A Computational Model for Processing Object Motion Based on Retina Neural Mechanism*

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Abstract - In this paper, a bioinspired neural model for detecting object motion based on retina computational machanism is proposed based on synthesizing representative works on modeling retina and incorporating some latest findings on retina mechanisms. To understand more in-depth the retina machanism of motion detection, the spatio-temporal properties of each type of neurons in the retina motion pathway are then mathematically analyzed. And then a set of experiments and quantitative analysis of the experimental results are accomplished for assessing the model performance on motion detection. Experimental results show the effectiveness of this proposed model on detecting object motion.

Index Terms - retina neural mechanism, retina neural network, object motion detection, computational model.

I . Introduction

The ability to detect motion in the visual scene is a fundamental computation in the visual system that is firstly performed in the retina[1]. As for complete models of retina motion extracting channel, Boahen etc. proposed[2~3] a retinomorphic system, which uses four different kinds of neurons for firing specific spikes in response to concrete stimuli and representing the input data. F. Barranco[4] designed and implemented an event-driven processing scheme based on artificial retinas for the detection of spatiotemporal features. Stephen A. Baccus[5] etc. investigated the circuit basis for detecting object motion by recording intracellularly from all classes of retinal interneurons while simultaneously recording the spiking output of many ganglion cells.

These findings and works sketch the structural scheme of motion processing channel in retina. However, mathematical analysis of the models and their applications to motion processing are insufficient without exception. Fortunately, numerous neurophysiological findings[1-3][6] on retina information processing pathways have been revealed. These new findings provide great source of ideas for our modeling the retina more reasonably.

So mechanism as well as models of computing object motion in retina incorporating these latest findings will be dealt with.

This paper is organized as following. Model for processing object motion based on retina mechanism is firstly proposed in section 2. In section 3, experimental results and corresponding analysis is implemented. Finally, conclusions on the proposed algorithm are drawn out in section 4.

II. A Model for Processing Object Motion Based on Retina Neural Mechanism

In this section, a neural organization structure for processing object motion based on retina mechanism will be described at first. Then the spatio-temporal properties of each type of neurons in the motion pathway will be proposed and analyzed in succession.

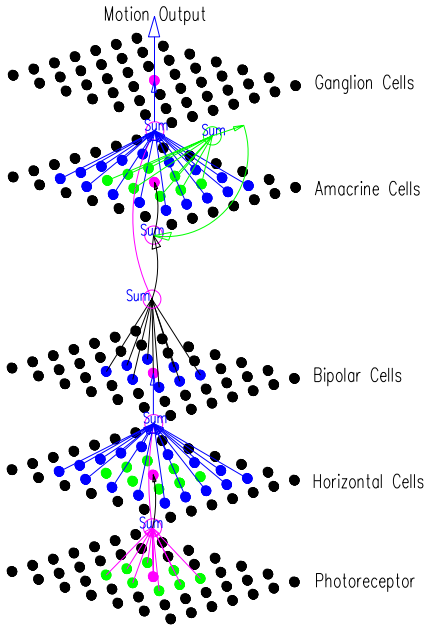

Fig.1 The wiring diagram of the cells which constitute retina motion pathway

A. A Model for Processing Object Motion Based on Retina Neural Mechanism

Experimental data [7] and theoretical analysis [8-9] show that directional selectivity is the result of local, postsynaptic, nonlinear interactions in the DS(directionally selective) cell. The light responses of cones and bipolar cells are not directionally selective[10]. The direction-selective circuit in the retina relies highly upon the selective wiring of synaptic contacts between SAC(starburst amacrine cell) distal dendritic tips and the dendrites of the DS GCs(ganglion cells). As a presynaptic interneuron, the SAC is asymmetrically connected to DS cells and delivers direct inhibition to DSGCs. The SACs

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pointing in the null direction deliver inhibition and those pointing in the preferred direction do not. They project inhibition laterally ahead of a stimulus moving in the null direction [11]. In addition, starburst inhibition is itself directionally selective: it is stronger for movement in the null direction [11]. Excitation in response to movement in null direction is reduced by an inhibitory signal acting at a site that is presynaptic to the DS cell. Thereby excitation is reduced by enhanced inhibition given stimulus of motion in the null direction, and thus the effect of directional selectivity is realized. Therefore, signaling between the cones, bipolar cell, SAC, and DSGC constitutes a neural network that generates the DS light responses of the DSGC[12]. The retina motion pathway, in a form of laminar organization, is shown as Fig.1.

