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A STUDY ON A BIONIC PATTERN CLASSIFIER BASED ON OLFACTORY NEURAL SYSTEM

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This paper presents a simulation of a biological olfactory neural system with a KIII set, which is a high-dimensional chaotic neural network. The KIII set differs from conventional artificial neural networks by use of chaotic attractors for memory locations that are accessed by, chaotic trajectories. It was designed to simulate the patterns of action potentials and EEG waveforms observed in electrophysiological experiments, and has proved its utility as a model for biological intelligence in pattern classification. An application to recognition of handwritten numerals is presented here, in which the classification performance of the KIII network under different noise levels was investigated.

Keywords: Olfactory neural network; artificial neural network; chaos; pattern classification.

1. Introduction

Artificial Neural Networks (ANN) form a class of models and methods inspired by the study of biological neural systems. Because ANN can simulate some important features of the Biological Neural Networks (BNN), especially the threshold behavior and plasticity of the synapse, it has had great success in solving many problems such as pattern classification, optimization, feedback control, etc. However, classical ANN are simplistic models in comparison with biological neural systems. Generally chaos is avoided in conventional ANN for engineering purposes because the trajectory of the system neither repeats nor converges and cannot provide a steady system output in chaotic states. Also, deterministic chaotic systems are sensitive to infinitesimal variation in the initial conditions; therefore, they are not compatible with pattern classification, because the required many-to-one generalization does not exist. For these reasons, only fixed-point attractors and limit cycle attractors are utilized in designing a feedback neural network system. But, is this the way a biological neural system works? Neuroscience based on the results gained from the research of EEG, shows that chaos seems to be a common phenomenon in brain. However, whereas deterministic chaos is stationary, noise-free, autonomous and low-dimensional, brain chaos is unstable with repeated state transitions, drenched in noise, high-dimensional, and engaged with the environment, therefore not autonomous in the sense of having no perturbation once initiated. This type has been called "stochastic chaos".

In recent years, the theory of chaos has been used to understand the mesoscopic neural dynamics, which is at the level of self-organization at which neural populations can create novel activity patterns [Freeman, 2000a]. From years of research in this field, it is now proposed that the chaotic attractor is an essential property of BNN. Derived from the study of olfactory system, the distributed KIII-set, is a high dimensional chaotic network, in which the interactions of globally connected nodes lead to a global landscape of high-dimensional chaotic attractors. After reinforcement learning to discriminate classes of different patterns, the system forms a landscape of low-dimensional local basins, with one basin for each pattern class [Kozma & Freeman, 2001]. This formation of local basins corresponds to the memory of different patterns; the recognition of a pattern follows when the system trajectory enters into a certain basin and converges to the attractor in that basin. The convergence deletes extraneous information, which is the process of abstraction. The output of the system is controlled by the attractor, which signifies the class to which the stimulus belonged, thus exercising generalization. Abstraction and generalization are powerful attributes of BNN not easily done with ANN; however, the use of chaotic dynamics by the KIII-set overcomes this limitation.

KIII model was built according to the architecture of the olfactory neural system to simulate the output waveforms observed in biological experiments with EEG and unit recording. The KIII-set based on deterministic chaos proved to be highly unstable. The introduction of noise modeled on the biological noise sources made the KIII network stable and robust [Freeman *et al.*, 1997], which introduced "Stochastic Chaos" and made the KIII model free from the sensitivity to variation of parameters and initial conditions, and provided a high-dimensional chaotic system capable of rapid and reliable pattern classification without gradient descent [Freeman, 2000b]. Here, we present a new application example of the KIII network for recognition of handwriting numerals [Freeman, 1997].

2. K Set Model Description

The central olfactory neural system is composed of olfactory bulb (OB), anterior nucleus (AON) and prepyriform cortex (PC). In accordance with the anatomic architecture, KIII network is a multi-layer neural network model, which is composed of hierarchical K0, KI and KII units. Figure 1 shows the topology of KIII model, in which M, G represent mitral cells and granule cells in olfactory bulb. E, I, A, B represent excitatory and inhibitory cells in anterior nucleus and prepyriform cortex respectively.

