some contact sensors to sense force and pressure or to recognize forms of objects have reported, but not many a sensor to recognize material has been studied.

As a fundamental study, Russell designed a sensor to recognize materials by thermal conductivity[1], and suggested a possibility to discriminate objects using heat conducting relation. It is hard to make this method to practical use, because it takes a lot of time to reach the steady state and the characteristic of heat conduction is changed according to ambient temperature.

A practical method was studied to discriminate material comparing the three points of temperature response for an unknown material with those of the look-up table in memory[2]. But this method has a drawback that the values are influenced by the experimental noise on the temperature responses.

In this paper, we propose a method in order to overcome the above problems using curve fitting of temperature response and fuzzy neural network(FNN) learned for various ambient temperatures as shown in Fig. 1. The initial transient state of temperature response(T_s) has the trend of exponential function. The exponential function approximated by curve fitting has two parameters: coefficient(C) and exponent(E). By using these two parameters, full temperature response data can be represented without noise and reserved memory. Two parameters were measured for the change of ambient temperature(T_a) with the interval of 5[°C]. The FNN is learned by three input variables - coefficient, exponent and ambient temperature – and an output variable - thermal conductivity(TC) of material. The thermal conductivity of the material can be inferred on every ambient temperature using the FNN. So the material can be recognized by the inferred thermal conductivity.

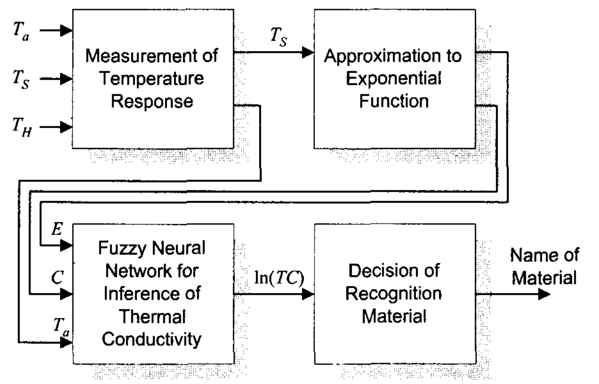

Fig. 1. Procedure of material recognition using fuzzy neural network.

II. Sensor and heat conduction

1. Principle of the Sensor

The sensor is a contact sensor which has a similar structure with human finger. There is blood with uniform temperature of 36.5[°C] which is flowing inside the finger and nerve cells which feels temperature are distributed near the skin, as shown in Fig. 2 (a). So we can feel the degree of cold according to the thermal conductivity of the contacting material. The higher thermal conductivity the material has the colder we feel. Fig. 2 (b) shows the one-dimensional model of the contacting sensor and object.

2. Relation of Heat Conduction

Sensor and object are supposed to be plane as Fig. 2 (b). And thermal resistance of conduct area is neglected. So it is regarded as the heat conduction of composite media. From heat conduction equations and boundary conditions, temperature equations of sensor and object are obtained as follows

$$T_A(z,t) = SS_A + \sum_{n=1}^{\infty} A_n \sin(S_{nA} z)\exp(-S_{nA}^2 \alpha_1 t) \quad (1)$$

$$\text{iif, } 0 < z < L_1$$

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$$T_B(z,t) = SS_B + \sum_{n=1}^{\infty} A_n C_n \sin(S_{nB}(L_1 + L_2 - z))\exp(-S_{nB}^2 \alpha_2 t) \quad \text{iif}, L_1 < z < L_1 + L_2 \ , \tag{2}$$

where SS_A and SS_B are steady state solutions of sensor A and object B respectively. A_n, C_n, S_{nA}, and S_{nB} are results from boundary conditions.

When the sensor is out of contact with an object, the temperature distribution at initial instant is shown as dotted line, and after the sensor gets in touch with an object, the steady state distribution is shown as a solid line in Fig. 2 (c).

At the steady state, T_S, the temperature of sensing point L_S is expressed as follows.

$$T_S = T_H - \frac{(T_H - T_a)}{(L_1 + L_2 K_1 / K_2)} L_S \ . \tag{3}$$

From the equation (3), thermal conductivity of object, K_2 can be obtained. Although theoretical realization of the recognition of an unknown material using K_2 is possible, it is of no practical use because it takes a lot of time to reach the steady state.