B. Spatio-Temporal Properties of Cone Cells

Photoreceptor cells sample optical signals and convert the light information into biological signals. Some studies[11] have shown that the conversion is nonlinear processing and the input-output dynamic characteristics of photoreceptor cells can be described as mathematical formulas [7]:

$$O_p(x,y,t)=\mu_p I_p(x,y,t)k_p(x,y,t) \tag{1}$$

Where $O_p(x,y,t)$ represents the output of the light-sensitive cell (x,y) at time point t , $I_p(x,y,t)$ for the brightness distribution, $k_p(x,y,t)$denotes the pigment concentration, and between $I_p(x,y,t)$and $k_p(x,y,t)$ there exists a relationship as equation:

$$\tau_p \frac{d}{dt}k_p(x,y,t)+\left(1+\mu_p I_p(x,y,t)\right)k_p(x,y,t)=1 \tag{2}$$

Where the parameter τ_p represents the time constant for updating the pigment, and μ_p denotes the pigment bleaching constant.

C. Spatio-Temporal Properties of Horizontal Cells

Horizontal cells accept the input of the photoreceptor cells[8] , acting as a low-pass filter in the transmission of information from responses of receptors[11].

When suitable parameters are given, the receptive field of a horizontal cell can be modeled [13] as:

$$W_h(x,y;x_0,y_0)=w_h \exp\left(-\frac{(x_0-x)^2+(y_0-y)^2}{2\sigma_h^2}\right) \tag{3}$$

Where w_h represent the amplitudes of the Gaussian weight components, whose standard deviations is σ_h, in $W_h(x,y;x_0,y_0)$. And (x_0,y_0)represent a neighbor area of cell (x,y).

Signals converge into horizontal cell $(\mathbf{x},\mathbf{y})$ is:

$$I_h(x,y)=\sum_{x_0,y_0\in R_h} W_h(x,y;x_0,y_0)O_p(x_0,y_0) \tag{4}$$

Where $O_p(x_0,y_0)$ represents the output signals from a photoreceptor located at (x_0,y_0)in the R_h of cell (x,y).

The response dynamics of a horizontal cell (x,y) to its stimulus is described as following equation [7]:

$$\tau_h \frac{d}{dt}O_h(x,y,t)-\gamma^2\frac{d^{(2)}}{dt^2}O_h(x,y,t)+\left[1+\lambda I_h(x,y,t)\right]O_h(x,y,t)=\lambda I_h(x,y,t) \tag{5}$$

Where $O_h(x,y,t)$ is the output of a horizontal cell (x,y), and $I_h(x,y,t)$ the input of the cell; parameter γ is the extended length of excitement field, τ_h time constant of the horizontal cell, and λ the feedback factor.

C. Spatio-Temporal Properties of Bipolar Cells(BCs)

Bipolar cells are the only ones with receptive field properties that match the requirements for the essential part of motion computation of nonlinear spatial summation over small subunits in the ganglion cell receptive field center.

Center-surround antagonistic receptive field (CSARF) organization is the basic synaptic circuit for spatial information processing in the visual system. BCs are the first neurons along the visual pathway that exhibit CSARF organization. In both the receptive field center and the antagonistic surround region, the bipolar cell's temporal filter followed a biphasic time course. The surround response was delayed and inverted in sign relative to the center.

Motion in the object region drives these bipolar cells, and their outputs are rectified before summation by the ganglion cell [14-15].