Among these models, the dynamics of every node is described with a second order differential equation [see Eq. (1)], which is derived from measurement of open-loop impulse responses (evoked potentials in electro-physiological experiments under deep anesthesia):

$$\frac{1}{a\cdot b}[x_i''(t)+(a+b)x_i'(t)+a\cdot b\cdot x_i(t)] = \sum_{j\neq i}^{N}[W_{ij}+Q(x_j(t),q_j)]+I_i(t). \tag{1}$$

Here $i = 1, \ldots, N$, where N is the number of channels. In this equation $x_i(t)$ represents the state variable of ith neural population, $x_j(t)$ represents the state variable of jth neural population, which is connected to the ith, while W_{ij} indicates the connection strength between them. $I_i(t)$ is an input function which stands for the external input to the ith channel. The parameter $a = 0.220\,\text{ms}^{-1}$, $b = 0.720\,\text{ms}^{-1}$ reflect two rate constants. $Q(x_j(t), q_j)$ is a static nonlinear sigmoid function derived from the Hodgkin–Huxley model and is expressed as Eq. (2).

$$Q(x_j(t),q)=\begin{cases} q(1-e^{-\frac{e^{x}(t)-1}{q}}), & \text{if } x(t)>x_0\\ -1, & \text{if } x(t)<x_0 \end{cases},$$
$$x_0=\ln\left(1-q\ln\left(1+\frac{1}{q}\right)\right). \tag{2}$$

In this equation q represents the maximum asymptote of the sigmoid function, which is also obtained from biological experiments. Each node represents a neural population or cell ensemble. If the cell ensemble does not contain any interaction among its neurons, it is represented by a K0 model. KI model represents neural populations that are mutually connected, with excitatory or inhibitory synaptic connections. KII is a coupled nonlinear oscillator used to simulate channels in OB, AON and PC layers with both positive and negative connections. The KIII network describe the whole olfactory neural system, the populations of neurons, local synaptic connection, and long forward and distributed time-delayed feedback loops. In the topology of the KIII network, R represents the olfactory receptor, which is sensitive to the odor molecule, and offers the input to the KIII network. The periglomerular (PG) layer and the olfactory bulb (OB) layer are distributed, which in this paper contain 64 channels. The AON and PC layer are only composed of single KII network. The

