Shaping the Ultra-Selectivity of a Looming Detection Neural Network from Non-linear Correlation of Radial Motion

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Abstract*—In this paper, a numerical neural network inspired by the lobula plate/lobula columnar type II (LPLC2), the ultra-selective looming sensitive neurons identified within visual system of Drosophila, is proposed utilising non-linear computation. This method aims to be one of the explorations towards solving the collision perception problem resulted from radial motion. Taking inspiration from the distinctive structure and placement of directionally selective neurons (DSNs) named T4/T5 interneurons and their post-synaptic neurons, the motion opponency along four cardinal directions is computed in a non-linear way and subsequently mapped into four quadrants. More precisely, local motion excites adjacent neurons ahead of the ongoing motion, whilst transfers inhibitory signals to presently-excited neurons with slight temporal delay. From comparative experimental results collected, the main contribution is established by sculpting the ultra-selective features of generating a vast majority of responses to dark centroid-emanated centrifugal motion patterns whilst remaining nearly silent to those starting from other quadrants of receptive field (RF). The proposed method also distinguishes relatively dark approaching objects against brighter background and light ones against dark background via exploiting ON/OFF parallel channels, which well fits the physiological findings. Accordingly, the proposed neural network consolidates the theory of non-linear computation in *Drosophila*'s visual system, a prominent paradigm for studying biological motion perception. This research also demonstrates potential of being fused with attention mechanism towards utility in devices such as unmanned aerial vehicles (UAVs), protecting them from unexpected and imminent collision by calculating a safer flying pathway.

I. Introduction

In complex real-world environments during foraging and homing, timely and accurately identifying impending collision is a life-critical matter for animals from small-sized flying insects to us human beings to recognise imminent hazard so that avoidance moves can be made [1]–[9]. When objects on a colliding course approaching from various regions of the entire visual field, the approaching or looming motion creates edge-expanding pattern in retina, gradually taking large portion of or even covering the receptive field [10]. Thus, one of the effective solutions to the collision perception problems is to extracting edge expansion.

Thousands of centuries evolutional development has endowed animals from vertebrates such as pigeons to invertebrates crabs, particularly fruit flies *Drosophila* and desert locusts elaborate visual systems for accurately extracting types of motion patterns so that wandering or cruising in complex physical world is not a problem most of the time [11]–[16]. Taking inspiration from flying insects, mathematical neural networks have shown their advantages in terms of whole RF collision perception, that is regardless the initial position of the approaching object [17]–[19]. One of the excellent examples is desert locusts, which usually rove in swarm. In their visual systems, the lobula giant movement detectors (LGMDs), namely the LGMD1 and LGMD2 have been identified as looming sensitive neurons with distinct characterization and hence been researched further to establish numerical models [20]–[23]. Their solid works have been demonstrating efficacy and positive impacts on solving the collision perception, from any regions or areas of the RF.

Inside flies' visual pathway, recent research outcomes also identified one neuropile, namely the LPLC2 neuron, which is tested to most strongly respond to centroid-emanated dark approaching objects on a straight colliding course whilst remain suppressed against those emanated from other regions of RF [24], [25]. Consisting of four sorts of cardinal-direction sensitive pre-synaptic neurons named lobula plate tangential cells (LPTCs) in particular placement, this ultra-selective visual projection neuropile demonstrates marvellous potential and huge possibility on addressing the collision perception problem via radial motion pattern perception.

However, how DSNs being peculiarly placed makes difference and how radial motion estimation along four cardinal directions is correlated remains to be researched.

Therefore, based upon solid and prominent evidences, a method inspired by LPLC2 in fly's visual pathways [25], is proposed in this paper to shape its ultra-selectivity characterization via non-linear motion correlation. By means of mimicking the architecture and of LPLC2 neuropile and peculiar placement of its pre-synaptic LPTCs, the proposed model calculates motion opponency in each cardinal direction, with separate ON/OFF channel transferring luminance increments and decrements respectively. The output information

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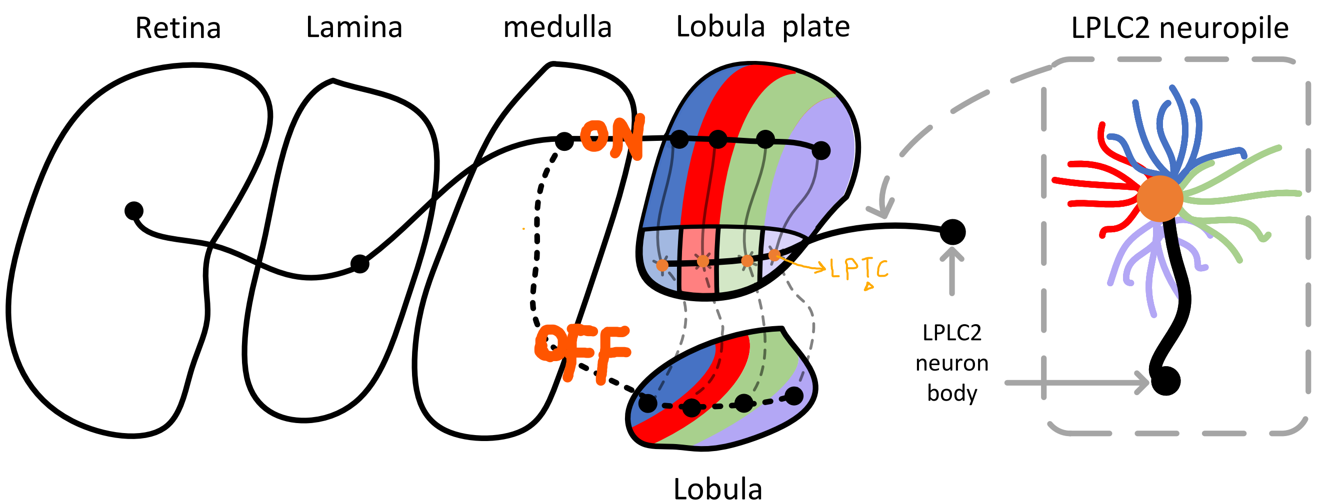

