A Bio-Inspired Collision-Detection Framework with Feed-back Learning

PhD research proposal

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Contents

Abstract

Collision detection is a fundamental and pivotal requirement for the safe and efficient operation of autonomous systems. Designing real-time, robust, and low-cost collision detection solutions remains an open challenge. Mainstream approaches such as LiDAR and depth-based perception are typically expensive, power-intensive, and bulky, which makes them unsuitable for lightweight or resource-constrained platforms. In contrast, biological visual systems demonstrate remarkable motion perception and collision avoidance capabilities, inspiring the development of efficient artificial motion perception systems. However, most existing bio-inspired architectures are limited by feed-forward and fixed structures, constraining their adaptability in the ever-changing environments.

This project aims to develop, for the first time, an online learning framework for bio-inspired visual collision detection, exploring a feed-back architecture beyond conventional feed-forward designs. We focus on the LPLC2 neurons of the fruit fly, which exhibit ultra-selectivity to looming stimuli: (1) Developing the first bio-inspired collision detection model capable of forming adaptive selectivity through online feed-back learning; (2) Introducing dual-timescale learning to achieve both rapid adaptation and long-term stability in a lightweight model; (3) Drawing inspiration from lifelong learning in machine learning to investigate how this biologically observed property can enhance the capability of bio-inspired motion perception models.

The proposed model will be rigorously evaluated on both offline datasets and real robotic platforms, and benchmarked against state-of-the-art bio-inspired methods. We hypothesize that it will provide a lightweight, real-time, and adaptive collision detection paradigm, achieving robustness, selectivity, task accuracy, and latency comparable to current state-of-the-art models with only modest computational overhead. Importantly, under cross-scenario testing, the feed-back online learning model is expected to surpass all known bio-inspired collision detection models in adaptation.

Furthermore, it represents a lightweight alternative to large neural networks in vision-based autonomous systems, significantly reducing hardware and computational costs. Its cross-scenario adaptability will also expand the application range of autonomous systems requiring lightweight and robust collision perception. Beyond engineering applications, these findings may deepen our understanding of the intricate structures of biological systems and provide insights that foster a synergistic feed-back loop between biology, computer science, and robotics.

1 Introduction

1.1 Background

Collision detection is a fundamental requirement for ensuring the safe operation of autonomous systems[1,2]. Robust and efficient collision detection mechanisms hold broad applicability across domains such as autonomous driving[3], drone navigation[4–11], and ground mobile robotics. In safety-critical environments – including self-driving vehicles[3] and human–robot collaborative factories[12] – the ability to detect and predict potential collisions in real time is indispensable. Such capabilities provide the foundation for higher-level strategies such as avoidance planning, velocity adjustment, and emergency stopping.

Nevertheless, for autonomous robots operating in complex and unfamiliar environments, the design of effective and efficient collision perception solutions remains an open challenge, often constrained by the trade-off between computational cost and performance[1,2]. Machine learning-based collision detection methods often require large training datasets[3,13], while sensor-based approaches[9–11], such as LiDAR, are typically expensive and limited in application contexts[1,2] (see section 1.2.1 and 1.2.2). To address this tension between computational efficiency and robustness, increasing attention has been directed toward biologically inspired mechanisms, which offer compact yet highly effective solutions as demonstrated in natural organisms[14–20].

Over millions of years of evolutionary pressure, insects have evolved remarkably efficient neural systems in their miniature brains, enabling robust motion perception that supports behaviors such as mate chasing, predation, predator avoidance, and foraging[21]. In contrast to human vision, insect visual systems contain only tens of thousands of neurons organized into a few neuropils, yet they achieve rapid and precise collision detection[22]. Neural motion detectors in the insect visual pathway, which underlie this capability, have been extensively studied[14,23,25? –31]. Their combination of efficiency and robustness provides a strong biological basis for developing artificial collision-detection mechanisms.

1.2 Literature Review

1.2.1 Classical Collision Detection Solutions

Mainstream Hardware Analysis: In collision avoidance research with limited onboard resources, the choice of sensing hardware directly determines the real-time performance, energy consumption, and environmental

adaptability of the system. The mainstream sensors include LiDAR, RGB-D cameras, stereo cameras, millimeter-wave radar (MMW Radar), infrared cameras (IR Camera), and ultrasonic sensors[32–37].