And the weight distribution in bipolar receptive field can be denoted as:

$$W_b(x,y;x_0,y_0)=w_{b1}e^{-\frac{(x_0-x)^2+(y_0-y)^2}{2\sigma_{b1}^2}}-w_{b2}e^{-\frac{(x_0-x)^2+(y_0-y)^2}{2\sigma_{b2}^2}} \tag{6}$$

where w_{b1} and w_{b2} represent the amplitudes of two Gaussian weight components, whose standard deviations are σ_{b1} and σ_{b2} respectively, in $W_b(x,y;x_0,y_0)$.

Signal converge into bipolar cell $(\mathbf{x},\mathbf{y})$ is:

$$I_b(x,y)=\sum_{x_0,y_0\in R_{b,c}} W_b(x,y;x_0,y_0)O_p(x_0,y_0)-\sum_{x_0,y_0\in R_{b,s}} W_b(x,y;x_0,y_0)O_h(x_0,y_0) \tag{7}$$

where $R_{b,c}$ and $R_{b,s}$ represent the *center* and *surround* region of center-surround antagonistic receptive field, $O_p(x_0,y_0)$ and $O_h(x_0,y_0)$ represent respectively the output signals from PCs and HCs located at (x_0,y_0) in CSARF.

The response dynamics of retina BCs to stimulus is described as following equation[29]:

$$\theta_b \frac{d}{dt}O_b(x,y,t)+O_b(x,y,t)=I_b(x,y,t) \tag{8}$$

where $O_b(x,y,t)$ and $I_b(x,y,t)$ represent the membrane potential of a bipolar cell (x,y) and its input signal respectively, and θ_b is a time constant.

D. Spatio-Temporal Properties of Starburst Amacrine Cells

Amacrine cells are served to integrate, modulate and interpose a temporal domain to the visual message presented to the ganglion cell. Experiments [5][15] show that SAC are wired to suppress the visual response of DSGCs through presynaptic inhibition of a bipolar terminal.

The weight distribution in receptive field of SACs is described as:

$$W_{SAC}(x,y;x_0,y_0)=A_1 e^{\frac{(x_0-x)^2+(y_0-y)^2}{2\sigma_{a1}^2}}-A_2 e^{\frac{(x_0-x)^2+(y_0-y)^2}{2\sigma_{a2}^2}} \quad (9)$$

Where A_1 and A_2 are respectively the amplitude of two components, and σ_{a1} and σ_{a2} are standard deviation of Gaussian shape components.

Inputs convergence into a SAC can be represented in following equation:

$$I_{SAC}(x,y)=\sum_{(x_0,y_0)\in centre} W_{SAC}(x,y;x_0,y_0)O_b-\sum_{(x_0,y_0)\in surr} W_{SAC}(x,y;x_0,y_0)O_{SAC} \quad (10)$$

Where *centre* and *suur* respectively represent the *centre* and *surround* region in receptive field of SACs.

The dynamic property of SACs is represented as [16]:

$$\frac{d}{dt}O_{SAC}(t)=-AO_{SAC}(t)+[B-O_{SAC}(t)]e(t)-[D+O_{SAC}(t)]i(t)+\sum_{k=1}^{n}W_{SAC}O_k(t) \quad (11)$$

Where $e(t)$ and $i(t)$ respectively represent the excitatory and inhibitory inputs. O_{SAC} represents the membrane potential of SAC locates at (x,y), while O_k is the membrane potential of the neuronal element which makes lateral connections with SAC element (x,y). A, B and D are constants for respectively represent the rate of potential decay, the saturation levels for the excitatory and inhibitory inputs, W_{SAC} is the lateral connections to the neuron of interest, i.e. SAC(x,y).

E. Spatio-Temporal Properties of Directionally Selective Ganglion Cells

DSGCs signal the direction of image motion across their receptive fields by firing action potentials in a 'preferred' direction, other than in the opposite 'null' direction. A key circuit module of retinal DSGCs is a spatially asymmetric inhibitory input from starburst amacrine cells [17-19].