Fig. 1. Schematic of visual system of *Drosophila*. ON channel is represented by solid line while OFF channel by dashed line. Blue, red, green and purple areas show different type DSNs. More specifically, the blue one represent neurons interesting in upwards motion whilst the purple one prefers downwards motion; the red line and green shows preference to leftwards and rightwards movement respectively. The dot-headed line shows pathway of visual signals accepted by photoreceptors in retina layer, which are firstly dealt with in lamina, and subsequently separated in medulla into parallel ON/OFF channel with polarised selectivity. After that, signals in ON are passed to various types of DSNs (T4s) in lobula plate layer channel for directional motion calculation. These visual signals estimated by T4 interneurons are then combined with T5 neurons in OFF channel, and further filtered through to lobula plate tangential cells (LPTCs, represented by orange dots within slightly transparent areas). Note number of lines shall not be the actual number of neurons within *Drosophila* visual system

is subsequently mapped within the regions of four individual quadrants and eventually summarised by the LPLC2 neuron.

To validate the feasibility of this proposed structure-oriented neural network, computer-generated stimuli such as dark or white circles expansion against high-contrast background from various regions of RF are used, plus one certain chaotic-backgrounded video signal. The comparative results demonstrate effectiveness and efficacy of shaping ultra-selectivity of LPLC2 neurons with non-linear computation on distinguishing different approaching patterns and in its wake addressing the collision perception problem. Thus, this research shows it is promising to be further combined with attention mechanism to realise collision perception in a more precise manner so that it is possible to be applied to devices such as UAVs for safer cruising timely in the cluttered physical world.

The structure of this paper is organised as follows: in the section II, most related works are briefly reviewed. Section III presents the proposed model with formulation as well as parameter settings. The following section IV evaluates the experimental results in detail. The last section V concludes this study with discussion.

II. Related Works

In this section, the most relevant research including 1) physiology on fly's LPLC2 neuropile and 2) classic bio-inspired neural models for collision perception, including LGMD1, LGMD2 and one LPLC2 neural network based on learning.

A. LPLC2 neuropile

The lobula plate/lobula columnar may explain itself a bit that it is a widely ramifying neuropile originated from the lobula plate and terminated after the lobula layer. In the lobula plate, the header of the LPLC2 neuropile is called T4 interneurons whilst in the lobula it is called T5, both of which are consisting of four sorts of directionally-sensitive neurons, respectively preferring one of the four cardinal directions. In fig.I, coloured areas show distribution of aforementioned DSNs. Herein, blue indicates upward-sensitive neurons, red and green represent respectively the contrary motion directions leftwards and rightwards. The purple one indicates downwards-preferring neurons. Specially, the T4 interneurons forwards ramify as the post-synaptic neurons receiving ON channel signals whilst T5 dendrites are fed with OFF channel signals. Afterwards, T4/T5 interneurons pass through motion estimation information to the LPTCs for channel information integration. Hundreds of directionally-selective LPTCs anatomically terminate at the LPLC2 neuron, where the final membrane potential determines whether its post-synaptic Giant Fibres are activated and whether further movement should be made or not [15], [25]–[27].

B. Bio-Inspired Neural Networks for Collision Perception

Currently, two types of LGMD neurons have been identified inside flying locust neural pathways of processing natural visual cues. Generally speaking, they respond to outwards edge expansion however with distinctive selectivity to brightness of the looming object. LGMD1 neuron was firstly physiologically discovered as movement detector by O'Shea et al. nearly half century ago [28], then was verified to spike most frequently to objects on a colliding course whilst to be weakly activated by translating motion. In [12], Rind et al. proposed a architecturally-resembling LGMD1 model for collision perception, followed by Gabbiani et al. in [21] mathematically modelling focused on angular velocity within the whole RF.

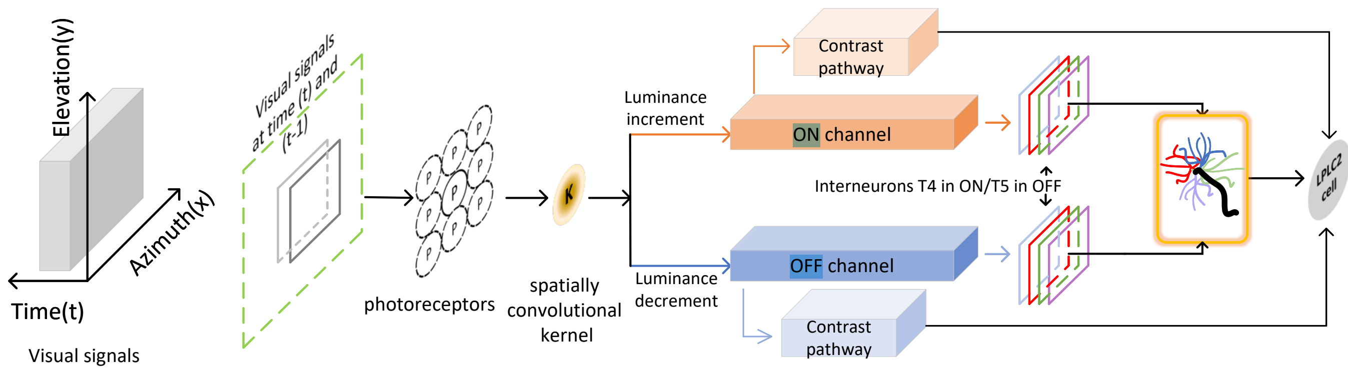

Fig. 2. Schematic of our proposed neural network. Visual signals (image sequences) at two consecutive frames are firstly accepted by photoreceptors to acquire the temporal differences, which are then convoluted via a Gaussian-like kernel. Afterwards, convoluted edge changes are separated into ON/OFF parallel channels, from where the contrast pathway is established. Following ON channel, polarised T4 interneurons extract motion estimation information (MEI), which subsequently, together with MEI from T5 cells is taken as input of the LPTCs (within the orange box. Please refer to fig.3) for summation. Particularly, the distinctive placement of LPTCs is thought to make difference to motion opponency correlation, where the final motion information is reckoned in a non-linear way by LPLC2 neuron. Note that the directionally selective interneurons in various colours represent neurons with different directional preference, correspondingly to those in fig.I.