LiDAR provides high-precision distance measurements and is suitable for complex 3D mapping tasks[36,37], but it is costly, power-hungry, and bulky, making it unsuitable for lightweight or low-power platforms. RGB-D and stereo cameras[38–40] achieve a balance between cost and resolution. However, RGB-D cameras—particularly structured-light types—are sensitive to ambient illumination, and strong or direct light can cause measurement errors. Stereo cameras rely on sufficient texture for disparity matching, so their depth accuracy degrades in low-texture or homogeneous environments. Millimeter-wave radar (MMW Radar) is robust under adverse weather conditions and capable of long-range detection, but its angular spatial resolution is relatively low, making it difficult to capture fine object contours. Infrared (passive or short-range ToF) and ultrasonic sensors are structurally simple and low-cost, but their detection range and spatial resolution are limited, rendering them unsuitable for complex obstacle recognition and fine-grained collision avoidance.

Mainstream Algorithm Analysis: Algorithmically, existing on-board collision avoidance methods can be broadly categorized into three classes: geometric optimization-based methods, learning-driven methods, and fusion-based modeling methods.

The first class is geometric modeling and trajectory optimization. For example, B. Zhou et al.[32] construct an Euclidean Signed Distance Field (ESDF) by fusing stereo depth maps; Park and Cho[36] build a collision cone model based on point clouds; Tordesillas et al.[39] fuse depth information from RGB-D cameras to generate ESDF/T-SDF maps. These methods can precisely represent obstacle boundaries but rely on global mapping or dense point clouds, resulting in high computational cost and slow response, and they often fail in fast dynamic scenarios.

The second class is data-driven and deep learning methods. In UAV collision avoidance research, deep learning-based vision methods[41–43] can directly extract obstacle features and generate avoidance strategies in an end-to-end manner. However, these approaches have significant drawbacks: first, they heavily rely on large-scale labeled data and training resources, and their models are typically large, resulting in long inference latency on resource-constrained platforms; second, even in lightweight designs, such as Carrio et al.'s deep learning system running on a small quadrotor, the onboard frame rate is only 16 Hz (about 62.5 ms per frame)[41], while Wang et al.'s RGB-D-based dynamic collision avoidance system requires less than 30 ms to build

the 3D occupancy grid in the dynamic perception module and less than 7 ms to generate local trajectories in the planning module[43].

The third class is fusion-based or multi-modal sensing methods, which integrate information from multiple sources to enhance robustness. For instance, H. Yu et al.[33] use an Extended Kalman Filter (EKF) to fuse optical flow and MMW radar features; Kong et al.[44] detect small obstacles using LiDAR OctoMap and ESDF; Lu et al.[40] construct real-time maps in parallel on GPUs. While these approaches improve certain performance metrics, they remain limited by high computational demands and accumulated latency.

Overall, traditional non-bio-inspired collision avoidance algorithms struggle to balance accuracy, real-time performance, robustness, and cost, leaving significant room for further exploration.

1.2.2 Biologically-Inspired Vision Systems

In contrast, bio-inspired approaches offer significant advantages in temporal resolution, computational efficiency, and robustness. Representative developments such as Intel's neuromorphic research chip Loihi 2[45,46] and event cameras (DVS)[47] demonstrate the potential of brain-inspired architectures to achieve ultra-low-power, event-driven computation through spiking neural dynamics. Similarly, the lightweight neural networks inspired by insects' visual system can perform millisecond-level or faster frame processing on extremely low-computation hardware, such as STM32 microcontrollers, enabling stable, low-latency real-time collision avoidance[17,48,49]. These characteristics make bio-inspired approaches particularly suitable for the application of real-time motion perception.

Hardware Level: The Bio-Inspired Dynamic Vision Sensor (DVS): Event cameras, as a neuromorphic vision sensor, are inspired by the biological retina and output asynchronous events representing changes in brightness rather than fixed frames. They provide microsecond-level temporal resolution ($\sim 1\,\mu$s), a dynamic range exceeding 120 dB, and extremely low data redundancy and power consumption[10,50,51]. This asynchronous event stream maintains stable output even in high-speed motion or strong light variation scenarios, significantly reducing computational load and energy consumption.

On robotic platforms, event cameras provide low-latency, low-power, and highly robust visual inputs for real-time collision avoidance and dynamic scene perception. In this project, we will explore integrating event cameras as a core perception module for subsequent neuro-dynamic visual models, while keeping compatibility with traditional frame-based, lower-cost cameras.

Algorithm Level: Bio-Inspired Collision Detection Model: Existing bio-inspired visual perceptual models span a wide range of functionalities, including small-target detection[52], collision detection[5,15,17,19,20,48,53–56], directional motion detection[57–59], and navigation guidance[60–63], among others. Some bio-inspired models have been tested in simulated robotic environments (e.g. the LPLC2-inspired)[8,20,61,64], while others (e.g. the LGMD-inspired) have been deployed on real robotic platforms operating in physical-world settings[4–7,17,65,66]. Their effectiveness has been demonstrated through extensive systematic experiments, including the analysis of confusion matrices on large offline datasets (covering true/false positives and true/false negatives) and online robotic experiments evaluating collision avoidance success rates across multiple robots, scenarios, and speeds.

