研 究 速 報

3D Particle Imaging Thermometry and Velocimetry (PITV) using Liquid Crystal

—3rd Section; A Color-to-temperature Calibration Method using a Neural Network—

感温液晶粒子を用いた3次元粒子画像温度・速度計測法

—第3報; ニューラルネットワークによる温度と色の較正—

Deoghee DOH*, Toshio KOBAYASHI** and Tetsuo SAGA**

都 徳 熙・小 林 敏 雄・佐 賀 徹 雄

1. Introduction

For the measurement of temperature of thermal fluid flow using the thermo-sensitive liquid crystal particles, it is necessary to know the relation between the color and the temperature of the particles. Therefore, an experiment for color-to-temperature calibration should be advanced before commencing the main experiment for temperature measurement. The data acquired by the calibration experiment are used for deciding the temperature of those particles suspended in the thermal fluid flow. Besides the optical characteristic, bragg-type scattering, which had been explained in the second section of this paper, the color-to-temperature characteristic of the microcapsulated liquid crystal particle is also peculiar showing a non-linear characteristic. In this section of this paper, a new color-to-temperature calibration method is stated.

There are two main ideas of acquiring the color-to-temperature characteristic curves in using the liquid crystal. The one is the optical filtered method and the other is to use the colormetry based method. Goldstein et al.[1] could get isothermal contours by using optical filters on the study of impinging jet. Akino et al.[2] also developed a method using narrow band pass filters, by which more than 10 isotherms and map for the existence of intermediate color bands. Fortunately, recent delicate video and image processing systems have enabled many researchers to apply colormetry based methods replacing the optical filtered methods which have been suffered from the deficits of low resolution of colors.

In this study, a colormetry method is used applying a color-to-temperature matching method in which a neural network is suggested.

Generally, the color interpretation is based on the tristimulus values, R(red), G(green), and B(blue). The interpreting method of color images of liquid crystal will be able to be divided into three main routes, MUNSELL color notation, CIE rgb and XYZ coordinates, and NTSC RGB notation based on the tristimulus R, G, and B. In the present instances, true-color interpretation can be obtained, from which surface temperature is to be obtained for each pixel of the images, using a chromatic calibration of the liquid crystal material. This requires describing each perceived color by a set of three scalars, RGB components. All of these ideas are commonly used to construct Hue values for the production of color-to-temperature calibration curves[3),4)]. Another alternatives, widely used at present, for the production of color-to-temperature calibration are the multiregression method[2)] and computer look-up table method[5)].

The two most important sets of primaries are the NTSC RGB system used in color video transmission and the X, Y, Z tristimulus values used as the historical basis for color calculation. Usually, the Hue value, representing the most dominant wavelength of any color, is calculated by RGB or XYZ tristimulus and is used for chromatic interpretation.

*Department of Refrigeration and Air-Conditioning Engineering, Korea Maritime University, Pusan Korea

**2nd Department, Institute of Industrial Science, University of Tokyo

And the dominant wavelength is related to the chromatic coordinates, r, g, and b. Based on these values, a new concept of acquiring the calibration curve of color-to-temperature is considered using a neural network of which layer is three layers, input, hidden, and output layer.

2. Color-to-temperature Relations

For quantifying the color that corresponds to a certain temperature, a quantification process is adopted. At first, the color of the particle is visualized by a halogen cold light. Secondly, the visualized color of particles is recorded on the optical disc through the color camera and after this the recorded color is digitized into 256 (through 8-bit A/D converter) intensity levels by a color image processor, which was explained in the previous section. This quantified intensity levels produce digitized NTSC RGB primaries. The acquired intensity R, G, and B through by the measurement system are nomalized as r, g, and b as in the equation (1).

$$r=R/(R+G+B),\ g=G/(R+G+B),\ b=B/(R+G+B) \tag{1}$$

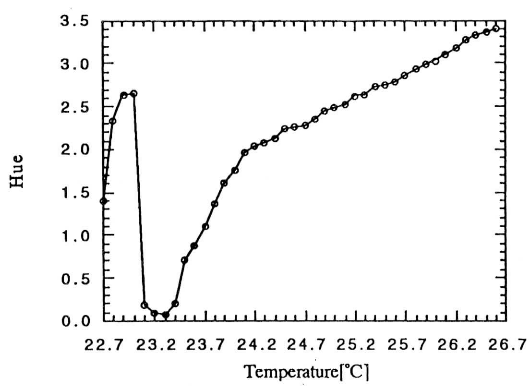


Fig. 1　Relation between temperature and Hue value

$$\text{Hue}=\theta \quad ;\ \text{when, } g>b \text{ and } g=b.$$
$$\text{Hue}=2\pi-\theta \quad ;\ \text{when, } g<b.$$
$$\text{Here, } \theta=\cos^{-1}(2r-g-b)/(6c)^{1/2}$$

where,

$$c=[(r-1/3)^2+(g-1/3)^2+(b-1/3)^2]^{1/2}$$

These values are used for temperature decision by a neural network which is applied for the reason that the

