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著者	閻 晨陽
著者別表示	YAN CHENYANG
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Dissertation Abstract

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HRCモデルに基づく物体運動方向および速度検 出の人工視覚システムに関する研究

Graduate School of Natural Science and Technology Kanazawa University

Division of Electrical Engineering and Computer Science

Student ID: 2024042001 Name: Chenyang Yan Chief Advisor: Yuki Todo Date of Submission: January 2023

Introduction

Seeing motion is relevant to the survival of numerous visual animals. Since Exner presented the first drawing of a neural network in 1894, research on motion detection has lasted for over a century. In order to understand the mechanism underlying signal processing in direction-selective neurons (DSNs), scientists have proposed a variety of computational models. In 1956, Hassenstein and Reichardt proposed the first biologically based correlation-type model, the so-called HRC model. The HRC model is considered the modern theoretical framework for motion direction detection because it encourages scientists to understand the selectivity of motion direction from the perspective of neural computations. Till now, a good number of bio-inspired motion detection AVS have been proposed and many of them have been applied in robots.

Despite many research results have been achieved in understanding direction selectivity at the cellular level, the full systemic mechanism of motion detection in animal brains remains elusive. Besides, it is difficult to investigate the mechanisms underlying visual motion pathways only through limit neuronal inputs and physiological experiments. Therefore, searching for reliable motion detection mechanisms is important not only for future research in neuroscience, but also for the development of computer science.

The main purpose of this research is to validate the mechanisms we proposed for global motion direction detection and global motion speed perception in a two-dimensional view. In order to obtain the local motion information, we cited the core computation of the HRC model and realize the local motion-sensitive directionally detective neurons and local velocity-sensitive directionally detective neurons. In the study of AVS for global motion direction detection, we propose the Full-neurons scheme motion detection mechanism for detecting the direction of global motion. Through a series of experiments, we prove the reliability of our AVS and conclude that the mechanism is qualified for global motion direction detection in a two-dimensional view. Then, we extend our study on global motion speed perception based on both the characteristics of HRC model and the biological findings. The Temporal-based multi-neurons scheme motion detection mechanism is proposed for detecting the direction and speed of global motion. Through a series of experiments, we conclude that our proposed system is not only reliable in detecting the global motion, but also stable in noise resistance.

AVS for global motion direction detection

Local motion-sensitive directionally detective neurons

In this research, we designed the local motion-sensitive directionally detective neurons based on the core computation of the HRC model. Figure 1a shows the theoretical structure of a rightwards local motion-sensitive directionally detective neuron. If we use notations $X_{(i, j, T)}$ to indicate the signal from the centrally located photoreceptor $P_{(i, j)}$ at time T, and $X_{(i+1, j, T+\Delta T)}$ denote the signal from its right-side photoreceptor $P_{(i+1, j)}$ at time T+ Δ T. The calculation in Figure 1b can be expressed by the following equation:

$$\mathbf{Y}_{\mathbf{R}(\mathbf{i},\mathbf{j})} = \mathbf{X}_{(\mathbf{i},\mathbf{j},\mathbf{T})} \cdot \mathbf{X}_{(\mathbf{i}+1,\mathbf{j},\mathbf{T}+\Delta\mathbf{T})}$$

If - and only if – the activation result of $Y_{R(i, j)}$ is 1, the rightwards local motion-sensitive directionally detective neuron located at $P_{(i, j)}$ will be activated.

Furthermore, the proposed neurons can be easily extended for a two-dimensional multidirections detection. With reference to the receptive field of simple cells, we employ eight local motion-sensitive directionally detective neurons for detecting eight directions, respectively (as shown in Figure 1c).



Figure 1. (a) The theoretical structure of the rightwards local motion-sensitive directionally detective neuron. (b) Schematic of 0° -detective neuron. (c) Schematic of eight local motion-sensitive directionally detective neurons.

Full-neurons scheme motion detection mechanism

Inspired by biophysical investigations of *Drosophila*, we propose an artificial visual system using the Full-neurons scheme motion detection mechanism. We hypothesize that each light spot in the visual field can be received by 8 local motion-sensitive directionally detective neurons and accumulate the number of the activated neurons with the same preferred direction and regard it as the activation strength in that direction. The AVS will give the detection result based on the maximum value of activation strength in eight directions. The process of the AVS in detecting a 1-pixel object has been shown in Figure 2.



Figure 2. Flowchart of the AVS in detecting 1-pixel object.

Simulation and Result

To validate the reliability of our AVS, we conduct a series of experiments with a background size of 32×32 , the shapes and positions of the object are set to arbitrary. In the first series of experiments, we test our AVS within the background with no noise. The dataset has totally 192,000 images (each size of object has 24,000 images) and the detection results are presented in Table 1.

