Enhancing LGMD’s Looming Selectivity for UAV With Spatial–Temporal Distributed Presynaptic Connections

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Abstract—Collision detection is one of the most challenging tasks for unmanned aerial vehicles (UAVs). This is especially true for small or micro-UAVs due to their limited computational power. In nature, flying insects with compact and simple visual systems demonstrate their remarkable ability to navigate and avoid collision in complex environments. A good example of this is their ability to detect looming rather than background movements. Our model is, therefore, tuned to preferred image angular velocities and selectively suppress the nonpreferred visual motions. This spatial–temporal competition between excitation and inhibition in our model is implemented to compete with the distributed excitation and selectively suppress the nonpreferred visual movements. This spatial–temporal competition between excitation and inhibition in our model is, therefore, tuned to preferred image angular velocity representing looming rather than background movements with these distributed synaptic interactions. Systematic experiments have been conducted to verify the performance of the proposed model for UAV agile flights. The results have demonstrated that this new model enhances the looming selectivity in complex flying scenes considerably and has the potential to be implemented on embedded collision detection systems for small or micro-UAVs.

Index Terms—Collision detection, distributed presynaptic connection-based Lobula giant movement detector (D-LGMD), dynamic complex visual scene, presynaptic neural network, unmanned aerial vehicles (UAVs).

I. INTRODUCTION

AUTONOMOUS flying robots or unmanned aerial vehicles (UAVs), especially small and microaerial vehicles (MAVs), have increasingly displayed considerable potential for serving human society as a result of their flexibility and capability of flight. However, autonomous MAVs remain unable to fly automatically and perform tasks safely. One of the reasons is that they have not been equipped with efficient collision detection capabilities. Traditional technologies of collision detection, such as laser [1], ultrasonic [2], and simultaneous localization and mapping (SLAM) [3], are computationally expensive or greatly rely on objects texture and physical characters, such as its ability to absorb and/or reflect light. These impediments make these methods unsuitable for MAVs. On the other hand, vision sensors can capture rich information of the real world and consume less power. However, exploiting the abundant information comes with a cost, which, in this case, is a demand for an efficient algorithm to extract task-specific features for collision detection.

Nature has demonstrated many successful solutions for dynamic collision detection. For example, locusts can fly with agility in a swarm of millions while avoiding collision. Their remarkable collision avoidance relies on a visual motion-sensitive neuron: the Lobula giant movement detector (LGMD) [4]. The LGMD neuron has a characteristic preference for looming obstacles (i.e., objects approaching on a direct collision course) other than translating or receding objects, which makes it an ideal model for detecting collisions automatically [5], [6]. Although some of the LGMD inspired models have been successfully embodied on mobile robots for collision detection [7], [8], we also showed that an LGMD can detect collision in simple flying scenes with a constant flying speed [9]. However, these LGMD models cannot distinguish looming clearly from other visual cues, such as complex background movements caused by UAV agile flight. To address this issue, we proposed a new model implementing distributed spatial–temporal synaptic interactions, which is inspired by recent findings in locusts’ synaptic morphology. We first introduced the locally distributed excitation to enhance the excitation caused by visual motion with preferred velocities. Then, radially extending temporal latency for inhibition is incorporated to compete with the distributed excitation and selectively suppress the nonpreferred visual motions. This spatial–temporal competition between excitation and inhibition in our model is therefore tuned to preferred image angular velocity representing looming rather than background movements with these distributed synaptic interactions. Systematic experiments have been conducted to verify the performance of the proposed model for UAV agile flights. The results have demonstrated that this new model enhances the looming selectivity in complex flying scenes considerably and has the potential to be implemented on embedded collision detection systems for small or micro-UAVs.
A typical LGMD model consists of a few layers, including photoreceptors, excitation, inhibition, synaptic summation, feed-forward inhibition, and an LGMD neuron [4], [12]. The synaptic interactions in the current models are simple, for example, the excitation is one-to-one connected from the photoreceptor layer to the summation layer; the lateral inhibition is spatially distributed but not considering temporal distribution.

Recent studies on locusts’ LGMD neurons indicated that both excitatory [13] and inhibitory [14] synaptic pathways are exquisitely structured and locally distributed to interact with neighbors. The retinotopic mapping seems to play an important role in LGMD’s preference for looming [15], which has been underestimated in previous models. These findings support the assumption that LGMD’s synapses do discriminate spatial–temporal patterns that are embedded across its thousands of synaptic inputs [11].

Inspired by these findings, we propose the distributed presynaptic connection (DPC) structure and incorporate novel morphological strategies to implement a spatial–temporal filter on image angular velocity to cope with agile flights. The DPC structure involves novel strategies: 1) locally distributed excitation to enhance the excitation caused by visual motion with preferred velocities and 2) radially distributed temporal latency for inhibition to compete with the distributed excitation and selectively suppress the nonpreferred visual motions. We experimentally analyzed how the spatial–temporal distributions contribute to LGMD’s looming selectivity and demonstrated that the proposed model performs well in agile flights.

In summary, the contributions of this article are threefold.
1) We proposed a new LGMD model with locally distributed excitation for enhancing image motion with preferred angular velocity (on image) to better cope with agile flights.
2) Temporal distribution is considered and defined in a radially extending manner to compete with the distributed excitation and form the spatial–temporal filter for looming cues.
3) We demonstrated in experiments that the proposed model exhibited a distinct preference for looming objects in agile flights and, therefore, is competent for collision detection for UAVs.

The remainder of this article is organized as follows. In Section II, we review related work on the LGMD models and UAV collision detection. In Section III, our proposed model is formally described with formulations. In Section IV, materials and the experimental setup are described. In Section V, the results of experiments are presented and discussed. Section VI concludes this article.