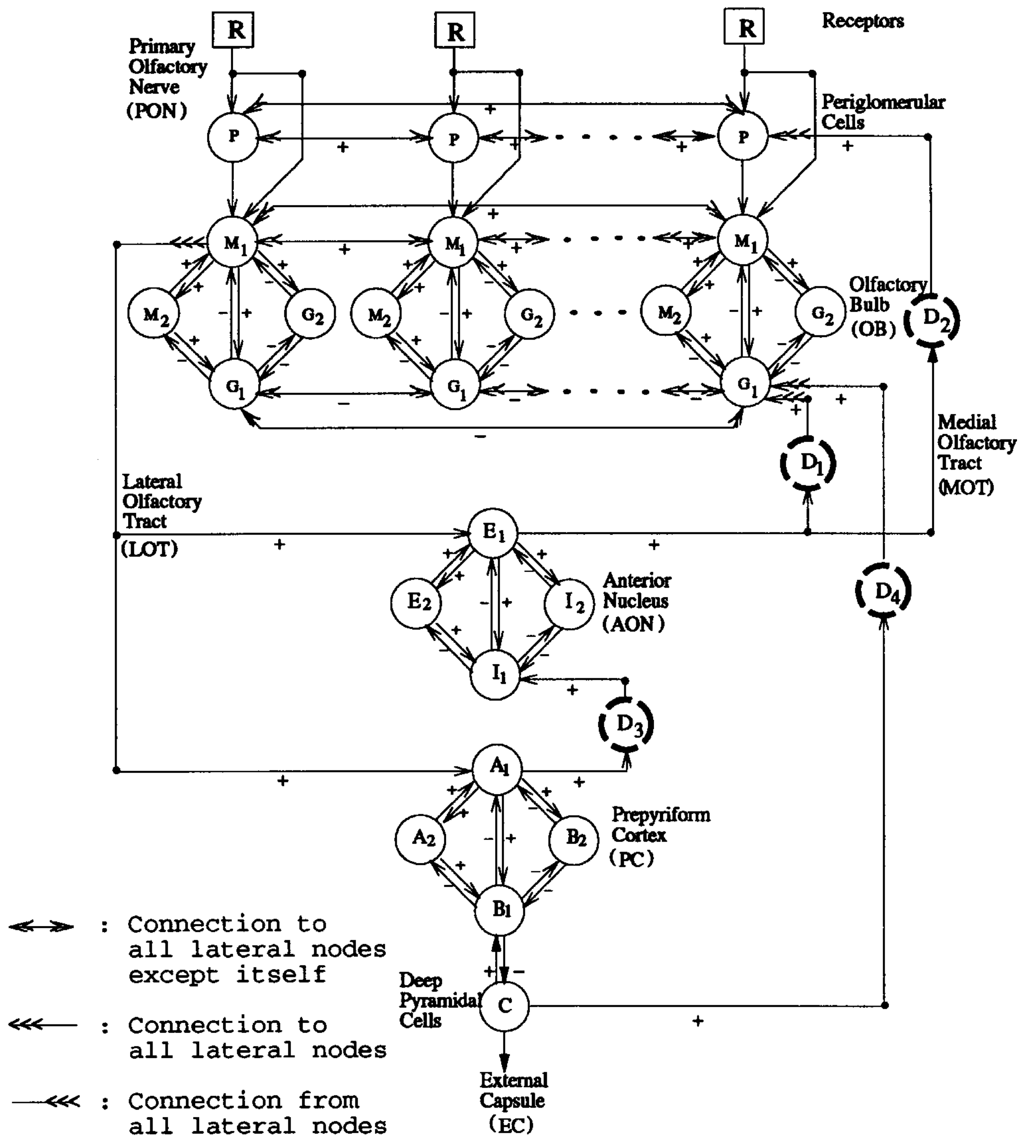

Fig. 1. Topology of the KIII network. Adapted from [Chang & Freeman, 1998a].

parameters in the KIII network, including the connection strength values between different nodes and the gain values of the lateral connections, feedforward and feedback loops, were optimized by measuring the olfactory evoked potentials and EEG, simulating their waveforms and statistical properties, and fitting the simulated functions to the data by means of nonlinear regression [Freeman, 2000c]. After the parameter optimization, the KIII network generates EEG-like waveform with $1/f$ power spectra [Chang & Freeman, 1996, 1998c]. Some numerical analysis of the KIII network, using the parameter set in reference [Chang & Freeman, 1998a], is shown in Figs. 2 and 3. When there is no stimulus, the system presents an aperiodic oscillation, which indicates that the system is in its basal state — a global chaotic attractor, see Fig. 2. When there is a stimulus, corresponding to some odor molecule captured by the olfactory receptor, the trajectory of the system soon goes to specific local basin and converges to an attractor. The true series appears as a gamma range quasi-periodic burst. The system resides in the local basin for approximately the duration of the external stimulus. After the stimulus is terminated, the KIII network returns to its basal state.

Figure 3 shows some phase maps of several pairs of nodes in the KIII network. It is also another indirect description of the basal chaotic attractor and the state transitions that take place when the stimulus begins and ends. This kind of state transition often takes less than 10 ms. During

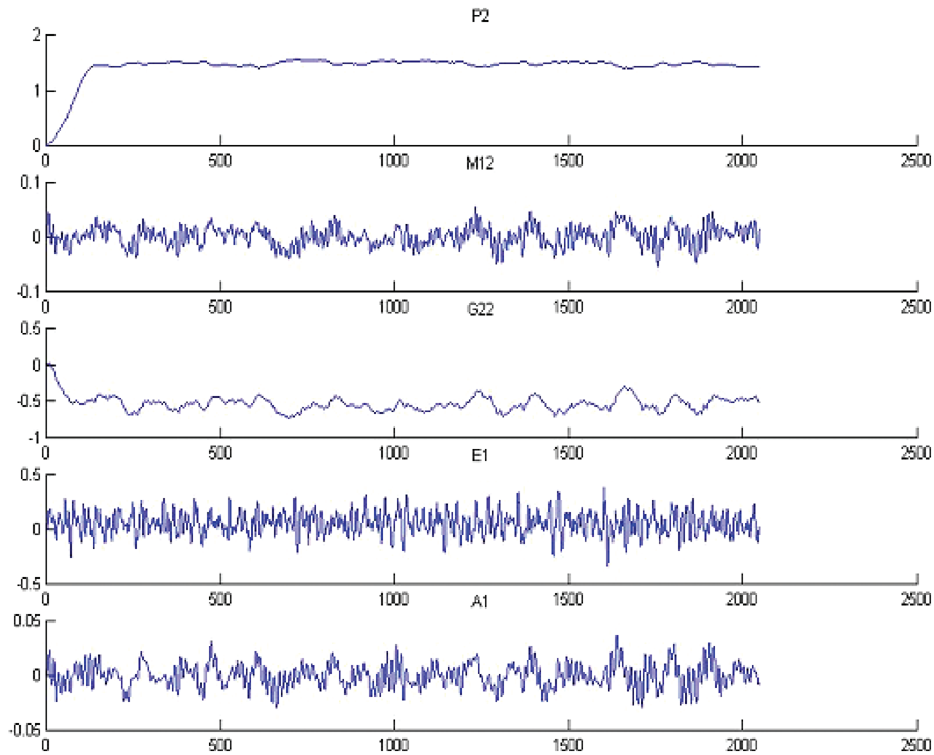

Fig. 2. Output of several nodes of KIII network with no stimulus.

