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Algorithm for Texture Image Generation Based on a Bionic Model of Olfactory Neural Networks

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Abstract This paper presents a novel bionic model based on olfactory systems to generate texture image. The model simulates one of the olfactory neural networks. The chaotic characters of Logistic function are used to adjust the parameters of model during iteration. A simple periodic function is used as the activation function of node in the model to generate periodic texture. And a random noise is introduced to simulate the background noise of brain when processing information. The experimental results show that the model can generate plentiful and multivariant texture images. The introduced random noise plays an important role and enriches the variety of texture images obviously. In addition, the model efficiency to generate texture image outperforms the conventional back propagation neural network model.

Keywords olfactory neural networks, bionic model, texture image, random noise

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基于嗅觉神经网络仿生模型的纹理图像生成算法

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摘　要　提出了一种基于嗅觉系统生成纹理图像的仿生模型。该模型结构模拟嗅觉神经网络的结构,利用 Logsitic 函数的混沌特性调整每次迭代过程中的模型参数,使用简单的周期函数作为模型节点的激活函数实现纹理的重复,并引入随机噪声来模拟脑在进行信息处理时的背景噪声。实验结果表明,该模型可以生成丰富而多变的纹理图像,引入的随机噪声也起到了积极的作用,可以明显地丰富纹理图像的变化。此外,模型生成纹理图像的效率也高于传统的 BP 神经网络模型。

关键词　嗅觉神经网络　仿生模型　纹理图像　随机噪声

1　Introduction

The technology of texture image generation[1] is one of the important research directions in the fields of digital image processing and computer graphics. It has been widely used in the area of image analysis and processing. Researchers have proposed many algorithms to generate texture image, such as the fractal geometry[2], Markov random field model[3]. These algorithms can be divided into two classes: structural models and statistic models. A structural model is

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generally used to describe the regular texture structure, while a statistic model generates random nature texture structure, but it is difficult to generate both kinds of texture images using only one kind of models. Although the back propagation (BP) neural network has been used to generate texture images[4,5] according to the character of nonlinear dynamics of artificial neural networks, the similarity of generated texture images increases with continuous iteration. Zheng et al. proposed a chaotic mapping method to adjust the connection weights to generate more texture images[5].

Based on the K set models[6~8], a bionic olfactory neural network is proposed to generate texture images. The structure of model is constructed based on olfactory neural networks. In order to make the model working at a non-convergent chaotic state, the connection weights and thresholds of the model are adjusted according to Logistic chaotic mapping. Random noise is introduced in the model to simulate the background noise of brain when processing information. Experimental results show that the model can be in non-convergent chaotic state and generate more abundant texture images compared with BP neural network. Random noise plays a key role in the model, which makes texture images with multi-variance and different effects compared with conventional neural networks.

2 Bionic model of olfactory neural networks

2.1 Structure of the olfactory neural network

According to anatomy, the whole olfactory system consists of four main parts: the receptor array (R), the olfactory bulb (OB), the anterior nucleus (AON) and the prepyriform cortex (PC), as shown in Fig. 1[7]. Different olfactory receptors (R) that are sensitive to different odorants can detect a large variety of odor molecular and then send information through their axons to olfactory bulb (OB). The OB is mainly composed of two kinds of cells, excitatory mitral cells (M) and inhibitory granule cells (G). It is the local negative feedback between the M and G cells that creates the oscillations in gamma range observed in the bulbar EEG. The bulbar neurons send their axons by way of the lateral olfactory tract (LOT) to the anterior olfactory nucleus (AON) and the prepyritorm cortex (PC). In the AON and PC there are also excitatory (E) and inhibitory cells (I), and the negative feedback between these cells support oscillations in both AON and PC as in the OB but with different and incommensurate characteristic frequencies. The PC sends axons into the external capsule (EC) in the brain. In the other direction the AON and PC send axons back through the medial olfactory tract (MOT) to the OB. There are two subsidiary control elements in the olfactory system. One element is the periglomerular cells (P) in the outer layer of the OB, which preprocess receptor input to the OB. The periglomerular cells (P) are excitatory to each other and also forwardly to the mitral cells in the OB. The periglomerular cells provide a positive excitatory bias for the M and G cells to maintain the oscillation. The other 'chaotic' control element is the AON, to which controls are directed from other parts of the brain.

