Reaction Neuron Network Model for Image Perception

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Abstract: - A new neuron network model, as an assistance of image perception, is proposed in this paper. It is based on the retina. And it is shown that this neuron network model can both describe the transfer property of retina well and neglect subordinate details when processing an image. Specially, we also describe how to implement this model and make some experiments on it.

Key-Words: - Image Perception, Retina, Mach Effect, Receptive Field, Smoothing, Reaction Neuron Network Model

1 Introduction

The ultimate goal of image perception is to generate accurate description of environment from an original image. Given the difficulty of attaining this goal, it is worthwhile to consider, as an alternative or as an intermediate step, algorithms which can act as assistants, allowing perception task to be performed more easily, and more reliably. Many efforts have been made in this field. Deformable Template [1] [2] [3] and Anisotropic Diffusion [4] [5] [6] are two popular methods.

Deformable Template is an approach of shape matching. On one hand, it is capable of detecting a shape which is different from the template. A deformable template, on the other hand, is able to deform itself to fit the data, by transformations that are possibly more complex than translation, rotation and scaling.

Anisotropic Diffusion can remove the noise of less important information from an image by modifying the image via a partial differential equation (PDE) [7].

Unfortunately, all methods we have ever developed never perform as well as ourselves — human beings. As we all know, man has amazing abilities in image perception. And we believe that the physiological structure of human being must contribute to the fantastic performance to some extent. Therefore, we consider that a bionic model will perform better than general methods.

Retina is the first tissue in our body to sense the image. It is so important that scientists have made many experiments on it. Some result is valuable. One of them is Receptive Field [8], which implies the transfer property of retina neurons.

It has been known for over 40 years that the vertebrate retina utilizes lateral inhibition to create spatially opponent center-surround receptive fields. In both mammalian (Kuffler, 1953) and non-mammalian (Barlow, 1953) retina, ganglion cells show center-surround receptive fields. Receptive field surrounds are also found in non-mammalian bipolar cells (Werblin & Dowling, 1969; Matsumoto & Naka, 1972; Kaneko, 1973; Schwartz, 1974). [9] (See Fig.1)

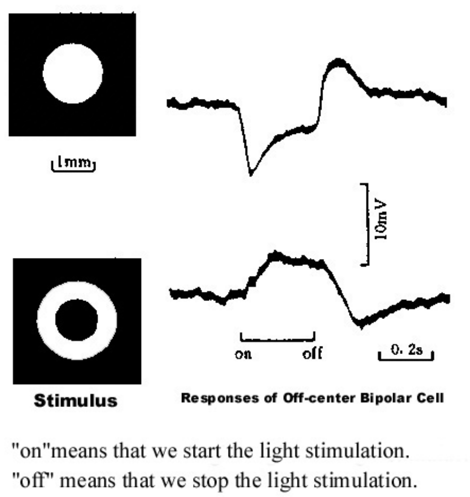

Fig.1 Response of Bipolar Cells [10]

Rodieck [11] proposed a DOG (Difference of Gaussian) model to simulate the response of the retina neurons illustrated in Fig.2. However, this model cannot explain the other experiment phenomena, for example, Mach Effect. Mach Effect is that we will feel a black paper darker than it actually is at the border between it and the white background. (See Fig.2)

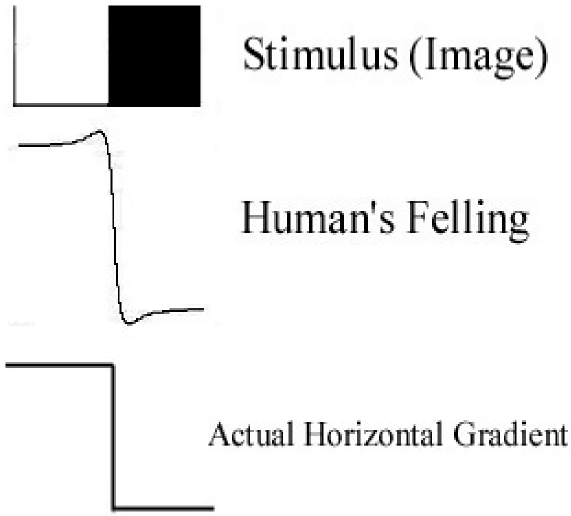

Fig.2 Approximate Representation of Mach Effect

Therefore, in this paper, we intend to propose a new ANN model, which can not only describe the transfer property of retina neurons but also assist to image perception.