II. RELATED WORK

In this section, we review the traditional methods used in UAV collision detection. This is followed by a consideration of bioinspired approaches. Finally, recent relevant biologic studies on the locust LGMD are introduced.

A. Traditional UAV’s Collision Detection

For UAVs, visual collision detection systems can be categorized into two strategic approaches. One is to sense depth and escape when an obstacle is located at a given distance. The other one is to utilize monocular features in the recognition of obstacles or potential risks of collision, without sensing depth. The first approach requires real-time knowledge about the 3-D environment. This can be obtained with the use of a stereocamera [16], LIDAR [17], [18], optic-flow-based distance maintenance [19], [20], or SLAM [3]. Such methods
are commonly used in UAVs that have sufficient power. However, they cannot discriminate between objects. They simply compute the distance to every object in the whole field of view (FoV), which requires excessive calculation power. Interestingly, in nature, only higher species or predators present depth-based detectors, whereas insects tend not to be able to perceive "depth" due to limitations resulting from the spacing between their eyes and the lack of overlap in their binocular field. As a consequence, they sacrifice accuracy for a gain in efficiency by making use of basic monocular visual cues that allow them to sense the risk of collision or danger.

The second strategy is to make plenty of use of monocular visual features, including, but not limited to, color, size, and image motion. For example, one can use a speed-up robust feature (SURF) algorithm to recognize objects by feature-point matching and avoid the objects in the frontal area [21], [22]. However, recognizing the object is not necessary nor sufficient for detecting potential collisions. It is indirect and, therefore, neither robust nor efficient. Based on the observation that images of looming objects expand rapidly and in a non-linear way in the run-up-to collision, some studies attempt to detect the expansion of image edges in order to identify approaching obstacles. For example, a SURF algorithm and a template matching method have been employed to detect the relative expansion of a looming object [23]. In addition, a scale-invariant feature transform (SIFT) algorithm and template matching have been used to detect the relative expansion [24]. Generally, these traditional recognition methods demand considerable computational power for handling data in complex dynamic scenes.

B. Bioinspired Collision Detection

Animals have evolved with efficient sensor systems specialized for their living environments, and many insects are equipped with a designated visual system for flight. For example, optic flow is such an insect (the fly)-inspired method for visual motion perception. The field of optic flow can be used for estimating UAV’s ego-motion [25] or collision detection by maintaining the balance of bilateral optic flow [19], [26]. However, it is not effective for detecting head-on collisions. In a complementary approach, the optic flow has been combined with the ability to detect expansion. This led to a head-on collision detection system based on divergent optic flow [27], [28].

LGMD is a visual neuron found in the locust’s vision system to provide collision detection. Its characteristic looming selectivity largely arises within its dendritic fan [29]. Because of its compact size and specialized sensitivity to looming objects, computational studies have modeled and applied the LGMD network to robots for head-on collision detection [7], [12]. In engineering applications, a typical LGMD network can be treated as three stages of the image process.

1) Motion information extraction and image preprocessing.
2) Simulated synaptic computation, including local interaction and global summation. This is the key stage of an LGMD model that underlies the ability to discriminate looming information.
3) Output signal process (to reduce noise and enhance the interested information).

A successful hypothesis for modeling the defining feature of the LGMD model (stage 2 process) is proposed by Rind and Bramwell [4] in 1996, which points that the LGMD neuron can extract fast-moving edges through the “critical race”1 formed by excitation and lateral inhibition. Based on this hypothesis, it can be deduced that a looming object can be identified by its fast-moving edges and the angular size that it occupied on the retina. After that, many researchers developed this model through image preprocessing or postprocessing. For example, Yue and Rind [12] introduced an extra grouping layer to enhance the clustered output and improve the performance. Fu et al. [30] proposed on and off pathways in the first stage and focused on dark objects in a light background. Another paper [31] feeds back the global intensity to mediate the inhibition weights in order to acquire adaptive sensibility according to different background complexity. Meng et al. [32] introduced additional cells in the third stage to acquire the change rate of the converged output so that the model can predict approaching or receding movements. He et al. [33] introduced image moment in preprocessing to enhance the resistance against ambient light change. However, these studies mainly contributed to stage 1 or 3 because it is still not exactly known how the synapses corporate to achieve looming information extraction, and it is hard to propose a new biological plausible model to mimic the synaptic process. Besides, there is another hypothesis about the LGMD’s synapses claimed that the synaptic interactions can involve multiplication [34], and based on this, Bermudez [35] modeled the presynaptic layer from the inspiration of (Reichart correlator-based EMDs [36]) to detect expanding edges. However, their model requires a unique preprocessing to predict expanded images, which has no evidence supported in biology. Despite this, because it is another related work to model the presynaptic interactions, we will also compare this model in Section IV-D.

Unfortunately, in agile UAV flights, the complex dynamic image motions generate spurious signals and will challenge the existing LGMD models with false positives. These false positives can hardly be solved by preprocessing or postprocessing, demonstrating that the synaptic interactions (in stage 2) of existing models are too simple to discriminate spatial-temporal patterns as we expected.

C. Emerging Biological Findings About LGMD

Due to technology development, recent biology can go further to explore the interneuron connections of the LGMD’s dendrite. Recent biological studies have highlighted the importance of the retinotopic reciprocal connections within the dendritic area. It is also reported that both excitatory and inhibitory presynaptic connections have a degree of overlap [14], [37], which is different from existing LGMD inspired models [6], [8], [10], [30]. Zhu et al. [13] suggested that the distributed excitation increases in response to coherently expanding edges. To conclude, these findings indicate that dendrites receive finely distributed retinotopic projections from the photoreceptors and interact with neighboring synapses before they

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1 Excitation caused by an edge motion must move fast to escape from the impact of laterally distributed inhibition; otherwise, it will lose the race and cannot reach the threshold to activate downstream synapses.

