A Class Identification Method Using Freeman's Olfactory KIII Model

Masanao Obayashi, Ryohei Suda, Takashi Kuremoto, and Shingo Mabu
Graduate School of Science and Engineering, Yamaguchi University, Ube, Japan
Email: {m.obayas, r044ff, wu, mabu}@yamaguchi-u.ac.jp

***Abstract*—In recent years, researches on the olfactory have been actively conducted. As one of models of olfactory function, there is KIII model proposed by Freeman *et al*. There have been some researches on the classification using KIII model. These class distinctions are performed by the particular feature, the amount of statistics, namely, the standard deviation of the time series signal in the KIII model. However, as the identification rates of them are low, there need to improve identification rates. In this study, we propose a high performance feature extraction method in the classification using Freeman's olfactory KIII model, making use of the cepstrum analysis often used in speech recognition field. Finally, through computer simulations, it is verified that the proposed method is superior to the conventional method.**

***Index Terms*—Freeman, KIII model, Fourier transform, discrete cosine transform**

I. Introduction

Recently, according to rapid 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 [1], [2].

The KIII model was 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, [3] 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 [4], Face Recognition [5], classification of handwriting numerical [6] and handwriting character classification [7].

On the other hand, response of the olfactory system has a chaotic nature [8], [9], it has also attracted many researchers.

In the application of the KIII model mentioned above, they performed the pattern recognition by using the standard deviation of time series response inside the KIII model corresponding to the inputted data which should be discriminated. In this paper, we propose a high performance identification method by making use of the cepstrum analysis, often used in speech recognition field, of the time series behavior of certain neurons in the KIII model. Finally, through computer simulations, it is verified that the proposed method is superior to the conventional method.

II. KIII Model

KIII is a recurrent neural network model created by Freeman *et al.*, based on biological olfactory structure [2]. The main part of the olfactory neural system is composed of Primary Olfactory Nerve (PON), Olfactory Bulb (OB), Anterior Nucleus (AON), and Prepyriform Cortex (PC) layers as shown in Fig. 1. According to the anatomic architecture, KIII model is a multilayer neural network model, in which M, G represent mitral cells and granule cells in OB layer.

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 different patterns, the system will form several low dimensional local basins [2]. 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 [2]. Every node is described as a second order differential equation as follows:

$$\frac{1}{ab}\left[\frac{d^2}{dt^2}x_i(t)+(a+b)\frac{d}{dt}x_i(t)+ab\;x_i(t)\right] = \sum_{j=1}^{N}\omega_{ij}Q(x_j(t),q_j)+\alpha_i I_i(t) \qquad (1)$$

$$Q(x_i(t),q)=\begin{cases} q\left(1-\exp\left(-\dfrac{\exp(x_i(t))-1}{q}\right)\right), & x_i(t)>x_0 \\ -1, & ,x_i(t)\le x_0 \end{cases} \qquad (2)$$

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

Manuscript received June 17, 2016; revised September 20, 2016.

©2016 Journal of Image and Graphics
doi: 10.18178/joig.4.2.130-135

$x_i(t)$: state variable of the ith node at time t, w_{ij}: the connection weight from jth to ith node, a, b: rate constants ($a = 0.220, b = 0.720$) derived by the electro-physiological experiments on biological olfactory system, q: shape of sigmoid function. α_i: coefficient as to the effect of the input, $I_i(t)$: input (external stimuli, $i = 1, \cdots, n$), $N(= 5n + 13)$: the number of neurons, n: number of input channels

An example of the time-series behavior of the internal state of a M_1 node in OB layer and its S segmentations are shown in Fig. 2.