(a)

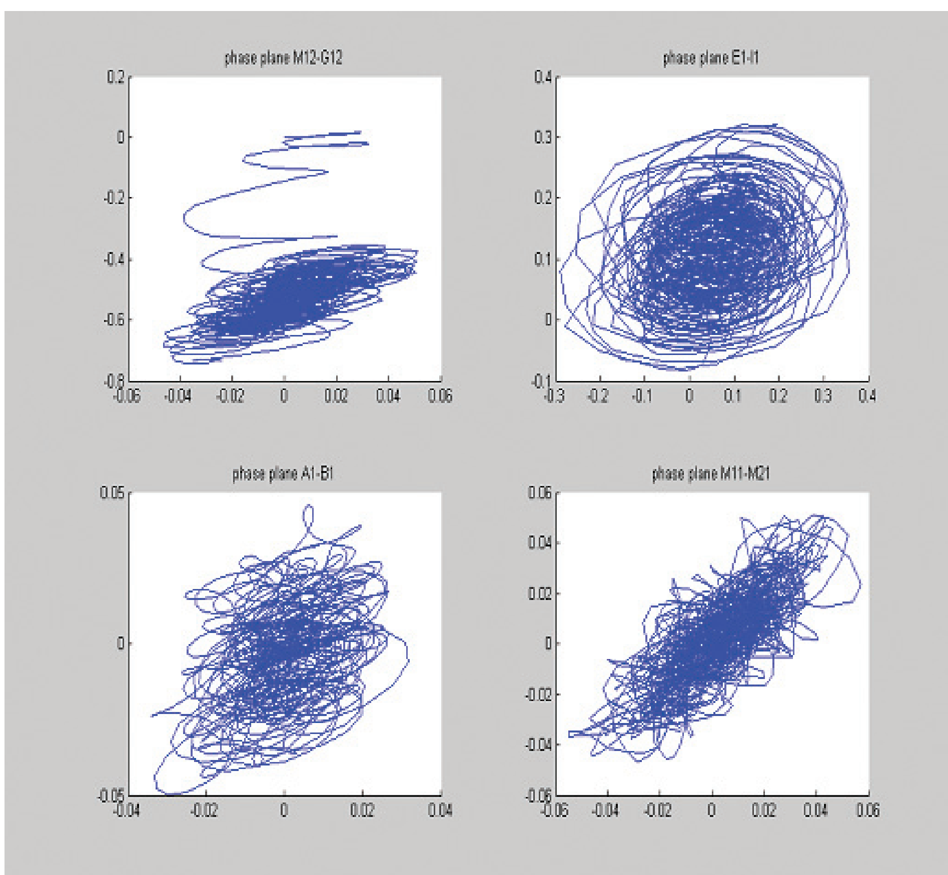

Fig. 3. The phase map of M1-G1, E-I, A-B, M1-M2, (a) without stimulus and (b) with stimulus.

(b)

