

Dynamic Signal Suppression Increases the Fidelity of Looming Perception Against Input Variability

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Abstract—The perception of looming objects moving in depth is a basis of artificially dynamic vision system, which has been widely used in robots for autonomous obstacle detection-and-avoidance. How to reliably detect looming objects in chaotic environments is prerequisite, however, still a challenging problem. The current looming perception models or neural networks are greatly affected by input variability on visual contrast between looming object and its background. In this case, the responses of looming detection neurons in animals are robust, which suggests that contrast cues are well encoded in biological visual neural pathways. Considering the physiological homology between *Drosophila* and locust, this paper draws lessons from the progress of *Drosophila* physiology to improve the current locust-inspired looming perception model. Two contrast computation schemes herein are proposed: (1) In the early stage of visual processing, the instantaneous feedback mechanism based contrast normalisation dynamically suppress the preliminary motion signals with respect to time. (2) In the later stage of processing, a parallel channel dedicated to calculating local contrast of motion signal is converged to weaken high-contrast signals. Through the comparative tests against many pure and natural scenes, the proposed method works effectively and robustly to reduce fluctuation and variance of response against high input variability on contrast. Here we highlight the effectiveness of temporally dynamic suppression to motion signals in the proposed neural network model, which significantly improves the fidelity of looming perception. This study also shows its competitiveness in the repository of bio-inspired looming perception models.

Index Terms—neural modelling, looming perception, dynamic signal suppression, visual contrast computation

I. INTRODUCTION

Looming perception plays an indispensable role in insect predation [1], defense against natural enemy attacks [1] and clustering [2]. In the human world, looming perception is also a frontier issue of building collision-free artificial vision system. It has been widely used in UAV [3] and automatic driving [4] of automobile and obstacle avoidance technology of micro robot [5]–[8]. Traditional looming sensing methods mainly rely on sensor technology, such as radar [9], infrared [10] and ultrasonic [11]. Although the sensor consumes less resources, it is also vulnerable to the impact of the environment, making vehicles and robots lose the ability to effectively deal with critical emergencies. Although the new technology represented by deep learning has good performance in reality, it needs large-scale data sets and consumes a lot of computing resources for training.

In order to solve the contradiction between computing resources and model robustness, people's attention is gradually

attracted by natural ability. For example, insects have evolved in the repeated struggle to obtain survival resources. The motion perception neural systems in their tiny brains thus have been evolved to be efficient and robust to perform within chaotic environments guiding a variety of behaviours like chasing mates, preying, escaping from predators, and etc.

Taking the locusts as a prominent example, they always migrate in swarm for hundreds of miles free of collision. Although the brain volume of locusts is small and the number of nerve cells is rare, they demonstrate amazing looming perception ability in complex natural scenes. Physiologists have found a group of lobula giant movement detectors (LGMDs) interneurons in the visual neuropile layers of locusts, which play the major roles of approaching object detection. Most importantly, such neural pathways demonstrate reliable capability against input variability, in which the visual contrast between looming objects and their backgrounds is well encoded. In other words, the robust looming perception neural systems decently resolve the local contrast issue which, however, sets major challenges to artificial vision systems.

Although the LGMDs have been investigated and modelled intensively [12], the models or neural networks are significantly influenced by spatial contrast, the difference of illumination between adjacent local areas in the receptive field, i.e., the model response always fluctuates with high variance against high input variability, e.g., natural scenarios. The causality would be (1) the non-linear property of the motion detection model and (2) the large change of local contrast in natural images [13]. More precisely, the LGMD models enlarge the high variability of natural images several times through network calculation, resulting in considerable false positives on looming perception against input variability. Accordingly, the performance gap between organisms and models implies the significance of investigation on contrast computation in neural modelling though very little has been known in association with underlying neuronal circuits.

In recent years, some research progress has been made on fruit fly *Drosophila*, the most typical insect for studying biological motion perception paradigm [14]. Since the neural circuit of *Drosophila* has been most systematically explored [15], the visual contrast computation pathways and mechanisms have been investigated by neuroscientists, which have been proved crucial roles of robust motion vision against natural signals [16], [17]. In fact, such contrast computation

is a general mechanism for neurons to process signals, not only in *Drosophila*, but also in different species and even different sensory systems, for example, the olfactory system of *Drosophila* [18] and the acoustic system of mammals [19].

Learning from neuroscience studies, Fu et al. proposed a *Drosophila* motion vision neural network model based on contrast computation to reduce fluctuation of model response during the estimation of many moving natural scenes [20]. However, this important circuit mechanism has never been investigated in looming sensitive neural systems leaving concerns on whether this can also alleviate the impact of input variability on looming perception.

