Material Recognition Using Temperature Response Curve Fitting and Fuzzy Neural Network

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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 temperatures and known thermal conductivity, the thermal conductivity of the material can be inferred on various ambient temperatures. So the material can be recognized by the thermal conductivity.**

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 been reported, but not many a sensor to recognize material has been studied.

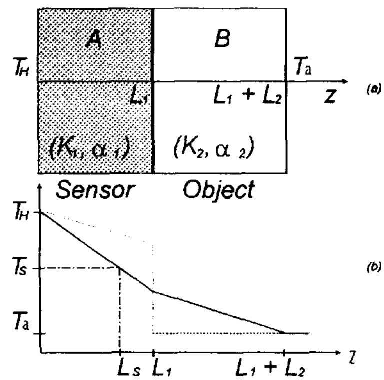
As a fundamental study, Russell designed a sensor to recognize materials by thermal conductivity[1], and suggested a possibility to discriminate objects using heat conducting relation. It is hard to make this method to practical use, because it takes a lot of time to reach the steady state and the characteristic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

A practical method was studied to discriminate materials 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. The initial transient state of temperature response has the trend of exponential function. The exponential function approximated by curve fitting has two parameters : coefficient and exponent. 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 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 of material. The thermal conductivity of the material can be inferred on every ambient temperatures using the FNN. So the material can be recognized by the inferred thermal conductivity.

II. SENSOR AND HEAT CONDUCTION

2.1 Basic principle of the sensor



T_H : temperature of heating part
T_S : temperature of sensing part
T_A : temperature of sensor
T_B : temperature of object
Ta : ambient temperature
α_1 : diffusion factor of sensor
α_2 : diffusion factor of object
K_1 : thermal conductivity of sensor
K_2 : thermal conductivity of object
L_1 : thickness of sensor
L_2 : thickness of object

Fig. 1. Contacting sensor and object
(a) One dimensional model
(b) Change of temperature distribution from initial contact to steady state
Dotted line : Temperature distribution at initial contact
Solid line : Temperature distribution at steady state

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. 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. 1(a) shows the one dimensional model of the contacting sensor and object.

2.2 Relation of heat conduction

Sensor and object are supposed to be plane as Fig. 1(a). 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

$$T_A(z,t) = SS_A + \sum_{n=1}^{\infty} A_n \sin(S_{nA} z)\exp(-S_{nA}^2 \alpha_1 t) \quad (0 < z < L_1) \qquad \text{......(1)}$$

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

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 steady state temperature distribution 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. 1(b).

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

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

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.

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 as dotted line in Fig. 2.

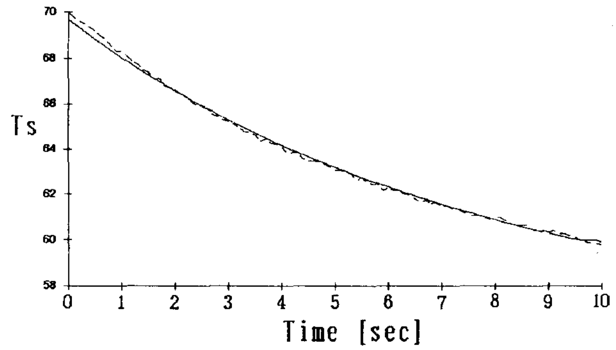


Fig. 2. Temperature response curve and approximation of an unknown material
Dotted line : measured temperature response
Solid line : approximated exponential curve

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

$$T_S = C\ e^{Et}\ . \qquad ......(4)$$

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

$$\ln\ T_S = \ln\ C + Et\ . \qquad ......(5)$$

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

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

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

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

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

......(8)

and the curve of approximated exponential function (8) is shown as solid line in Fig. 2.

IV. INFERENCE OF THERMAL CONDUCTIVITY USING FUZZY NEURAL NETWORK

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[4,5]. 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. 3. The number of inputs are three : coefficient(C), exponent(E) of the approximated exponential function and ambient temperature. 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.