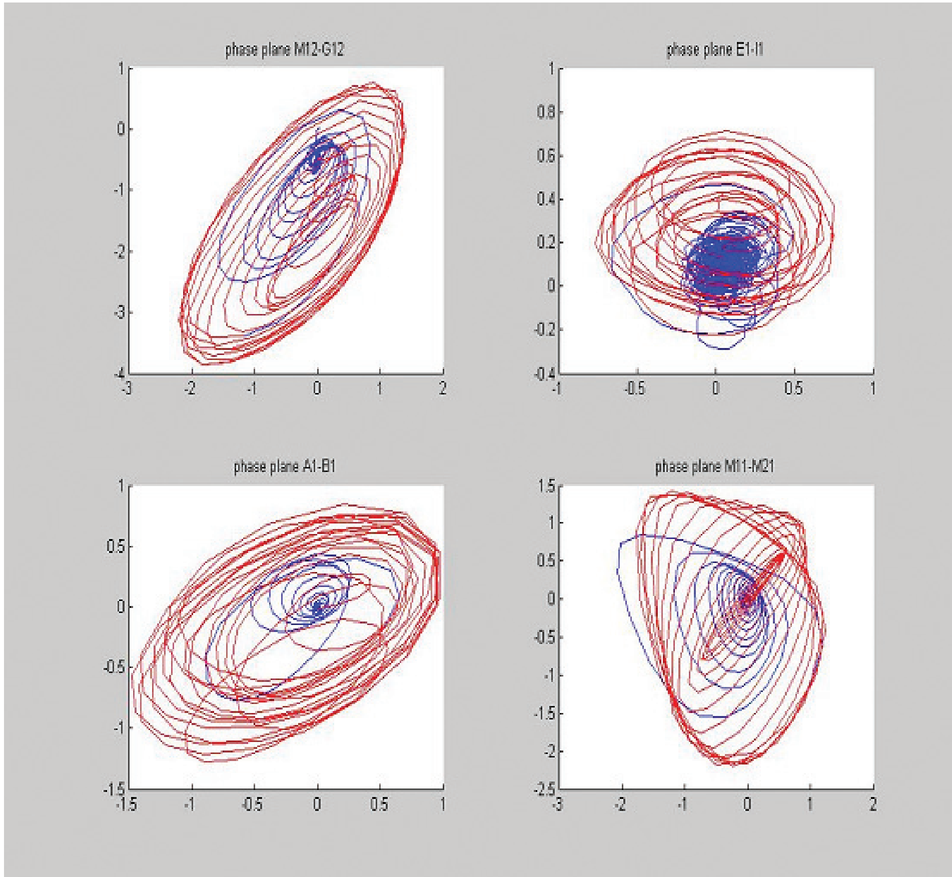

Fig. 3. (*Continued*)

the learning process, different stimulus patterns will form different local basins and different attractors in the system trajectory space. In KIII network, the formation and consolidation of these local basins are implemented through changing the weights between corresponding nodes, in accordance with the biological increase and decrease of the synaptic connection strengths, which have been evaluated by curve-fitting of solutions to the equations to impulse responses of the olfactory system to electrical stimuli [Freeman, 2000]. Compared with well-known low-dimensional deterministic chaotic systems such as the Lorenz, Rossler, and Logistics attractors, nervous systems are high-dimensional, nonautonomous and noisy systems [Freeman & Kozma, 2001]. In the KIII network, independent rectified Gaussian noise was introduced to every olfactory receptor to model the peripheral excitatory noise, and single channel of Gaussian noise with excitatory bias to model the central biological noise sources. The additive noise eliminated numerical instability of the KIII model, and made the system trajectory stable and robust under statistical measures, which meant that under perturbation of the initial conditions or parameters, the system trajectories were robustly stable [Chang & Freeman, 1998b]. Because of this stochastic chaos, the KIII network not only simulated the chaotic EEG waveforms, but also acquired the capability for pattern recognition, which simulated an aspect of the biological intelligence, as demonstrated by previous applications of the KIII network to recognition of one-dimensional sequences, industrial data and spatiotemporal EEG patterns [Kozma & Freeman, 2001; Principe *et al.*, 2001; Yao & Freeman, 1989].

3. Application on Handwriting Numeral Recognition

Pattern recognition is an important subject of artificial intelligence, also a primary field for the application of ANN. KIII network is a more accurate simulation of the biological neural network than conventional ANN. Here we give a new application example of the KIII network for recognition of handwritten Arabic numerals. In this application, the KIII network is used as a bionic pattern classifier. Its classification performance under different noise levels is also discussed.

3.1. *Learning rule*

For KIII network there are three main learning processes: Hebbian associative learning, habituation and normalization. Hebbian learning under reinforcement establishes the memory basins and attractors of classifying patterns, while habituation is used to reduce the impact of environment noise including noninformative background inputs to the KIII network. Global normalization is used to maintain the stability of the KIII network long-term over the changes in synaptic weights that typically increase the strengths of excitatory connections in association and reduce them during habituation. Normalization includes the modification of the Hebbian rule by imposing a maximal strength of mutual excitation to prevent runaway increases, and by requiring that Hebbian increases only occur under reinforcement. Habituation is otherwise automatic in the absence of reinforcement.

When an axon of cell A is near enough to excite a cell B and repeatedly or persistently takes part in firing it, some growth process or metabolic change takes place in one or both cells such that A's efficiency, as one of the cells firing B, is increased [Hebb, 1949]. The principles underlying this statement have become known as Hebbian Learning. Within connectionism, Hebbian learning is an unsupervised training algorithm in which the synaptic strength (weight) is increased if both the source neuron and target neuron are active at the same time. According to our specific requirements, we made some modifications in the Hebbian learning rule: (1) we designed two methods for increasing the connection strength which is described below; (2) we introduced a bias coefficient K to the learning process.