Considering the homology between *Drosophila* and locust, we herein propose novel contrast computation schemes combining with a classic looming perception neural network inspired by locust's LGMD neural pathway [21]. More specifically, the proposed methods include an instantaneous feedback mechanism based contrast normalisation for temporally suppressing preliminary motion signals, and a parallel contrast pathway to inhibit high-contrast local signal when converging with motion-induced excitations at the LGMD neuron. Here we highlight the temporally dynamic signal suppression in contrast normalisation, which will be introduced and investigated in the following Sections. To demonstrate the effectiveness of dynamic signal compression in contrast computation of looming perception, we carry out comparative experiments. The results collected verify that the fidelity of looming perception is increased by the proposed method indicating that contrast computation can be generic to different dynamic vision processing systems in neural modelling.

The rest of this paper is structured as follows: Section II briefly introduces the relevant works including both neuroscience and modelling researches. Section III elaborates the proposed model. The experimental process and results are illustrated in Section IV. Finally, conclusion and future research directions are discussed in Section V.

II. RELATED WORK

A. Locust-Inspired Looming Perception Model

Locusts, as one of the insects that can effectively detect looming objects, provide theoretical support of neurophysiology for this paper. After systematically studying the LGMD neurons of locusts, Rind and Simmons proposed an LGMD neural network with responsive preference to looming objects [22]. Later, for the application in automatic driving, Yue et al. improved the model with the help of signal filtering mechanism [21] to strengthen the edge information of moving targets. As the basis of the proposed method, their model will be detailed in Section III.

Although the improved model can effectively simulate the signal processing mechanism of looming object in locust vision, the output of the model shows large fluctuation and high variability in different scenes with contrast changes. Fu et al. introduced ON and OFF channels based mechanisms to encode the increase and decrease of object brightness, so as to enhance the selectivity of collision detection in complex

scenes [23], [24]. However, the problem against high input variability has not been solved.

In recent years, physiologists have found some new mechanisms mentioned in part II-B and part II-C below after extensive research on the visual system of *Drosophila*. In view of the biological homology between *Drosophila* and locust, this paper for the first time investigates them in LGMD model for looming perception.

B. Neural Pathway for Contrast Vision

Although the calculation of spatial contrast is commonly used in various visual behaviours, the specific computation mechanism has not been well explained in various organisms [16]. Pfeiffer et al. silenced the neural synapses of *Drosophila* by temperature sensitivity to identify related neurons [25]. When *Mi1* and *Tm3* cells were silenced together, *Drosophila*'s response to stimuli decreased. This shows that these two neurons are the key to contrast calculation. In addition, when *T4* and *T5* neurons were silenced at the same time, *Drosophila* was motion blind and did not produce direction selectivity [26], [27]. Moreover, in 2013, Takemura et al. found that *Mi1* and *Tm3* act on the ON channel in vision, which will converge on *T4* cells [28]. However, it is still unclear whether these neurons play a direct or indirect role in contrast computation.

On this basis, Bahl et al. used two types of illusions, the contrast motion illusion and the sign-field contrast asynchronous illusion, as tools to study the potential computation mechanism [16], and gave a simple mathematical model. Their results show that the contrast computation mechanism of *Drosophila* involves lateral inhibition and does not require the participation of *T4* and *T5* neurons. In other words, the spatial contrast is calculated in a pathway parallel to *T4* (ON) and *T5* (OFF) direction selective motion pathways. Then, the motion cues and contrast information are gathered with interaction in the lobular plate of *Drosophila*'s visual brain.

It appears that such parallel neural pathway is dedicated to encode visual contrast information in *Drosophila*'s robust motion vision, which will be included in the locust's LGMD neural network model and investigated in this paper.

C. Contrast Normalisation

As mentioned earlier, organisms can perform key survival tasks in complex real environments, but this poses a huge challenge for biologically inspired motion detectors [29] [30]. In the process of improving the model, there are various new mechanisms that can adapt to natural signals, such as processing of environmental statistics [31], [32]. However, these methods do not resolve the response fluctuation problem against highly variable input. In this regard, Drew et al. for the first time proposed that the contrast normalisation mechanism in *Drosophila*'s motion vision systems can robustly estimate input natural image speed against high input variability [17]. Before this work, various modelling studies have added similar compression transforms to the motion processing cascade [33],

[34], but there is no physiological theoretical basis, and it is necessary to make a choice in image resolution and time.