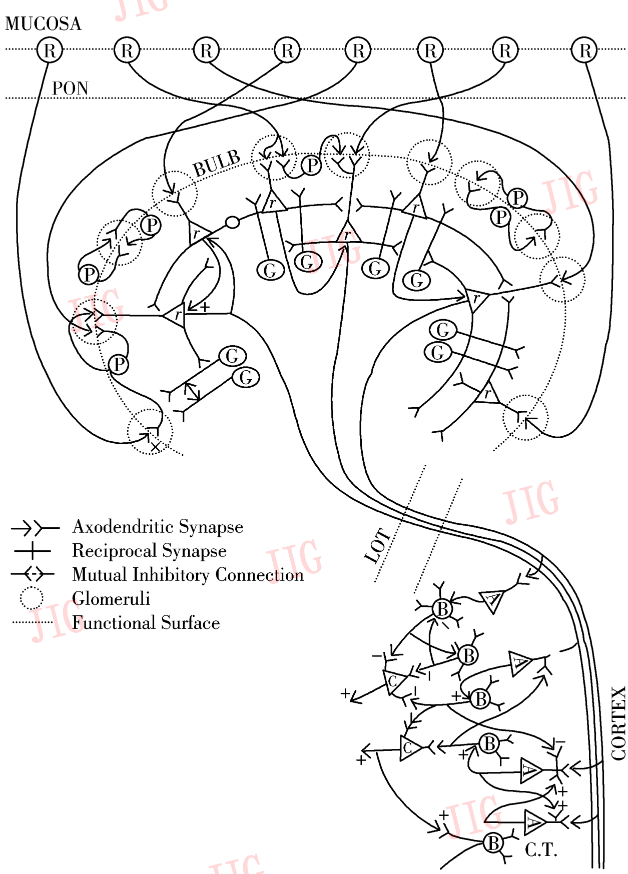

Fig. 1 Olfactory neural network

How olfaction is generated by olfactory neural systems can be described as follows: first, the odor molecules in the air reach the receptors, R; second, the signal generated by R is transmitted to OB through main olfactory nerve; third, the odor information is transmitted to anterior nucleus, PC and cone cells through lateral olfactory tract to generate olfaction. OBs play a very important role in this procedure. OBs receive the input not only from R, but also from nerve fiber of AON and PC, and are considered to have the function to process information to some extent. Though the anatomic structure of olfactory neural network is well known, how information is coded, transmitted and stored are still an open question, which is beyond the area we discuss here.

2.2　Bionic model based on olfactory neural network

2.2.1　Model structure

According to the structure of olfactory system shown in Fig. 1, a simplified olfactory model is proposed. The model simulates the framework of olfactory systems and random noise is introduced to simulate the background noise of brain.

The whole structure of model is shown in Fig. 2, which is different from conventional neural networks. The model consists of an input layer, a hidden layer I, a hidden layer II and an output layer, which are described in detail as follows.