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the use of nonlinear angular velocity for collision detection.

and endows with the potential to be applied on microembedded systems.

The proposed presynaptic filter is based on linear processing in complex scenes. Compared to traditional visual methods, our model exhibits greatly enhanced robustness as a result of the spatial–temporal structure of synaptic activity is determined by an overall spatial–temporal distribution in the distributed presynaptic connection (DPC) layer. In experiments, selective response to images with different angular velocities is initiated after the retinotopic mapping in the DPC layer and before the postsynaptic inhibition [the feedforward inhibition (FFI)], demonstrating that the DPC process has successfully simulated the preference for looming of LGMD neuron. As a result, our model exhibits greatly enhanced robustness in complex scenes. Compared to traditional visual methods, the proposed presynaptic filter is based on linear processing of luminance change, which makes it computationally efficient and endows with the potential to be applied on microembedded systems.

III. MODEL DESCRIPTION

This section formulates the proposed distributed presynaptic connection-based LGMD model (named “D-LGMD”). Considering that the neural process is continuous, the whole model is reformed in continuous integral format, but the contribution of this article is focused on stage (2) process of LGMD. Besides, in order to retain the looming selectivity during complex background motion, some modification has been made to the threshold process in Section III-D.

A. Mechanism and Schematic

As determined from geometric analysis, the image of an ideal looming object shows a sharp nonlinear expansion as the object nears the collision point. The angular size and angular velocity of the image both increase nonlinearly [38], as shown in Fig. 2. The nonlinear angular velocity symptom of a looming object is very unlikely to be produced by other sources of visual stimuli, such as receding or translating objects. Therefore, we aim to form a spatial–temporal filter in the DPC layer to discriminate angular velocities of images on the retina. Following the idea of “critical race” by Rind and Bramwell [4], the DPC layer boosts signals derived from fast-expanding edges of looming objects and eliminates interfering stimuli caused by other visual sources. Different from previous models [10], [12], [30], the proposed DPC layer can achieve accurate image angular velocity preference through a combination of locally distributed excitatory and the spatial–temporal race against inhibition.

A schematic of the proposed D-LGMD model is presented in Fig. 3. The D-LGMD model is comprised of three stages of image processing: 1) motion information extraction (photoreceptors); 2) synaptic local interaction and global summation; and 3) output feedback or forward and feature enhancement. The photoreceptors extract image motion and divide it into excitatory and inhibitory pathways. Then, the synapses interact with neighbors through the morphologic mapping in the DPC layer. After that, inhibition and excitation sum up and will be thresholded after grouping and decay (GD). In addition, the feedforward inhibition (FFI) component, as a side pathway of postsynaptic inhibition [39], mediates the threshold to regulate output MP within a dynamic range. This function is termed FFI mediated grouping and decay (FFI-GD).

Finally, a single output terminal, of which the MP reflects the threat level of collision in the whole FoV, instructs...
downstream motion systems to avoid collisions. The morphology of the proposed D-LGMD is shown in the neural model in Fig. 4. In summary, there are three main differences compared to previous LGMD models.

1) Excitatory and inhibitory synaptic pathways are both locally distributed and interact with neighbors. They compete in space but also boost coherently expanding edges if they win the competition.

2) The inhibitory latency is radially distributed and increases as the transmission distance extends. This pattern of latency boosts the competition between excitatory and inhibitory synaptic afferents.

3) In the side pathway, FFI no longer switches off the output MP. It mediates the decay threshold after grouping. This new mechanism keeps the output MP in a dynamic range and enables the detector to remain sensitive to looming stimuli in a rapidly changing FOV (as occurs during attitude motion).

B. Photoreceptor Layer

The first layer of the proposed model is a photoreceptor layer (P layer). To behave as a motion-sensitive visual model, the input layer monitors changes in the absolute luminance hitting each pixel

\[ P(x, y, t) = |L(x, y, t) - \int L(x, y, s) \delta(t - s - 1) ds| \]  

where \( \delta \) is the unit impulse function, \( P(x, y, t) \) denotes the change in luminance of pixel \( (x, y) \) at time \( t \), and \( L(x, y, t) \) refers to the luminance at time \( t \). The P layer responds to all image motion equally and does not discriminate between backgrounds or foregrounds, translational, receding, or looming movements.

C. DPC Layer

Below the P layer, image changes of the whole FOV are extracted, and only the information on moving edges is input to the subsequent DPC layer. The proposed DPC layer defines the second stage of the D-LGMD process, which is the key stage that forms the looming selectivity. This layer enhances stimuli from images of looming or high-speed objects and inhibits those from objects involved in lateral translation or from the background. Fig. 3(b) illustrates the DPC process in pixel manner. Note both the excitation and inhibition are locally distributed. In relation to the current body of research, concerning the LGMD neuron in locusts, the characteristic of the DPC layer is consistent with the following principles.

1) Both excitatory and inhibitory pathways are locally interconnected [14].

2) The strength of connection tapers along the diameter from the root toward the dendritic tip [40], [41].

3) The time race between excitation and inhibition is essential for the preference to image angular velocity [4].