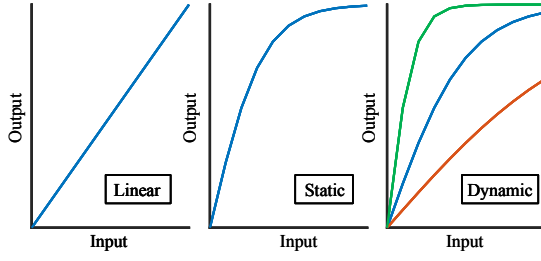


Fig. 1. The relationships between input and output in linear model, static and dynamic normalisation model. LGMD model is linear. In this paper, static and dynamic normalization models are proposed, and the three models are compared through experiments.

More precisely, the feedback normalisation mechanism compresses the different contrast to a fixed range through dynamic adjustment to remove the high-order correlation in the natural signal [20], [35], [36]. The researchers also compared three forms of linear, static, and dynamic normalisation models, as illustrated in Fig. 1, and demonstrated the temporally dynamic model can better encode contrast in motion vision that matches well the physiological responses of *Drosophila* [17]. There are similar algorithms in other kinds of animals, which yet are not completely consistent. For example, the normalisation mechanism of mammalian V1 cells is based on a feed-forward manner [37], while the *Drosophila* depends on a feedback mechanism [17]. In general, Drew et al. revealed a general key function of sensory signal processing.

III. PROPOSED METHOD

This section is mainly composed of the detailed description, structure picture and specific parameters of the proposed neural network model. Based on the LGMD model, the proposed model highlights the parallel contrast computation pathway and dynamic contrast normalisation mechanism. Fig. 2 depicts the structure of the model.

The new model obtains visual information from the photoreceptor(P) layer in the locust compound eye and normalizes the contrast. Then the excitation(E) layer, inhibitory(I) layer, summation(S) layer and grouping(G) layer in LGMD model are regarded as motion information pathway, and the contrast is computed through another parallel pathway. Finally, the information of the two channels is processed and activated into the membrane potential of LGMD nerve cells.

P Layer : As illustrated in Fig.2, the difference in brightness obtained by photoreceptor cells from Retina. Let $P(x, y, t)$ represent the output of P cells. Then, $P(x, y, t)$ can be defined as:

$$P(x, y, t) = L(x, y, t) - L(x, y, t - 1) \quad (1)$$

Where x and y represent the position of the cell and the coordinates of the pixels in the image flow, and t represents temporal positions. $L(x, y, t)$ represents the brightness of the

image stream captured by the photoreceptor in the current frame, and $L(x, y, t - 1)$ represents the previous frame.

The signal output from the P layer will undergo an instantaneous directional feedback operation, that is, the contrast suppression mechanism. This paper focuses on the following two mechanisms. The first is the dynamic contrast normalisation mechanism, which can be expressed by the following formula:

$$M(x, y, t) = \tanh\left(\frac{P(x, y, t)}{\alpha_1 + \hat{P}(x, y, t)}\right) \quad (2)$$

The second is static and is given below:

$$M(x, y, t) = \tanh\left(\frac{P(x, y, t)}{\alpha_1}\right) \quad (3)$$

Where $\hat{P}(x, y, t)$ represents the result of the convolution of $P(x, y, t)$ with Gaussian convolution kernel.

$$\hat{P}(x, y, t) = \sum_{i=-4}^4 \sum_{j=-4}^4 P(x+i, y+j, t) * W_G(i+4, j+4) \quad (4)$$

$$W_G = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{i^2 + j^2}{2\sigma^2}\right) \quad (5)$$

The signal operated by contrast normalisation will enter two pathway, one is the contrast computation pathway, and the other is the motion information pathway.

A. Motion information calculation pathway

The motion information detection pathway is composed of E layer, I layer, S layer and G layer.

E Layer : the brightness change perceived by P layer is directly transmitted to excited cells, which simply transmit the signal without delay.

$$E(x, y, t) = M(x, y, t) \quad (6)$$

I Layer : the lateral inhibitory cells accept the output of layer P, but there is a delay of one frame. The calculation can be processed by convolution operation. So, I layer can be defined as the following:

$$I(x, y, t) = \sum_{i=-1}^1 \sum_{j=-1}^1 M(x, y, t - 1) * W_I(i + 1, j + 1) \quad (7)$$

Where W_I is the convolution mask that representing the local inhibiting weight, given by

$$[W_I] = \begin{bmatrix} 0.125 & 0.25 & 0.125 \\ 0.25 & 0 & 0.25 \\ 0.125 & 0.25 & 0.125 \end{bmatrix} \quad (8)$$

S Layer : excitation information from layer E and inhibition information from layer I are linearly subtracted in layer S. Usually subtraction is determined by the following formula:

$$s(x, y, t) = E(x, y, t) - I(x, y, t) * \theta \quad (9)$$

Where θ is the inhibition weight coefficient.