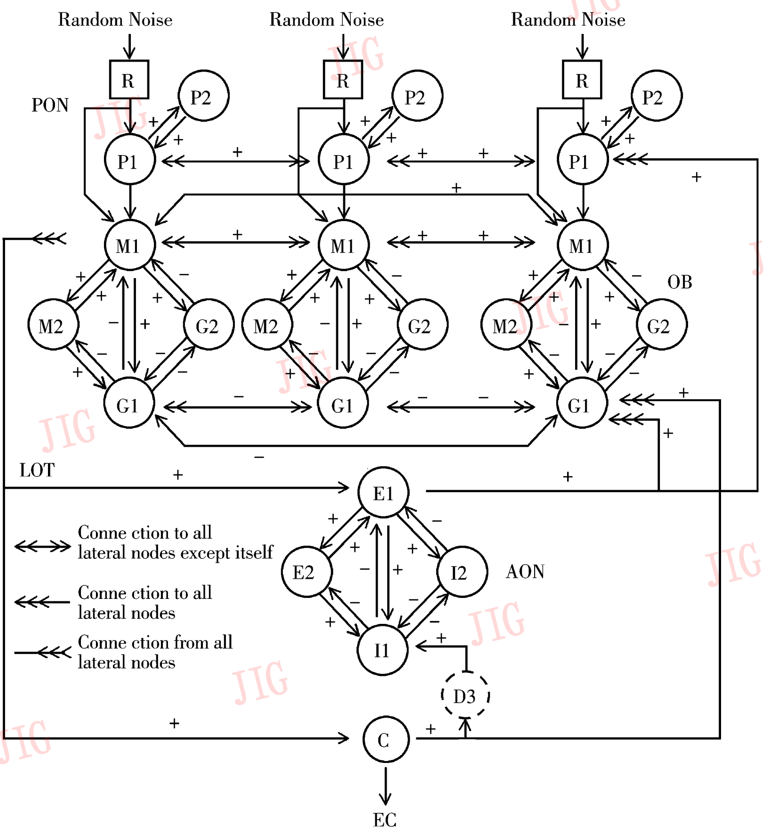

Fig. 2　Olfactory bionic model

Input layer: R and P denote the receptor array and the periglomerular cells, respectively. As a whole, P and R compose the input layer in the model.

Hidden layer I: M (mitral cells), which receives the input from the input layer, and G (granule cells) compose a nerve loop. Consistent with the real function, M is excitatory and G is inhibitory in the model. M and G composes hidden layer I, OB layer.

Hidden layer II: the information processed by OB layer reaches AON through LOT. AON is composed by E and I, which are similar to M and G to form a nerve loop. In this layer, E provides the feedback to the Hidden layer I.

Output layer: output layer simply consists of only one node, C, to provide the feedback.

In the model, feedback from different layers is introduced to different nodes in the model to simulate real olfactory neural networks. Some parts, such as PC, are simplified to keep the model effective. It should be pointed out that the random noise is added from R to simulate the background noise of brain during information processing[8].

2.2.2 Activation function and the rule of parameters adjustment

Considering the periodicity character of texture images, one simplest functions, sine function $f(x) = \sin(ax)$, is used as an activation function of the nodes, in which a is a real number related to periodicity. Sine function is selected because its periodicity is very simple and can be adjusted easily so that the texture image can realize a regular repetition.

Regarding the rule of parameter adjustment, the main idea is to keep the model in non-convergent state, which is totally different from conventional artificial neural networks. So, a typical chaotic function, Logistic function, is utilized to adjust the connection weights and thresholds. Logistic function is shown in Eq. 1 and Eq. 2.

$$L(t+1) = aL(t)(1-L(t)) \tag{1}$$

$$\begin{cases} 0 < L(0) < 1 \\ 3.57 \leqslant a \leqslant 4.0 \end{cases} \tag{2}$$

$$p(t+1) = c + bL(t) \tag{3}$$

where $L(t)$ is a chaotic variable, a satisfies Eq. 2, p denotes the parameters of model, b and c are used to scale $L(t)$ according to Eq. 3. The connection weights and thresholds are adjusted repeatedly to make the model in a non-convergent state.

The input/output relation of nodes in first M-G group is given in Eq. 4 as an example of the input/output relation in the model:

$$\begin{cases} y_i^{M1}(t+1) = f(k_{m1r}r_i(t) + k_{m1p}p_i(t) + k_{m1m2}m_2(t) + \\ \qquad \sum k_{m1m1}m_1(t) - k_{m1g1}g_1(t) - \\ \qquad k_{m1g2}g_2(t) - th_{m1}) \\ y_i^{M2}(t+1) = f(k_{m2m1}m_1(t) + k_{m1g1}g_1(t) - th_{m2}) \\ y_i^{G1}(t+1) = f(k_{g1m2}m_2(t) + k_{g1m1}m_1(t) + \\ \qquad k_{g1g2}g_2(t) - \sum k_{g1g1}g_1(t) - th_{g1}) \\ y_i^{G2}(t+1) = f(k_{g2g1}g_2(t) + k_{g2m1}m_1(t) - th_{g2}) \end{cases} \tag{4}$$

where k_{ij} denotes the connection weights from node j to node i; th_i denotes the threshold of node i; and $f(x)$ is the activation function of the node. The input/output equation of the other nodes in the model can be expressed easily according to Fig. 2.

3 Algorithm to generate texture images based on the bionic model

In the model, there is no special requirement about the input source images. Abundant and multivariable texture images can be obtained with a simple achromatic image. Based on the proposed bionic model, the algorithm to generate texture images is very simple.