In our experiments, we implemented the above Hebbian learning rule into the following formula. The output of the KIII network at the mitral level (M) is taken as the activity measure of the system. The activity of the ith channel is represented by $SD_{\alpha i}$, which is the mean standard deviation of the output of the ith mitral node (Mi) over the period of the presentation of input patterns, as Eq. (3). The response period with input patterns is equally divided into segments and the standard deviation of the ith segment is calculated as $SD_{\alpha ik}$, $SD_{\alpha i}$ is the mean value of these s segments. SD_{α} is an $1 * n$ activity vector containing the activity measure of all nodes in mitral level. SD_{α}^{m} is the mean activity measure over the whole OB layer with n nodes [Eq. (4)].

$$SD_{\alpha i} = \frac{1}{S}\sum_{k=1}^{S} SD_{\alpha ik} \tag{3}$$

$$SD_{\alpha}^{m} = \frac{1}{n}\sum_{k=1}^{n} SD_{\alpha i} \tag{4}$$

The modified Hebbian rule holds that each pair of M nodes that are co-activated by the stimulus have their lateral connections, $\omega(mml)_{ij}$, strengthened. Here $\omega(mml)_{ij}$ stands for the connection weights both from Mi to Mj and from Mj to Mi. Those nodes whose activities are larger than the mean activity of the OB layer are considered activated; those whose activity levels are less than the mean are considered not to be activated. Also, to avoid the saturation of the weight space, a bias coefficient K is defined in the modified Hebbian learning rule, as in Eq. (5)

$$\begin{array}{ll} \mathit{IF} & SD_{\alpha i} > (1+K)SD_{\alpha}^{m}\ \mathit{AND}\ SD_{\alpha j} \\ & \quad < (1+K)SD_{\alpha}^{m} \\ \mathit{THEN} & \omega(mml)_{ij} = w(mml)^{\text{high}},\ \text{Algorithm 1} \\ \mathit{OR} & \omega(mml)_{ij} = r \star \omega(mml)_{ij},\ \text{Algorithm 2} \end{array} \tag{5}$$

Two algorithms to increase the connection weight are presented; algorithm 1 is to set the value to a fixed high value $w(mml)^{\text{high}}$ as in previous references and in algorithm 2, $\omega(mml)_{ij}$ is multiplied by a coefficient $r(r > 1)$ to represent the Hebbian reinforcement.

For the habituation learning, a decrease in excitatory output synapses occurs continuously at each time of stimulus presentation (not the digitizing step) for every node that receives input without reinforcement. Unlike Hebbian learning, this reduction does not require pairwise activation, and it is reversible. For example, as for continuous habituation parameter $h_{\text{hab}} = 0.9995$ and a 400 ms simulation period, if the connection weight is not influenced by any other learning rule, it decreases at the habituation rate h_{hab} and reaches $0.9995^{400} = 0.819$ of the original value at the end of this simulation period.

At the end of a training session for all three types of learning, the connection weights are fixed to perform pattern classification tests. During training, several samples for each class are given. The amplitude of the N activity outputs is measured and expressed as a feature vector for every trial, as well as the mean activity of those trials that belong to the same class. The feature vector defines a point in N-space (usually $N = 64$); a set of training trials with the same class of stimulus forms a cluster of points in N-space; the mean is defined as the center of gravity of the cluster representing the class. Inputs of different classes that the system is trained to discriminate form multiple clusters of feature vectors, each with its center of gravity. When a test pattern is given, its feature vector is calculated. The Euclidean distances from the corresponding point of the feature vector to those training pattern cluster centers are calculated, and the minimum distance to a center determines the classification. To ensure correct classification, a threshold was introduced. When the difference between the minimum Euclidean distance and the secondary minimum distance was less than the threshold value, the trial was regarded as a recognition failure.

3.2. *Classification of handwriting numerals*

Automatic recognition of handwriting characters is a practical problem in the field of pattern recognition, and was here selected to test the classification performance of the KIII network. The test data set contains 200 samples in 20 groups of handwritten numeric characters written by 20 different students. One group included 10 characters from zero to nine. Figure 4 shows three groups of samples of the test data set. In this application, a 64-channel KIII network was used with system parameters as reference [Chang & Freeman, 1998a]. Each simulation trial either for training or for classification lasted for 400 ms, while the first 100 ms was the initial period in which the KIII network entered into its basal state. The input persisted 200–300 ms. Every character in the test data was preprocessed to get the 1×64 feature vector and to place a point in a 64-dimensional feature space. The preprocessing was in two steps. The first step included image cropping, noise removal and the "thin" operation (a digital image processing method which shrinks an object to its minimal connected stroke). Every character is picked out and transformed to its skeleton lines [Haralick & Robert, 1992; Pratt & William, 1991]. The second step is to extract features. The character image obtained after the first step preprocessing is first divided into $2 \times 2 = 4$ small rectangular regions according to its pixel mass center. Similar as the previous step, each small rectangular region is divided into $2 \times 2 = 4$ smaller rectangular regions, thus the whole character is separated into $4 \times 4 = 16$ rectangular regions. In every small region the ratios of four kinds of lines in four different directions are calculated. Thus the 64 features are given as input to the KIII network as a stimulus pattern in the form of a 1×64 feature vector.