We have, therefore, constructed the DPC layer with two distributions for excitatory and inhibitory pathways. Furthermore, the time race between excitation and inhibition is integrated into distribution functions as follows:

\[ E(x, y, t) = \iint P(x, y, t) W_E(x - u, y - v) du dv \]  

\[ I(x, y, t) = \iint P(x, y, t) W_I(x - u, y - v, t - s) du dv ds \]  

where \( E(x, y, t) \) and \( I(x, y, t) \) are excitation and inhibition at each pixel, respectively. \( W_E \) and \( W_I \) are the distribution functions of excitation and inhibition, respectively. In relation to principle 3, \( W_I \) contains distributions not only in the spatial domain but also in the temporal domain. In agreement with principle 2, a Gaussian kernel is chosen to describe the two distributions in the spatial domain

\[ \begin{align*} 
W_E(x, y) &= G_{\sigma_E}(x, y) \\
W_I(x, y, t) &= G_{\sigma_I}(x, y) \delta(t - \tau(x, y)) 
\end{align*} \]  

(4)

In (4), \( \sigma_E \) and \( \sigma_I \) are standard differences of excitation and inhibition distribution (note that, in application, another parameter \( r \) will be involved to limit the size of the kernels\(^2\)). \( \tau(x, y) \) is the temporal mapping function of inhibitory pathways. The latency is distance determined and increases as transmission distance extends

\[ \tau(x, y) = \frac{1}{\beta + \exp(-\lambda^2(x^2 + y^2))} \]  

(5)

In (5), \( \alpha, \beta, \) and \( \lambda \) are time constants. An example of the temporal latency distribution is shown in Fig. 5 (note that, when \( \alpha = \beta = \lambda = 0, \) \( \tau(x, y) = 1 \)). Time latency is necessary to form the spatial–temporal race between excitation and inhibition, which has been well-explained previously [4]. In this research, we further put forth that the radially extending temporal distribution sharpens the output curve because it

\(^2\)In application, \( r \) can be smaller as long as it is plenty to possess the characters of the spatial–temporal mappings adequately.
Fig. 6. Contrast of inhibitory impact received by slower stimulus (A) and faster stimulus (B) under different time latency types. The time latency \( \tau(x, y) \) is constant in (a) while radially distributed in (b) (with this in mind: a single \( \tau(x, y) \) ). 1 frame delay for 1 pixel distance and 2 frame delay for 2 pixel distance, is given as an example of radially distributed latency. In (a), with constant latency, inhibition passes to the latest frame \( t_2 \) are “isolated” (indicated by blue arrows), no matter the stimulus moves slow (A) or fast (B). In (b), with radially extending latency, inhibition passes to \( t_2 \) is accumulated at position A, where stimulus A receives “replicate” inhibitory impact (indicated by red arrows). Contrarily, stimulus B completely escapes from the range of the impact, and therefore, it is released from inhibition. This demonstrates that a radially distributed latency \( \tau(x, y) \) will selectively enhance the inhibition to slowly changing stimuli and let through the preferred (fast) stimuli. (a) Constant \( h(t) \) = 1. (b) Distributed \( h(t) \).

produces a gradient in the temporal domain for inhibition. It, thus, selectively enhances the barrier against visual cues that are comparatively slow. Fig. 6 elucidates this mechanism by comparing the inhibitory impact under constant latency [see Fig. 6(a)] and radially distributed latency [see Fig. 6(b)]. In Fig. 6(a), both stimulus A (the slow one) and stimulus B (the rapid one) at \( t_2 \) only receive an “isolated inhibition” (indicated by blue arrows) from the previous time stage \( t_1 \). In contrast, with distributed latency in Fig. 6(b), stimulus A receives “replicate inhibition” (indicated by red arrows) from both the previous stage \( t_1 \) and the before-previous stage \( t_0 \), while stimulus B completely escapes from the inhibitory range. Therefore, the radially extending latency distribution allows the rapid/preferred stimuli to stand out in the model (more discussion about the advantage of radially distributed latency is given in Section IV-C).

Subsequently, the distributed interconnections, excitation and inhibition, are integrated by a linear summation (note that inhibition has the opposite sign against excitation)

\[
S(x, y, t) = E(x, y, t) - a \cdot I(x, y, t). \tag{6}
\]

In (6), \( S(x, y, t) \) is the presynaptic sum corresponding to each pixel at time \( t \), and \( a \) is the inhibition strength coefficient. Since, in addition, synapses stimuli are not suppressed to give negative values, a rectified linear unit (ReLU) is introduced

\[
S(x, y, t) = \text{ReLU}(0, S(x, y, t)) \tag{7}
\]

where \( \text{ReLU}(x) = \max(0, x) \).

Using the above formulations, the DPC layer forms a spatial–temporal filter, of which the input comprises the motion of the image, and the output consists only of coherently edges from dangerous looming objects whose image on the retina moves relatively fast. Under the DPC manipulation, the temporal information of the image, which results from the latency between E and I pathways, cooperates with the spatial distribution and determines the character of preferred angular velocity. Specifically, the coherent excitations will mutually enhance but must move faster to escape from the rejection band; otherwise, they will be inhibited. Therefore, only rapidly changing profiles of truly dangerous looming objects stand out after information has passed through the “spatial–temporal filter,” while the stimuli caused by slowly translating objects or backgrounds are dramatically attenuated and are further eliminated by the threshold in the subsequent layer. The spatial–temporal distributions \( W_E, W_I, \) and \( \tau(x, y) \) regulate the competition between excitation and inhibition; therefore, they are critical to shaping the selectivity for objects with different angular velocities. Importantly, since the DPC layer discriminates on the basis of angular velocity, if an object is close enough, to the extent that it occupies a large area of the retina and laterally translates at an extreme angular speed, it is also labeled as a “dangerous target.” As a consequence, the model triggers an alarm. This character is consistent with empirical experiments that show locust behavior toward a sudden translational movement [42].