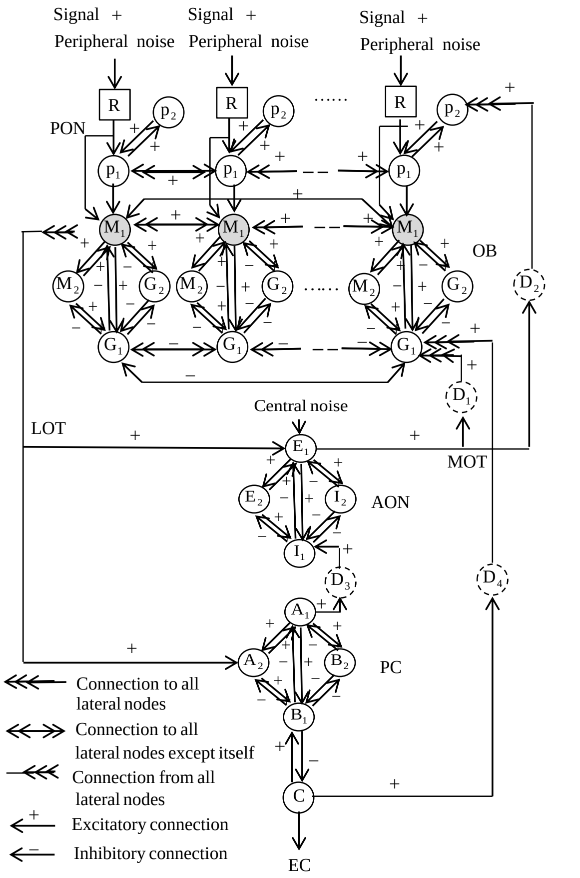


Figure 1. Structure of the KIII model (from [5], [7]).

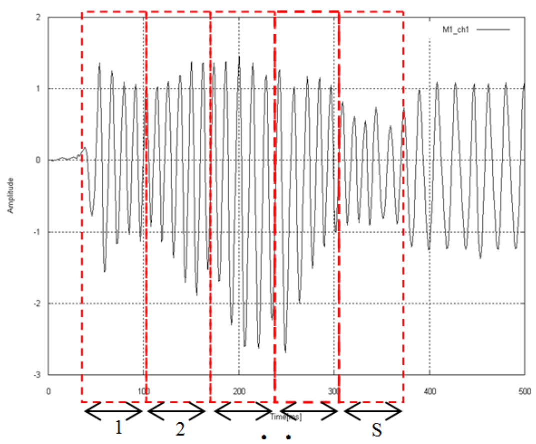


Figure 2. Example of the time-series behavior of the internal state of a M_1 node and its S segmentations.

III. KIII Model

Usually, when doing pattern recognition using the KIII model in general, we should create a feature vector from the characteristics of the behavior of M_1 node dynamics. The state of OB layer mitral level is used as the strength of activity of the KIII model. The learning process only adjusts connection weights among the mitral level nodes. A modified Hebbian learning rule and a habituation rule are employed to KIII model.

When signals are input to the KIII model via receptor R with n channels, the behavior of each node is represented as time series signal 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 deviation of these segments.

$$SD(k) = \frac{1}{S}\sum_{l=1}^{S} SD_{kl}, \quad k = 1, \cdots, n \tag{3}$$

$$SD = [SD(1),\ SD(2),\ \ldots,\ SD(n)] \tag{4}$$

SD, composed of all the $SD(k)$ in the OB layer, depicts the activities of the all channels, it is defined as activated vector for each different input signal I, as feature of input signal.

$$SD_m = \frac{1}{n}\sum_{k=1}^{n} SD(k) \tag{5}$$

According to the modified Hebbian learning rule (6) and habituation rule (7), the connection weights are adjusted.

$$\text{IF } SD(i) > (1+K)\cdot SD_m \quad \text{AND } SD(j) > (1+K)\cdot SD_m$$

$$\text{THEN } w'_{ij} = h_{Heb}\cdot w_{ij}, \quad w'_{ji} = h_{Heb}\cdot w_{ji} \tag{6}$$

$$\text{ELSE } w'_{ij} = h_{hab}\cdot w_{ij}, \quad w'_{ji} = h_{hab}\cdot w_{ji} \tag{7}$$

w_{ij}, w_{ij}': connection weights between M_1 nodes before change and after one, respectively, K: bias, h_{Heb} $(1 < h_{Heb})$: strengthening coefficient for Hebbian learning, h_{hab} $(0 < h_{hab} < 1)$: weakening coefficient for refinement learning. The learning for connecting weights continues while under changing.