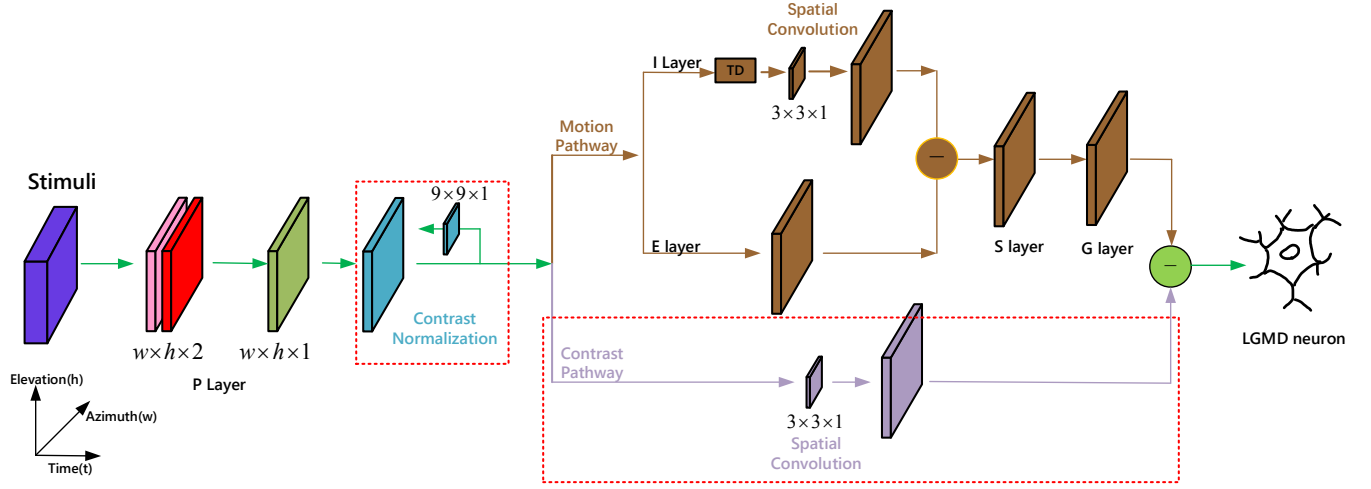


Fig. 2. Illustration of the proposed model with multiple layers. The red dashed box represents the dynamic contrast normalization mechanism and parallel contrast computation pathway respectively. These two bio-inspired mechanisms are used to upgrade the LGMD model.

Considering that the excitation information and inhibition information may have opposite symbols in value, a judgment needs to be added to the S layer output to avoid wrong positive pixels.

$$S(x, y, t) = \begin{cases} 0 & \text{if } E(x, y, t) * I(x, y, t) \leq 0 \\ s(x, y, t) & \text{otherwise} \end{cases} \quad (10)$$

G Layer : Yue and Rind applied LGMD model to the experiment of micro robot, in order to improve the robustness of collision detection, a new mechanism called grouping incentive mechanism was introduced [38]. Grouping mechanism can improve the edge characteristics of colliding objects in complex background and ignore background detail caused isolated excitation points.

This mechanism is implemented by the following three parts. Firstly, the transfer coefficient C_e of S layer is calculated, which depends on the surrounding pixels and can be calculated through the convolution kernel with equal weight, as follows

$$C_e(x, y, t) = \sum_{i=-1}^1 \sum_{j=-1}^1 S(x, y, t) * W_e(i, j) \quad (11)$$

Where W_e represents the influence of its neighbors and operation can be simplified as a convolution mask

$$[W_e] = \frac{1}{9} \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix} \quad (12)$$

Second, multiply the output of the S layer by the transfer coefficient and a scale, which needs to be calculated from each frame with the following formula.

$$W = 0.01 + \max |C_e(x, y, t) * C_w^{-1}| \quad (13)$$

$$G(x, y, t) = S(x, y, t) * C_e(x, y, t) * W^{-1} \quad (14)$$

where W is a scale and C_w is a constant.

