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Handwriting Character Classification Using Freeman's Olfactory KIII Model

Masanao Obayashi*, Shinnosuke Koga*, Ling-Bing Feng*, Takashi Kuremoto*, and Kunikazu Kobayashi*

*Graduate School of Science and Engineering, Yamaguchi University
2-16-2 Tokiwadai, Ube, Yamaguchi, 755-8611, Japan
{m.obayas, n017vk, n007we, wu, koba}@yamaguchi-u.ac.jp)

Abstract: Recently, researches on smell sense that is one of the sensory organs of man have been actively done. The KIII model is one of the olfactory models that is thought out by Freeman referring to a physiological structure of mammal's olfactory system. In this paper, we propose a commonly used feature extraction method that applies Fourier transformation to the behavior of the time series and also propose to use the dynamics of chaotic neuron instead of the Hodgkin-Huxley equation to reduce computation time. Our introduced structure of the chaotic neuron has the simple structure and that it makes possible the chaotic operation same as the Hodgkin-Huxley equation. Paying attention to the point that the human brain does a similar processing to any sense of information, the hand-written image recognition problem that uses the KIII model is adopted as the computation simulation. Through the computer simulation of the handwriting character classification, it is shown that the proposed method is useful in the point of both computation time and the recognition accuracy.

Keywords: Handwriting character classification, Freeman, KIII model, Fourier transformation, Chaotic neuron

I. INTRODUCTION

Recently, according to development of non-invasive measurement techniques (CT, PET, fMRI, NIRS etc.), experimental research on higher-order brain functions has been advancing dramatically and the latest researches have been used in many fields. One of those high-order systems, the olfactory system, has also come to be actively done. As a model of the olfactory system, there is KIII model proposed by Freeman et al. [1][3].

The KIII model has been modeled based on the physiological structure of the mammalian olfactory system, and there are many applications using pattern recognition ability of the olfactory system. For example, J.Fu et. al[2] combined KIII model and the electronic nose with chemical sensors, and applied it to discriminate six typical volatile organic compounds in Chinese wine. The KIII is also applied to Tea Classification problem (Yang et. al[4]), Face Recognition (Li et. al. [6]), On the other hand, response of the olfactory system has a chaotic nature [5][7], it has also attracted many researchers.

In this paper, we apply the KIII model to handwriting character classification. In the application of the KIII model mentioned above, they performed the pattern recognition by using standard deviation of time series response inside the KIII model corresponding to the inputted data which should be discriminated. In this paper, we propose to use Fourier transform as the feature extraction method.

On the other hand, in KIII model, output of the neuron is obtained by solving second order ordinary differential equations and as a result, that leads to the problem that enormous processing time is required. Therefore, in this study, we aim reduction of the processing time, maintaining the chaotic characteristic of each neuron, by adopting the simplified output formula.

II. KIII MODEL

KIII is a recurrent neural network model created by Freeman et al, based on biological olfactory structure [1]. The main parts of the neural olfactory neural system is composed of primary olfactory nerve (PON), olfactory bulb (OB) , anterior nucleus (AON), and prepyriform cortex (PC). According to the anatomic architecture, KIII network is a multi layer neural network model. Fig. 1 shows the structure of the KIII model, in which M, G represent mitral cells and granule

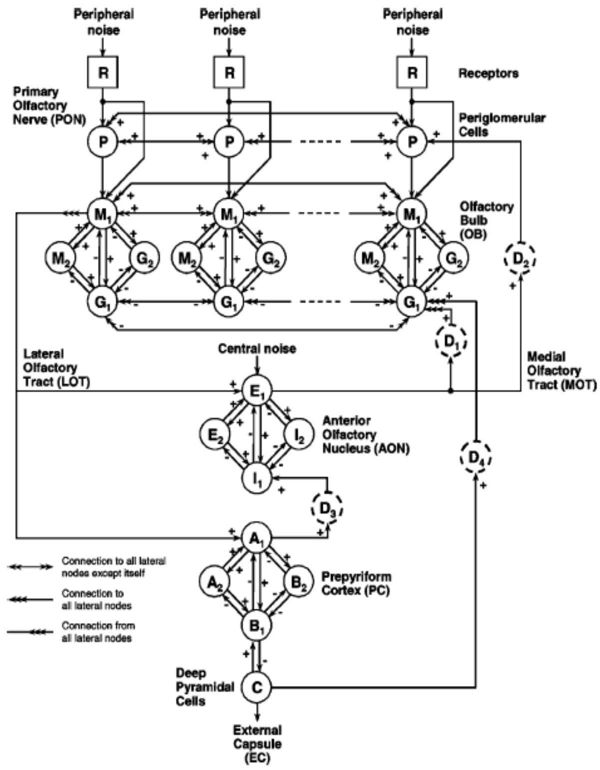

Fig. 1 Structure of the KIII Model (from [5][6])