The algorithm consists of following steps:

(1) Select one image as the seed image, S, with $N \times M$ nodes (pixels);

(2) Randomly set the initial thresholds, the connection weights and $L(0)$ within $[0,1]$ when $t=0$;

(3) Calculate $L(1)$ according to Eq. 1, adjust thresholds and connection weights according to Eq. 3;

(4) Assume the value of grey scale of node at (x,y) in S is $s(x,y)$, construct a triple, $(x, y, s(x, y))$, and add a random noise to the triple as the input of the model;

(5) Extract the output of $M1$ as the output of the whole model. It should be pointed out that the output of C is not the output of the model, which is different from BP neural networks. After all pixels in S are calculated, one texture image is generated. Countless different texture images can be generated by simply setting a loop variable.

4 Evaluation

Some texture images generated by the model are used to evaluate the performance of model. The effect of the random noise in the model is also tested. In the experiments, the main parameters are pre-set. The input is 3-dimension vector, $(x, y, \text{gray-value}(x,y))$, in which x and y denote the coordinate of any point in the source image and gray-value(x,y) denotes the gray value at (x,y). The number of M-G group is equal to 3 in hidden layer I, and the random noise is uniformly distributed pseudo-random numbers. In Eq. 1 and

Eq. 3, $a=4$, $b=3$, $c=-2$.

Figures 3 and 4 are two group texture images taken from M1. Figure 3 is the result without random noise, while Fig. 4 shows the result after introducing random noise. From the two group texture images, it is illustrated that the random noise added can improve the diversification of texture image obviously and the texture image is very humdrum without random noise. It implies that random noise has positive function when processing information, which consists with the opinion of the reference[8] to differ from previous opinions.

Figures 6 and 7 are the outputs of the first and second M1, respectively, in the hidden layer I in one trial. From the two groups of texture images, it is clear that the results are very different even with the same condition and hidden layers. Compared to the images generated by the BP neural network[4] (as shown in Fig. 5), the texture images generated by the bionic model are better. The texture images output from the first M1 are much ampler while those output from the second M1 are more regular and clear in macroscopic viewpoint. The bionic model is more efficient than the BP neural network, because the bionic model can generate two texture images at the same time while BP neural network can generate one texture image in one trial[4,5].