The preferred direction of the cells and the strength of the directional tuning of the DSGCs can be calculated from responses to stimuli in each of stimulus directions evenly spanning 360 °. With directional tuning data, the response R of a DSGC to stimulus from the direction χ can be described by a von Mises distribution [20] as:

$$R(\chi)=R_{\max}e^{\left(\kappa\cos\left(\frac{(\chi-\mu)\pi}{180}\right)\right)}/e^{\kappa} \quad (12)$$

Where $R_{\max}$ is the maximum response, μ becomes the preferred direction in degrees, and κ is the concentration parameter, which accounts for the width of the directional tuning.

The weight distribution of excitory component and inhibitory component in DSGCs receptive field can be represented respectively as:

$$W_{gang}^{exc}(x,y;x_0,y_0)=\frac{1}{\sqrt{2\pi\sigma_g}}e^{\frac{(x-x_0)^2+(y-y_0)^2}{\sigma_g^2}},\ x_0,y_0\in R_{exe} \quad (13)$$

$$W_{gang}^{inh}(x,y;x_0,y_0)=\frac{1}{\sqrt{2\pi\sigma_{g1}\sigma_{g2}}}e^{\frac{(x_0-x)^2}{\sigma_{g1}^2}+\frac{(y_0-y)^2}{\sigma_{g2}^2}},\ x_0,y_0\in R_{inh} \quad (14)$$

Where σ_g, σ_{g1} and σ_{g2} represent the standard deviation of two DSGCs receptive field weight distributions respectively. R_{exe} and R_{inh} represent a symmetric and an asymmetric region in receptive field of DSGC (x,y) respectively.

Inputs convergence to a DSGC (x,y) is:

$$I_{gang}(x,y)=\sum_{x_0,y_0\in R_{exc}} W_{gang}^{exc}(x,y;x_0,y_0)O_b+\sum_{x_0,y_0\in R_{inh}} W_{gang}^{inh}(x,y;x_0,y_0)O_{SAC} \quad (15)$$

Where O_b and O_{SAC} represent the output from bipolar cells in R_{exe} and amacrine cells in R_{inh}.

TABLE I Parameters of the Proposed Retina Neural Network

Cell Type	Width of RF (pixels)	Standard deviation of Gaussians	Other parameters
Photoreceptor cells	Null	Null	$\mu_p=0.5$
Horizontal cell	*27*	$\sigma_h=4.5$	$\lambda=0.03$, $w_h=1$
Bipolar cell	*5*	$\sigma_{b1}=0.6$, $\sigma_{b2}=5.4$	$w_{b1}=w_{b2}=1$
Starburst amacrine cells	*15*	$\sigma_{a1}=0.6$, $\sigma_{a2}=5.4$	$A=1; B=2; D=0.5;$, $A_1=1;\ A_2=11.2$
Ganglion cell	*21*	$\sigma_g=0.498;$ $\sigma_{g1}=\sigma_{g2}=0.632$	$\kappa=20;\ R_{\max}=10$

TABLE II Mean Square Error (MSE) of Motion Velocity Matrices Detected by Using Different Methods