Finally, isolated and attenuated excitation points can be ignored by setting a threshold.

$$G(x, y, t) = \begin{cases} G(x, y, t) & \text{if } G(x, y, t) * C_{de} \geq T_{de} \\ 0 & \text{otherwise} \end{cases} \quad (15)$$

Where C_{de} and T_{de} represent attenuation coefficient and attenuation threshold respectively.

B. Contrast computation pathway

The signal from layer P contains rich spatial contrast information. According to the experimental conclusion of Bahl et al., Medulla cells $MI1$ and $TM3$ from a centre surround for contrast calculation [16], which is computed by competing with lateral inhibitions [20].

$$C(x, y, t) = M(x, y, t) - \sum_{i=-1}^1 \sum_{j=-1}^1 M(x, y, t) * W_{Con}(i+1, j+1) \quad (16)$$

$$\hat{C}(x, y, t) = C(x, y, t) - C(x, y, t-1) + \hat{C}(x, y, t-1) \quad (17)$$

Where W_{Con} is defined as

$$[W_{Con}] = \frac{1}{8} \begin{bmatrix} 1 & 1 & 1 \\ 1 & 0 & 1 \\ 1 & 1 & 1 \end{bmatrix} \quad (18)$$

The motion information pathway and spatial contrast information pathway compete here. It is worth noting that the contrast signal has a negative impact on the motion signal, thereby weakening the high contrast in the motion signal flow. The calculations can be expressed as follows:

$$\hat{C}(x, y, t) = \begin{cases} \hat{C}(x, y, t) & \text{if } \hat{C}(x, y, t) * C_{de} \geq T_{de} \\ 0 & \text{otherwise} \end{cases} \quad (19)$$

$$k(x, y, t) = [\alpha_2 G(x, y, t) - \alpha_3 \hat{C}(x, y, t)]^+ \quad (20)$$

Where α_1 and α_2 are two gain coefficients, indicating the competitive relationship between them. Then the $[x]^+$ here indicates $\max(0, x)$.

Finally, K_t represents the membrane potential of LGMD cells at frame t , which is calculated by the following formula. The fidelity of looming perception is mainly affected by the size of membrane potential.

$$K_t = \sum_{x=0}^w \sum_{y=0}^h k(x, y, t) \quad (21)$$

The parameters used by all companies are listed in table I.

TABLE I
NETWORK PARAMETERS

Parameter	Description	Value
α_1	baseline contrast sensitivity	3
σ	standard deviation in contrast normalisation	5
θ	inhibition coefficient of layer I	0.4
C_w	Grouping decaying strength	4
C_{de}	G layer threshold	0.5
T_{de}	grouping coefficient	1.5
α_2, α_3	gain factors	1, 2.5

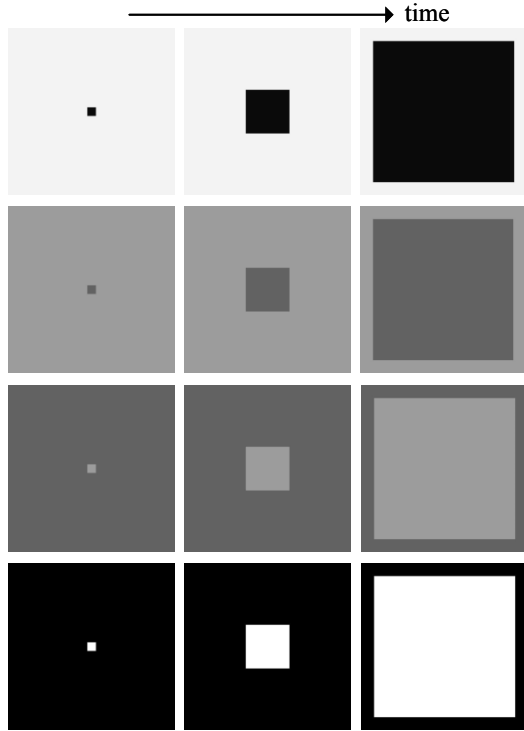


Fig. 3. Samples of looming process with different contrast in pure scenes

IV. EXPERIMENTAL EVALUATION

This paper evaluate the performance gap between the proposed model and LGMD model through comparative experiments. In order to fully show the basic characteristics of

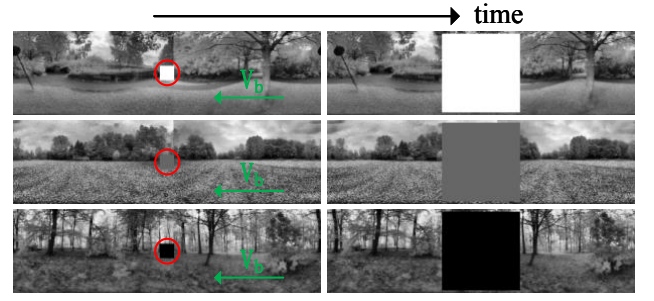


Fig. 4. Samples of approaching process in nature scenes amongst the dataset including one hundred and ten testing visual scenes: the background images shift leftward at constant angular velocity.