Based on researches of Rind et al., Yue and Hu et al. continued to work on LGMD1 structure by adding a novel *Group* layer to further enhance edge expansion information, making it properly work on an affordable micro-robot platform called *Colias* [19], [29]. Additionally, a specialised decision-making mechanism coordinates with the integrated model, achieving more reliable and robust responses to cluttered background. After further optimised, LGMD1 neural network is applied to small quadcopters by Zhao et al., equipping them with ability of sensing impending collision and conduct evasive behaviours [30]. As an interneuron of LGMD1, LGMD2, though shares most of the selective features to approaching objects, it has been proved that different from the former, the LGMD2 neural networks discriminate dark and light looming objects. More specifically, it shows preference to dark centrifugal motion against brighter background [31]. It is after 2015 that he numerically modelling for the particular selectivity has been proposed by Fu et al., with computational ON and OFF parallel channel [17]. Therein, ON channels, where inhibitions and temporally delayed excitations are produced, and OFF channels where direct excitation and temporally delayed inhibition are generated, are meeting and summarised in a non-linear way [22].

Though aforementioned creative and excellent works of bio-inspired neural networks have made huge positive impact on addressing the collision perception problems, they are focused on the whole visual field looming motion patterns instead of the motion patterns which are initialised and emanated from a designated region or point.

Recently, Zhou et al. in [10] proposed a bio-plausible LPLC2 neural network, which is trained to identify visual signals containing impending collision. Their proposed linear receptive field (LRF) Units correspond to the directional selective interneurons in the lobula plate (LP). More specifically, each of the LP interneurons can only be activated by motion along one of four cardinal directions (represented by blue, red, green and purple in fig.I and fig.2). These activated units are then simply combined for further training purposes. By training various amounts of such LRF units, their proposed model realises certain features of LPLC2 neurons concluded in [25].

Their work for the first time made amazing contributions to solving the centroid-emanated collision problems. However, their algorithm can be hard for devices with limited computational power such as UAVs to be loaded on for real-time calculation while flying in unknown cluttered physical environments.

III. Formulations

In this section, the strategy of the proposed LPLC2 neural network is presented with formulations as well as parameter configurations.

Sharing properties of photoreceptors in various species, the proposed method firstly receives brightness changes as its retina layer input, and can be defined as:

$$P(x,y,t) = B(x,y,t) - B(x,y,t-1) \tag{1}$$

where $B(x,y,t)$ and $B(x,y,t-1)$ respectively represent the luminance value at pixel (x,y) in grey-scale at moment t and $t-1$.

It is right after the luminance change information transferred to the lamina layer that it is pre-filtered by the lamina monopolar cells (LMCs). More specifically, to mimic the function of LMCs of delivering both excitation and inhibition, a (3×3) convolutional kernel with plus core is applied to extract local excitation information whilst a (5×5) kernel with minus periphery forms the inhibition filtered through to adjacent neurons, which can be calculated as:

$$\hat{P}(x,y,t) = \sum_{i=-n}^{n} \sum_{j=-n}^{n} P(x+i, y+j, t) \cdot K(i,j,\sigma) \tag{2}$$

Note that the $\hat{P}$ stands for both excitatory ($\hat{P}_e$) and inhibitory signals ($\hat{P}_i$) to be subsequently passed, depending on which of the aforementioned Gaussian-like convolutional kernels is used. The n is defined as kernel radius, varying correspondingly to the signal property, excitatory (n_e) or inhibitory (n_i). The kernel $K_\sigma(i,j)$ is then decided by

$$K(i,j,\sigma)=\frac{1}{2\pi\sigma^2}\exp\left(-\frac{i^2+j^2}{2\sigma^2}\right) \tag{3}$$

where σ is the standard deviation, varying depending on signal type similarly to the kernel radius n.

Subsequently, the peripheral inhibition is subtracted by the central excitation with polarity selectivity, which is:

$$LA(x,y,t)=\begin{cases}|P_e(x,y,t)-P_i(x,y,t)|, & \\ \quad if\ P_e\geq 0\ and\ P_i\geq 0 & \\ -|P_e(x,y,t)-P_i(x,y,t)|, & \\ \quad if\ P_e<0\ and\ P_i<0 & \end{cases} \tag{4}$$

The polarised information is then separated into the ON/OFF channel via half-wave rectifying procedure, which can be described as:

$$\begin{aligned}ON(x,y,t)&=[LA(x,y,t)]^{+}+ON(x,y,t-1)\cdot\alpha_1,\\ OFF(x,y,t)&=-[LA(x,y,t)]^{-}+OFF(x,y,t-1)\cdot\alpha_1.\end{aligned} \tag{5}$$

where the operator $[x]^+$ obtains the greater between x and 0 whilst $[x]^-$ derives the smaller between x and 0. α_1 is a small real number as a residual factor, allowing a small portion of signal at $t-1$ into calculation.

Following the separation, interneurons in the medulla layer ramify such that in each parallel channel the revealed edge information is also reached, which forms another neuronal pathway parallel to each of ON/OFF channel. Numerically, this leak is realised via competition between local excitation and lateral inhibition. The entire proposed establishment can be gathered by:

$$\begin{aligned}\hat{ON}(x,y,t)&=\sum_{i=-5}^{5}\sum_{j=-5}^{5}ON(x+i,y+j,t)\cdot G(i,j,\sigma_3)\\ \hat{OFF}(x,y,t)&=\sum_{i=-5}^{5}\sum_{j=-5}^{5}OFF(x+i,y+j,t)\cdot G(i,j,\sigma_3)\end{aligned} \tag{6}$$

where $\hat{ON}$ and $\hat{OFF}$ is the compressed luminance change information. G is a Gaussian kernel with radius of 5 (unit: $pixel$) which can be calculated similarly by equation (3), and σ_3 is defined as its input of standard deviation.