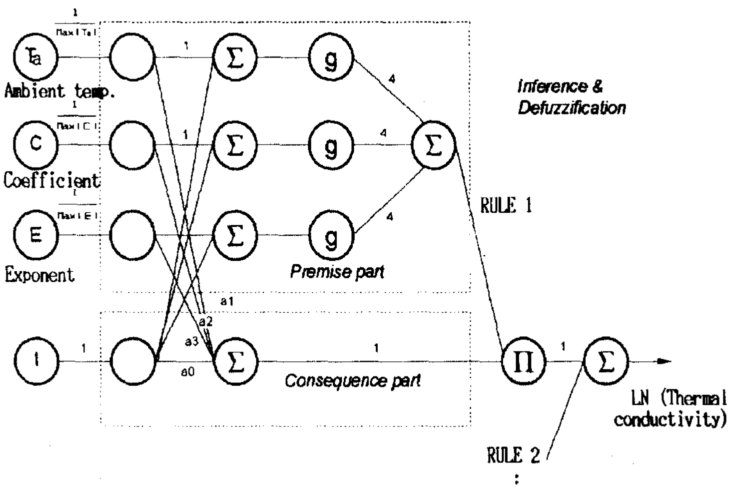
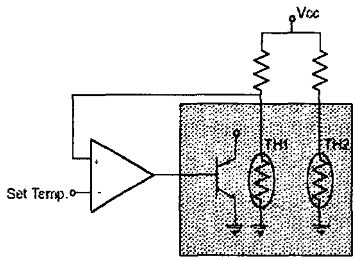


Fig. 3. Simplified inference procedure of the fuzzy neural network

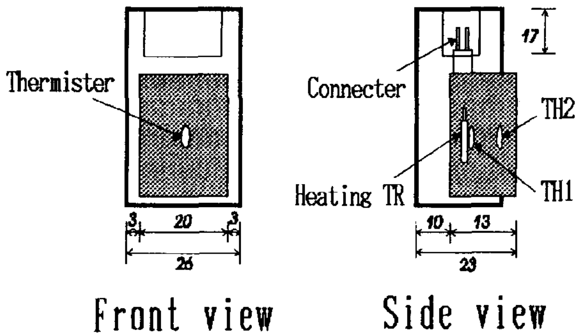
V. Hardware Configuration

5.1 Sensor structure

Basic structure, shape and size of the sensor is shown in Fig. 4. 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) Basic structure



(b) Shape and size of the sensor

Fig. 4. sensor structure and size

5.2 Hardware configuration

The hardware configuration is shown in Fig. 5. There are a testing robot, a sensor, an IBM-PC, a D/A converter and an A/D converter.

Temperature setting of the heating part is controlled by D/A converter. As soon as the measuring operation 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 PC through RS-232C line.

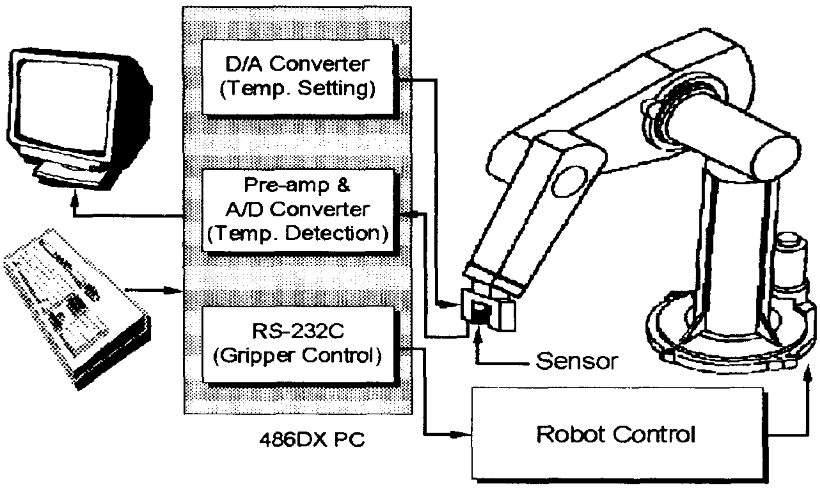


Fig. 5. Hardware configuration

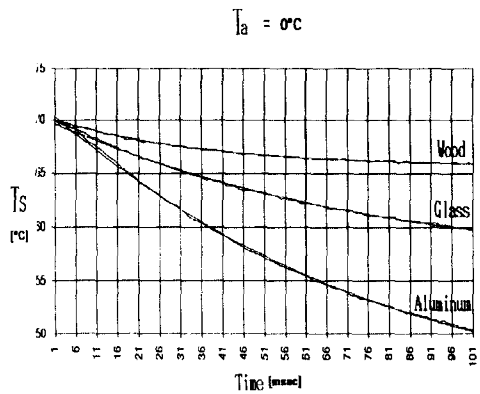
VI. Experimental Results and Discussion

6.1 Temperature response curve fitting

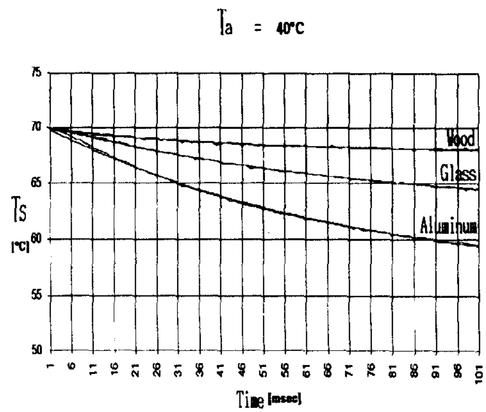
Temperature response of material is influenced not only by the thermal conductivity of the material, but also by the ambient temperature.