the proposed model, all experiments can be divided into the following two categories: (1) simulate visual stimulation in a pure background, which is a square block that expands over time. The change of contrast is simulated by the change of the brightness value of the background and square block. The contrast of the pure scene can be calculated by the following formula [39]:

$$\text{Contrast} = \frac{I_{max} - I_{min}}{I_{max} + I_{min}} \quad (22)$$

Where I_{max} and I_{min} refers to the maximum and the minimum luminances of scene. (2) Similar to the first group of experiments, but the background is a natural scene moving to the left ($V_b = 20$ degrees per second). In each experiment, the gray value of the square block changes, which can simulate the looming perceptual vision of locusts during flight, and test the robustness of the proposed model.

A. Pure Scene Setting

In this group of experiments, we simulate the looming process of an object by generating a square block gradually larger with time under a pure background. There are twelve separate experiments in this group. The data set used in this experiment is video with a resolution of $600 * 600$. The gray values of background and foreground vary from 0.0 to 1.0. Different gray values of foreground and background produce different contrast. In addition, the looming motion of the foreground occurs at frame 6 and ends at frame 38. Fig. 3 is a schematic diagram of a part of this experiment. In order to show the performance of the model, the parameter T_{de} of this group of experiments is set to 0. It can be seen from the experimental results that the response of LGMD model represents great fluctuation and high variability. The response of the proposed model to the looming process of the object fluctuates less. In addition, we also compare the response of the proposed model in the absence of parallel contrast computation pathway and static suppression, and count the average and variance of the response under different contrast.

B. Nature Scene Setting

In the natural scene, LGMD and the proposed model will face greater challenges. If the natural scene is used as the background and is still moving, it will bring great variability