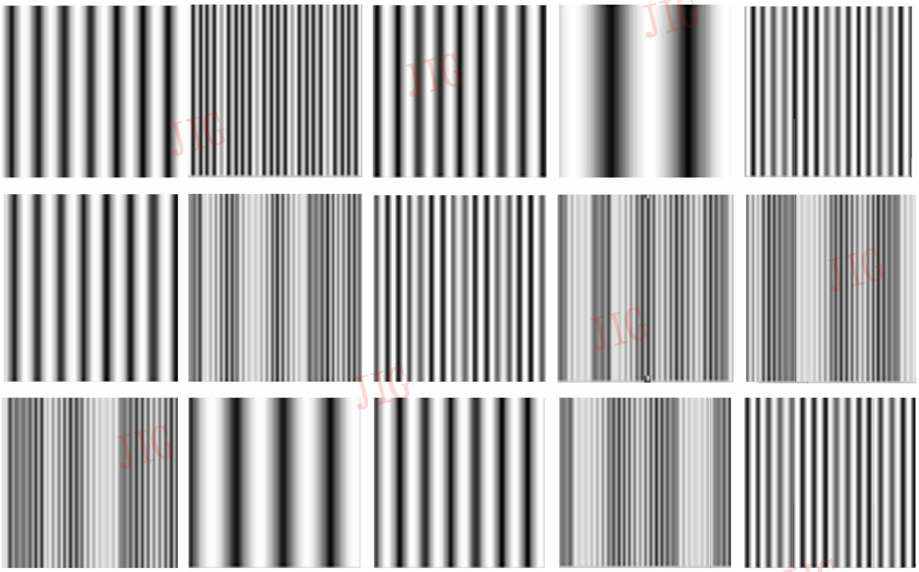

Fig. 3　The output of node M1 without random noise

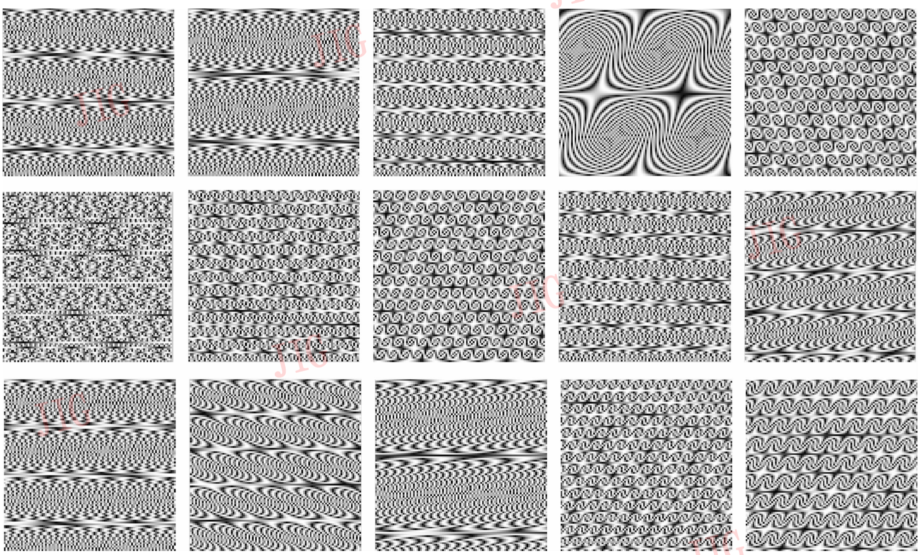

Fig. 4　The output of M1 after introducing random noise

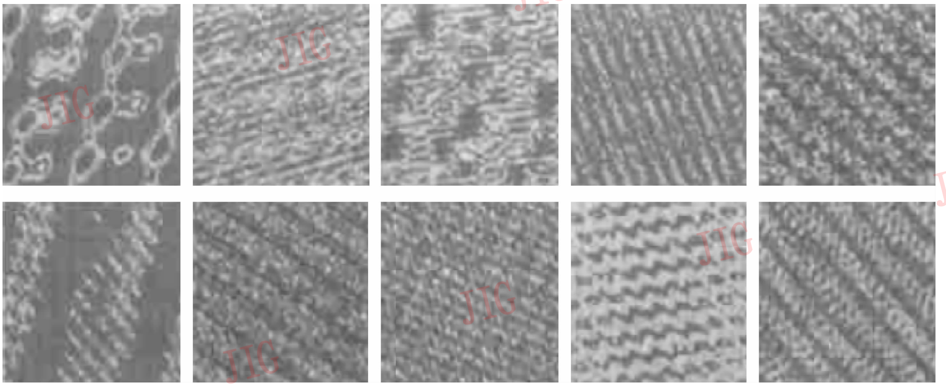

Fig. 5 The texture image generated by BP neural network[4]