After the compression in each channel, the centre-periphery antagonising medulla cells derive contrast information $\hat{C}$ standing for both $\hat{C}_{on}$ in ON channel and $\hat{C}_{off}$ in OFF channel from:

$$C(x,y,t)=|R(x,y,t)-\frac{1}{9}\cdot\sum_{i=-1}^{1}\sum_{j=-1}^{1}R(x+i,y+j,t)|\quad j\neq 0, if\ i=0. \tag{7}$$

$$\hat{C}(x,y,t)=(C(x,y,t)-C(x,y,t-1)+\hat{C}(x,y,t-1))\cdot\alpha_2. \tag{8}$$

where R stands for the compressed ON channel $\hat{ON}$ and the OFF one $\hat{OFF}$ and α_2 is a coefficient for smoothing discrete signals, which is decided by

$$\alpha_2=\tau_2/(\tau_2+\tau_i) \tag{9}$$

where τ_2 is a time constant and τ_i is determined by the interval in milliseconds between two successive frames.

While equations(6) to (9) depict the formulation of contrast pathway, the signals within ON/OFF channels is temporally convoluted, conforming to the following equation:

$$DI(x,y,t)=\alpha_3\cdot R(x,y,t)+(1-\alpha_3)\cdot R(x,y,t-1) \tag{10}$$

where DI is defined representing delayed information of both ON and OFF channel and α_3 is a weighing factor, gained by:

$$\alpha_3=\tau_i/(\tau_i+\tau_3) \tag{11}$$

τ_3 is a time constant.

With the compressed information R and delayed information DI, the motion is estimated in a non-linear method:

$$\begin{aligned}ME(x,y,t,d)=&\ DI(x,y,t)\cdot R(x,y,t)\cdot R(x,y+\mu,t)\\ &-R(x,y,t)\cdot DI(x,y+\mu,t)\cdot R(x,y+\mu,t)\end{aligned} \tag{12}$$

where μ measures the bias from the every pair of neurons, indicating the motion direction representative variable d. Therefore, ME in equation (12) represent the calculation of upward motion in the ON channel whereas motion estimation information on rest of cardinal directions in both ON and OFF channels can be easily inferred.

Next, the cardinal movement sensitive T4 neurons initialised in medulla layer accept ME from ON channel at moment t together with a small portion of residual from $t-1$ to generate directionally-polarised output. Similarly, T5 interneurons in the lobula plate receive ME from OFF channel. The process can be expressed as:

$$\begin{aligned}T4(x,y,t,d)=&\ [\alpha_4\cdot ME(x,y,t,d)\\ &+(1-\alpha_4)\cdot ME(x,y,t-1,d)]^{+}\\ T5(x,y,t,d)=&\ [\alpha_5\cdot ME(x,y,t,d)\\ &+(1-\alpha_5)\cdot ME(x,y,t-1,d)]^{+}\end{aligned} \tag{13}$$

where α_4 and α_5 denote two time-related weights, allowing residual to make slight difference. They can be calculated by:

$$\begin{aligned}\alpha_4&=\tau_i/(\tau_i+\tau_4)\\ \alpha_5&=\tau_i/(\tau_i+\tau_5)\end{aligned} \tag{14}$$

where τ_4 and τ_5 are time constant for T4 and T5 interneurons respectively.

Afterwards, prior to being summarised by the LPLC2 neuron, each pair of directionally-selective T4/T5 neurons integrate motion information derived from ON and OFF channel,

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which will be delivered to their post-synaptic neurons called LPTCs [18]. It is defined as:

$$
\begin{aligned}
Motion(t, d) = \sum_{x=1}^{w}\sum_{y=1}^{h} (\\
(w_1 \cdot T4(x, y, t, d) - w_c \cdot \hat{C}_{on}(x, y, t))^{\beta_1} \\
+(w_2 \cdot T5(x, y, t, d) - w_c \cdot \hat{C}_{off}(x, y, t))^{\beta_2})
\end{aligned}
\tag{15}
$$

where β_1 and β_2 are set to weigh each group of T4/T5 neurons. w_1, w_2 are weight factors respectively for ON and OFF channel. w_c is for balancing the affection of the parallel contrast pathways from equation (8).The specialised placement of these LPTCs is carefully considered for its being significantly impacting the eventual non-linear summation calculation.

Eventually, the motion information in four cardinal direction is extracted to be summarised by the LPLC2 neuron. Accordingly, horizontal and vertical motion information at certain moment is then collected. When the motion direction representative variable d falls within the list $[1, 2, 3, 4]$, it corresponds to the motion to right side, left side, floor and ceiling. Here, rightward and downward motion direction is defined as positive while the others are set to less than 0. Horizontally and vertically, opposite motion is firstly summarised by

4 2 1 3

$$
\begin{aligned}
H(t) &= Motion(t, 1) - Motion(t, 2) \\
V(t) &= Motion(t, 3) - Motion(t, 4)
\end{aligned}
\tag{16}
$$

The horizontal and vertical motions are then mapped into four quadrant by the following equation:

$$
\begin{aligned}
Q(t, 1) &= g(H(t)) + g(-V(t)) \\
Q(t, 2) &= g(-H(t)) + g(-V(t)) \\
Q(t, 3) &= g(-H(t)) + g(V(t)) \\
Q(t, 4) &= g(H(t)) + g(V(t))
\end{aligned}
\tag{17}
$$

where $Q(t, i)$ represents regional output within the i^{th} quadrant and the $g(x)$ is an approximate Gaussian Error Linear Units utilised as activate the motion subtraction. The regional information is then summarised in a non-linear way by

$$
LPLC2(t) = [Q(t, 1)]^{+} \cdot [Q(t, 2)]^{+} \cdot [Q(t, 3)]^{+} \cdot [Q(t, 4)]^{+} \tag{18}
$$

Parameter configuration refers to the table I. This proposed neural network is open sourced and available at the following URL: https://github.com/sauceFlavoured256/LPLC2-OpenSource-Code.