Characterized by real-time processing, low computational demand, freedom from pre-training, and strong dynamic perception, these models show strong potential for next-generation artificial intelligence. Representative neurons in bio-inspired collision perception paradigms are the lobula giant movement detector (LGMD) neuron[22] and the lobula plate/lobula columnar type 2 (LPLC2) neuron[31].

1.2.3 Insect-Vision-Inspired Collision Perception Model

Locust-Inspired LGMD Collision Detector: Research on the Lobula Giant Movement Detector (LGMD) neuron began in the early 1970s, when collision-selective neurons were discovered in the optic lobe of locusts that respond specifically to approaching objects[14,23,67]. Initially, these large neurons were considered general motion detectors; however, subsequent studies established their specialized role as looming-sensitive neurons. Over the past two decades, LGMD-inspired models have evolved into low-power, fast, and reliable visual strategies for robotic obstacle avoidance[49]. For example, Hu demonstrated the first implementation of an LGMD model on a compact ARM-based board, verifying the feasibility of embedded vision for autonomous robots and achieving an average collision avoidance success rate of about 95% in laboratory experiments[17]. Later, Fu proposed a polarity-specific LGMD2 neural network model that improved selectivity, achieving up to 97.89% success rate in systematic experiments under controlled conditions[49]. With a more refined understanding of LGMD neuronal mechanisms[24,68], subsequent research has extended LGMD-based models to both ground and aerial robotic platforms. Most recently, the composite LGMD architectures have further enhanced robustness in complex natural scenes, achieving up to 96.25% avoidance success rate[69]. These results highlight the significant potential of insect-vision-inspired approaches in achieving robust

and real-time collision avoidance.

However, LGMD-based bio-inspired neural networks still face notable limitations, particularly in selectivity. The LGMD neuron possesses a massive dendritic tree covering the entire lobula structure; as a result, most LGMD-inspired computational models remain relatively coarse in spatial resolution. Although several studies have attempted to improve the selectivity of LGMD-based looming detection[48,70,71], these models are still easily disturbed by translational motion and illumination changes. Furthermore, the LGMD model typically only generates a global alert signal at the perceptual level, limiting its applicability in more complex decision-making or adaptive control frameworks.

Fly-Inspired LPLC2 Collision Detector: The fruit fly *Drosophila* provides a complementary source of inspiration for collision perception. Recent studies have revealed that the lobula plate/lobula columnar type 2 (LPLC2) visual projection neurons in the optic lobe possess distinctive anatomical features[31,72].

Specifically, single-cell analyses show that LPLC2 neurons exhibit cross-shaped dendritic trees, with each branch extending into a motion-sensitive layer aligned with its preferred motion direction. This morphology enables strong responses to outward motion emanating from the center of the receptive field. Each dendritic arm also receives directionally selective inhibitory inputs for inward motion, forming a mechanism of radial motion opponency that suppresses responses to contraction, wide-field translation, and luminance changes[31].

Motion Pattern	LGMD1	LGMD2	LPLC2
Dark Looming	2 (✔)	2 (✔)	2 (✔)
Dark Receding	1 (✗)	0 (✔)	0 (✔)
Bright Looming	2 (✔)	0 (✗)	2 (✔)
Bright Receding	1 (✗)	1 (✗)	0 (✔)
Grating Motion	0 (✔)	0 (✔)	0 (✔)
Translation	1 (✗)	1 (✗)	0 (✔)

Table 1. *Neural responses of LGMD1, LGMD2, and LPLC2 to various motion stimuli. 0: nearly silence; 1: weak response; 2: response. ✔/✗: ideal/non-ideal response for a looming detection system. The ultra-selective response of LPLC2 to looming motion makes it an ideal inspiration for motion detector design.*

This unique structure renders individual LPLC2 neurons highly selective – responding strongly to specific approaching motion patterns while remaining silent to non-collision-related movements, a property referred to

as *ultra-selectivity*. Such characteristics highlight the strong potential of LPLC2-inspired architectures for developing next-generation bio-inspired collision detectors. In comparison with the LGMD neurons in locusts, their responses to different types of motion stimuli can be summarized as shown in Table 1.

Motivated by these properties, several modeling efforts have been conducted. Zhou et al.[19] employed machine learning to capture LPLC2's selective tuning, while Hua et al.[73] modeled LPLC2 using nonlinear computations and ON/OFF channel mechanisms. Zhao et al.[20] further advanced this work through population encoding and nonlinear integration, demonstrating effectiveness in virtual robotic experiments. Shuang et al.[74] proposed an opponency-based looming detector inspired by LPLC2 synaptic processing. Liu and Fu[75] introduced an attention-driven mLPLC2 model capable of detecting and localizing multiple approaching targets. Most recently, Liu et al.[66] investigated leveraging LPLC2-inspired models to enhance robotic perception and motion in real-world environments.