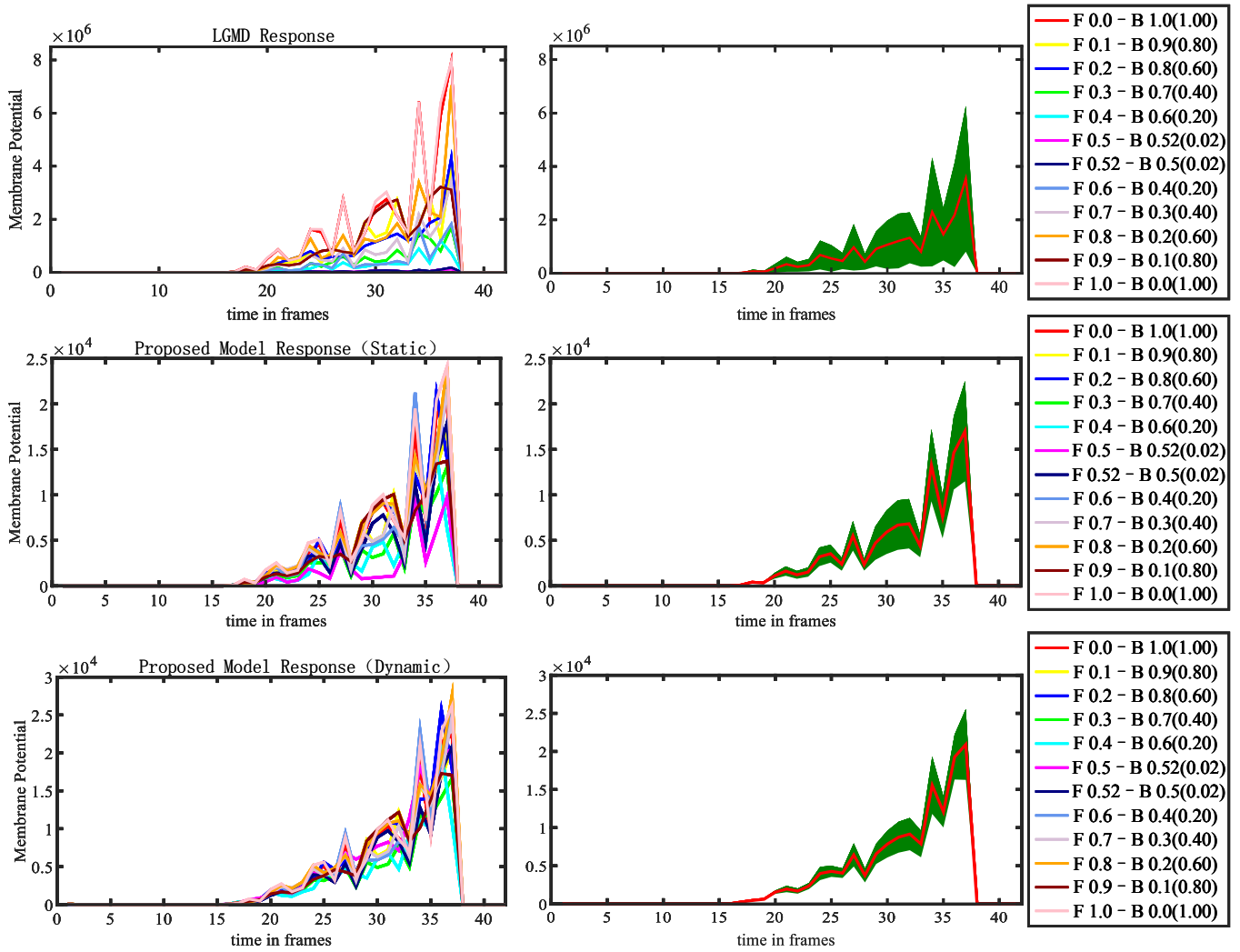


Fig. 5. Comparative statistics of responses of different models to different contrasts in pure scenes: the pictures in the left column represent the membrane potentials of different models. Right column shows the degree to which the corresponding model is affected by the contrast change: the red line and green shadow represent the average value and standard deviation of the response respectively. The figure legend is the calculated contrast value.

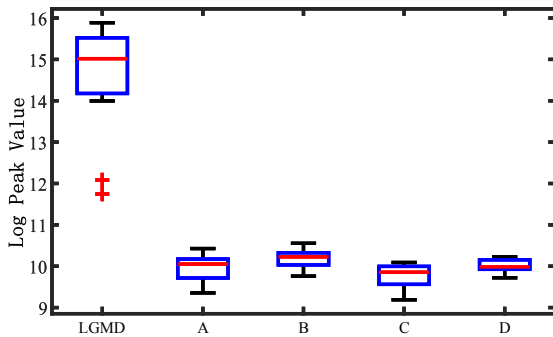


Fig. 6. Statistical results of responses in pure scenes: A and B indicate the proposed model (static normalisation) without and with parallel contrast pathway, respectively; C and D indicate the proposed model (dynamic normalisation) without and with parallel contrast pathway.

and fluctuation to the input of the model. We generate a

square block gradually expanding with time in the moving natural scene to simulate the looming perception vision of locusts during flight. Fig.4 is a schematic diagram of a part of this experiment. Ten different backgrounds were used in this experiment. In each background, the gray value of the looming block changed from 0.0 to 1.0. So a total of 110 test cases were generated. To test the robustness of the proposed model to different contrast in natural background. It should be noted that the value of the proposed model parameter T_{de} is changed to 1.5. In addition, we explore the performance of the proposed model based on static suppression for nature scenes.

C. Results

In Fig.5, the performance of each model is tested through the comparative test in the pure scene. The statistical results show that the LGMD model is largely affected by the change of contrast. This comparative experiment mainly compares