D. FFI Mediated Grouping and Decay

The output of the DPC layer is sent to a grouping and decay (GD) layer and to further reduce the noise and smooth the output. The grouping mechanism allows clusters of excitation from the DPC layer to easily pass to its corresponding GD counterpart and provides a greater MP output. This mechanism is implemented by multiplying the summation in the DPC layer with a passing coefficient \( C_e \) as in the following equation:

\[
G(x, y, t) = S(x, y, t) \cdot C_e(x, y, t) \tag{8}
\]

where \( G(x, y, t) \) is the excitation that corresponds to each dendritic cell in the \( G \) layer and \( C_e \) is the integration from its neighborhood and is given by

\[
C_e(x, y, t) = \iiint_{\Omega} S(x, y, t) \cdot k dx dy \tag{9}
\]

where \( k \) is a constant and \( \Omega \) is the neighborhood area. \( \Omega \) is set to be a \( 4 \times 4 \) matrix in this article. \( G \) layer is followed by a threshold to filter out decayed signals

\[
\tilde{G}(x, y, t) = \begin{cases} G(x, y, t), & \text{if } G(x, y, t) \geq T_{de}(t) \\ 0, & \text{otherwise}. \end{cases} \tag{10}
\]

After that, a decay threshold \( T_{de}(t) \) is involved to reduce the interneuron output of inactive afferent. \( T_{de}(t) \) is mediated by the results of side pathway postsynaptic inhibition, the FFI, and is given by

\[
T_{de}(t) = \frac{\text{FFI}(t)}{n_{cell} \cdot m} \cdot T_0. \tag{11}
\]

\( T_0 \) is the baseline threshold, \( n_{cell} \) is the total number of pixels in a single frame, and \( m \) is a constant. \( \text{FFI}(t) \) is calculated by the previous image changes in the whole FoV, calculated as follows:

\[
\text{FFI}(t) = \iint |P(x, y, t - 1)| dx dy ds. \tag{12}
\]
The side pathway FFI no longer switches off the output MP but mediates a threshold level for all single-synaptic afferents according to the luminance change in the FoV. This new FFI-GD mechanism further suppresses the edges caused by background motion and keeps the output MP within a dynamic range. Moreover, it preserves the ability of D-LGMD to work in complex and dynamic scenes.

E. LGMD Cell

Finally, the MP of the LGMD cell \( K(t) \) is the summation within the G layer derived from the whole FoV

\[
K(t) = \int \int |\vec{G}(x, y, t)| dx dy. \tag{13}
\]

If the MP \( K(t) \) exceeds the threshold, a spike-like response is produced

\[
S^\text{spike}_f = \begin{cases} 
1, & \text{if } K(t) \geq T_{MP} \\
0, & \text{otherwise}. 
\end{cases} \tag{14}
\]

In application, an impending collision can be confirmed if successive spikes last consecutively for no less than \( n_{sp} \) frames

\[
C^\text{LGMD}_f = \begin{cases} 
1, & \text{if } \sum_{f=n_{sp}}^{} S^\text{spike}_f \geq n_{sp} \\
0, & \text{otherwise}. 
\end{cases} \tag{15}
\]

The LGMD detector will generate an “avoid” command to the quadcopter if the spikes last \( n_{sp} \) frames. Regular parameters are listed in Table I. These parameters are consistent in all the conducted experiments.

IV. EXPERIMENT RESULTS AND DISCUSSION

The proposed D-LGMD model includes a spatial–temporal filter, which allows discrimination of angular velocity and warns of an imminent collision when the output MP exceeds a specified threshold. Systematic experiments were conducted with the aim of assessing the capability of the D-LGMD model when operating in different visual scenes. We conducted both qualitative comparisons with other LGMD models to reflect the success of the proposed synaptic mappings and also quantitative parameter sensitivity experiments to analyze the feature of D-LGMD. Both simulation and real flight first-person-view (FPV) video experiments demonstrate that the proposed D-LGMD model has enhanced selectivity to looming. This is particularly the case when the quadcopter performs agile flight in complex visual scenes.

### TABLE I

| Parameter | Description | Value |
|-----------|-------------|-------|
| \( k \) | Amplifying constant in Eq. (9) | 1 |
| \( L_0 \) | Threshold baseline in Eq. (11) | 0.5 |
| \( m \) | Constant coefficient in Eq.(11) | 0.4 |
| \( T_{MP} \) | LGMD spiking threshold in Eq. (14) | 0.4 |
| \( n_{sp} \) | Minimum spikes to alarm in Eq. (15) | 2 |

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because the D-LGMD model is sensitive only to the preferred image angular velocity and not to other visual cues. It is, therefore, more effective at distinguishing between an object that is closing dangerously, and one that is far away. Similarly, the D-LGMD model also demonstrated a greater capability to reject receding objects than LGMD model 1, as can be seen from Fig. 9(b). Hence, analogous to working characteristics of the real LGMD neuron of a locust when facing receding objects [5], the MP of the D-LGMD model dropped to zero soon after the initial activation. In contrast, the LGMD model 1 did not demonstrate the ability to effectively ignore receding objects. This result indicates that the proposed D-LGMD model is robust against receding interfering stimuli.

We designed the proposed DPC structure as a spatial–temporal filter with the purpose of selectively attenuating the signal in reaction to the different angular velocities of the images. Here, we can define the “attenuation” of the DPC layer as the log-transformed function of the summation of DPC pixels and summation of input luminance changes

\[
\text{Attenuation}(t) = 10 \log \left( \frac{\int \int S(x, y, t) dx dy}{\int \int P(x, y, t) dx dy} \right)
\]  

(16)

Experiments demonstrate that the attenuation is greatly dependent on the angular velocity of the image. For example,

![Fig. 8. Dissection of each layer’s image process with unity rendered input scene. For better resolution, the P layer, S layer, and G layer results are transformed to a heat map and presented with a color bar. (a) Example of Unity generated input scenario. (b) Sampled frames of each layer (the whole approaching process lasts 82 frames, and the presented figures are sampled at 1, 50, 65, 75, and 80 frames, respectively). It is noted that, in the heat map, the intensity tends to be congested to the two extreme ends of the color bar, as the results of the DPC filter.](image)

![Fig. 9. Comparative response for (a) looming and (b) receding object between the LGMD and D-LGMD models. The input stimuli are simulated image sequences of a looming or receding cube (sampled and stamped on the graph).](image)

Fig. 10 illustrates the changes in attenuation by the D-LGMD model during a looming process. The attenuation of the LGMD model was moderate when reacting to relatively lower angular speeds as shown in the initial stages and steadily became less intense (i.e., less negative) as the object moved closer. In contrast, the attenuation by the D-LGMD model was stronger (i.e., more negative) during the initial period and showed a sharper reduction (i.e., became less intense) near the collision point. This means that the D-LGMD model has a much stronger ability to discriminate between the stimuli since the angular velocity of a looming object always increases in a nonlinear way.