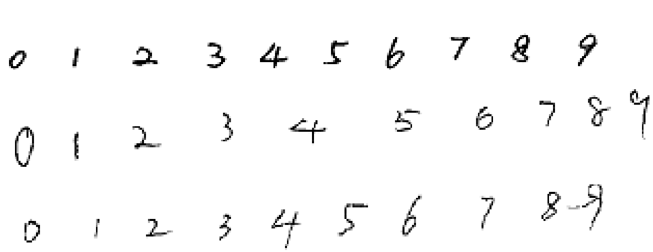

Fig. 4. Sample of the test data set.

As described in the learning rule [Freeman, 2000a], the period with stimulus patterns is divided into five segments to calculate the nodes' activity with each segment lasting 40 ms. Because there are ten inter-related patterns for classification, algorithm 2 for Hebbian learning rule is chosen for this classification problem with the bias coefficient $K = 0.4$. The values of $s = 5$ and $K = 0.4$ are chosen based on the previous experiments of the application of KIII model [Kozma & Freeman, 2001; Principe *et al.*, 2001; Yao & Freeman, 1989]. The increasing rate r is set to 1.2. We chose 1.2 arbitrarily in the interval (1.0, 1.5). If $r > 1.5$, $\omega(mml)_{ij}$ will soon become too large and thus, the KIII model cannot work properly as a classifier. Moreover, the threshold value mentioned above was set to one twentieth of the distance between the test data cluster centroid and the training data cluster centroid. In our experiments, we have totally 200 groups of handwriting numeral characters. Each group consists of ten characters (from "0" to "9"). We arbitrarily chose 10 groups for training and used all the 200 groups for classification. The classification results using KIII are shown in Table 1.

Furthermore, we compared our classification rates with those given by using the following types of traditional ANN: the linear filter, the multilayer perceptron (MLP) and the Hopfield network respectively, to classify these same handwriting numeral characters. The selections of the training set and the testing set were both same as those of the experiments of KIII. The linear filter was very simple and has very limited classification capacity.

Table 1. Classification result — using KIII.

Pattern	Correct	Incorrect	Failure	Reliability
0	196	3	1	98.49
1	185	10	5	94.87
2	192	4	4	97.96
3	177	12	11	93.65
4	179	11	10	94.21
5	181	7	12	96.28
6	191	1	8	99.48
7	189	7	4	96.43
8	174	9	17	95.08
9	186	9	5	95.38
Total	1850	73	77	96.20
Rate	92.5	3.65	3.85	96.20

In the MLP, we used two layers of perceptrons: an input layer of 64 neurons and an output layer of 10 neurons. The input layer used log-sigmoid transfer function and the output layer used a linear transfer function. We took each column of a 10×10 identity matrix as the target output of the MLP, corresponding to one kind of numeric character in the training set (i.e. the first column corresponding to the character "0", etc.). The weight and bias values in the MLP were updated according to Levenberg–Marquardt optimization with all the learning rates set to 0.01. The Hopfield network did not have a learning law associated with it. It was not trained, nor did it learn on its own. Instead, a design procedure based on the Lyapunov function was used to determine the weight matrix. We considered the column vector in the training set, that is, a 64×10 matrix, as the set of stable points in the network and designed a Hopfield network with a single layer using symmetric saturating linear transfer function. The test procedure of the MLP and Hopfield network were very similar. After giving the testing input set to the network, we compared the outputs of the network to the predesigned target vectors. The target vector that had the minimal variance with the output vector determined the category of the testing set.

The training time of all these ANNs was much shorter than that of KIII, although in prior usage of the KIII set for classification the number of training objects was far less than the requirements for the MLP. Likewise, the testing time was negligible for the ANN compared to that of KIII, mainly because of the time required for numerical solution of the arrays of ordinary differential equations. However, their classifying performances were poorer than that of the KIII algorithm. While a high overall reliability of 96.20% was gained using KIII, the reliability of the linear filter, the perceptron and the Hopfield network was merely around 60%. Obviously, the KIII model shows its excellence in practical pattern classification, which justifies efforts to embody the equations in analog VLSI [Principe *et al.*, 2001]. Table 2 shows the comparison of the classification test results.