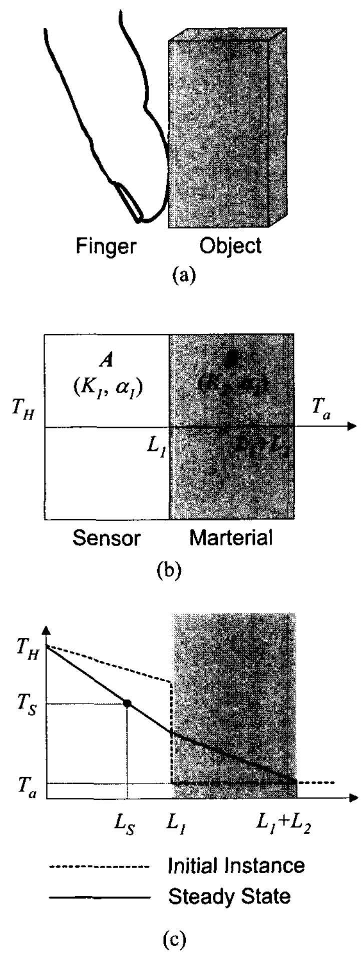


Fig. 2. Principle of sensor. (a) Contact of finger and object. (b) One-dimensional model of sensor and material. (c) Temperature distribution at initial instance and steady state.

III. Thermal response curve fitting

The temperature response has transient and steady state. For practical use, we are interested in only initial transient state. The initial transient state can be approximated to exponential function. An example of measured temperature response is illustrated in Fig. 3.

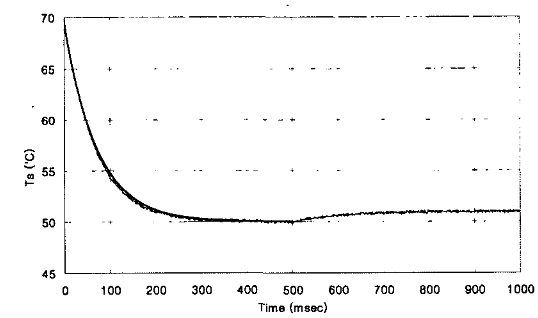


Fig. 3. Measured temperature response curve.

The raw data of the temperature response have noisy components and require too many memories. One practical way to overcome such problems is to approximate the measured data to exponential function and find out the parameters by using minimum square method. Exponential function can be expressed as

$$T_S = Ce^{Et} \ . \tag{4}$$

And natural log is taken to the both sides of (4) in order to transform the curve to linear equation.

$$\ln T_S = \ln C + Et \ . \tag{5}$$

In the equation, coefficient (C) and exponent (E) are obtained by minimum square method as follows :

$$C = \exp\left(\frac{n\sum_{i=1}^{n} t_i (\ln T_S)_i - \sum_{i=1}^{n} t_i \sum_{i=1}^{n} (\ln T_S)_i}{n\sum_{i=1}^{n} t_i^2 - \left(\sum_{i=1}^{n} t_i\right)^2} \right) \tag{6}$$

$$E = \frac{\sum_{i=1}^{n} t_i^2 \sum_{i=1}^{n} (\ln T_S)_i - \sum_{i=1}^{n} t_i (\ln T_S)_i \sum_{i=1}^{n} t_i}{n\sum_{i=1}^{n} t_i^2 - \left(\sum_{i=1}^{n} t_i\right)^2} \ , \tag{7}$$

where t_i is i-th time instant and n is the number of data used for the approximation of temperature response curve. Thus, the final result can be written

$$T_s = \exp\left(\frac{n\sum_{i=1}^{n} t_i (\ln T_S)_i - \sum_{i=1}^{n} t_i \sum_{i=1}^{n} (\ln T_S)_i}{n\sum_{i=1}^{n} t_i^2 - \left(\sum_{i=1}^{n} t_i\right)^2} \right) \cdot \exp\left(\frac{\sum_{i=1}^{n} t_i^2 \sum_{i=1}^{n} (\ln T_S)_i - \sum_{i=1}^{n} t_i (\ln T_S)_i \sum_{i=1}^{n} t_i}{n\sum_{i=1}^{n} t_i^2 - \left(\sum_{i=1}^{n} t_i\right)^2} \right) t \ , \tag{8}$$

and the curve of approximated exponential function (8) is shown as shown as thick solid line in Fig. 3.