IV. Experimental Evaluation

In this section, firstly the experimental setup is introduced, including materials that have been tested and how comparative experiments are carried. Secondly, the gathered experimental results are evaluated.

A. Experimental setup

To verify the proposed neural network, several computer-generated stimuli of 400×400 are used, as well as a rotating-chaotic-backgrounded one at resolution of 540×270, as some snapshots are shown in Fig.4. Since the proposed LPLC2 neural network aims at addressing the centroid-initialised collision perception problem with preference to dark approaching objects, the first group of feasibility experiments take dark and white approaching and recessing circle from the heart or one of the cardinal quadrants as input to the LPLC2 model. The same stimuli are also received by LGMD1 neural network for collision perception for systematic comparison. In the second group, it is pushed further for robustness test with simulative stimuli within natural environments. Experiments of the proposed neural network's responses regarding darking translating bar are further investigated.

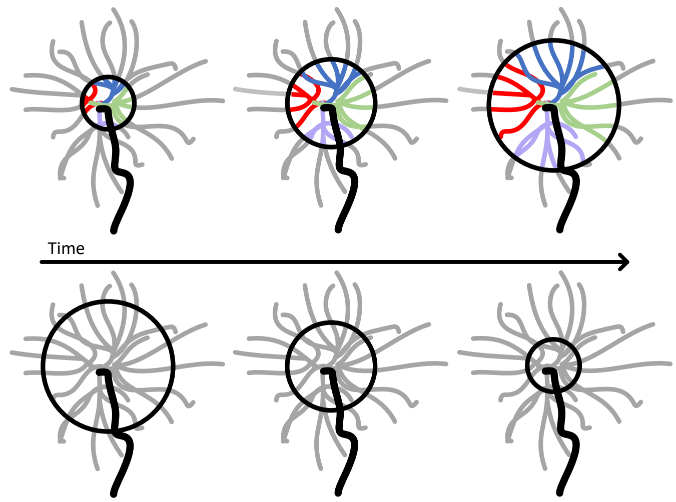


Fig. 3. Illustration of directionally-selective neurons LPTCs being activated by edge expanding (top) and remaining silent against recession (bottom). The black circle represents one dark looming motion pattern. As it expands, four sorts of T4/T5 interneurons in four colours sense motions along one of the four cardinal directions (equation (12)). Directional informations are then estimated within the T4 or T5 pathway.(equation (13)). The ON channel motion estimation in T4 and OFF channel motion in T5 are then summarised by their post-synaptic structure LPTC neurons. The particular placement of LPTC neurons as shown is considered to impose impacts on the following non-linear combining calculation of LPLC2 neuron.

TABLE I
Parameter Configuration

Parameter	Description	Value
α_1	ON/OFF residual coefficient	0.1
$\{\beta_1, \beta_2\}$	exponent on ON&OFF signals	$\{0.9, 0.5\}$
μ	delayed information sampling length	1
σ	standard deviation in LMCs	1,2
σ_3	standard deviation in contrast pathway	5
τ_i	time interval constant between frames	1000/30(ms)
τ_2	time constant in contrast pathway	500(ms)
τ_3, τ_4, τ_5	time constant in ON/OFF channel	30(ms)
w_1, w_2	motion calculation weighing factor	1,1
w_c	contrast weighing factor	1
n	LMCs kernel radius	1,2

B. Experimental results

The first group of experimental results are illustrated in fig.5 to 7. In fig.5(a), dark approaching and recessing circles are utilised. It can be clearly told that the classic LGMD1 neural network responds to both types of stimuli, whilst the ultra-selective LPLC2 neural network only fires spikes to the

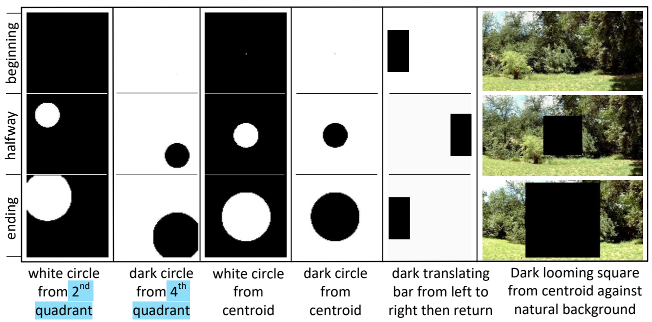
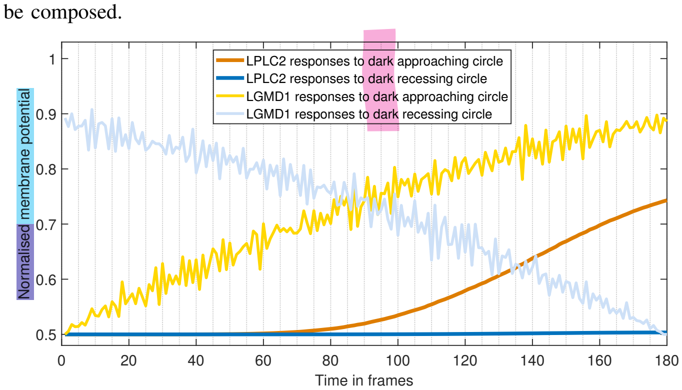
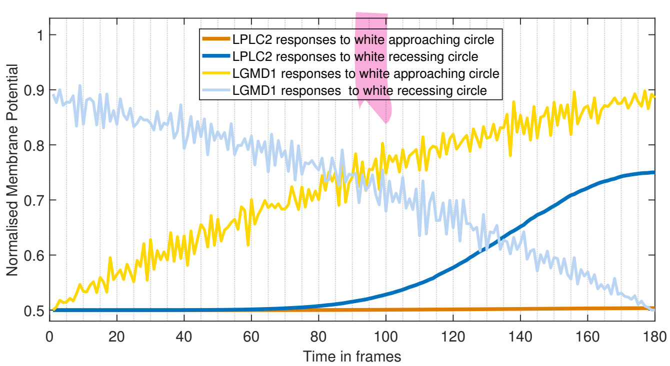


Fig. 4. Example snapshots of stimuli at three stages, the beginning, half of signal length and the ending. Approaching motion pattern can be synthesized sequentially from the beginning to the ending, and reversely can the recession be composed.