IV. Feature Extraction

A. Conventional Cepstrum Feature Extraction Method

Each state of M_1 nodes is the continuous time signal as same as audio signal. In case of audio signal, cepstrum is commonly used as the feature of the audio signal. The procedure of commonly used cepstrum extraction method is shown in Fig. 3. Hamming window function w_{hamming} in Fig. 3 used in this paper is as follows.

$$w_{\text{hamming}}(n) = \begin{cases} 0.54 - 0.46\cos\left(\dfrac{2\pi n}{L-1}\right) & 0 \le n \le L-1 \\ 0 & \text{otherwise} \end{cases} \tag{8}$$

here, L means width of window.

The following shows the procedure of cepstrum feature extraction method.

Step 1: Multiply a window function to time-series signal.

Step 2: Obtain a power spectrum of the signal by discrete Fourier transform (DFT).

Step 3: Take the logarithm of the power spectrum.

Step 4: Perform inverse discrete Fourier transform (IDFT) of the log power spectrum.

Step 5: Extract some cepstrum features.

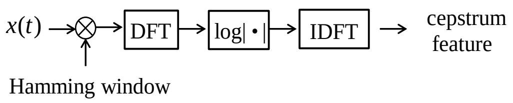


Figure 3. Procedure of the cepstrum feature extraction method.

However, we propose the modified cepstrum as a feature of the signal in the KIII model to increase the success rate of the classification of signals.

B. *Modified Cepstrum Feature Extraction Method*

We propose a modified cepstrum feature extraction method. In this method, the Inverse of Discrete Fourier Transform (IDFT) in Fig. 3 is changed to Discrete Cosine Transform (DCT). This is derived from the following reasons that use of DCT is less reduction of the amount of information than use of IDFT [10].

DCT used in this paper is expressed by the following equation.

$$c = \mathrm{T} \cdot x \tag{9}$$

here, $x = [x_1, \cdots, x_{n-1}]^t$: input signal vector, $c = [c_1, \cdots, c_{n-1}]^t$: coefficient cepstrum vector after transformation. t denotes transpose. $\mathrm{T} \in \mathrm{R}^{n \times n}$ is a transformation matrix and elements of ith row and jth column of T is as follows:

$$\mathrm{T}_{ij} = \sqrt{\frac{2}{n}} k_i \cos\left[\frac{(i-1)(j-\frac{1}{2})}{n}\right] \tag{10}$$

here, k_i $(i = 0, 1, 2, \cdots, n-1)$ is also set as follows:

$$k_i = \begin{cases} 1/\sqrt{2} & (i = 0) \\ 1 & (i \neq 0) \end{cases} \tag{11}$$

V. Class Discrimination

In this section, we explain four class discrimination methods, such as the conventional method, our proposed KIII model with modified cepstrum method, KIII model with modified cepstrum and support vector machine (SVM) used method.

A. *KIII Model with Euclidean Distance Used Conventional Method*

The flow chart of class discrimination using KIII model is shown in Fig. 4. For classification, vector SD feature (4) is acquired for each classification. The minimum distance class is the estimated class of input data. We call this method the conventional method in this paper.

Procedure of the conventional discrimination method:

Training stage:

Step 1: Prepare M KIII models, such as shown in Fig. 4 for classification.

Step 2: Using training data for each class, learn the parameters of the KIII models corresponding to each class data (M_1 Node connection weights of each other) by the described in Section III.

Step 3: Store the connection weights that have been learned, and also store the activity vector SD for each input signal as the activity cluster center vectors (Completion of configuration of the KIII model).

Test stage:

Step 4: Give a test input to M KIII models, and calculate the activity vector SD of the input signal.

Step 5: Calculate the Euclidean distances between the activity cluster center vector of each class that have already learned and the activity vector SD of the test data, recognize the class that corresponds to the smallest distance model.

B. *KIII Model with Modified Cepstrum Used Method*

This is the method that in case of the above conventional method, the modified cepstrum coefficient vector is taken as the feature, instead of the activity vector SD.

