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Journal
ADVANCES IN NEURAL NETWORKS - ISNN 2006, PT 2, PROCEEDINGS, 3972

ISSN
0302-9743

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Publication Date
2006

Peer reviewed

Tea Classification Based on Artificial Olfaction Using Bionic Olfactory Neural Network

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Abstract. Based on the research on mechanism of biological olfactory system, we constructed a K-set, which is a novel bionic neural network. Founded on the groundwork of K0, KI and KII sets, the KIII set in the K-set hierarchy simulates the whole olfactory neural system. In contrast to the conventional artificial neural networks, the KIII set operates in nonconvergent 'chaotic' dynamical modes similar to the biological olfactory system. In this paper, an application of electronic nose-brain for tea classification using the KIII set is presented and its performance is evaluated in comparison to other methods.

1 Introduction

The sense of smell is a chemical and neural process whereby odorant molecules stimulate the olfactory receptor cells that are located high up in the nose in the olfactory epithelium. Broad patterns of response are shown by the olfactory system consisting of a large number of nonspecific receptors [1]. The axons extended by these receptors converge synaptically and link to a limited number of secondary neurons that in turn drive the olfactory cortex of the brain [2]. To simulate the biological olfactory system, the concept of artificial olfaction, whose applicable product is called electronic nose-brain, is introduced.

Basically, an electronic nose-brain has the olfaction as a model and consists of a sensor array with partially overlapping selectivities and a pattern recognition algorithm. The sensor array simulates the receptors in the olfactory epithelium and the pattern recognition algorithm simulates the neural networks of the olfactory bulb, nucleus and cortex. The sensor with overlapping selectivities has broad responsiveness to different odorants as the odor receptor. Several kinds of sensors were selected to form the sensor array, such as metal oxide sensor, conducting organic polymer sensor, quartz crystal microbalance, etc. As stated above, the pattern recognition algorithm is a significant component in the electronic nose-brain system, which provides electronic nose-brain the capability in classifying a variety of odors. Derived from

J. Wang et al. (Eds.): ISNN 2006, LNCS 3972, pp. 343 – 348, 2006.

study on olfactory system, Freeman introduced a novel olfactory model called KIII [3]. Recently, some applications to bar code, figures and handwriting numbers recognition were performed using KIII model [4]. We built a preliminary prototype of electronic nose-brain using KIII model to separate three kinds of simple gases.

Traditionally, the classification of tea depends on human sense. However, it is inaccurate, laborious and time consuming owing to adaptation, fatigue and state of mind. Considering the wide variety of organic compounds in tea, it is really hard to hold out a common standard for tea classification [1]. One of those significant factors to distinguish different kind of tea is the aroma. At this point, we propose to explore whether the electronic nose-brain, which can avoid the limitations of the human sense, might offer a reliable alternative to traditional methods in tea classification.

2 Description of KIII Model

2.1 KIII Model

Generally, in conventional artificial neural network (ANN), chaos should be avoided for engineering purpose, because the trajectory of the system neither repeats nor converges and could not provide steady system output in chaotic state. However, in recent years, the theory of chaos is commonly used to understand the mesoscopic neural dynamics [5]. From recent research, it is believed that chaotic attractor is some kind of essential character of biological neural network [6]. The KIII network 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 [7]. Therefore, the memory for different patterns might be regarded as the formation of local basins, while the recognition process refers to the transition from one basin to another. And the introduction of noise modeling the biological noise source made the KIII net work stable and robust [8].

From a standpoint of bionics, the olfactory neural system is composed of primary olfactory nerve (PON), olfactory bulb (OB), anterior nucleus (AON) and prepyriform cortex (PC). Fig. 1 [7] shows the topological structure of KIII network, in accordance with the anatomic architecture of olfactory neural system. In this model, PON is a KI [9] network; R represents the olfactory receptor, which offers input to the KIII network; the OB layer, AON and PC are composed of KII [9] units; The parameters in KIII network, such as connection strength values between different nodes, were optimized to fulfill features observed in lots of electro-physiological experiments [7].