Model	1	2	4	8	16	32	64	128
AVS	100%	100%	100%	100%	100%	100%	100%	100%

Table 1. Detection results of the AVS within the background with no noise.

In the second series of experiments, we test our AVS within the background with 1% to 10% separated noises. The dataset has totally 192,000 images (each size of object has 24,000 images) and the detection results are presented in Table 2.

Model	1	2	4	8	16	32	64	128
1%	100%	100%	100%	100%	100%	100%	100%	100%
2%	100%	100%	100%	100%	100%	100%	100%	100%
5%	100%	100%	100%	100%	100%	100%	100%	100%
10%	100%	100%	100%	100%	100%	100%	100%	100%

Table 2. Detection results of the AVS within the background with separated noises.

In the third series of experiments, we test our AVS within the background with 1% to 10% connected noises. The dataset has totally 192,000 images (each size of object has 24,000 images) and the detection results are presented in Table 3.

Model 1 2 4 8 16 32 64 128 1% 81.6% 96.0% 99.8% 100% 100% 100% 100% 100% 2% 56.7% 84.0% 97.9% 99.9% 100% 100% 100% 100% 5% 75.0% 100% 36.6% 52.1% 95.1% 99.8% 100% 100% 10% 30.7% 100% 37.8% 52.3% 74.1% 94.5% 99.8% 100%

Table 3. Detection results of the AVS within the background with connected noises.

In the last series of experiments, we do the comparison with the time-considered CNN and the EfficientNetB0 in detecting the dataset with separated noises and the dataset with connected noises. The detection results are shown in Figure 3.



Figure 3. Folding line chart of the comparison detection results.

AVS for global motion speed perception

Local velocity-sensitive directionally detective neurons

Based on the characteristic that the single motion detector of the HRC model is not only sensitive to the preferred direction, but also responds best to both the speed and the signal intensity, in this research, we proposed three kinds of local velocity-sensitive directionally detective neurons based on the core computation of the HRC model. The proposed neurons can be easily extended to detect multi-directions in a two-dimensional view. In this research, we limit our discussion to detect the movement in eight major directions. As shown in Figure 4, they are: Rightward (V1_R, V2_R, V1/2_R), Upper Rightward (V1_{UR}, V2_{UR}, V1/2_{UR}), Upward (V1_U, V2_U, V1/2_U), Upper Leftward (V1_{UL}, V2_{UL}, V1/2_{UL}), Leftward (V1_L, V2_L, V1/2_L), Lower Leftward (V1_{LL}, V2_{LL}, V1/2_{LL}), Downward (V1_D, V2_D, V1/2_D), and Lower Rightward (V1_{LR}, V2_{LR}, V1/2_{LR}). 16 neurons are output signals at time T+ Δ T and the rest 8 neurons are output signals at time T+ Δ T.



Figure 4. Schematic of local velocity-sensitive directionally detective neurons.

Temporal-based multi-neurons scheme motion detection mechanism

In this research, we propose an artificial visual system which use the Temporal-based multineurons scheme motion detection mechanism to detect the speed and direction of global motion. Figure 5 shows the AVS in detecting 1-pixel object under the temporal frequency T+ Δ T. Without loss of generality, we use 16 neurons scan every region simultaneously from P_(1, 1) to P_(5, 5) over the two-dimensional receptive field at time T and respond to yield the local motion directions of the regions.



Figure 5. Flowchart of the AVS in detecting 1-pixel object.

Simulation and Result

To validate the reliability of our AVS, we conduct a series of experiments with a background size of 32×32 , the shapes and positions of the object are set to arbitrary. We conduct the experiments within the background with no noise and the detection results are presented in Table 4.

Dataset	1	2	4	8	16	32	64	128
V1	100%	100%	100%	100%	100%	100%	100%	100%
V2	100%	100%	100%	100%	100%	100%	100%	100%
V1/2	100%	100%	100%	100%	100%	100%	100%	100%

Table 4. Detection results of the AVS within the background with no noise.

We also conduct the experiments within the background with separated noises and connected noises and the detection results are presented in Table 5 To further validate the reliability of our AVS, we do the comparison with a 2-channels CNN in detecting Dataset V1 and Dataset V2 with separated noises and connected noises. The detection results are presented in Table 6.