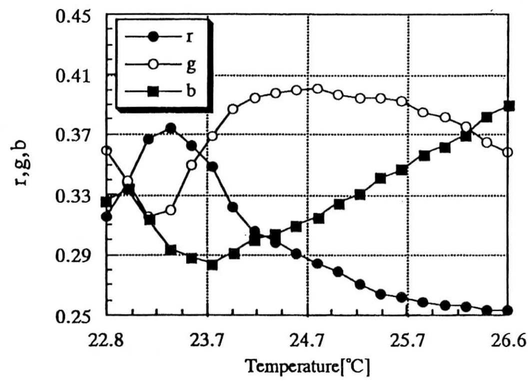
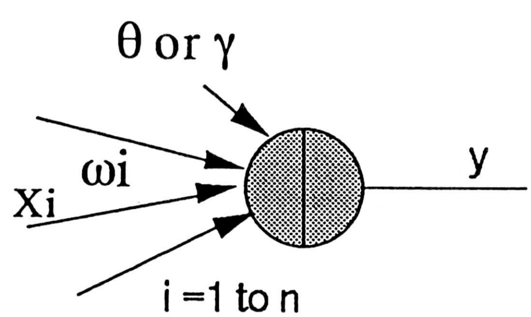


Fig. 2　Relation between temperature and r, g, and b

chromatic characteristic of liquid crystal against temperature change is strong non-linearity as shown on the figure 1. The Hue value is defined as on the figure by the tristimulus R, G, and B. This characteristic is derived from the relation between the color of the used liquid crystal particles (R23CW3, ϕ=0.3 mm) and the temperature as shown on the figure 2. From the figure 1 it can be said that it is difficult for the Hue value to be used in wide range of colors with the color changes. At a lower temperature, there exist multiple temperatures of one Hue value. This makes the liquid crystal particle difficult to be used as a temperature sensor especially in the case of wide range use of temperature up to the lowest visible temperature range. To solve this problem a neural network is applied here.

3. Color-to-temperature Calibration by a Neural Network

Neural networks, as they are known today, originate from the work of McCulloch and Pitts[6] who demonstrated, in 1943, the ability of interconnected neurons to calculate some logical functions.



$$y=\Sigma\omega_i x_i+\theta\ (\text{or}\ \gamma)$$

Fig. 3　Neuron model

Artificial neural networks, coupled with an appropriate learning algorithm, can be used to learn complex relationship from a set of associated input-output vectors. In this study, the input vector is the color of the micro-capsulated liquid crystal particle and output vector is its temperature.

A neuron, schematically represented in the figure 3, is the basic building block of neural network which performs a non-linear transformation of the weighted sum of the incoming inputs to produce the output of the neuron. And the unit response for the neuron is sigmoid function. Inputs and outputs of the network are normally numeric values scaled between 0 and 1. The input to a neuron can come from other neurons or from outside the network.

In this study, a three-layer feedforward network was used, that is a network with a single hidden layer as shown in the figure 4. The values r, g, and b of the micro-capsulated liquid crystal particle are used for the input layer and the temperature of the same color is used as a teaching for the output layer.

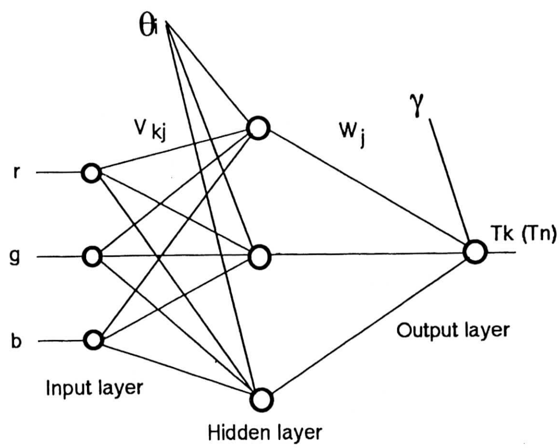


Fig. 4 Neural network used for temperature deciding

The details of the calculation using a three-layer neural network are summarized as the procedure to be explained using sets of equations. The learning algorithm for this feedforward layered network is the most versatile backpropagation in which a quadratic cost function is minimized by a modified gradient descent[7].