Taking the noise level as a parameter, the influence of the noise level on the KIII network classification performance was investigated. As the stimulus pattern, which is considered as the signal, was composed of corresponding feature values, whose range is 0 to 1, the standard deviation of the Gaussian noise added at the receptor site was defined as the noise/signal rate. Repeated tests were taken as the noise level was increased. Results

Table 2. Classification results — comparison.

Pattern	Reliability			
	Linear Filter	Perceptron	Hopfield	KIII
0	74.50	100	59.79	98.49
1	55.85	89.5	78.89	94.87
2	71.0	53.68	78.42	97.96
3	35.5	67.37	79.87	93.65
4	39.44	44.13	41.99	94.21
5	48.73	49.36	21.17	96.28
6	83.5	69.95	89.23	99.48
7	58.59	51.59	64.0	96.43
8	76.53	46.88	87.93	95.08
9	64.06	63.5	64.29	95.38
Overall reliability	60.99	64.84	66.76	96.20

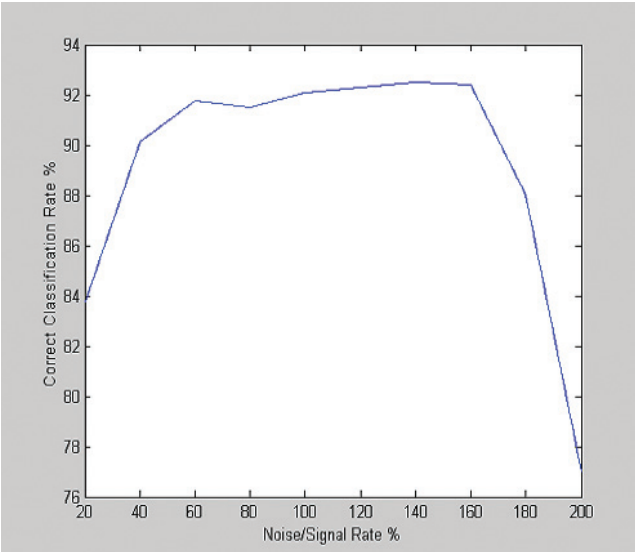

Fig. 5. Classification performance of KIII.

(Fig. 5) showed that as the noise level increased the correct classification rate of the KIII network increased to a plateau and then decreased. In previous work done by Kozma [Kozma & Freeman, 2001], an optimal noise/signal rate was found for the best classification performance of KIII, which was named "chaotic resonance" in comparison to stochastic resonance. However, in this result, it seems difficult to find an apparent optimal noise/signal rate. The correct classification rate of the KIII network remained above 90% when the noise/signal rate was varied from 40% to 160%. This result indicated that the KIII network performance was insensitive to the noise level over a relatively broad range.

4. Discussion

There are two points that should be noted in the exploration of the classification ability of KIII network by applying it on classification of handwriting numerals. The first is about the feature extraction in preprocessing. Although the feature space is used in this application as it is commonly used in the practical problem of pattern recognition, it is sometimes believed that feature space does not exist in a real biological system. A good example is the feature-binding problem of human face recognition in which the face pattern is considered as a whole pattern, not the combination of features. The second point is about the modification of Hebbian learning rule. The new algorithm for increasing the connection weight makes KIII network able to memorize and classify more patterns than it used to. In previous research, the pattern volume was limited to 5–8 patterns for a 64-channel KIII network to classified. Also, it is more reasonable to believe that the connection weights, which represent the biological synaptic connections, change gradually in the learning process.

Another important aspect in this research concerns the role of noise in the KIII model. It is demonstrated by electrophysiological experiment and computer simulation that the additive noise in KIII network could maintain the KII components at nonzero point attractor and could stabilize the chaotic attractor landscape formed by learning [Freeman, 1999]. However in this application an optimal classification performance was not found while adapting the noise intensity. Instead, the KIII network performs well when the noise parameter is in a broad range. This phenomenon may also indicate that the real biological olfactory neural system could work well under a certain scope of noise level and not just at an optimal point.

Compared with conventional ANN, KIII network gives a more complicated and more accurate model in simulating the biological olfactory neural system, especially in respect to simulating the biological signal observed in experiments such as EEG signals. Moreover, KIII model also has good capability for pattern recognition as a form of the biological intelligence. It also needs much fewer learning trials than ANN when solving problems of pattern recognition. Although when considering the pattern volume and processing speed, the KIII network still cannot replace the conventional ANN for solving practical problems, it is surely a promising research for building more intelligent and powerful artificial neural network when the speed is increased by implementing the KIII in analog VLSI [Principe *et al.*, 2001]. In the present research the KIII network is still implemented by digital computer, which differs fundamentally from the analog real olfactory neural system. More work will be required in simulating the olfactory neural system with analog devices.

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