Motion direction		Frames												
		1	2	3	4	5	6	7	8	9	10	11	12	13
0 °	Retina model	0.0525	0.0525	0.0525	0.0520	0.0501	0.0501	0.0501	0.0501	0.0501	0.0501	0.0501	0.0501	0.0501
	Optical flow	0.0532	0.0532	0.0532	0.0532	0.0532	0.0532	0.0532	0.0532	0.0532	0.0532	0.0532	0.0532	0.0722
45 °	Retina model	0.0742	0.0742	0.0742	0.0730	0.0723	0.0723	0.0723	0.0724	0.0724	0.0724	0.0724	0.0724	0.0724
	Optical flow	0.0750	0.0750	0.0750	0.0750	0.0750	0.0750	0.0750	0.0750	0.0750	0.0750	0.0750	0.0750	0.1024
90 °	Retina model	0.0525	0.0525	0.0525	0.0520	0.0519	0.0519	0.0519	0.0519	0.0519	0.0519	0.0519	0.0519	0.0519
	Optical flow	0.0577	0.0577	0.0577	0.0577	0.0577	0.0577	0.0577	0.0577	0.0577	0.0577	0.0577	0.0577	0.0732
135 °	Retina model	0.0742	0.0742	0.0742	0.0731	0.0731	0.0731	0.0731	0.0731	0.0731	0.0731	0.0731	0.0731	0.0731
	Optical flow	0.0750	0.0750	0.0750	0.0750	0.0750	0.0750	0.0750	0.0750	0.0750	0.0750	0.0750	0.0750	0.1024
180 °	Retina model	0.0525	0.0525	0.0525	0.0520	0.0501	0.0501	0.0501	0.0501	0.0501	0.0501	0.0501	0.0501	0.0501
	Optical flow	0.0532	0.0532	0.0532	0.0532	0.0532	0.0532	0.0532	0.0532	0.0532	0.0532	0.0532	0.0532	0.0722

III. Experimental Results and Corresponding Analysis

To evaluate the effect of the proposed retina model on motion detection, quantitative analysis and comparasion with other method (here it is optical flow based algorithm) are both accomplished. For achieving this, the criterion on performance evaluation of motion detection algorithms will be firstly given in this section. Obviously, for a method of object motion detection, accuracy, universality and timeliness are the three most important factors that should be used to construct a formula for measuring system performance on motion detection. The following expression is one of this kind of representations:

$$\hat{e}_v \sqrt{\frac{1}{H \cdot V} \sum_{i=1}^{H} \sum_{j=1}^{V} \left(E_h^2(i,j) + E_v^2(i,j) \right)} \tag{13}$$

Where $\hat{e}_v$ denotes the mean square error (MSE) of detected motion velocity on real one, *H*and *V* are respectively the pixels on horizontal and vertical direction, accordingly E_h and E_v are respectively error matrices for representing the horizontal and vertical component of velocity vector field, and they read:

$$E_v = R_v - \frac{\hat{R}_v}{\max\limits_{1 \le i \le H, 1 \le j \le V} \left(\sqrt{\hat{R}_h^{\,2}(i,j) + \hat{R}_v^{\,2}(i,j)} \right)} \tag{14}$$

$$E_v = R_v - \frac{\hat{R}_v}{\max\limits_{1 \le i \le H, 1 \le j \le V} \left(\sqrt{\hat{R}_h^{\,2}(i,j) + \hat{R}_v^{\,2}(i,j)} \right)} \tag{15}$$

Where $\hat{R}_h$ and $\hat{R}_v$ are respectively the matrices for representing the horizontal and vertical component of velocity vector field that that have been detected by using certain motion detection algorithm , while R_h and R_v are matrices for real motion velocity components. Table II shows the mean square error (MSE) of motion velocity matrices detected by using different methods (the proposed retina model vs. Optical Flow).

As can be seen from the above table, the two methods show similar motion sensitivities as well as good accuracy on the direction of 0 °, 90 °, 180 °and 315 °. And generally, the proposed retina model shows better performance on motion detection than the traditional optical flow based algorithms. Or it has a lower value of MSE than that with traditional optical flow based algorithms.

IV. Conclusions

In this paper, a bioinspired neural model for detecting object motion based on retina computational machanism is proposed based on synthesizing those representative works on modeling retina and incorporating some latest findings on retina mechanisms. To understand more in-depth the retina machanism of motion detection, the spatio-temporal properties of each type of neurons in the retina motion pathway is also mathematically analyzed. For evaluating the model performance on motion detection, a set of experiments and quantitative analysis of the experimental results are accomplished. The experimental results show that this proposed model can be used to detect object motion effectively.

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