(a) LPLC2 and LGMD1 responses to dark circle



(b) LPLC2 and LGMD1 responses to white circle

Fig. 5. Comparative response to simulative visual signals. (a) LPLC2 shows preference of dark approaching motion to the recession. (b) LPLC2 is activated roughly to the same extent by white approaching circle. In (a) and (b), LGMD1 neural network displays same membrane since its whole RF sensitivity.

approaching one, which resembles edge change pattern when there is imminent collision. In fig.5(b), white stimuli at same angular velocity are passed through. The LGMD1, for its sensitivity to the whole RF without dark and light polarisation, is triggered with fluctuation in a similar way, whilst the LPLC2 shows preference of the recession motion pattern to the approaching one. With regards to the stimuli where dark and white circles move centrifugally from the heart of each cardinal quadrants, in all eight sub-figures, outward motion patterns representing collision are sensed by LGMD1 whilst LPLC2 on the contrary, shows little responses. Therefore, three figures in

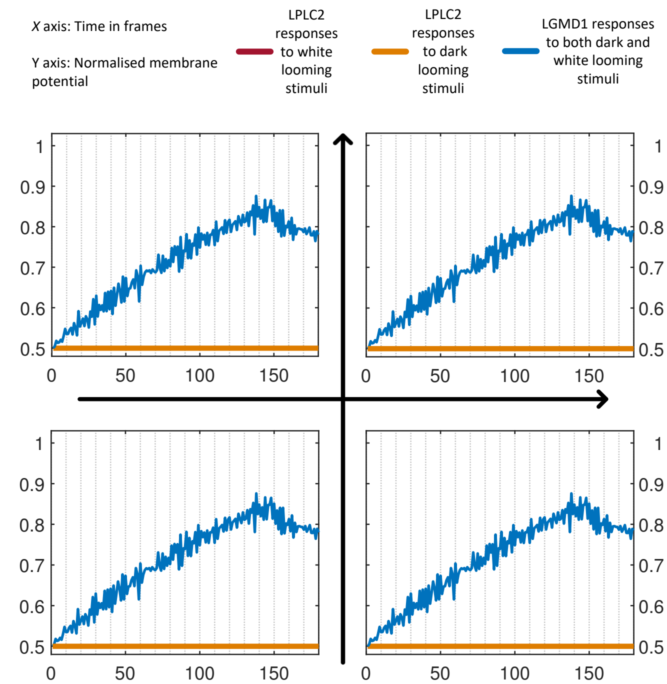


Fig. 6. Comparative responses of LPLC2 and LGMD1 neural networks to the dark looming stimuli from centroid of each quadrant. On the top is the legend for fig.6 and 7. The placement of each sub-figure represents where the stimuli are positioned, e.g. the left conner one represents both model's responses to dark looming stimuli from 2^{nd} quadrant. and so on. In each sub-figure, LGMD1 demonstrates almost the same curve to dark approaching circle wherever it is initialised, while the LPLC2 neuron remain inactivated to the marginally-emanated looming pattern.

the first group of experiments considered, it is acknowledged that the proposed LPLC2 shows its capability of detecting radial edge expansion from centroid while ignoring that from other quadrants. In further investigation regarding LPLC2's robustness against more cluttered background (results in fig.8, stimuli in fig.4, last column), LGMD1 fails to recognise the looming motion since the chaotic background is also turning. Contrarily, our proposed LPLC2 neural network properly discriminates desired dark square from background. In the translating responses experiment (in fig.9), the proposed model remains silent to both left to right and right to left translating movement, while LGMD1 is continuously activated.

Fig.6 and 7 illustrates LPLC2, as well as LGMD1, responses to dark and white, approaching and recessing circles emanated from each quadrant. As mentioned above, the LGMD1 neurons can be recognised as a whole RF looming sensitive neuron without preference to dark or white object. Thus, 1) LGMD1 is activated intensively; and 2) almost every plotted curve has the same value in axis y. It is also obviously told that the LPLC2 neuron remains silent against quadrant-emanated stimuli. From above two group of experiments, it can be summarised that the proposed LPLC2 neural network manages to depict an ultra-selective neuron that prefers centroid-emanated collision to marginal collision.

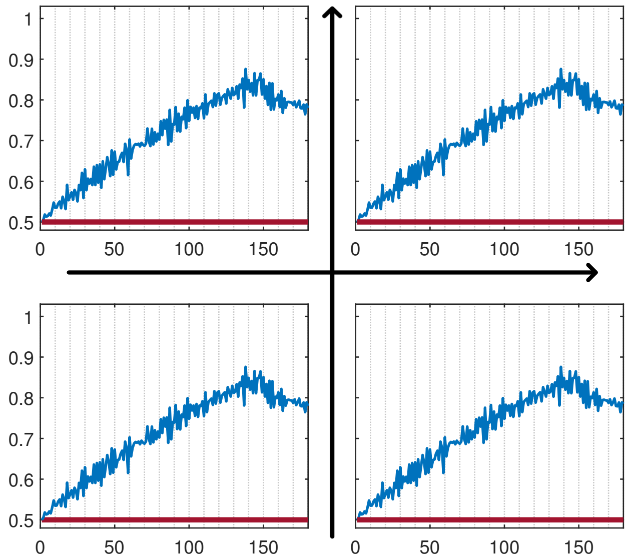


Fig. 7. Comparative responses of LPLC2 and LGMD1 neural network. In each sub-figure, same as the corresponding one in fig.6, LPLC2 demonstrates completely different responses from LGMD1 neural network against the same white looming stimuli.