IV. Inference of thermal conductivity using fuzzy neural network

Generally, the fuzzy inference has a distinguished feature of being able to incorporate expert's inference rules using linguistic descriptions of the rules. However, most experts often learn the inference rules through trials and errors without clear linguistic expressions and they sometimes learn rules unconsciously. The identification of the inference rules from the expert's experience is time consuming. Furthermore, tuning of the membership functions of the fuzzy logic needs "experts of the fuzzy inference". Thus, FNN can automatically identify the expert's inference rules and tune the membership functions from the expert's inference data[3]-[6].

This paper adopts a novel FNN which has advantages of both the fuzzy logic and the neural network, which makes it possible to avoid complex mathematical analysis of temperature response and reduce a lot of memory of database for various ambient temperature. The FNN is initially created by extracting rules from a set of input-output data using FCM clustering algorithm[7][8]. Then, the FNN is learned to reduce the output errors through two steps of error back-propagation learning process. In the first step, the consequence parameters of the FNN are tuned by learning data. In the second step, the fuzzy membership functions of premise part are adjusted during learning. The simplified model of the FNN for a rule is shown in Fig. 4. The number of inputs are three; coefficient(C), exponent(E) of the approximated exponential function and ambient temperature(T_a). The output is natural log of the thermal conductivity due to the exponential characteristic of thermal conductivity for various materials. When the learning is completed, the FNN is able to infer the thermal conductivity of the materials at investigated ambient temperature as well as the one that is not investigated.

1. Configuration

Fig. 4 shows a configuration of the proposed fuzzy inference using a neural network. The fuzzy model is of a linear hybrid model.

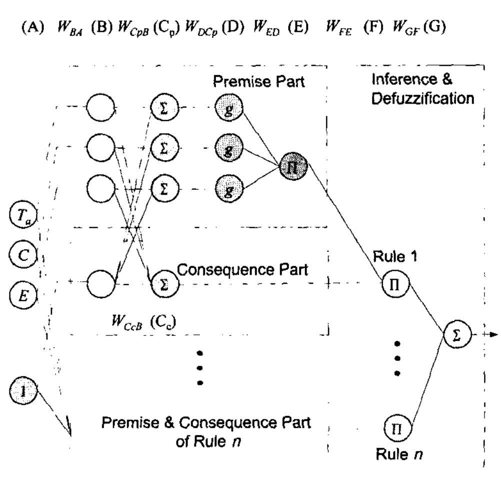


Fig. 4. Architecture of the fuzzy neural network.

$$
\begin{aligned}
R^i &: \text{if } x_1 \text{ is } A_1^i, \text{ and } \cdots, \\
&\quad x_j \text{ is } A_i^i, \text{ and } \cdots, \\
&\quad x_n \text{ is } A_n^i \\
&\text{then } y^i = a_0^i + a_1^i x_1 \cdots + a_n^i x_n
\end{aligned} \tag{9}
$$

$$
w_i = \prod_{j=1}^{m} A_j^i(x_j) \tag{10}
$$

$$
y^o = \frac{\sum_{i=1}^{n} w^i y^i}{\sum_{i=1}^{n} w^i} \tag{11}
$$

where R^i is the i-th fuzzy rule, x_j is the j-th input variable, A_j^i is the i-th fuzzy variable for the j-th input variable, n is the number of rules, y^i is the i-th inferred output value, a_j^i is the coefficient, w_i is the true value in the premise and y^o is the inferred output value.

2. Premise

The network consists of seven layers and uses the back propagation algorithm for learning of the network as shown in Fig. 4. The figure shows the case where the controller has n-inputs($x_1, x_2, ..., x_n$) layer (A layer), one-output layer (G layer), and hidden layer for an unit rule. The outputs of the units with symbols denote sums of their inputs and denote products of their inputs. The inputs into (A)-layer x_j are normalized by the connection weights W_{BA}. Normalized input variables, x_j are given by

$$
x_j = \frac{x_j}{\text{Max } |x_j|} = W_{BA} x_j \tag{12}
$$

The sigmoid function $f(x)$ are given by

$$
f(x) = \frac{1}{1+\exp(-W_{DCp}(x+ W_{CpB}))} \tag{13}
$$

where W_{CpB} and W_{DCp} are to be modified through learning.