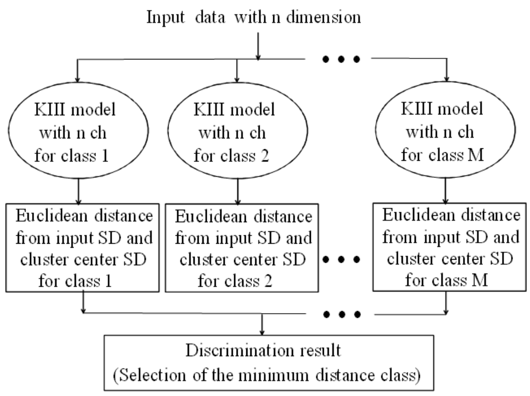


Figure 4. Flowchart of class discrimination using Euclidean distance with KIII model.

C. *KIII Model with Modified Cepstrum and Support Vector Machine Used Method*

We intended to improve the discrimination success rate by the modified cepstrum in this subsection. Here, in addition to improving the feature extraction, we propose the discrimination method combining the KIII model with modified cepstrum and support vector machine (SVM), one of the learning models currently known to the most excellent recognition system among class identification methods.

The procedure of the KIII model with the modified cepstrum and SVM method is as follows:

Step 1: Prepare M KIII models, such as shown in Fig. 4 for classification.

Step 2: Using training data for each class, learn the parameters of the KIII models corresponding to each class data (M_1 node connection weights of each other) by the described in Section III, store the time series behavior of M_1 node using the parameters at that time

Step 3: Performs the modified cepstrum analysis on the time series behavior of the M_1 node, and extract features as shown in Section IV *B*.

Step 4: Discriminate the class by entering the extracted features for both training data and test data into the SVM.

The last case of the discrimination method used in this paper is the method that only SVM is used for class discrimination. We call this SVM method in this paper. We use SVM method with Gaussian function kernel. Details are omitted, refer to [11]. In the case of SVM method, data of the *Iris* are directly used as features.

VI. Computer Simulation

We confirm the usefulness of the proposed method through the computer simulation using *Iris* flower data set [12]. Summary of *Iris* data set used in the simulation are as follows.

- Varieties (number of classes) of *Iris* is three: setosa, versicolor, virginica.
- One data set has four data: length and width of sepal, length and width of petal.
- For one of the varieties there are 50 pieces, total is 150 pieces. Refer to [12] for details of the *Iris* data

A. *Simulation Condition*

Assigning of training data and test data, defining of identification rate and way of the simulation are as follows:

Simulations are executed using such data, for each variety with 50 pieces, 40 pieces are randomly selected as training data from 50 pieces of data, and the remaining 10 is for test data. This is repeated 10 times, and the average value of 10 times of the identification rate is set to the final recognition rate.

B. *Configuration of Olfactory KIII Model*

TABLE I. Initial Values of Internal Parameters in KIII Model [1]

$q^{(P)}$	1.824	w_{MG}	-2.063	w_{ID3}	0.500
$q^{(OB)}$	5.000	w_{GM}	2.323	w_{GD4}	4.000
$q^{(AON)}$	5.000	w_{GG}	-2.445	k_{PR}	20.000
$q^{(PC)}$	5.000	w_{EE}	1.202	k_{MR}	3.000
w_{PPL}	0.900	w_{EI}	1.426	$T_1^{(s)}$	20.000
w_{MP}	0.779	w_{IE}	1.372	$T_1^{(e)}$	10.000
w_{MML}	2.500	w_{II}	-1.571	$T_2^{(s)}$	26.000
w_{EM}	1.300	w_{AA}	0.823	$T_2^{(e)}$	15.000
w_{AM}	1.700	w_{AB}	1.938	$T_3^{(s)}$	25.000
w_{GGL}	-1.000	w_{BA}	1.947	$T_3^{(e)}$	12.000
w_{CB}	-1.300	w_{BB}	-2.354	$T_4^{(s)}$	39.000
w_{BC}	1.187	w_{GD1}	0.500	$T_4^{(e)}$	24.000
w_{MM}	-2.445	w_{PD2}	4.000		

The initial parameters of the olfactory model to be used in this simulation are shown in Table I. The number of channels n in the PON layer is 4 for the *iris* data. Further, the learning factor, h_{Heb}=0.035, h_{hab}= 0.8607, and K = 0.2. The number of divided segments for learning s is 5 shown in Fig. 2 and the five standard deviations from 50 [sec] to 350 [sec] are calculated.