However, our understanding of the complex anatomy of the Drosophila remains very limited. The lightweight, efficient, and robust collision perception capabilities of fruit flies continue to motivate further exploration.

1.3 Knowledge Gaps

Despite significant progress in modeling biological lightweight perception mechanisms, the field still lacks a critical capability that is fundamental to natural intelligence – the ability to continuously learn and adapt through real-time interaction with the environment.

Many models directly encode biological motifs into fixed network structures and manually chosen parameters[21,73], while others tune parameters via offline training[19,56,76]. Once optimized for a given dataset or scenario, these models cannot adapt during deployment, leading to performance degradation in novel conditions. The root cause is their *feed-forward architectures* without plasticity.

In contrast to current bio-inspired models that rely on fixed structures or pre-trained parameters, biological organisms never stop learning; they refine their neural representations as they move, sense, and act within changing surroundings.

1.3.1 Limitations of Existing LPLC2-Inspired Models

Existing LPLC2-based models are mostly built on biologically inspired feed-forward architectures. Although the unique structure of LPLC2 provides

strong selectivity, these models still struggle to replicate the robustness and adaptability observed in biological systems. In particular, adapting to different environments often requires parameter tuning for each specific scenario. For example, Hua et al.[73] first modeled a single LPLC2 neuron using simple multiplicative operations to integrate direction-selective motion signals from four directions. While they successfully achieved ultra-selectivity for looming objects, their experiments were limited to extremely simple motion patterns and scenes. In Zhao et al.'s modeling, a similar neural approach as in Hua et al. was adopted. While they also successfully reproduced ultra-selectivity in a single neuron, responses remained noisy in complex scenes (as discussed in the paper). They eventually employed a population coding strategy to shape the responses of LPLC2 neural clusters, enabling relatively robust collision detection. However, the number of experiments in complex backgrounds and real-world scenarios remained extremely limited, similar to Liu et al.[75], leaving performance across diverse scenarios uncertain. Liu et al.'s latest work[66] brought LPLC2-inspired models into real-world applications for the first time. Nevertheless, their focus was on exploring the benefits of *Drosophila*-inspired attention-based collision avoidance in miniature robotic systems, rather than developing a robust, truly cross-scenario ultra-selective collision perception model.

It's notable that Zhou et al. used machine learning to achieve responses similar to biological LPLC2 neurons across different motion patterns[19]. However, the trained model essentially represents a two-dimension filter with different weights, and all datasets consisted of computer-generated simple spherical objects without any background noise. Although this work represents a significant exploration of selectivity through machine learning, the reliance on synthetic datasets and large-scale offline training confines the model to a simulated level, limiting its applicability to real-world scenarios.

In contrast, *Drosophila* can rapidly detect threats and escape in any environment, whether indoors or in complex, cluttered outdoor scenes. How do they achieve truly robust, interference-resistant ultra-selectivity?

The ability of biological systems to continuously interact with their environment and learn from it may hold the key to addressing this problem[77,78]. In this project, we aim to endow a bio-inspired visual system with online learning capabilities that allow it to continuously interact with and learn from its environment, thereby shaping a truly robust neural network capable of operating across diverse environments, similar to the adaptability exhibited by the biological organism.

1.3.2 Insights from Lifelong Learning in Machine Learning

In the broader machine learning community, the paradigm of lifelong learning (or continual learning) has emerged as a critical step toward creating adaptive and autonomous agents[77]. Unlike traditional models that rely on large-scale pretraining or fixed offline datasets, lifelong learning emphasizes continuous adaptation through interaction with the environment[77,78], enabling systems to integrate new experiences without catastrophic forgetting[79].

To address this challenge, the lifelong learning community has developed a variety of effective mechanisms to preserve stability while maintaining plasticity. Representative examples include elastic weight consolidation[80], which stabilizes important parameters through synaptic-like regularization; experience replay, which mimics biological memory by selectively revisiting past experiences[81]; and modular or dynamically expandable architectures, which allocate new capacity when encountering unfamiliar sensory patterns[82–84]. Recent advances also integrate meta-learning[85] and self-stabilizing plasticity rules to enable rapid adaptation with minimal interference to existing knowledge. Together, these techniques allow artificial systems to remain plastic yet stable – an essential property for agents operating in non-stationary and open-world environments.