**C. Parameter Sensitivity Analysis**

The response preference of the D-LGMD model is determined by the spatial–temporal distribution. In this section, we discussed several parameters which are critical to define this preference. These comprise the inhibition strength \(a\), standard deviations of excitation and inhibition distributions \(\sigma_E\) and \(\sigma_I\), and time race coefficients \(a, \beta,\) and \(\lambda\). Parameters sets used in later experiments are listed in Table II for comparison. Please note that parameter sets 1–3 present the D-LGMD model without radially distributed latency (when \(a = \beta = \lambda = 0\) and \(\tau(x, y) = 1\)), and they will be compared in Fig. 12(a).
Fig. 11. Attenuation analysis in relation to image speed. The input stimuli consist of translating cubes at four different velocities: 1, 2, 3, and 4 (pixels/frame), which is equivalent to 9, 18, 27, and 36 ($\circ$/s) in a 120$\circ$, 30 frame rate camera. Note the color in each subpicture represents a different intensity of attenuation. In general, the attenuation is much stronger for objects with relatively lower speeds. Note that this figure helps to understand the speed selection of the DPC structure. For example, if the parameters are located in the blue region of the top-left subfigure, considering that this region almost does not suppress pixels at speed 2, 3, and 4 in the other subfigures, this will be a filter that selectively suppresses pixels moving at speed 1 pixel/frame.

Fig. 12 demonstrates the advantage of radially extending latency, whose morphological mapping is tuned by time race coefficients $\alpha$, $\beta$, and $\lambda$. The radially distributed latency $\tau(x,y)$ sharpened the normalized output curve of both MP and normalized MP. Moreover, in the enlarged details of Fig. 12(a), the parameter sets that presented weaker responses in the beginning climbed over in the later looming period. This indicates that, as the parameter $\sigma_I$ increases, the performance improves not only during the looming period (with a stronger output MP) but by showing stronger attenuation when the stimuli are of lower angular velocities. In this case, adjusting $\sigma_I$ for a stronger response to stimuli in the looming period does not sacrifice the attenuation toward stimuli that are far away. This occurs because the radially distributed time latency makes it easier for stimuli of higher angular velocities to win the inhibition race, as explained previously in Fig. 6.

D. Performance in UAV FPV Videos

Finally, the model was challenged with recorded real flight videos. Various input scenes were tested, including a cluttered indoor environment, taking off, multiaxis attitude motion, self-rotation, acceleration, and deceleration. Details of the input sequences are listed in Table III.

In the beginning, the D-LGMD model was challenged by the aforementioned conundrum (the same scene as Fig. 1) during agile flight (input sequences: group 2). The results are presented in Fig. 13. We compared the performance in the same scene of three models: our previous LGMD
Fig. 13. Response of three LGMD models toward the aforementioned conundrum i.e., input the same scene with Fig. 1 (input sequences: group 1, D-LGMD parameters: set 9; and example frames are sampled at: 1, 35, 50, 80, and 100). LGMD model 1: our previous LGMD model applied in simple UAV flight [10]. LGMD model 2: the EMD-based multiplicative LGMD model by Bermudez et al. [35]. Red triangle: first false-positive peak of LGMD result; red star: the collision point. The flight experienced five periods as labeled in (f): (i) hovering, (ii) pitching, (iii) accelerating, (iv) approaching obstacle (looming), and (v) program controlled decelerating (to avoid hardware damage). Note that the false positive of LGMD model 1 and 2 in periods (ii) and (iii) is eliminated in the output of D-LGMD model. (a) Gray samples. (b) P layer samples. (c) DPC layer samples. (d) G layer samples. (e) Colourmap. (f) Normalized output. 

model [10] (blue dashed curve), the EMD-based multiplicative LGMD model [35] (green dashed curve), and the proposed D-LGMD model with/without FFI-GD (yellow and purple curves). It is notable that both dashed curves experienced strong false positives in the pitching and accelerating period. While in contrast, the D-LGMD model remains almost silent in these noncollision periods. Instead, as it nears the collision point, the D-LGMD responded to a swift activation, and the output MP rises sharply to a high peak. The yellow curve (D-LGMD, without FFI-GD) demonstrates that a strong preference for looming emerges after the DPC structure; the performance is satisfactory so that it can even work without postprocessing. The purple curve (D-LGMD, with FFI-GD) shows that the FFI-GD strategy works well to eliminate small spikes and smooth the curve.