The learning process consists in determining the weight matrices, Vkj and Wj, that produce the best fit of the predicted outputs over the entire training data set. The basic procedure is to first set the weights between adjacent layers to random values. An input vector is then impressed on the input layer and it is propagated through the network to the output layer. The difference between the computed output vector of the network and the scaled target output vector is then used to adapt the weight matrices using an iterative optimization technique in order to progressively minimize the sum of squares of the errors. The process is repeated over the entire training set, a great number of times, to achieve the desired degree of accuracy.

Since the backpropagation algonithm minimizes the error function Et, the expression is the equation (2). Here, Tk is a teaching value of k pattern and Ok is the output of the learned neural network for the Tk.

$$Et=\Sigma(Tk-Ok)^2/2 \qquad (2)$$

The output Ok is expressed as the equation (4), called sigmoid function, using the inner potential Sk of the output layer in the equation (3) in which Hj is the output of the hidden layer. The output Hj of the hidden layer is also obtained through the same sigmoid function that uses inner potential of the input layer of which equation is same pattern as the equation (3).

$$Sk=\Sigma\, WjHj+\gamma \qquad (3)$$

$$Ok=1/(1+\exp(-Sk)) \qquad (4)$$

To obtain the whole weight coefficients between layers, the weight coefficients are calculated in readjusting manner in which the influence of each weight coefficient to the error function E_t in the equation (2) is examined in a partial differential manner expressed in the equation (5).

$$\Delta Vkj=-\alpha\frac{\partial Et}{\partial Vkj} \quad \text{for hidden layer,}$$

$$\Delta Wj=-\beta\frac{\partial Et}{\partial Wj} \quad \text{for output layer} \qquad (5)$$

The above equation (5) can be rewritten by using the equations (2), (3), and (4). For minimizing the error function E_t, new weight coefficients are decided by readjusting the old weight coefficients as shown on the equation (6). The values α and β are relaxation constants for calculation.

$$Vkj=Vkj+\Delta Vkj,\quad Wj=Wj+\Delta Wj \qquad (6)$$

After obtaining the whole weight coefficients, a teaching for the learned neural network is done by putting the whole values of r, g, and b of the input temperatures of the micro-capsulated liquid crystal particle used in this jet experiment. The number of patterns is 40 from 22.8°C to 26.7°C by 0.1°C step.

The circle points Tn are the obtained temperature through the neural network and the dotted line means the ideal condition (Tn=Tr) when the temperature (Tr) obtained through the experiment of color-to-temperature calibration, which is set as an input of the neural network, is the same as the temperature obtained through the neural network. The result from the teaching is shown on the figure 5. This curve is used as the calibration data for the measurement of temperature in this study. In other words, before using the neural network, the experiment of calibration for color-to-temperature should be done, and after that the data from the experiment are used for the neural network which can recall the desired temperature straightforwardly.

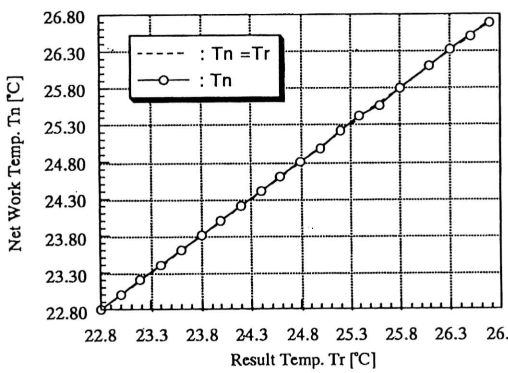


Fig. 5 Recovered temperature by the neural network

The average error of this network was 0.005°C and the the learning was 200000 times. It can be said that the efficiency of the restoration of the temperature of the colors is very good. And it was possible for the colors at lower temperature to have only one value rather than the case of using the Hue value, in which two or three temperature values existed for one color. The principle of the temperature measurement in this study is to use this neural network.

4. Conclusions

Since the relation between the temperature and the color of the liquid crystal particle shows a strong nonlinearity, a new mapping technique for the non-linearity has been considered using a neural network. The dynamic range of the temperature measurement has been widen by applying the three layered neural network, showing a good curve fitting of color-to-temperature.

Indeed, it is necessary to present all examples of the learning set many thousand times. However, once an appropriate set of weights has been obtained, the use of the neural model to recall stored information is straightforward.

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