The output of the unit in (D)-layer $g(x)$ is derived by removing the magnitude of the differentiated value of the sigmoid function $f(x)$. The output of (D)-layer $g(x)$ is the bell-shaped membership function that has a center of W_{CpB} and slope of W_{DCp}.

$$
g(x) = \frac{1}{1+\exp(-W_{DCp}(x+ W_{CpB}))} \cdot \left\{1 - \frac{1}{1+\exp(-W_{DCp}(x+ W_{CpB}))}\right\} \tag{14}
$$

3. Consequence

The consequences are expressed by linear equations. As shown in Fig. 4, the neurons of (B)-layer are connected with the neuron of (C_c)-layer through weight W_{CcB}, which expresses coefficient a_j^i of the linear equations. Therefore, the output of (C_c)-layer is expressed as follow:

$$
y^i = a_0^i + a_1^i x_1 + \cdots + a_n^i x_n \tag{15}
$$

The inferred value of the neuro-fuzzy is obtained from the product of the true values in the premises and the linear equations in the consequences.

$$y^{i*} = \frac{w^i y^i}{\sum_{k=1}^{n} w^k} \quad (16)$$

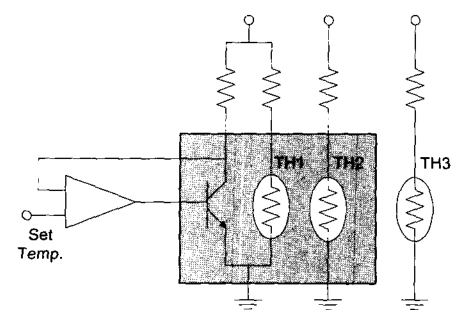
The output of (G)-layer can be expressed as follow:

$$y^* = \sum_{i=1}^{n} y^{i*} \quad (17)$$

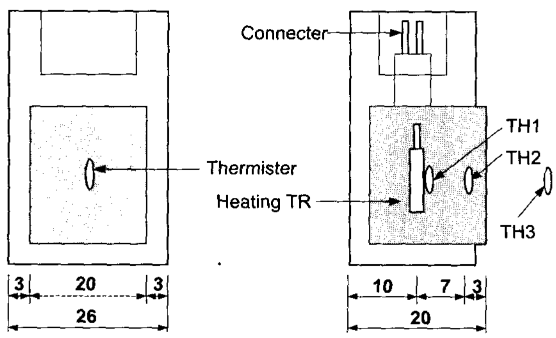
V. Experimental hardware configuration

1. Sensor structure

Basic structure, shape and size of the sensor is shown in Fig. 5. The sensor is composed of two parts, heating part and sensing part. A power transistor is used as the heating source and the first thermistor(TH1) provides feedback for a temperature stabilizing circuit And the second thermistor(TH2) measures the temperature drop caused by heat flow into the gripped object. The third thermistor(TH3) measures the ambient temperature. Because of its flexible elasticity, silicon rubber works like skin of the human finger.



(a)



(b)

Fig. 5. Structure of sensor (a) Circuit (b) Dimension.

2. Hardware configuration

The hardware configuration for experiment is shown in Fig 6. There are a testing robot, a sensor, a computer, a D/A converter and an A/D converter, etc. Temperature setting of the heating part is controlled by D/A converter. As soon as the measuring operating begins at work, the temperature of the heater, the ambient temperature and the temperature of the sensor are measured through the A/D converter. Robot gripper is controlled by the computer through RS-232C line.

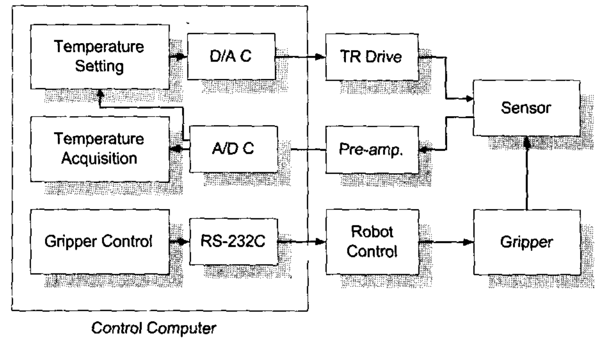


Fig. 6. Hardware configuration for experiment.