These advances provide conceptual inspiration for the bio-inspired perception community, which has so far focused more on structural imitation[21,22] than adaptive learning dynamics. Instead of directly adopting the complex mechanisms developed in lifelong learning, our aim is to distill their core principles – such as stability-plasticity balance and experience-driven adaptation – and integrate them into lightweight, real-time bio-inspired visual systems. By incorporating these ideas, bio-inspired models could evolve from static feed-forward detectors into efficient, self-adaptive learners capable of maintaining robust and context-aware perception across diverse environments, much like fruit flies in nature.

2 Objective and Scientific Questions

Real-time, efficient, robust, and low-cost collision detection systems are of significant practical importance – they form the core of autonomous navigation, UAV obstacle avoidance, and self-driving technologies. Bio-inspired collision detection models based on insect visual systems are known for their low energy consumption, minimal computational overhead, and strong real-time performance, making them particularly advantageous for platforms with limited computational resources. However, existing bio-inspired models are mostly based on fixed feed-forward architectures, lacking the ability to continuously adapt to open and dynamic environments, which limits their suitability for long-term continuous operation.

Therefore, our research objective is:

> **Enable bio-inspired visual collision-detection neural networks to continuously adapt to varying scenes and environmental conditions during operation, thereby achieving online, lifelong adaptability similar to that observed in biological systems.**

From this objective, we derive the following research questions:

RQ 1. Can the collision selectivity of bio-inspired neural networks (e.g., the ultra-selectivity of LPLC2 neurons) be achieved through online learning?

Success criterion: Achieve ultra-selectivity to looming patterns among various motion types, similar to that of real LPLC2 cells reported by Klapoetke et al.[31], and to attain a comparable level of collision-detection accuracy compared to existing bio-inspired looming detectors under equivalent computational constraints.

RQ 2. How can a bio-inspired collision-detection model rapidly adapt to new operational scenarios and environmental changes?

Success criterion: The model should achieve rapid adaptation in sequentially presented unseen environments, reaching collision-detection accuracy comparable to parameter-optimized state-of-the-art bio-inspired models in each environment. It should also be capable of continuously performing online learning under dynamically changing conditions, achieving effective adaptation to each new environment with only a small number of data samples.

RQ 3. How can lightweight bio-inspired neural networks with environmental adaptability overcome catastrophic forgetting, particularly under constrained onboard computational resources?

Success criterion: Retention of at least 80% of prior-task performance (accuracy retention), acknowledging that earlier tasks may exhibit lower retention, after sequential collision-detection learning across different environments, with only marginal increases in model complexity or latency within acceptable onboard limits.

Hypothesis: We hypothesize that a model successfully addressing the above research questions will: (1) remain lightweight; (2) operate in real time within limited onboard resources; and (3) acquire online learning capability to adapt across diverse environments and approaching-object velocities. Such a system would constitute a real-time, robust collision-detection network, exhibiting adaptive performance and environmental resilience comparable to that of fruit flies.

3 Significance and Contribution

a. Theoretical Significance:

Towards Current Feed-forward Framework: By drawing inspiration from biological processes of learning and evolution, for the first time, this project will develop a lightweight bio-inspired neural network for collision detection with real-time *online learning capability*, thereby enhancing robustness and enabling cross-environment adaptability.

Model	Architecture	Learning	Mode	Selectivity	Deployment	Adaptability
LGMD1[17]	Feed-forward	No	Offline	Medium	**Micro-Bot**	N/A
LGMD2[49]	Feed-forward	No	Offline	High	**Micro-Bot**	N/A
LGMD+[90]	Feed-forward	**Yes**	Offline	High	N/A	N/A
Compound-LGMD[69]	Feed-forward	No	Offline	High	**Micro-Bot**	N/A
DNF-based LGMD[86]	Feed-forward	No	Offline	High	**Micro-Bot**	N/A
Feed-back LGMD[71]	Feed-forward & **Feed-back**	No	Offline	High	N/A	N/A
Bi-DSN[76]	Feed-forward	**Yes**	Offline	High	N/A	Medium
ANN model[56]	Feed-forward	**Yes**	Offline	High	N/A	N/A
Single Neuron LPLC2[73]	Feed-forward	No	Offline	**Ultra**	N/A	N/A
LRF/RI Model[19]	Feed-forward	**Yes**	Offline	**Ultra**	N/A	N/A
Population Coding LPLC2[20]	Feed-forward	No	Offline	**Ultra**	Simulated Robot	Medium
Attention-Driven LPLC2[66,75]	Feed-forward	No	Offline	**Ultra**	**Micro-Bot**	N/A
Proposed Online LPLC2 Model	Feed-forward & **Feed-back**	**Yes**	**Online**	**Ultra**	**Real Robot**	**High**

Table 2. *Comparison between the proposed online feed-back-based LPLC2 model and existing bio-inspired visual collision detection models. The comparison covers network architecture, learning capability, operation mode, selectivity, deployment environment, and adaptability. The proposed model explores the online learning and feed-back framework among other feed-forward models.*

Unlike most existing bio-inspired models shown in Table 2 that rely

solely on feed-forward architectures, the proposed framework introduces a *feed-back learning pathway*, representing a conceptual transition toward a new generation of adaptive, feed-back-driven neural systems. This design preserves the lightweight structure and real-time efficiency of feed-forward models while enabling *continuous adaptability* to diverse and dynamically changing environments.