cells in olfactory bulb.R represents the olfactory receptor, which offers input to the KIII model. E, I, A, B represent excitatory and inhibitory cells in anterior nucleus and prepytiform cortex, respectively. The KIII model based on the olfactory neural system is a high dimensional chaotic network. In this model, the interaction of connected nodes leads to a high-dimensional chaotic attractor. After learning from different patterns, the system will form several low-dimensional local basins[3]. Therefore, the memory for different patterns might be regarded as the formation of the local basins, while the recognition process refers to the transition from one basin to another.

The parameters of the KIII model, such as connection weights between different nodes, were optimized to fulfill features observed in lots of electro-physiological experiments [3]. Every nodes is described as a second order differential equation as follows:

$$\frac{1}{ab}[\ddot{x}_i(t)+(a+b)\dot{x}_i(t)+abx_i(t)]=\sum_{j\neq i}^{N} w_{ij}Q(x_j(t),q_j)+k_i r_i(t),$$

$$Q(x(t),q)=\begin{cases} q\left(1-\exp\left(-\dfrac{\exp(x(t))-1}{q}\right)\right), & x(t)>-x_0 \\ -1, & x(t)\le -x_0 \end{cases}, \tag{1}$$

$$x_0=-\ln\left(1-q\ln\left(1+\frac{1}{q}\right)\right).$$

$x_i(t)$: state variable of the ith node, w_{ij}: the connection weight from j to ith node, a, b, q: constants derived by the electro-physiological experiments on biological olfactory system. k_i: coefficient as to the effect of the input, $r_i(t)$: input (external stimuli), N: the number of neurons

III. FEATURE EXTRACTION

Usually, when doing pattern recognition using the KIII model in general, we should create a feature vector from the characteristics of the behavior of M1 node dynamics.

Feature extraction by the standard deviation

(Commonly used)

The state of OB layer mitral level is used as the strength of activity. The learning process only adjusts connection weights among the mitral. A modified Hebbian learning rule and a habituation rule are employed to KIII model.

When feature data are input to the KIII model with n channels, the behavior of each node is represented as an output time series as shown in Fig. 2. To get the characteristics of the kth channel's state, a value $SD(k)$ is extracted. The period with input patterns is divided into S segments (Fig. 2) and $SD(k)$ is the mean standard deviations of these segments. SD, composed of all the $SD(k)$ in the OB layer, depicts the activities of the all channels.

$$SD(k)=\frac{1}{s}\sum_{r=1}^{s}SD_{kr},\quad k=1,\ 2,\ \ldots,\ n\ , \tag{2}$$

$$SD_m=\frac{1}{n}\sum_{k=1}^{n}SD(k),\quad SD=[SD(1),SD(2),\cdots,SD(n)]. \tag{3}$$

According to the modified Hebbian learning rule Eq. (4), the connection weights are adjusted.

$$\begin{aligned}&\text{IF}\quad SD(i)>(1+K)SD_m \quad \text{AND} \quad SD(j)>(1+K)SD_m\\ &\qquad\text{THEN}\quad w'_{ij}=h_{Heb},\quad w'_{ji}=h_{Heb}\\ &\qquad\text{ELSE}\quad w'_{ij}=h_{hab}w_{ij},\quad w'_{ji}=h_{hab}w_{ji}\end{aligned} \tag{4}$$

w_{ij}, w'_{ij}: connection weights between M1 nodes before change and after one, respectively, K: bias, h_{Heb}: strengthening coefficient for Hebb learning, h_{hab}: weakening coefficient for refinement learning.

The learning for connecting weights continues while it is under changing.

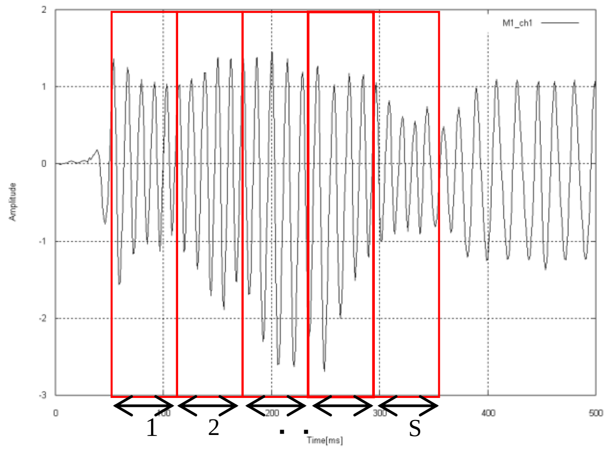

Fig. 2 Example of segmentation in the time-series behavior of the internal state of a M1 node

Fourier transform feature extraction method

(Proposed)

Feature vectors are extracted as power spectrum and their frequency obtained by the discrete Fourier transform of time-series data of M1 node as shown in Fig. 3. Which shows an example of the power frequency spectrum.