Among the KIII models, every node is described as a second order differential equation as follows:

$$\begin{gathered}\frac{1}{a\cdot b}\left[x_i''(t)+(a+b)x_i'(t)+a\cdot b\cdot x_i(t)\right]=\sum_{j\neq i}^{N}\left[W_{ij}\cdot Q(x_j(t),q_j)\right]+I_i(t)\\ Q(x,q)=\begin{cases} q(1-e^{-(e^x-1)/q}) & x>x_0\\ -1 & x<x_0\end{cases}\\ x_0=\ln(1-q\ln(1+1/q))\end{gathered} \quad . \tag{1}$$

Here x_i(t) represents the state variable of the ith node, while W_{ij} indicates the connection strength from j to i. I_i(t) is external input to the ith node. The parameters a, b and q are constants derived from the electro-physiological experiments on biological olfactory system. $Q(\cdot)$ is a static sigmoid function derived from the Hodgkin-Huxley equation and evaluated by experiments.

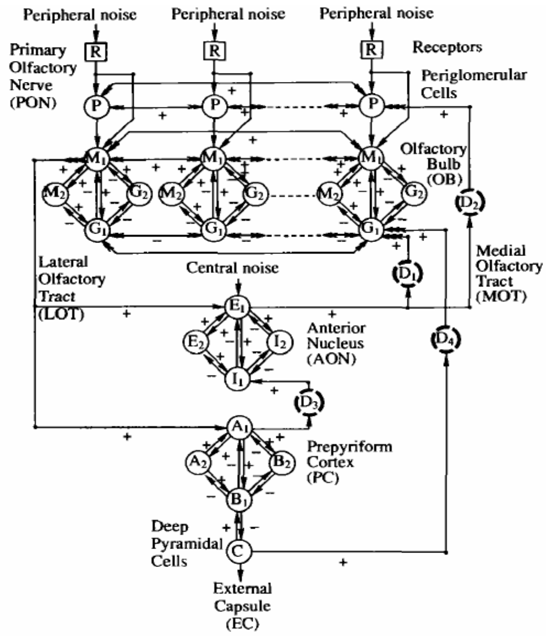

Fig. 1. The topological structure of the KIII network [7]

2.2 Learning Rules

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

To measure the *ith* channel's activity, a value SD_i is extracted. The period with input patterns is divided into S segments and SD_i is the mean standard deviations of these segment. SD, composed of all the SD_i in the OB layer, depicts the activities of all the channels and SD^m is the mean activity measure of the whole OB layer.

$$SD_i = \frac{1}{S}\sum_{k=1}^{s} SD_{ik}, \quad S^m = \frac{1}{n}\sum_{i=1}^{n} SD_i, \quad SD = [SD_1, SD_2, ..., SD_n] \ . \tag{2}$$

The modified Hebbian learning rule in Equ.(3) means that each pair of M nodes co-activated should have their connection strengthened. K is inducted to avoid the saturation of weight space. And the habituation rule works at each node as in Equ.(4).

$$\begin{array}{ll} \textit{if} \quad SD_i > (1+K)SD^m \quad \textit{and} \quad SD_j > (1+K)SD^m \\ \textit{then} \quad W_{ij} = R_{hebb} \times W_{ij} \quad \textit{and} \quad W_{ji} = R_{hebb} \times W_{ji}, \quad (R_{hebb} > 1) \end{array} . \tag{3}$$

$$W_{ij} = W_{ij} \times r_{hab}, \quad (0 < r_{hab} < 1) \ . \tag{4}$$

During training, we acquire *SD* vectors with inputs of different patterns. After that, the cluster centers of *SD* in each pattern are calculated respectively. For classification, *SD* is obtained with inputs for classifying. The Euclidian distance from this *SD* to each cluster center is calculated. The minimum distance refers to the certain pattern.

3 Application in Tea Classification

Metal Oxide Semiconductor (MOS) sensors are commonly used in electronic nose-brain applications for its convenience in operating and steadiness in features. We made a sensor array to acquire the volatiles emitted by tea with seven metal oxide sensors of Figaro Co. (TGS2610, TGS2611, TGS800, TGS813, TGS822, TGS826, TGS880). A tea sample is heated before data acquirement. The mean value of the voltage signal during the steady state is acquired as the raw data of this sample. Sometimes there has some peak signal brought by noises. For this reason, a median filter must be added.

We firstly made a classification between green tea and black tea. To build up a testing set, thirty samples were acquired for each kind of tea while training set contains three samples of green tea and three samples of black tea.

Different from the application on classifying simple gases, the raw data of different kinds of tea are quite similar. Owing to this fact, four pre-processing methods, R_{odor}, $ln(R_{odor})$, R_{odor}/R_{air} and $ln(R_{odor})$-$ln(R_{air})$, were employed on the raw data. R_{air} and R_{odor} are the impedances of the sensor array during steady state phase in the air and exposed in the volatiles. The data, raw and pre-processed, should be normalized to avoid the influence of concentration. In the application, a seven-channel input KIII network is used with system parameters in reference [7]. All the data in the training set are used only once. The results are listed in Tab. 1.