VI. Experimental results and discussion

1. Temperature response curve fitting

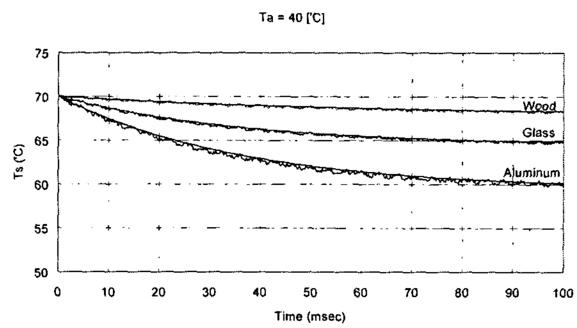


Fig. 7. Measured temperature response at ambient temperature 40[°C] by experiment and approximated exponential function by curve fitting.

Temperature response of material is influenced not only by the thermal conductivity of the material, but also by the ambient temperature. The three materials - Aluminum, Glass and Wood - were used as the experimental objects and all materials have the same shape and size - 65 × 35 × 5 [mm]. From 0[°C] to 40[°C] of ambient temperatures, the temperature response curves of the three materials were measured with the interval of 5[°C]. The temperature response data were generalized to exponential function by curve fitting. Fig. 7. shows measured curves and approximated curves for each material. Agreement between measured and approximated curve is reasonable.

2. Learning data

The approximated exponential function has two parameters - coefficient and exponent - which represent temperature response. The coefficient and exponent of the exponential function according to various ambient temperature are used for the inputs of the FNN and the value corresponding to the thermal conductivity of material used for the output. Fig. 8 shows the learning data for three materials. The FNN is learned to reduce the output errors through two steps of error back-propagation learning process. In the first place, the consequence parameters of the FNN are tuned and secondly the fuzzy membership functions of premise part are adjusted by the learning data. The FNN can be used as a inference system to recognize materials.

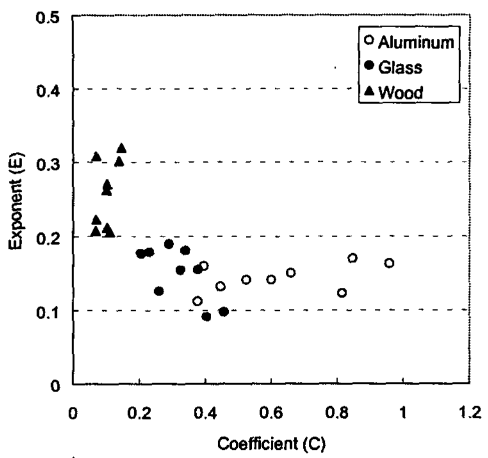


Fig. 8. Distribution of experimental data of three materials.

3. Experimental results

Experimental results are shown in Table 1. The difference between expected and inferred output is to the learning error of the FNN. It is, however, considerably small and makes no trouble to discriminate materials among aluminum, glass and wood. On every ambient temperature, it was able to recognize the material exactly. As shown in Table 1, for example, it was possible to recognize materials on the ambient temperature of 18[°C] where learning was not carried out.

Table 1. Inference results at various ambient temperature where learning was not carried out.

Ambient Temp. (°C)	Material	Expected Output	Inference Output	Error
3	Aluminum	1	0.9.5989	0.094011
	Glass	0.378825	0.457008	-0.07818
	Wood	0	-0.13489	0.134890
18	Aluminum	1	0.985992	0.014008
	Glass	0.378825	0.426604	-0.04778
	Wood	0	-0.11272	0.112718
27	Aluminum	1	0.966333	0.033667
	Glass	0.378825	0.414050	-0.03523
	Wood	0	-0.03732	0.037321
32	Aluminum	1	1.001507	-0.00151
	Glass	0.378825	0.408062	-0.02924
	Wood	0	-0.04298	0.004298

VII. Conclusion

We described in this paper an intelligent technique that can be used to recognize materials regardless of ambient temperature change. Using curve fitting of temperature response, full temperature response data could be represented by exponential function which has two parameters - coefficient and exponent. Consequently, a method using curve fitting removes the problems of memory and noise. And excellent agreement was obtained between measured curve and approximated curve in experimental result. Using FNN, the problem caused by the change of ambient temperature was overcome. The thermal conductivity of material was inferred on every ambient temperature using the FNN. So, the material could be recognized by the inferred thermal conductivity. In the future, we will apply the proposed recognition system to various materials.

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