The organization of this paper is as follows. In Section 2, we describe the new ANN model and the details how it works. And the experimental results are given in Section 3, followed by discussions in Section 4.

2 Reaction Neuron Network Model

2.1 Basic Principles of Reaction Neuron Network Model

2.1.1 Structure of Reaction Neuron Network

Illumined by the structure of the retina, we design a new model to simulate human's retina. (see Fig.3)

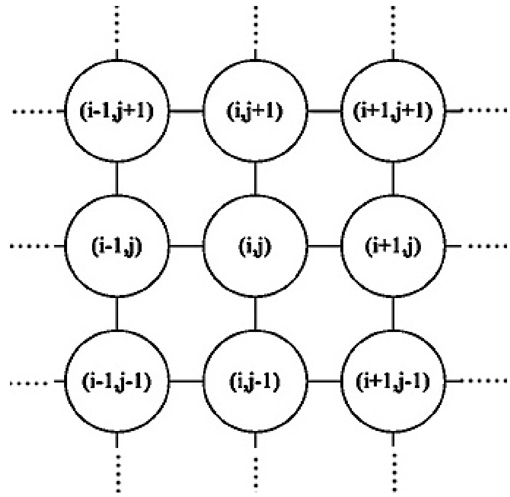

Fig.3 The Net Structure of Reaction Neuron Network (Every circle is a unit)

In the following discussion, we call the *Unit* at position (i,j) as Unit(i,j) and Reaction Neuron Network Model as RNN for short.

2.1.2 Two hypotheses

RNN is based on two hypotheses:

- In every unit there exists a reaction system. (See Fig.9) And in this system, there are three kinds of substances, viz., positive ion A^+, negative ion B^-, and atom C. The reaction formulae (a) ~ (d) are all presented in Fig.4. In addition, the positive ion A^+ will increase the units' output while the negative ion B^- decreases the output. Because C doesn't carry any electron, it will never affect the units' output.
- These substances are not fixed. They are able to flow from the unit with higher concentration to the adjacent one with lower concentration. The flowing speed of the substance is given by the equation $V = p_x \cdot \Delta C$. (Where ΔC is the difference of the concentration between two units and p_x is the coefficient of substance x — A^+, B^- or C.)

$$h\upsilon \xrightarrow{k_1} A^+ \quad \text{(a)}$$

$$A^+ \xrightarrow{k_2} B^- \quad \text{(b)}$$

$$B^- \xrightarrow{k_3} A^+ \quad \text{(c)}$$

$$B^- \xrightarrow{k_4} C \quad \text{(d)}$$

Fig.4 Hypothesis 1: Reactions formulae in Units

2.2 An Implement of RNN Model

2.1.1 Formulae and Rule

First we define a structure Unit(i,j) as follows:

```
Unit(i,j)
{
    Amount_A;
    Amount_B;
    Output;
}
```

2.1.1.1 Generation Formulae

Every unit will process the corresponding pixel in the image. V(i,j) represents the value of a pixel in the image at position (i,j).

Generation Formulae:

- ✧ $\text{Unit}(i,j)^{t,0}.\text{Amount\_A} = \text{Unit}(i,j)^{t-1,2}.\text{Amount\_A} + k_1 \times V(i,j) + \text{Unit}(i,j)^{t-1,2}.\text{Amount\_B} \times k_3$; (1)
- ✧ $\text{Unit}(i,j)^{t,0}.\text{Amount\_B} = \text{Unit}(i,j)^{t-1,2}.\text{Amount\_B} + \text{Unit}(i,j)^{t-1,2}.\text{Amount\_A} \times k_2$; (2)

2.1.1.2 Consuming Formulae

Next step we get the formulae from (b), (c) and (d) in Fig.4.