The method using $ln(R_{odor})$ performs better. It is considered to be the most effective method. So in the later classification, this method is used as default. The result Euclidean distances to the cluster centers of the two patterns are provided in Fig. 2.

Fig. 3 shows the change of connection weight matrix in the mitral level. With the learning times increases, the difference of weight matrix between current and previous learning times descends rapidly. It is an important factor to scale learning speed. That means KIII network could be trained with a small quantity of learning times.

Table 1. Rate of correct recognition of different kinds of tea with five pre-processing method

	Raw Data	R_{odor}	$ln(R_{odor})$	R_{odor}/R_{air}	$ln(R_{odor})$-$ln(R_{air})$
Green tea	53.3%	76.7%	100%	53.3%	70%
Black tea	50%	60%	90%	46.7%	83.3%

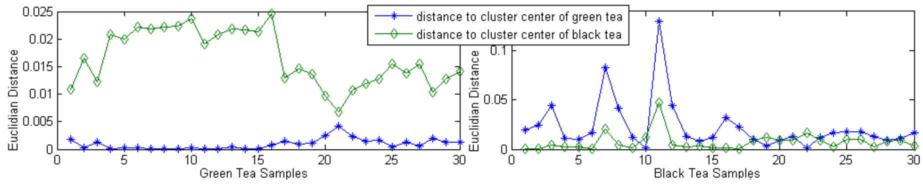

Fig. 2. The distances of different tea samples to the cluster centers of green tea and black tea

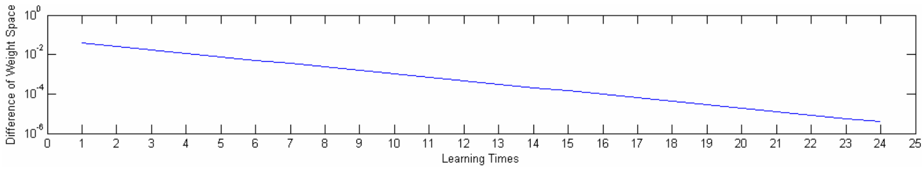

Fig. 3. Convergence curve of weight space in the OB layer mitral level of KIII network

To make a further step, we tried to classify more patterns using KIII model. The number of patterns increases to four, using data set composed of four kind of tea listed in Tab. 2. Fifteen samples of each kind of tea are acquired to build a testing set while 3 samples for each kind are introduced in the training set. At this time, a conventional artificial neural network, BP network, is carried out for comparing. And also, we invited 30 volunteers with normal olfaction to make the tea classification. All the volunteers were trained to remember the odor of each kind of tea. After that, they made the classification by smelling without seeing.

The results were recorded in Tab. 2. Obviously, BP and KIII are both efficient. However, the average classification rate of BP is a little lower. The maximum classification rate of BP is 100%, but the minimum goes down to 66.7%. While to the KIII network, it varies from 80% to 93.3%. The volunteers performed not so well as the electronic nose, because of some physiological and psychological factors [1].

Table 2. Rate of correct recognition of four kinds of tea

	Chinese Green Tea	Japanese Green Tea	Indian Black Tea	Chinese Black Tea	Average
KIII	86.7%	93.3%	93.3%	80%	88.3%
BP	100%	80%	66.7%	93.3%	85%
Human	46.7%	80%	83.3%	50%	65%

4 Discussion

In pattern recognition, KIII model shows good features. Compared with conventional artificial neural network, it is an accurate model in simulating the olfactory system. Fewer training times and less training sets are needed. Its weight matrix converges rapidly during learning. And the classification efficiency is relatively good. Different from the former work on KIII pattern recognition, which mostly used “0-1” digital data as input, a new way is provided to input with decimal. It is proved that decimal input also works effectively and indicates the possibility to reduce the required input channels contributed to pre-processing method. As a result, only a seven-channel KIII network is used instead of introducing more channels. However, it still has potential to be improved. In this work, the classification algorithm is quite simple. In fact, there are a lot of classification algorithms valid for KIII model. How to select a more effective algorithm that can be integrated with KIII model is part of our future works.

Acknowledgements

This research is partially supported by the National Natural Science Foundation of China (No. 60421002) and the National Basic Research Program of China (973 Program, No. 2004CB720302).

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