The three materials - Aluminum, Glass and Wood - were used as the experimental objects and all materials have the same shape and size - 65 x 35 x 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. 6 shows measured curves and approximated curves for each material. Excellent agreement was obtained between measured and approximated curve.



(a) Ambient Temp. = 0 °C



(b) Ambient Temp. = 40 °C

Fig 6. Measured response curves and approximated curves

6.2 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 temperatures are used for the inputs of the FNN and the value corresponding to the thermal conductivity of material is used for the output.

Fig. 7. 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.

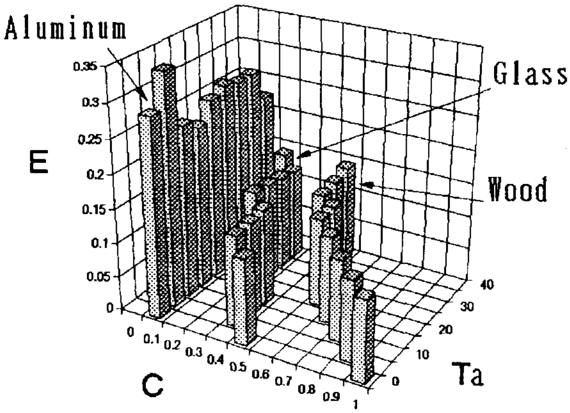


Fig 7. Three dimensional view of the learning data

6.3 Experimental results

Experimental results are shown in table 1. The difference between expected and inferred output is due 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. Comparison the expected outputs with the inferred outputs

Ambient Temp.	Material	Expected output	Inferred output	Error
5 °C	Aluminum	1	0.950047	0.049953
	Glass	0.378825	0.444380	-0.06555
	Wood	0	-0.08765	0.087650
18 °C	Aluminum	1	0.985992	0.014008
	Glass	0.378825	0.426604	-0.04778
	Wood	0	-0.11272	0.112718
30 °C	Aluminum	1	0.929522	0.070478
	Glass	0.378825	0.412852	-0.03403
	Wood	0	-0.06078	0.060778

The graphic display for on-line measurement and experiment is shown in Fig. 8. In this case, the recognition of aluminum on the ambient temperature of 18[°C] is carried out. Measured temperature, approximated exponential curve, ambient temperature, heating part temperature, sensing part temperature, coefficient, exponent, inferred output and the name of recognized material are shown on the screen.

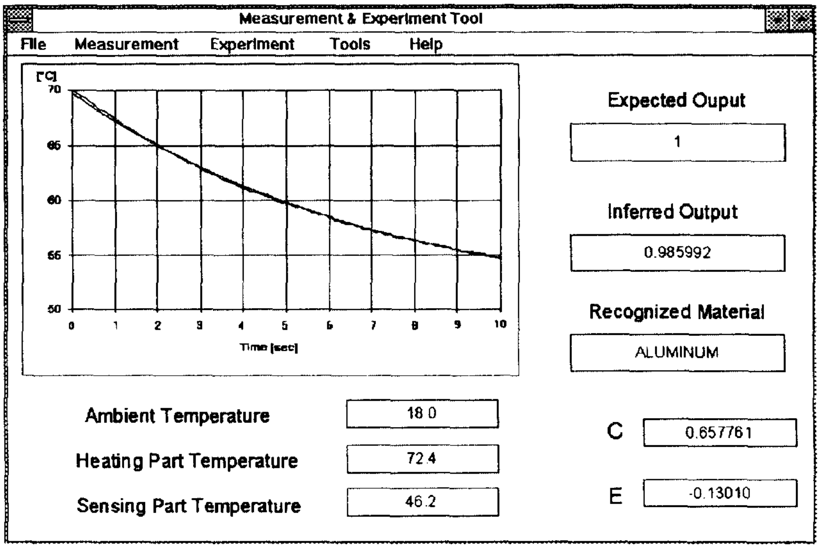


Fig. 8. On-line software for the recognition of an unknown material

VII. Conclusions

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 overcomed. 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.

For the purpose of on-line measurement and experiment, sensor, interfacing hardware and the software for Windows was developed.

References

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