Consuming Formulae:

- ✧ $\text{Unit}(i,j)^{t,1}.\text{Amount\_A} = \text{Unit}(i,j)^{t,0}.\text{Amount\_A} - \text{Unit}(i,j)^{t-1,2}.\text{Amount\_A} \times k_2$; (3)
- ✧ $\text{Unit}(i,j)^{t,1}.\text{Amount\_B} = \text{Unit}(i,j)^{t,0}.\text{Amount\_B} - \text{Unit}(i,j)^{t-1,2}.\text{Amount\_B} \times (k_3 + k_4)$; (4)

2.1.1.3 Diffusion Formulae

In order to explain this rule more clearly we define two auxiliary equations (5) and (6):

- ✧ $\text{DiffAt} = 4\text{Unit}(i,j)^{t-1,2}.\text{Amount\_A} - \text{Unit}(i-1,j)^{t-1,2}.\text{Amount\_A} - \text{Unit}(i+1,j)^{t-1,2}.\text{Amount\_A} - \text{Unit}(i,j-1)^{t-1,2}.\text{Amount\_A} - \text{Unit}(i,j+1)^{t-1,2}.\text{Amount\_A}$; (5)
- ✧ $\text{DiffBt} = 4\text{Unit}(i,j)^{t-1,2}.\text{Amount\_B} - \text{Unit}(i-1,j)^{t-1,2}.\text{Amount\_B} - \text{Unit}(i+1,j)^{t-1,2}.\text{Amount\_B} - \text{Unit}(i,j-1)^{t-1,2}.\text{Amount\_B} - \text{Unit}(i,j+1)^{t-1,2}.\text{Amount\_B}$; (6)

Diffusion Formulae:

- ✧ $\text{Unit}(i,j)^{t,2}.\text{Amount\_A} = \text{Unit}(i,j)^{t,1}.\text{Amount\_A} - p_A \times \text{DiffAt}$; (7)
- ✧ $\text{Unit}(i,j)^{t,2}.\text{Amount\_B} = \text{Unit}(i,j)^{t,1}.\text{Amount\_B} - p_B \times \text{DiffBt}$; (8)

2.1.1.4 Convergence Rule

The issue now is when the process will converge. We consider that the system has converged if the following inequations is satisfied.

- ✧ $\sum_i \sum_j (\text{Unit}(i,j)^{t,2}.\text{Amount\_A} - \text{Unit}(i,j)^{t-1,2}.\text{Amount\_A}) \leq \Delta$; (9)
- ✧ $\sum_i \sum_j (\text{Unit}(i,j)^{t,2}.\text{Amount\_B} - \text{Unit}(i,j)^{t-1,2}.\text{Amount\_B}) \leq \Delta$; (10)

2.1.2 Basic Algorithm

The details of the algorithm are provided in the list below:

Step.1 Initialize the parameters (k_1, k_2, k_3, k_4, p_A, p_B and Δ).

Step.2 Get the image matrix V, set t = 1, and set all elements of matrices $\text{Unit}^{0,2}$.Amount_A and $\text{Unit}^{0,2}$.Amount_B to zero.

Step.3 Calculate matrices $\text{Unit}^{t,2}$.Amount_A and $\text{Unit}^{t,2}$.Amount_B with generation formulae, consuming formulae and diffusion formulae.

Step.4 Compute the Output of Unit.

- ✧ $\text{Unit}(i,j)^{t,2}.\text{Output} = \text{Unit}(i,j)^{t,2}.\text{Amount\_A} - \text{Unit}(i,j)^{t,2}.\text{Amount\_B}$; (11)

Step.5 **IF** system has converged **THEN goto** Step.6 **ELSE** t = t+1 and then **goto** Step.3

Step.6 Output the result matrix O.