C. *Simulation Results*

At first, results of the conventional method are described below. Table II shows the averages of the activity vector SD of each of *Iris* data. Fig. 5 and Fig. 6 show example of behavior of amplitude and modified cepstrum for channel 2 of setosa of *Iris* data, respectively. Fig. 7 shows four features in the modified cepstrum used in this simulation. Table III shows averages of four cepstrum features of setosa, versicolor and verginica in four channels.

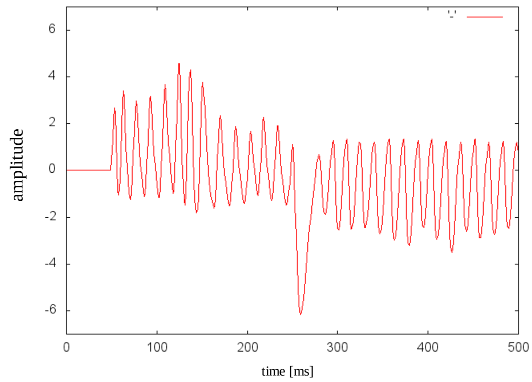


Figure 5. Example of amplitude for channel 2 of setosa of *Iris* data.

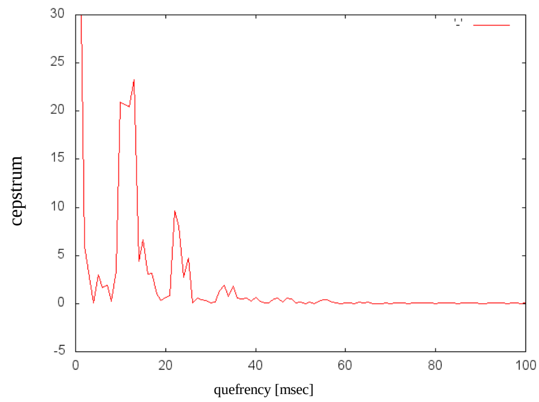


Figure 6. Example of modified cepstrum for channel 2 of setosa of *Iris* data.

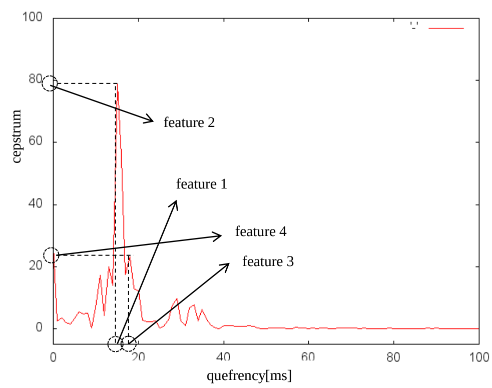


Figure 7. Four features in the modified cepstrum used in this simulation.

TABLE II. THE AVERAGE OF THE ACTIVITY VECTOR SD OF EACH IRIS

	Ch 1	Ch 2	Ch 3	Ch 4
setosa	1.87	0.60	1.14	1.70
versicolor	1.63	1.71	0.68	1.59
virginica	1.63	1.68	1.42	1.71

TABLE III. AVERAGES OF FOUR MODIFIED CEPSTRUM FEATURES OF SETONA, VERSICOLOR AND VIRGINICA IN EACH CHANNEL

	setosa	versicolor	virginica
Ch 1	22.23	23.08	23.03
	13.09	9.85	13.65
	29.05	26.93	25.18
	3.39	3.41	5.71
Ch 2	23.43	23.38	26.93
	7.94	7.53	7.68
	28.70	30.60	30.18
	4.02	5.65	5.63
Ch 3	24.30	25.63	25.20
	2.76	6.59	8.40
	23.25	27.25	26.75
	1.24	4.71	5.20
Ch 4	23.28	23.83	24.48
	6.36	2.74	7.85
	26.23	27.98	27.95
	3.45	1.53	4.65