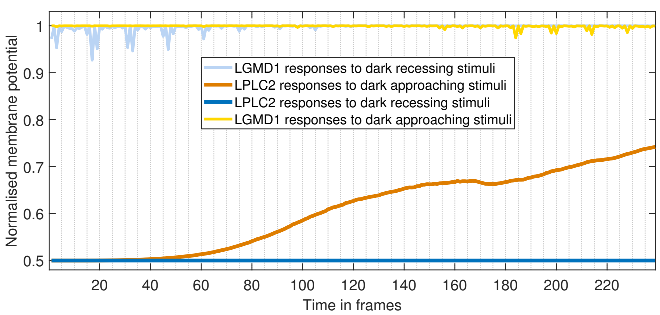


Fig. 8. Membrane potential curves of LPLC2 and LGMD1 neural networks against dark square within a chaotic environment. The orange curve represents our proposed model responses to centroid-looming pattern whilst the blue one is responses to recessing pattern. LGMD1 responses to both approaching and recessing motion are around maximum with much overlay, failing to extract collision.

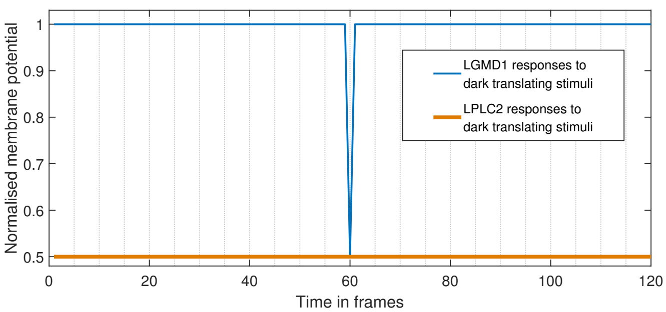


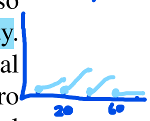
Fig. 9. To dark translating stimuli, LGMD1 generates spikes most of time. Our proposed LPLC2 model for collision perception retains stability all along. Compared to experimental results from [18], which is also a translating motion sensitive neural network inspired by the directionally selective neurons named LPTCs inside the visual pathway processing natural signals, though sharing properties such as T4/T5 interneurons as well as their post-synaptic constructions taken into consideration, our proposed method demonstrates completely diverse results.

V. Conclusion and Discussion

To summarise, in this paper, a numerical model is proposed to shape the main ultra-selectivity feature of the LPLC2 neuropile with specialised non-linear computation inspired by the particular placement of visual pathway in *Drosophila*. Compared to the whole RF sensitive LGMD1 neural network for collision perception, the proposed method owns its ultra-selective features, which are: 1) substantially sensitive to the radial edge expansion emanated from the centroid of the RF, whilst much less interested in that from other quadrants; 2) demonstrating preference to dark objects on a colliding course against relatively lighter background, whilst remaining inactivated to light ones against dark background. Our comparative experimental results illustrate that building LPLC2 neural network can be promising as a simple solution to the aforementioned centroid-emanated collision problem and it is possible to be optimised to be fused with attention mechanism in order to conduct advanced collision perception more precisely such as self-adaptive focusing point once there is swift intrusion of visual field. For small-sized aerial devices, it may be a computational-power-affordable scheme to timely calculate and plan safe flying way.

2017. Page 15. Fig4. h.

However, in the research of the LPLC2 neuropile, it is also verified that the initial angular size of the colliding objects also triggers membrane potential differently in terms of intensity. To be more specific, the inverse V-like curve peaks at initial angular size of 20 degrees and gradually goes down to zero at 60 degrees. It is subsequently inferred that the lateral inhibition intensity differs at the first moment of visual field being intruded. How lateral inhibition mechanism works on the peculiar ultra-selectivity to the initial angular size remains to be further explored.



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References

[1] F. Gabbiani, H. G. Krapp, and G. Laurent, "Computation of object approach by a wide-field, motion-sensitive neuron," *Journal of Neuroscience*, vol. 19, no. 3, pp. 1122–1141, 1999.

[2] H. Sun and B. J. Frost, "Computation of different optical variables of looming objects in pigeon nucleus," *Nature neuroscience*, vol. 1, no. 4, pp. 296–303, 1998.

[3] S. M. King, C. Dykeman, P. Redgrave, and P. Dean, "Use of a distracting task to obtain defensive head movements to looming visual stimuli by human adults in a laboratory setting," *Perception*, vol. 21, no. 2, pp. 245–259, 1992.

[4] K. Sato and Y. Yamawaki, "Role of a looming-sensitive neuron in triggering the defense behavior of the praying mantis tenodera aridifolia," *Journal of neurophysiology*, vol. 112, no. 3, pp. 671–682, 2014.

[5] I. Temizer, J. C. Donovan, H. Baier, and J. L. Semmelhack, "A visual pathway for looming-evoked escape in larval zebrafish," *Current biology*, vol. 25, no. 14, pp. 1823–1834, 2015.