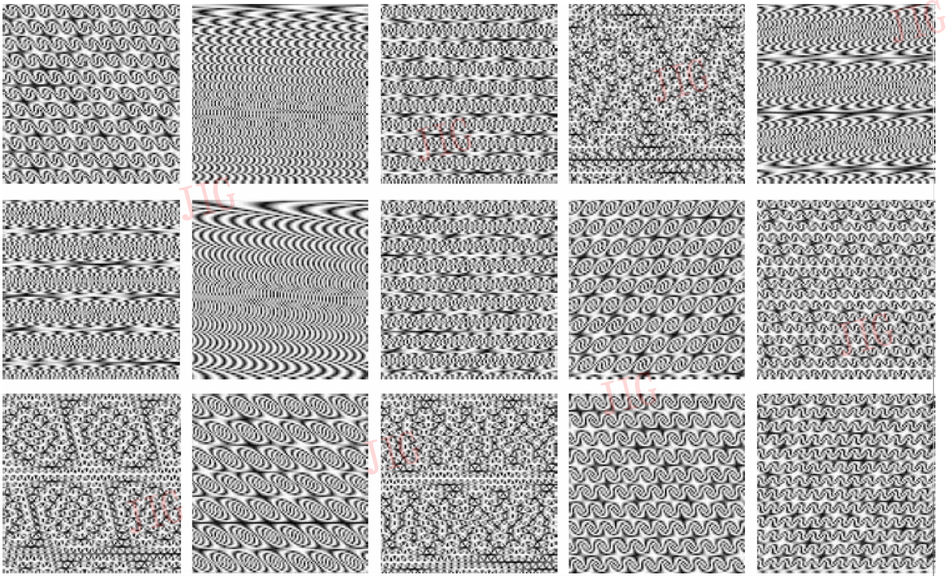

Fig. 6 The output of first M1

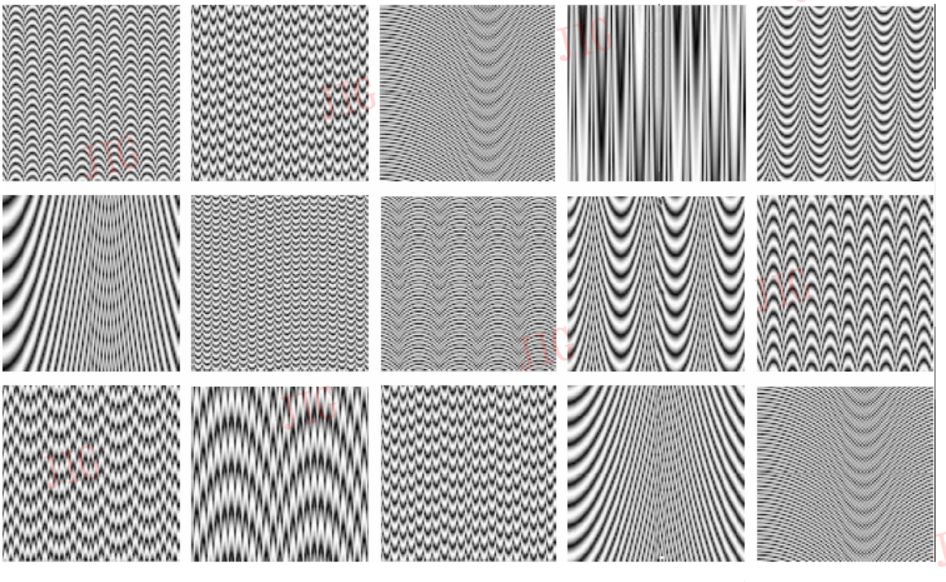

Fig. 7 The output of second M1

5 Conclusion

This paper propose a bionic model to generate texture images. The structure of model simulates the framework of olfactory systems. The model uses chaotic variable to adjust thresholds and connection weights to make the model in non-convergent states, and introduce random noise to simulate the background noise of brain when processing information. Simulation results show that the model can generate abundant and multivariable texture images even the source image is a simple achromatic image. The efficiency outperforms the BP neural network.

This paper is the elementary research of bionic model of olfactory neural network. There are still many problems to be solved, such as the dynamics of the nodes, the function of random noise. They will be our feature works.

References (参考文献)

1 Wei Li-yi, Marc Levory. Texture synthesis over arbitrary manifold surfaces [A]. In: Proceedings of 28th Annual Conference on Computer Graphics and Interactive Techniques [C], New York: ACM Press, 2001:355～360.

2 Mandelbrot B B. The Fractal Geometry of Nature [M]. San Francisco, CA: Freeman, 1982:1～6.

3 Rupert Page, Id Longstaff. Texture synthesis via a noncausal nonparametric multiscale Markov random field [J]. IEEE Transactions on Image Processing, 1998, **7**(6):925～931.

4 Wu Xiao-pei, Zhou He-qin, Feng Huan-qing. The texture image generation based on neural netowrk [J]. Journal of Image and Graphics, 2000, **5**(6):484～488. [吴小培,周荷琴,冯焕清. 基于神经网络的纹理图象生成[J]. 中国图象图形学报, 2000, **5**(6): 484～488.]

5 Zheng Li-ying, Tian Kai, Wang Ke-jun. The Method of texture image generation based on chaotic mapping [J]. Journal of Image and Graphics, 2002, **7**(10):1009～1011. [郑丽颖,田凯,王科俊. 基于混沌映射的纹理图象生成方法[J]. 中国图象图形学报, 2002, **7**(10): 1009～1011.]

6 Kensaku Mori, Hiroshi Nagao, Yoshihiro Yoshihara. The olfactory bulb: coding and processing of odor molecule information [J]. Science, 1999, **286**(22): 711～715.

7 Li Guang, Zhang Jin, Walter J. Freeman. Face recognition using a neural network simulating olfactory systems [A]. In: Proceedings of Third International Symposium on Neural Networks [C], Chengdu, China, 2006, **3972**: 93～97.

8 Kozma R, Walter J Freeman. Chaotic Resonance—Methods and Applications for Robust Classification of Noisy and Variable Patterns [J]. International Journal of Bifurcation and Chaos, 2001, **11**(6): 1607～1629.