Insights for Biological Research: Furthermore, this research may deepen our understanding of how biological organisms adapt to changing conditions. Patterns and insights derived from computational and robotic experiments can generate hypotheses about unknown principles in complex biological visual systems. This establishes a feed-back loop in which bio-inspired engineering not only benefits from biology but also provides inspiration for future biological research.

b. Applications and Potential Impact:

Engineering Applications and Practical Impact: This research addresses the trade-off between performance and cost in engineering systems. While high-end solutions (e.g., LiDAR or large-scale deep learning models) offer excellent accuracy at high hardware and energy costs, traditional bio-inspired vision models are lightweight but lack adaptability. The proposed framework bridges this gap by enabling real-time, online learning within lightweight architectures, allowing deployment on micro aerial vehicles, portable robots, and other resource-limited platforms.

If successful, the expected engineering impacts include: (1) significantly reducing dependence on costly sensors such as LiDAR or depth cameras, thereby lowering overall system cost; (2) providing small autonomous vehicles, medical delivery drones, and agricultural microrobots with an efficient and robust collision-detection scheme that functions autonomously under limited resources; (3) enhancing the adaptability of embedded robotic systems in dynamic environments, thereby extending their usability and robustness across diverse real-world scenarios.

Cross-Disciplinary Significance: Beyond engineering applications, this research holds *cross-disciplinary significance*. From a neuroscience perspective, the proposed model may offer new insights into how *LPLC2 neurons* in the fly visual system achieve selective and adaptive responses to looming stimuli, deepening the understanding of neural plasticity mechanisms in motion perception. From an artificial intelligence standpoint, the study provides a biologically grounded framework for advancing *neuromorphic AI systems* that integrate online learning and feed-back modulation, thereby bridging the gap between biological adaptability and artificial efficiency.

4 Methods

This chapter addresses the research questions outlined in Section 2. We focus on the LPLC2 neuron, which is recognized for its ultra-selectivity in looming detection and represents one of the most promising neural types in this field. We propose to construct an online feed-back learning framework that enables the LPLC2-based model to acquire plasticity and adaptability. The core approach is to integrate online learning, allowing the model to continuously update and evolve during operation, thereby achieving cross-scenario and cross-environment adaptability.

At each stage, the resulting models will be systematically compared with state-of-the-art bio-inspired models, including the locust-inspired models and the fruit fly-inspired models reviewed in Section 1.2.3. The comparison will span multiple dimensions, such as runtime performance on identical hardware, response characteristics and collision selectivity under the same stimuli, and cross-environment robustness (corresponding to the solutions to RQ2 and RQ3).

It should be noted that:

i. *The methods presented in the following sections will not repeat established biological knowledge, biologically inspired structures, or existing mature computational models. Instead, the focus is on the* feed-back learning pathway, *which represents our main contribution.*

ii. *These methods represent only one preliminary and feasible approach toward achieving the stated objectives. Their concrete implementation will require continuous refinement and enhancement through iterative exploration.*

4.1 Developing Ultra-Selectivity through Online Learning

> **RQ 1.** *Can the collision selectivity of bio-inspired neural networks (e.g., the ultra-selectivity of LPLC2 neurons) be achieved through online learning?*

a. Methodology

i. Shaping the Response of the LPLC2 Neuron: We propose an online learning mechanism in which the model continuously evolves during operation. Our goal is to train the LPLC2 neuron to achieve ultra-selectivity.

For an LPLC2 neuron, the membrane potential is modeled as

$$V(t) = \sum_i w_i \big(\mathrm{ON}_i(t) + \mathrm{OFF}_i(t)\big) \cdot \big(R_i(t) - \beta q_i(t)\big) - \theta_{\mathrm{th}}, \qquad (1)$$

where w_i denotes the weight of pixel i within the receptive field; $\mathrm{ON}_i(t)$ and $\mathrm{OFF}_i(t)$ represent the responses of the luminance increment and decrement channels at time t; $R_i(t)$ is the outward (looming) radial motion component; $q_i(t)$ is the inward (receding) radial motion component; β is the inhibitory coefficient regulating suppression of receding motion; and θ_{th} is the firing threshold.