[6] D. Regan and K. Beverley, "Looming detectors in the human visual pathway," *Vision Research*, vol. 18, no. 4, pp. 415–421, 1978.
[7] J. Carbone, A. Yabo, and D. Oliva, "Characterization and modelling of looming-sensitive neurons in the crab neohelice," *Journal of Comparative Physiology A*, vol. 204, pp. 487–503, 2018.
[8] D. Oliva and D. Tomsic, "Computation of object approach by a system of visual motion-sensitive neurons in the crab neohelice," *Journal of Neurophysiology*, vol. 112, no. 6, pp. 1477–1490, 2014.
[9] J. R. Kohn, S. L. Heath, and R. Behnia, "Eyes matched to the prize: The state of matched filters in insect visual circuits," *Frontiers in Neural Circuits*, vol. 12, 2018.
[10] B. Zhou, Z. Li, S. Kim, J. Lafferty, and D. A. Clark, "Shallow neural networks trained to detect collisions recover features of visual loom-selective neurons," *eLife*, vol. 11, p. e72067, 2022.
[11] F. Gabbiani and R. B. Dewell, "Collision avoidance: Broadening the toolkit for directionally selective motion computations," *Current Biology*, vol. 28, no. 3, pp. R124–R126, 2018.
[12] F. C. Rind and D. I. Bramwell, "Neural network based on the input organization of an identified neuron signaling impending collision," *Journal of Neurophysiology*, vol. 75, no. 3, pp. 967–985, 1996.
[13] L. Li, Z. Zhang, and J. Lu, "Artificial fly visual joint perception neural network inspired by multiple-regional collision detection," *Neural Networks*, vol. 135, pp. 13–28, 2021.
[14] M. S. Drews, A. Leonhardt, N. Pirogova, F. G. Richter, A. Schuetzenberger, L. Braun, and A. Borst, "Dynamic signal compression for robust motion vision in flies," *Current biology*, vol. 30, no. 2, pp. 66–68, 2020.
[15] J. M. Ache, J. Polsky, S. Alghailani, R. Parekh, P. Breads, M. Y. Peek, D. D. Bock, C. R. von Reyn, and G. M. Card, "Neural basis for looming size and velocity encoding in the drosophila giant fiber," *Current biology*, vol. 29, no. 20, pp. 1089–1091, 2019.
[16] C. R. von Reyn, P. Breads, M. Y. Peek, G. Z. Zheng, W. R. Williamson, A. L. Yee, A. Leonardo, and G. M. Card, "A spike-timing mechanism for action selection." *Nature neuroscience*, vol. 17, no. 7, pp. 962–970, 2014.
[17] Q. Fu, C. Hu, J. Peng, F. C. Rind, and S. Yue, "A robust collision perception visual neural network with specific selectivity to darker objects," *IEEE Transactions on Cybernetics*, vol. 50, no. 12, pp. 5074–5088, 2020.
[18] Q. Fu and S. Yue, "Modelling drosophila motion vision pathways for decoding the direction of translating objects against cluttered moving backgrounds," *Biological Cybernetics*, vol. 114, no. 4, pp. 443–460, 2020.
[19] S. Yue and F. C. Rind, "Collision detection in complex dynamic scenes using an lgmd-based visual neural network with feature enhancement," *IEEE Transactions on Neural Networks*, vol. 17, no. 3, pp. 705–716, 2006.
[20] F. C. Rind and P. J. Simmons, "Seeing what is coming: building collision-sensitive neurones," *Trends in Neurosciences*, vol. 22, no. 5, pp. 215–220, 1999.
[21] F. Gabbiani, H. G. Krapp, C. Koch, and G. Laurent, "Multiplicative computation in a visual neuron sensitive to looming," *Nature*, vol. 420, pp. 320–324, 2002.
[22] Q. Fu, C. Hu, T. Liu, and S. Yue, "Collision selective lgmds neuron models research benefits from a vision-based autonomous micro robot," in *2017 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 2017, pp. 3996–4002.
[23] H. Meng, S. Yue, A. Hunter, K. Appiah, M. Hobden, N. Priestley, P. Hobden, and C. Pettit, "A modified neural network model for lobula giant movement detector with additional depth movement feature," in *2009 International Joint Conference on Neural Networks*, 2009, pp. 2078–2083.
[24] S.-y. Takemura, A. Bharioke, Z. Lu, A. Nern, S. Vitaladevuni, P. K. Rivlin, W. T. Katz, D. J. Olbris, S. M. Plaza, P. Winston, T. Zhao, J. A. Horne, R. D. Fetter, S. Takemura, K. Blazek, L.-A. Chang, O. Ogundeyi, M. A. Saunders, V. Shapiro, C. Sigmund, G. M. Rubin, L. K. Scheffer, I. A. Meinertzhagen, and D. B. Chklovskii, "A visual motion detection circuit suggested by drosophila connectomics," *Nature*, vol. 500, pp. 175–181, 2013.
[25] N. C. Klapoetke, A. Nern, M. Y. Peek, E. M. Rogers, P. Breads, G. M. Rubin, M. B. Reiser, and G. M. Card, "Ultra-selective looming detection from radial motion opponency," *Nature*, vol. 551, no. 7679, pp. 237–241, 2017.
[26] M. Wu, A. Nern, W. R. Williamson, M. M. Morimoto, M. B. Reiser, G. M. Card, and G. M. Rubin, "Visual projection neurons in the drosophila lobula link feature detection to distinct behavioral programs," *eLife*, vol. 5, p. e21022, 2016.
[27] M. S. Maisak, J. Haag, G. Ammer, E. Serbe, M. Meier, A. Leonhardt, T. Schilling, A. Bahl, G. M. Rubin, A. Nern, B. J. Dickson, D. F. Reiff, E. Hopp, and A. Borst, "A directional tuning map of drosophila elementary motion detectors," *Nature*, vol. 500, no. 7461, pp. 212–216, 2013.
[28] M. O' Shea and J. L. Williams, "The anatomy and output connection of a locust visual interneurone; the lobular giant movement detector (lgmd) neurone," *Journal of comparative physiology*, vol. 91, pp. 257–266, 1974.
[29] C. Hu, F. Arvin, C. Xiong, and S. Yue, "Bio-inspired embedded vision system for autonomous micro-robots: The lgmd case," *IEEE Transactions on Cognitive and Developmental Systems*, vol. 9, no. 3, pp. 241–254, 2017.
[30] J. Zhao, H. Wang, N. Bellotto, C. Hu, J. Peng, and S. Yue, "Enhancing lgmd's looming selectivity for uav with spatial-temporal distributed presynaptic connections," *IEEE Transactions on Neural Networks and Learning Systems*, pp. 1–15, 2021.
[31] J. Sztarker and F. C. Rind, "A look into the cockpit of the developing locust: looming detectors and predator avoidance," *Developmental neurobiology*, vol. 74, no. 11, pp. 1078–1095, 2014.