The D-LGMD was also tested in the same scene but changed a different obstacle with a different shape and pattern, as shown in Fig. 14 (input sequences: group 2), in order to
Fig. 14. Complex indoor flight (input sequences: group 2). The collision occurred at frame 140, and pitching and accelerating started at frame 40. Near frame 125 (the red circle), the quadcopter was program controlled to slow down (in order to reduce physical damage in the collision). Red triangle: first false positive in LGMD model, red circle: unexpected negative during program-controlled deceleration near the collision point, and red star: the collision point. Sets 3 and 7 each show a small response near frame 40 (pitching). This small response is eliminated in sets 6 and 8 when implemented with temporal distribution (set 6) or increased the calculating radius (set 8), respectively. Sets 3 and 6 were largely affected by the decelerating process and leading to drop downs near frame 120. This indicates that these two sets (with smaller \( \sigma_E \) and \( \sigma_I \) and calculating radius \( r \)) may not have consistent performance when faced with a decelerating looming object. (a) Input example. (b) Normalized output.

evaluate the parameter sensitivity (parameter sets 3, 6, 7, and 8). The selected parameter sets were not optimized but were chosen as follows.

1) Set 3 rarely has excitatory distribution, and the temporal latency is constant.
2) Set 6 involves distributed latency based on set 3.
3) Set 7 has wider spread excitatory and inhibitory distribution kernels but limits the calculating radius, which limits the size of the matrix in the DPC processing in realistic computing to 4 (\( r = 4 \) cannot fully reflect the kernel).
4) Set 8 involves extending the calculating radius to 6 and makes full use of the convolution kernel.

The results clearly show the different effects of modulating the parameters: sets 3 and 7 exhibit a small response near frame 40 (pitching). This small response is eliminated in sets 6 and 8 when adding temporal distribution or increasing the calculating radius, respectively. Sets 3 and 6 were largely affected by the decelerating process and led to a decrease in output MP near frame 120. This indicates that these two sets (with smaller \( \sigma_E \), \( \sigma_I \), and calculating radius \( r \)) may not perform consistently when facing obstacles during a deceleration.

The D-LGMD also worked well when faced with relatively simple backgrounds (see Figs. 15 and 16). The results show that both the LGMD and D-LGMD models are able to detect collision in these simple scenes. However, the results from the LGMD show that several small peaks remain during attitude motion. The attenuation curves provide further interpretation: the D-LGMD model showed stronger discrimination in different periods, strong attenuation is observed after taking off, and the attenuation curve prominently rose up during the looming periods. This demonstrates that, compared to the mussy image motions in the taking-off period, the model prefers the spatial–temporal pattern of the real looming object.

In addition, we challenged the D-LGMD model during self-rotation (yaw motion). Results in Fig. 17 indicate the D-LGMD model preserves the ability to discriminate looming cues during rotational flight.

E. Computation Complexity

The computational complexity of the proposed DPC layer is mainly determined by the 2-D convolutions of the input image sequences with \( W_E \) and \( W_I \) [see (2) and (3)], which can be implemented in \( O(2r^2mn) \) times for an \( m \times n \) input image and \( r \times r \) size kernel. In other words, the computational complexity is mainly determined by the calculating radius and input image size. (Calculate a formulation, including the latency with no latency comparison.) The calculating radius should cover a significant area of the kernel for its character to be established. Reducing input image size (provided that the image preserves important features of the looming process) would increase the ability to recognize a looming object because the D-LGMD discriminates between image velocities by pixel interconnections and resizing the input image size also redefines the kernel’s impact area corresponding to the real scene. Therefore, the D-LGMD model can work with extremely low-resolution input because reducing the image size makes the kernel cover a larger area and enhances the bar-
TABLE IV
COMPUTATION COMPLEXITY

| Calculating Radius (r) | Image resizing | Distinguish-ability (DA) | O (DPC) | PC Run Time (10 times average) |
|------------------------|----------------|--------------------------|---------|--------------------------------|
| 6                      | default        | 249.33                   | 2 × 6^4 × 1920 × 1080 | 9.18s  |
| 6                      | 0.5            | 978.28                   | 2 × 8^4 × 960 × 540  | 2.75s  |
| 6                      | 0.25           | > 10000                  | 2 × 6^4 × 480 × 270 | 1.06s  |
| 6                      | 0.1            | > 10000                  | 2 × 6^4 × 192 × 108 | 0.75s  |
| 6                      | 0.02           | 1354.10                  | 2 × 6^4 × 38 × 22  | 0.60s  |
| 4                      | default        | 33.44                    | 2 × 4^2 × 1920 × 1080 | 8.71s  |
| 4                      | 0.5            | 691.20                   | 2 × 4^4 × 960 × 540 | 2.54s  |
| 4                      | 0.25           | 4579.40                  | 2 × 4^4 × 480 × 270 | 0.98s  |
| 4                      | 0.1            | 1053.35                  | 2 × 4^4 × 192 × 108 | 0.70s  |
| 4                      | 0.02           | 184.54                   | 2 × 4^4 × 38 × 22  | 0.59s  |
| 3                      | default        | 9.1                      | 2 × 2^4 × 1920 × 1080 | 8.70s  |
| 3                      | 0.5            | 96.75                    | 2 × 3^4 × 960 × 540 | 2.53s  |
| 3                      | 0.25           | 1227.60                  | 2 × 3^4 × 480 × 270 | 0.97s  |
| 3                      | 0.1            | 36.13                    | 2 × 3^4 × 192 × 108 | 0.67s  |
| 3                      | 0.02           | 76.06                    | 2 × 3^4 × 38 × 22  | 0.57s  |
| 2                      | default        | 3.87                     | 2 × 2^4 × 1920 × 1080 | 8.67s  |
| 2                      | 0.5            | 11.09                    | 2 × 2^4 × 960 × 540 | 2.49s  |
| 2                      | 0.25           | 32.39                    | 2 × 2^4 × 480 × 270 | 0.95s  |
| 2                      | 0.1            | 11.76                    | 2 × 2^4 × 192 × 108 | 0.66s  |
| 2                      | 0.02           | 18.47                    | 2 × 2^4 × 38 × 22  | 0.57s  |

Note: DA is defined as the average output MP at peak point divided by average MP at false positive point:

\[ DA = \frac{\text{average}(MP_{\text{peak}})}{\text{average}(MP_{\text{false-positive}})} \]

The parameters used are consistent with set 7 in Table II (except r).