TABLE IV. DISCRIMINATION RESULTS OF CONVENTIONAL METHOD

Input \ Output	setosa	versicolor	virginica	Success rate	average
setosa	85	0	15	85	83.67
versicolor	0	77	23	77	
virginica	0	11	89	89	

TABLE V. DISCRIMINATION RESULTS OF OUR PROPOSED KIII MODEL WITH MODIFIED CEPSTRUM METHOD

Input \ Output	setosa	Versicolor	virginica	success rate	average
setosa	88	0	12	88	89.00
versicolor	0	93	7	93	
virginica	0	14	86	86	

TABLE VI. DISCRIMINATION RESULTS OF OUR PROPOSED KIII MODEL WITH MODIFIED CEPSTRUM AND SVM USED METHOD

	Ch 1	Ch 2	Ch 3	Ch 4
setosa	1.87	0.60	1.14	1.70
versicolor	1.63	1.71	0.68	1.59
virginica	1.63	1.68	1.42	1.71

In the Table IV, discrimination results of the conventional method are shown and their results say that result of versicolor is worse than others. Table V shows discrimination results of our proposed KIII model with modified cepstrum method. Results of KIII model with modified cepstrum method show that the success rate of the versicolor has increased clearly comparing with the conventional. Table VI also denotes success rate of our proposed KIII model with modified cepstrum and SVM method. In this case, the rates of two setosa and virginica other than the above versicolor have been improved dramatically. Finally, Table VII shows success rate of the SVM method. The results are superior to others.

Table VIII shows success rates of all the methods. From Table VIII, in case of the conventional method, versicolor had lower success rate, however, in our two proposed cases, such results could not be seen. This might happen by difference between standard deviation and cepstrum. The former is a vague value of the standard deviation, on the other hand, the latter is a clear nature representing the distinct features of the cepstrum.

TABLE VII. DISCRIMINATION RESULTS OF THE SVM USED METHOD

Input \ Output	setosa	Versicolor	virginica	success rate	average
setosa	100	0	0	100	96.00
versicolor	0	89	11	89	
virginica	0	1	99	99	

TABLE VIII. SUCCESS RATES OF ALL THE METHODS [%]

method	setosa	versicolor	virginica	average
conventional	85	77	89	83.67
KIII model with modified cepstrum	88	93	86	89.00
KIII model with modified cepsteum and SVM	100	91	94	95.00
SVM	100	89	99	96.00

VII. CONCLUSION

Our proposed both KIII model with modified cepstrum used method and the method of a combined KIII model with modified cepstrum and SVM, making use of the modified cepstrum analysis of the time series behavior of mitral level neurons M1 in the KIII model, have higher identification abilities than the conventional method. Our proposed methods also showed the almost same performance as SVM that is known to be very superior method in pattern recognition field.

KIII model has an interesting characteristic such that the behaviors of the nodes are also the same as the case of changing the positions of the input with n dimensional data corresponding to n receptors in KIII model. This means, for example, that in the case of extracting the features of image data, the KIII model is insensitive to the rotation and movement of the image. In the future work, we would like to introduce this characteristic into the object recognition in the image for convenience of the object recognition.

ACKNOWLEDGMENT

This work was supported by Grant-in-Aid for Scientific Research of Japan Society for the Promotion of Science (Nos. 25330287, and 26330254), Japan.

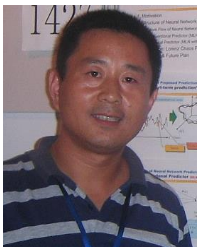
REFERENCES

[1] H. J. Chang, W. J. Freeman, and B. C. Burke, "Optimization of olfactory model in software to give 1/f power spectra reveals