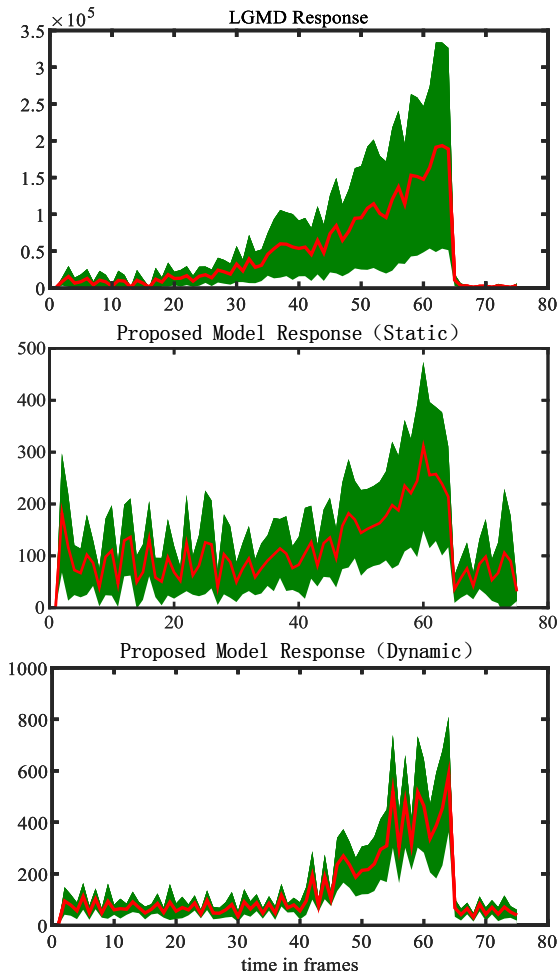


Fig. 7. Comparative statistics of responses of different models in natural scenes. Red lines and green shadows represent the mean and standard deviation of the response.

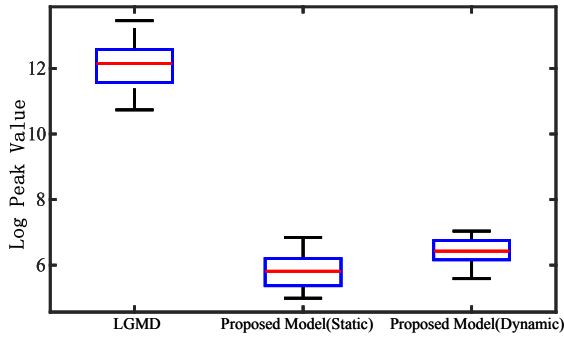


Fig. 8. Statistical results of different models in natural scenes

the performance gap between the model based on static contrast normalisation mechanism and the model based on dynamic contrast normalisation mechanism. The data in Figure 5 consists of the peak value of membrane potential in each experiment. It is worth noting that we should pay attention to the box size(inter quartile range, IQR) in the Fig.6 and Fig.8,

which represents the degree to which the model is affected by contrast. In addition, parallel contrast channels will also affect the performance of the model, and the relevant results are also shown in Fig.6.

Fig. 7 and Fig. 8 show the performance of different models in natural scenes. Because in the pure scene, the model with parallel pathway has better performance, this experiment only compares the gap between static normalisation mechanism and dynamic normalisation mechanism. The statistical results show that the dynamic model has better performance.

V. CONCLUSION AND DISCUSSIONS

This paper improves a classic LGMD-based looming perception neural network by introducing novel modelling of two contrast computation schemes. Through comparative experiments, we can summarise some results: (1) the variance and fluctuation of the response of the proposed model are greatly reduced in both pure and natural scenes. (2) In low contrast scenes, compared with LGMD model, the proposed model can detect the looming behaviour of objects. (3) It is confirmed that the parallel contrast calculation pathway is very important in the proposed model. (4) Dynamic contrast normalisation is more suitable for complex dynamic scenes than static normalisation, and can effectively improve the fidelity of looming perception.

In general, the parallel contrast calculation pathway and the static and dynamic methods in contrast normalisation will affect the performance of neural network. Therefore, the model proposed in this paper has a complete contrast vision computation mechanism. In view of the homology between organisms, this contrast computer theory has generalization ability and can be transplanted to other bionic visual neural networks, which deserves the attention of researchers.

Although this paper has done some tentative research on locust's looming perceptual vision, it involves the cross integration of multi-disciplinary fields such as neurophysiology, biology and cybernetics. Through our experiments, the following problems still need to be concerned and solved.

Firstly, we note that the contrast computation mechanism makes the proposed model reduce the variance of the response in the face of highly variable input, but the start time of the response is also delayed. This situation is not conducive to the survival of insects in the real world. In other words, in the nerve centre of locusts, there is a mechanism that we have not yet found. This mechanism may cooperate with the contrast computation mechanism to shorten the response delay and jointly improve the fidelity of locust looming perception. We will pay active attention to the progress of insect neurophysiology. Then, Fu et al. used a similar method in improving the estimation of image motion [20]. The model proposed in this paper is different from the model proposed by Fu as a whole, but some parts of the model structure are general, which leads to similar selection problems in some key parameters.

Secondly, the third result diagram in Fig. 7 shows that there is a high amplitude fluctuation in the output of the model between frames 55 and 65, which may be because the current

model is affected by the moving background to some extent. It is also possible that the parameter setting of the model is inappropriate, because this paper does not involve the learning mechanism.

Next, we will integrate these models and show a comprehensive insect visual neural network model as much as possible to deal with the complex spatio-temporal events in the real world (including looming motion, foreground and background movements). For some important parameters and weight matrices, we are building a batch of data sets and using learning to train these parameters to reduce the gap between the model and organisms.

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