- ✧ $O(i,j) = \text{Unit}(i,j)^{t,2}.\text{Output}$; (12)

2.1.3 How to Initialize Parameters

In order to implement the RNN, the initialization of parameters must obey the following regulations:

- $p_A < p_B$ and p_A, $p_B < 1/5$ (To guarantee the stability of system)
- k_1, k_2, k_3, $k_4 << 1$ (To control the speed of convergence)

In this paper we initialize the parameters as $k_1 = 0.01$, $k_2 = 0.01$, $k_3 = 0.001$, $k_4 = 0.02$, $p_A = 0.036$, $p_B = 0.18$ and $\Delta = 1 \times 10^{-7}$.

3 EXPEREMENTS ON RNN

3.1 Test one: Contrast Image

First we use a contrast image (see Fig.5) as stimulus to test this model.

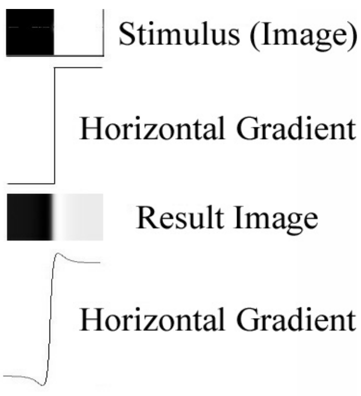

Fig.5 TEST ONE: Contrast Image

3.2 Test two: Annulus Image

Fig.6 presents the second test. Image (i) is the stimulus. Image (ii) shows the response of RNN. In addition, we observe the gradient on the line *OBSERVATION*, which is illustrated in figures (iii) and (iv).

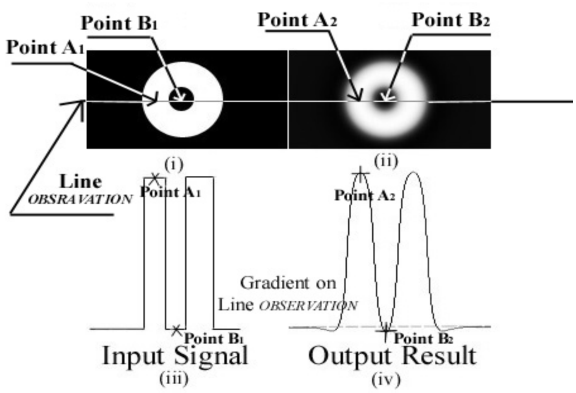

Fig.6 TEST TWO: Annulus Image

Note: 1) Point A_1 and point A_2 are of the same position in their respective images. 2) Point B_1 and point B_2 are of the same position in their respective images.

3.3 Test three: Natural Images

We compare RNN with the Gaussian smoothing method and Wiener adaptive smoothing method. And we use canny detector to search for the edges in all these results so that we can see the effect of the processing more clearly. (See Fig.7 (a), (b))

Obviously by using the RNN, we will get less useless information. In addition, at the position that we point out in Fig.7 (a) and (b) by arrows, we can see that the RNN with canny detector can keep most of the evident edge but the other two methods both miss part of the edge.