Outward motion contributes positively to the membrane potential, while inward motion is attenuated by β, thereby providing the neuron with selectivity for looming stimuli. The proposed online learning mechanism will iteratively update the weights w_i to enhance this ultra-selectivity.

ii. Ultra-Selectivity by Online Learning: During online learning, labeled supervision is unavailable, so we will design a self-supervised teaching signal by combining three predictive consistency terms. First, the network predicts the optical flow of the next frame $\hat{F}^{t+1}$ and compares it against the true flow F^{t+1}. Second, the network predicts the luminance pattern of the next frame $\hat{L}^{t+1}$, which is compared with the observed L^{t+1}. Third, the network predicts the radial outward motion $\hat{R}^{t+1}$, enforcing sensitivity to looming dynamics. The resulting reward signal is defined as

$$r_t = -\Big(\|F^{t+1} - \hat{F}^{t+1}\|^2 + \|L^{t+1} - \hat{L}^{t+1}\|^2 + \|R^{t+1} - \hat{R}^{t+1}\|^2\Big). \qquad (2)$$

Since ground-truth motion fields $F^{t+1}, L^{t+1}, R^{t+1}$ are not directly available during online operation, we propose to approximate these supervisory signals by leveraging low-level motion cues. Frame differencing can provide coarse optical flow estimates, while elementary motion detectors (EMDs)[87–89] extract local directional responses. By further aggregating EMD outputs into radial expansion or contraction patterns[74], we expect to obtain proxy targets suitable for self-supervised parameter updates. The design and acquisition of these self-supervised signals is central to online learning; we will continuously explore and improve this module to allow the model to achieve ultra-selectivity more quickly and accurately.

After each frame, LPLC2 neuron parameters θ are updated online according to

$$\theta \leftarrow \theta + \alpha \cdot r_t \cdot \nabla_\theta V(t), \qquad (3)$$

where α is the learning rate, and $\nabla_\theta V(t)$ is the gradient of the membrane potential with respect to the parameters. For example, the gradient with

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respect to the receptive field weight is

$$\frac{\partial V}{\partial w_i} = (\text{ON}_i(t) + \text{OFF}_i(t)) \cdot (R_i(t) - \beta q_i(t)), \qquad (4)$$

while the gradient with respect to the inhibitory coefficient is

$$\frac{\partial V}{\partial \beta} = -\sum_i w_i(\text{ON}_i(t) + \text{OFF}_i(t))q_i(t). \qquad (5)$$

Through this continuous update process, the LPLC2 network progressively reshapes its receptive field weights, inhibitory balance, and firing threshold. Over multiple exposures to video sequences containing collision events, the model gradually learns to generate strong, reliable responses exclusively to looming stimuli, while suppressing responses to translation or receding motion, thereby achieving ultra-selectivity in an online and adaptive manner.

b. Novelty

> **Paper 1.** *An LPLC2-Inspired Ultra-Selective Collision Perception Neural Network Shaped by Online Learning*

This is the first attempt to shape LPLC2 selectivity through online learning, enabling the model to evolve from minimal or no collision discrimination to acquiring ultra-selectivity with limited data. The derived plasticity principles will also lay the foundation for enhancing its environmental adaptability.

c. Risks and feasibility

Trade-off for Trainable Parts of the LPLC2 Model: A major challenge lies in defining the basic structure of LPLC2. The balance between the following two parts will directly influence the speed and effectiveness of model training: (1) manually defined parameters/structures inspired by LPLC2; (2) trainable parameters. Based on current evidence, manually modeling the basic selectivity of LPLC2 is feasible[20,73,75]. Therefore, we will start by learning critical parameters as described in Section 4.1. If the optimization of LPLC2 weights in Equation 1 proves unstable, guidance can be introduced by manually defining four quadrants to simulate the dendritic arbor zone of a single LPLC2 cell. In addition, focusing on a single neuron – predefining one LPLC2 neuron located at the center of the visual field – will greatly improve the likelihood of successful training.

Furthermore, the design and acquisition of self-supervised signals is central to online learning. We will continuously explore and improve how to design this module to allow the model to achieve ultra-selectivity more quickly and accurately.

Computational Feasibility of Real-Time Gradient-Based Updates: The proposed online learning strategy for LPLC2 neurons relies on explicit gradient calculations of key parameters, including receptive field weights w_i, inhibitory coefficients β, and firing thresholds θ_{th}, etc. By computing gradients analytically, the model avoids the overhead of automatic differentiation frameworks, allowing real-time updates on embedded platforms with moderate resources.