numerical instabilities in solutions governed by aperiodic (chaotic) attractors," *Neural Networks*, vol. 11, pp. 449-466, 1998.
[2] H. J. Chang and W. J. Freeman, "Biologically modeled noise stabilizing neurodynamics for pattern recognition," *Int. J of Bifurcation and Chaos*, vol. 8, no. 2, pp. 321-345, 1998.
[3] J. Fu, G. Li, Y. Qin, and W. J. Freeman, "A pattern recognition method for electronic noses based on an olfactory neural network," *Sensors and Actuators B*, vol. 125, pp. 485-497, 2007.
[4] X. Yang, J. Fu, Z. Lou, L. Wang, I. Guang, and W. J. Freeman, "Tea classification based on artifcial olfaction using bionic olfactory neural network," *LNCS*, pp. 343-348, 2006.
[5] G. Li, J. Zhang, Y. Wang, and W. J. Freeman, "Face recognition using a neural network simulating olfactory systems," *LNCS*, vol. 3972, pp. 93-97, 2006.
[6] X. Li, G. Li, L. Wang, and W. J. Freeman, "A study on a bionic pattern classifier based on olfactory neural system," *Int. J. of Bifurcation and Chaos*, vol. 16, no. 8, pp. 2425-2434, 2006.
[7] M. Obayashi, S. Koga, L. B. Feng, T. Kuremoto, and K. Kobayashi, "Handwriting character classification using Freeman's olfactory KIII model," *Artif Life Robotics*, vol. 17, pp. 227-232, 2012.
[8] W. J. Freeman, "Simulation of chaotic EEG pattern with a dynamic model of the olfactory system," *Biol. Cybern.*, vol. 56, pp. 139-150, 1987.
[9] C. K. Skarda and W. J. Freeman, "How brains make chaos in order to make sense of the world," *Behavioral and Brain Science*, vol. 10, pp. 161-195, 1987.
[10] C. Kamath, "Comparison of linear, logarithmic and mel-frequency filter-bank energy cepstra in automatic seizure detection using radial basis function neural network," 2014.
[11] N. Cristianini and J. S. Taylor, *An Introduction to Support Vector Machines and Other Kernel-Based Learning Method*, Cambridge University Press, 2000.
[12] Iris flower data set. [Online]. Available: https://en.wikipedia.org/wiki/Iris_flower_data_set#Data_set

Masanao Obayashi received the B.S. degree in electrical engineering from Kyushu Institute of Technology, Japan, in 1975, the M.S. and the Ph.D. degrees in engineering from Kyushu University, Japan, in 1977 and 1997, respectively. From 1977 to 1989, he was with Hitachi Ltd. From 1989 to 1998, he was with Kyushu University, where he was a Research Associate and an Associate Professor. From 1998 he is with Yamaguchi University, Japan, since July 2001 he has been a Professor in the Faculty of Engineering, Yamaguchi University. He is now with the Graduate school of Science and Engineering of the same university. His current research interests are intelligent computing and intelligent control. Prof. Obayashi is a member of SICE, IEEJ, JSAI, JSFTII and IEEE.

Ryohei Suda received B.E. degree in information science and engineering from Yamaguchi University, Japan, 2015. His research interests include neural networks, machine learning, and data analysis.



Takashi Kuremoto received the B.E. degree in System Engineering at University of Shanghai for Science and Technology, China in 1986, and M.E. and Ph.D. degrees at Yamaguchi University, Japan in 1996 and 2014, respectively. He worked as a system engineer at Research Institute of Automatic Machine of Beijing from 1986 to 1992 and is currently an assistant professor in Division of Computer Science & Design Engineering, Graduate School of Science and Engineering at Yamaguchi University, Japan. He was an Academic Visitor of School of Computer Science, The University of Manchester, U.K. in 2008. His research interests include bioinformatics, machine learning, complex systems, forecasting and swarm intelligence. He is a member of IEICE, IEEE, IIF and SICE.

Shingo Mabu received the B.E. and M.E degrees in electrical engineering from Kyushu University, Japan, in 2001 and 2003, respectively, and the Ph.D. degree from Waseda University, Japan, in 2006. From 2006 to 2007, he was a visiting lecturer in Waseda University, and from 2007 to 2012 he was an assistant professor in Waseda University. Since September 2012, he has been an assistant Professor in Graduate School of Science and Engineering, Yamaguchi University. His research interests are evolutionary computation, reinforcement learning and data mining. He is a member of SICE, IEEJ and IEEE.