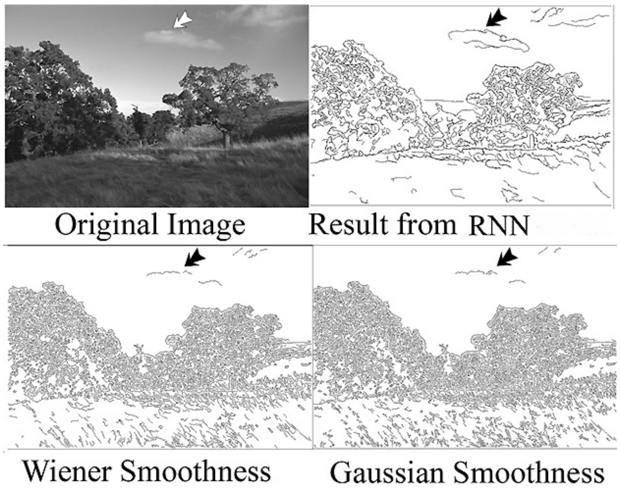

Fig.7 (a) Experiment 1: Grassland

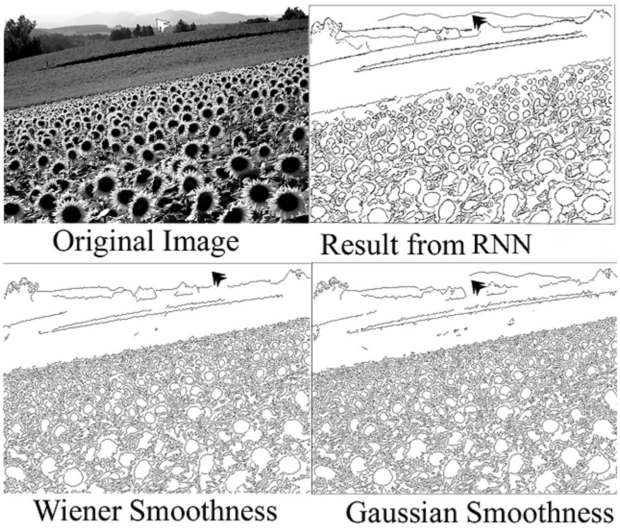

Fig.7 (b) Experiment 2: Sunflower

4 Discussion

4.1 The Convergence of RNN

The RNN is an iterative method. From the results of the experiment (see Fig.8) we find that the changes of the differences between two iterative steps are all monotonically decreasing. Therefore we believe that this model is a converging system approximately.

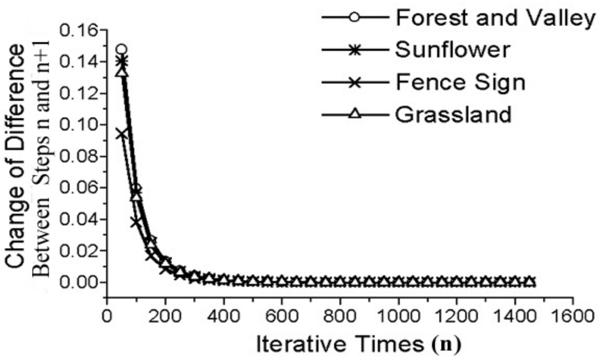

Fig.8 The Change of the Difference

4.2 Neurobiology Phenomena and Results of RNN

4.2.1 Mach Effect

In Section 3.1.1, the result of Test One is very similar to Mach Effect (See Fig.2 and Fig.5). Clearly, RNN performs better than DOG model in simulation of the Mach Effect. (See Fig.9)

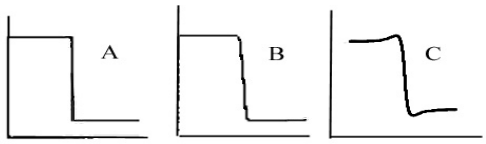

Fig.9 Approximate Representation of Results of Processing (A: Original Input; [12] B: Result of DOG model; [12] C: Result of RNN)

4.2.2 Receptive Field

According to what mentioned in section 1, Receptive Field can be summed up as follows.

i. When we stimulate a receptor cell, the center bipolar cells will have positive response.

ii. When we stimulate a receptor cell, the surrounding bipolar cells will have negative response.

And according to Test Two in Section 3.1.2, the performance of RNN can be summarized in the following list:

a) When we stimulate Unit(i,j), the output of Unit(i,j) is positive.(see point A_1 and A_2 in Fig.11)

b) When we stimulate Unit(i,j), some surrounding Units' output is negative.(see point B_1 and B_2 in Fig.11)

Comparing i. and ii. with a) and b), we conclude that RNN can well describe the transfer property of bipolar cells.

5 Conclusion

In this note, we have considered the case of a new retina model, Reaction Neuron Network Model, for the assistance of image perception. An iterative algorithm is used to implement this model. It has been shown that the model is capable of simulating the neurobiological phenomena of retina. And the performance of it is better than the DOG model, which is proposed by Rodieck. It has also been shown that Reaction Neuron Network Model can decrease the influence of less important details when processing an image, which is better than the usual Smoothness Operator.

On the whole, although a few problems may be left open, we are still convinced that the model mentioned in this paper is a very promising method in the field of image perception.

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