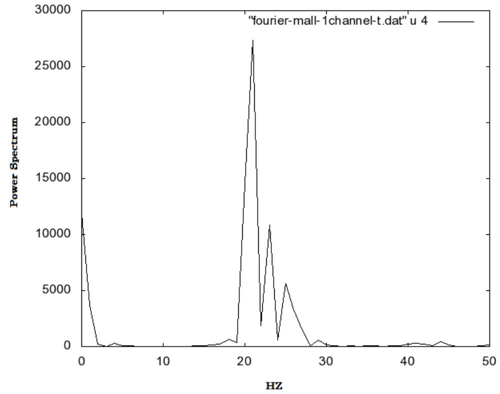

Fig.3 An example of power spectrum

IV. SIMPLIFICATION OF THE OUTPUT NONLINEAR FUNCTION OF THE NODE

The calculation of solutions of second order differential equations for determining the output of the neurons requires enormous processing time. This is a common problem in conventional method. Therefore, to reduce the computation time, we intend to simplify the second order differential equation. Furthermore, to produce chaotic response which are in the response of the above mentioned equations, we propose the two simplified equations referring to dynamics of chaotic neural network (CNN).

Dynamics of Chaotic neural networks

$$y_i(t+1) = ky_i(t) + \sum_{j=1}^{N} \omega_{ij} x_j(t) - \alpha x_i(t) + r_i(t)$$
$$x\ (t+1) = f\big(y(t+1)\big) \tag{5}$$

$y_i(t)$: internal state of the ith neuron, $x_i(t)$: output of the ith neuron, w_{ij}: connection weight from jth neuron to ith neuron, k: refractory decay coefficient, α: constant parameter, $r_i(t)$: input (external stimuli), N: the number of neurons, f: output function of a neuron.

Simplified equation I

$$y_i(t+1) = ky_i(t) + \sum_{j \neq i}^{N} \omega_{ij} Q(x_j(t), q_j) - \alpha x_i(t) + r_i(t)$$
$$x_i(t+1) = \frac{1}{1+\exp\left(-\dfrac{y_i(t+1)}{\varepsilon}\right)} \tag{6}$$

Simplified equation II

$$y_i(t+1) = ky_i(t) + \sum_{j \neq i}^{N} \omega_{ij} x_j(t) - \alpha x_i(t) + r_i(t) \tag{7}$$

V. HANDWRITING CHARACTER CLASSIFICATION

When performing the image pattern recognition using KIII model, there is a question of how to create input vectors of treating the image. In this research, two pre-treatment are carried to create the input vector.

Pixel Average (PA) method

By dividing the image to plural segments and taking the average of each pixel value of split images, we create input vectors which consist of them.

Discrete Cosine Transform (DCT) method

The DCT is one of ways to convert discrete signals into discrete frequency domain. It is mainly used for signal compression, in image processing, that is, the technique has been used in image compression such as

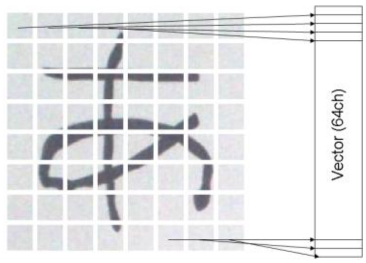

Fig. 4 Example of image segmentation

MPEG and JPEG. Compared to the discrete Fourier transform, this is characterized by the spectrum tend to be concentrated in specific frequencies. In the DCT, the DCT coefficients , that is, features in this research, are calculated by DCT basis functions and they are divided to the DC component (DC) and alternating component (AC). If you make the image DCT transform, the low frequency components (coefficients) are greater, conversely, high-frequency components become so smaller. The formula of DCT is shown in Eq. (8).

$$F_{k,l} = \sum_{j=0}^{N-1}\sum_{i=0}^{N-1} f_{ij}\phi_k[i]\phi_l[j]$$
$$f_{k,l} = \sum_{l=0}^{N-1}\sum_{k=0}^{N-1} F_{kl}\phi_k[i]\phi_l[j] \tag{8}$$
$$\phi_k[i] = \begin{cases} \dfrac{1}{\sqrt{N}} & k=0 \\ \sqrt{\dfrac{2}{N}}\cos\dfrac{(2i+1)k\pi}{2N} & k=1,2,\cdots,N-1 \end{cases}$$

We show the proposed system in Fig. 7.