The input scene is Group 1 in Table III. The PC Run Time covers the whole process of loading 120 frames of input images and running the model.

Fig. 15. Simple indoor flight (input sequences: group 4) results of (b) output MP and (c) attenuation. Collision occurred near frame 210; attitude motion periods are annotated on (b). (a) Input example.

Fig. 16. Simple indoor flight-2 (input sequences: group 5) results of (b) output MP and (c) attenuation. Collision occurred near frame 198; attitude motion periods are annotated on (b). (a) Input example.

We systematically analyzed the relationship between the ability to recognize [distinguish-ability (DA)] to looming, the calculating radius, input image size, and computational complexity by 200 trials running on PC. The results are listed in Table IV. The DA is quantified as the average output MP near the peak apex (five frames before and after) divided by average MP at a false positive point [i.e., Fig. 13(f)].

\[ DA = \frac{\text{average}(MP_{\text{peak}})}{\text{average}(MP_{\text{false-positive}})} \]

Theoretically, when DA ≤ 1, it is impossible to select out looming cues from dynamic backgrounds during agile flight. From experimental experience, if DA > 10, the model is very competent at filtering out the interfering stimuli and is foreseen to be robust for a range of scenes. As the input size ranging from default to 50th of the area, the DA initially increased and then decreased. Using parameter set 7 (except r), for all the calculating radii, the best DA results existed when input images were resized to 0.25× default area (480 × 270 pixels). The proposed model showed satisfactory DA results even at extremely low resolution (38 × 22 pixels). An insufficient DA was generated only when computing the default size (1080P) input with \( r = 2 \), resulting in a DA = 3.87. This would mean that the looming object would be distinguishable but not sufficiently prominent.
F. Discussion and Future Direction

As shown and discussed in Section IV, the proposed D-LGMD model has been verified systematically via the experiments both qualitatively and quantitatively. The qualitative results shown in Figs. 8–10 indicate that the D-LGMD model is excellent in discriminating image motion caused by looming objects from that of receding or translating ones. The capability of the DPC layer in filtering image motion based on its angular velocity has been explained in Fig. 8 and further demonstrated in the Supplementary Material Video 1. The quantitative analyses shown in Figs. 11 and 12 reflect that the characteristic preference on image angular velocity is tunable in our model. More specifically, Fig. 11 also reveals how to tune this model to filter different angular velocities for different scenarios. It is also shown in Fig. 12 that a constant temporal latency will lead to less nonlinear selectivity looming compared with radially extending latency.

Experiment results in flying scenarios have been shown in Figs. 13–17, which demonstrated that D-LGMD is excellent to cope with agile flights in different scenarios. For example, D-LGMD (with/without FFI-GD) has been compared with the other two models, where D-LGMD is robust in the pitching and accelerating periods of an agile flight. The proposed D-LGMD model with different spatial–temporal mappings (sets 3–8) is compared in Fig. 14—all of them performed much better than the previous LGMD. It is interesting to note that unexpected output drops (indicated by a red circle) appeared just before the collision was detected. These drops, on the other hand, demonstrated that the D-LGMD’s robustness is very much dependent on a minimal synaptic distribution radius \( r \), which should possess the characters of the spatial–temporal mappings adequately. The attenuation analysis can help to compare filter efficiencies in signal processing. The attenuation analyses on the DPC layer shown in Figs. 15 and 16 further reveal that the proposed D-LGMD can significantly suppress irrelevant input image motions at different agile flying periods, particularly in the taking off, pitching, and accelerating periods.

Recent neural physiological studies [13], [14] have discovered new characteristics of LGMD neurons in locusts to be considered in the model. These cutting-edge studies suggest that the retinotopic connections from photoreceptors to the LGMD neuron could be more complex than currently modeled. It is also noticed that ON/OFF separated LGMD models have also shown their ability in replicating looming detecting capacity [30]. The performance of an ON/OFF
channel separated model with the spatial–temporal distributed synaptic mappings is also a research topic to be investigated in the future. It is also notable that the proposed D-LGMD is not sensitive to small size objects, such as wires, leaves, or small stones, because it discriminates looming objects based on its image angular velocity and size, which are not possessed by small size looming objects. Recently, small target motion detector (STMD) of dragonflies [43], [44] demonstrated superior capability in detecting small moving targets. In the future, it might be helpful to integrate STMD mechanisms [45], [46] to make sure that various sizes of collision threats are detected.

V. CONCLUSION

This article proposed a computational presynaptic neural network model as a solution for collision detection in agile UAV flight applications. The agile flight of a UAV brings ego-motion of the camera, which leads to confusing false positives in visual motion-based collision detection algorithms. Our solution is to target the neural filter on the nonlinear image angular velocity of looming objects. This is achieved by integrating a series of locally distributed synaptic mappings into the second stage of the LGMD process (in the DPC layer). The proposed DPC structure selectively builds the barrier against stimuli from translating and background objects that have relatively lower image angular velocities, while the spatial–temporal pattern of looming objects is preferred. In addition, using an FFN-GD mechanism, the D-LGMD model preserves the ability to detect collision during UAV agile attitude motions, including pitching, acceleration, deceleration, and self-rotation. Systematic experiments have demonstrated that the proposed model dramatically enhances the distinguishability of looming objects from agile-flight-derived background noise. Thus, the model is robust in handling complex dynamic visual scenes. Moreover, the proposed model functions well even with extremely small input image sizes (38 × 32 pixels). In fact, reducing the size of input images did not harm the performance but increased the distinguishability toward looming objects. This notable character is likely to deliver a key success factor in energy-limited applications, such as embedded systems and MAVs.

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