Background Noises Obj 1%												òc	0%7							50/	0%C							1002	10.70				
Models Noise Types	ect Sizes Accuracy (%)		2	4	~	16	32	64	128	1	2	4	8	16	32	64	128	1	2	4	8	16	32	64	128	1	2	4	8	16	32	64	128
	Separated (Dataset V1)	71.80	96.84	99.95	100	100	100	100	100	23.98	73.03	97.93	66.66	100	100	100	100	0.02	0.84	22.61	83.70	99.73	99.99	100	100	0	0	0	0	7.28	81.17	99.82	100
	Connected (Dataset V1)	55.75	91.71	99.38	100	100	100	100	100	29.85	66.64	95.34	99.84	100	100	100	100	18.89	32.31	58.56	89.94	99.64	100	100	100	15.87	22.61	33.62	57.09	87.19	99.29	100	100
A	Separated (Dataset V2)	80.97	90.06	96.98	100	100	100	100	100	53.62	89.20	09.60	100	100	100	100	100	34.76	54.64	83.40	98.95	99.98	100	100	100	25.62	36.12	54.00	78.44	96.91	99.96	100	100
SV	Connected (Dataset V2)	65.06	94.95	02.66	100	100	100	100	100	37.83	74.69	97.46	96.96	100	100	100	100	16.69	33.50	62.61	93.49	99.84	100	100	100	12.61	18.72	31.70	58.48	90.26	99.73	100	100
	Separated (Dataset V1/2)	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100
	Connected (Dataset V1/2)	79.92	95.37	19.66	100	100	100	100	100	54.23	81.52	97.16	76.99	100	100	100	100	33.78	49.03	72.12	93.29	99.80	99.90	100	100	26.01	34.95	48.57	68.17	91.56	99.38	100	100

Table 5. Detection results of AVS within the background with separated noises and connected noises.

	tckground Noises Object				10/	1 %0		<u> </u>			<u> </u>	<u> </u>			<u> </u>						£ 0/	0 %C							1 00/	10%0			
Models Noise Types	Sizes Accuracy (%)		2	4	~	16	32	64	128	1	2	4	~	16	32	64	128	1	2	4	8	16	32	64	128	1	2	4	8	16	32	64	128
	Separated (Dataset V1)	29.91	50.54	79.60	93.96	98.12	99.41	99.89	99.97	20.77	25.95	39.25	64.25	84.08	94.16	98.74	99.78	16.05	19.32	22.95	26.07	37.88	55.41	71.34	87.73	13.75	15.97	19.84	26.07	27.60	38.83	49.11	55.90
2-channel	Connected (Dataset V1)	27.40	46.20	72.98	91.32	97.21	99.36	99.84	86.66	20.56	25.40	34.90	57.41	78.08	90.81	97.36	99.48	15.78	19.57	22.56	25.57	34.26	46.13	54.42	66.60	14.40	16.15	18.65	21.67	25.84	35.28	46.07	49.80
s CNN	Separated (Dataset V2)	0.02	2.52	31.53	80.75	96.71	99.50	99.88	99.98	0	0	1.27	18.17	61.57	91.02	98.33	77.66	0	0	0	0.03	3.77	20.99	59.20	88.12	0	0	0	0	0.03	1.12	11.08	47.56
	Connected (Dataset V2)	0	0.95	22.20	73.40	94.83	99.17	99.81	100	0	0	0.36	11.33	49.22	84.95	97.05	99.35	0	0	0	0	0.35	3.86	21.43	54.85	0	0	0	0	0	0	0.02	0.74

Table 6. Detection results of the 2-channels CNN within the background with separated noises and connected noises.

Conclusions

In this dissertation, we proposed two potential motion detection mechanisms that could be used for global motion direction detection and global motion speed perception in a two-dimensional view. We cited the core computation of the HRC model, and employed the local motion-sensitive directionally detective neurons to gather the direction of local motion. With reference to the concept of simple cells, we designed our neurons with 3 × 3 local receptive field and eight neurons are employed for multi-directions detection. Moreover, we based on the characteristic of single unidirectional motion detectors, extend our motion-sensitive neurons with different sampling base and temporal delay to local velocity-sensitive directionally detective neurons for local motion speed perception. Considering the ON motion pathway is sufficient to drive the optomotor response at the high pattern contrast, we assigned value 1 to the visual signals and value 0 to the background. Through a series of experiments, we validate the reliability of the Full-neurons scheme motion detection mechanism and the Temporal-based multi-neurons scheme motion detection mechanism. The comparison experiments have further proved our proposed AVS is not capable of global motion detection tasks, but also has excellent performance in noise resistance.

In this research, we only consider the excitatory inputs enhancement in the preferred direction and the simplest structure of the classical motion detector: the HRC model. Thus, the limitation of our research is the motion can only be detected in the binary dataset. However, it can be functionally extended with more architectures. For example, with the application of amacrine cells' concept, our AVS can be used for detecting the global motion direction in grayscale images. Furthermore, with the extension of binocular vision, the global motion direction can be detected in a three-dimensional view.

The visual systems have been the focus of research for past decades, however, our understanding of it is far from complete. With the development of technology, interdisciplinary integration is increasingly valued, such as the scanning mechanism which can both be applied to the field of computer vision and the field of electron microscopy (EM). We hope our research can encourage the biologists to quantify the global motion information from the perspective of fundamental units and contribute to the field of both neuroscience and computer vision.