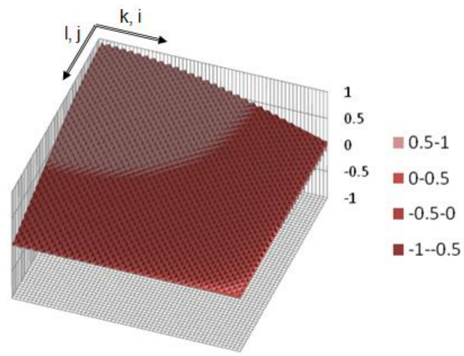

Fig.5 Values of DCT basis function (64×64) $\phi_k[i]\phi_l[i]$

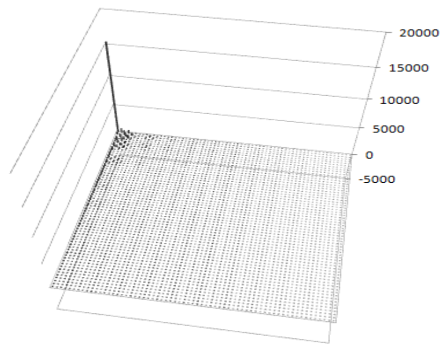

Fig.6 Example of DCT coefficients (64×64)

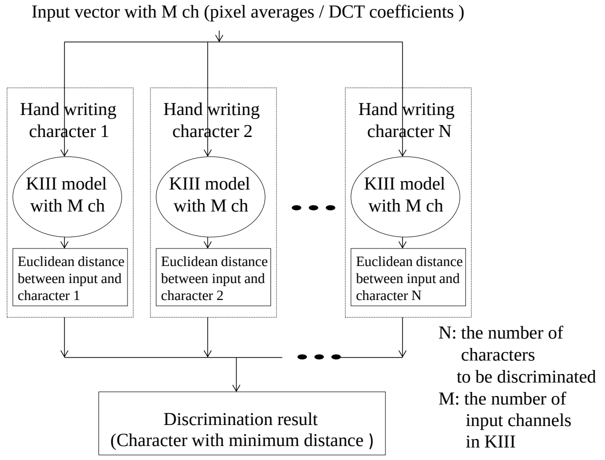

Fig. 7 Hand writing recognition system using KIII model

VI. COMPUTER SIMULATION

We confirm the usefulness of the proposed method under the conditions as follows,

・ Data format：bmp, ・ Data size：512×512
・ Subject：15 (Male), ・The number of channels : 64
・ The number of Japanese characters (refer to Fig.8)：
200 (= 10 males x 4 x 5 characters for training),
100 (= 5 males x 4 x 5 characters for testing)

Fig.8 Examples of hand writing images used in simulation

Simulation 1

We first verify usefulness of the Fourier transform comparing the standard deviation. Simulation results are shown in Table 1. The method using PA & FT is best.

Table 1 Success rates of 2 feature extraction methods

Model / Input feature extraction method	Standard Deviation	Fourier Transform
PA method	89.0%	94.0%
DCT method	84.0%	91.0%

Simulation 2

We next verify usefulness of two cases of simplified output functions of neurons comparing the conventional second-order differential equation. Simulation results are shown in Tables 2, 3 and 4.

Table 2 Success rates of the simplified KIII model I

Model / Input feature extraction method	α = 1.0 in Eqs. (6), (7)		α = 0.35 in Eqs. (6), (7)	
	SD	Fourier	SD	Fourier
PA method	51%	62%	47%	79%
DCT method	27%	58%	37%	62%

Table 3 Success rates of the simplified KIII model II

Model / Input feature extraction method	α = 1.0 in Eqs. (6), (7)		α = 0.35 in Eqs. (6), (7)	
	SD	Fourier	SD	Fourier
PA method	47%	68%	60%	61%
DCT method	40%	59%	34%	69%

Table 4 Computation times among 3 methods

Model	time(sec)
KIII model	3034
Simplified KIII model I	640
Simplified KIII model II	24

VII. DISCUSSION AND CONCLUSION

Recognition result of the feature vector extraction method by the Fourier Transform showed higher recognition rate than the conventional method, the Standard Deviation. In addition, processing times of the simplified two output functions of neurons introduced to make the enormous processing time of KIII model reduce are shortened by 1 / 150 of the conventional for the simplified formula I, 1 / 5 of the conventional for Formula II. However, the recognition rate of both simplified output functions came to be reduced.

Future work is as follows,

● Performance improvement of the proposed method making appropriate trade-off between improving the recognition rate and increasing the processing time, as increasing the number of dimensions of feature vectors.

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