On robot platforms such as *TurtleBot3*, the small scale of the network and the limited number of learnable parameters ensure that online gradient-based updates can be performed in real time without exceeding memory or computational budgets. This setup enables continuous adaptation to new environmental stimuli, enhancing collision selectivity dynamically as the robot operates. For microcontroller-based platforms with extremely limited resources (e.g., *e-puck* or *Colias*), full online gradient updates are infeasible. Instead, only a subset of core parameters may be allowed limited adjustment, with constraints on the magnitude of change to prevent instability. While this approach sacrifices some performance compared to full online learning, the inclusion of a feed-back learning pathway still provides improved adaptability relative to static, purely feed-forward models. Such a strategy balances computational feasibility with adaptive performance in highly resource-constrained hardware.

d. Evaluation Metrics and Outcomes

Dataset: Current available dataset to be used in the offline experiments consists of structured indoor visual stimuli and complex vehicle crash scenarios, adapted from a previous dataset[90]. The data categories and their respective sample sizes are summarized in Table 3.

This dataset is used to evaluate the collision detection model's performance in various real-world and synthetic scenarios. It is worth noting that although the proposed online learning framework does not require large-scale datasets for pre-training, we plan to collect additional datasets in the future for more systematic evaluation. This includes testing cross-scenario robustness under diverse conditions such as indoor/outdoor environments, urban/forest scenes, and varying illumination levels.

Metrics: For offline experiments in this project, we use the *confusion matrix* to evaluate the performance of our collision detection system.

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Category	Type	Amount
Synthetic Stimuli	approach	48
	recession	48
	elongation	48
	translation	48
	grating	66
Vehicle Stimuli	crash	26
	non-crash	10
Indoor stimuli	approach	20
	recession	20
	translation	52
Coherence Stimuli	approach	22
	recession	22
	translation	66

Table 3. *Summary of data collection used in experimental evaluation, including synthetic motion patterns, real-world vehicle crash scenes, indoor ball movement stimuli, and coherence-based motion stimuli. Coherence stimuli are motion patterns composed of partially correlated moving elements, used to evaluate a model's ability to perceive global approaching motion under noisy conditions.*

The confusion matrix provides a summary of how detected events correspond to actual occurrences of collisions and non-collisions. Although our online learning is unsupervised, for offline evaluation, we assign ground-truth labels to events (collision/non-collision) in the dataset to construct the confusion matrix. Each row represents the true event category, and each column represents the predicted category by the system. This allows us to compute key metrics, including true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). These values are then used to derive performance metrics such as accuracy, precision, recall, and F1-score.

To quantify the effectiveness of looming perception for all the investigated and compared models, we adopt accuracy as the primary metric. Accuracy is a widely used metric indicating the overall correct classification rate of the system. It is calculated as the ratio of correct predictions (true positives and true negatives) to the total number of tested events (true positives, true negatives, false positives, and false negatives), as shown below:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \times 100\% \qquad (6)$$

True positives (TP) refer to the number of tested stimuli for which the model correctly generates collision alerts for genuine collision scenarios. These are instances where the model detects an approaching object just at or before the instant of collision. False positives (FP) are the number of tested stimuli for which the model erroneously generates collision alerts for non-colliding stimuli, such as translational or receding motions. True negatives (TN) represent the number of tested stimuli for which the model correctly does not respond to non-colliding stimuli. Finally, false negatives (FN) account for the number of tested stimuli for which the model fails to respond to actual collisions.

This metric helps us evaluate how accurately the system distinguishes between collision and non-collision events across a variety of stimuli, providing insight into the overall performance of the system in real-world scenarios.

Outcomes: An LPLC2 neural network that achieves ultra-selectivity for looming objects through online learning.

Specifically, this LPLC2 network will retain continuous online learning capability, where the incoming data streams progressively shape and enhance its collision selectivity. Ultimately, the model aims to achieve ultra-selectivity to looming patterns among various motion types, similar to that of real LPLC2 cells reported by Klapoetke et al.[31], and to attain a comparable level of collision-detection accuracy compared to existing bio-inspired looming detectors under equivalent computational constraints.

4.2   Feed-back Differential Adaptive Pathway

> **RQ 2.** *How can a bio-inspired collision-detection model rapidly adapt to new operational scenarios and environmental changes?*

a. Methodology

i. Rapid Adaptation via Dual-Timescale Learning: To enable rapid adaptation to environmental changes while maintaining long-term stability, we introduce a dual-timescale learning mechanism. Each key parameter of the model is represented by two coupled components: a fast copy θ_f that updates rapidly to capture transient variations, and a slow copy θ_s

that evolves more gradually to encode long-term regularities. For example, receptive field weights, ON/OFF gains $w_{\mathrm{ON}}, w_{\mathrm{OFF}}$, the inhibitory coefficient β, and the firing threshold are all maintained in this dual form. The fast copies provide immediate plasticity against sudden changes such as illumination shifts or local disturbances, while the slow copies ensure global stability and prevent overreaction to noise.

Formally, let θ_f and θ_s denote the fast and slow components of a parameter, updated with distinct learning rates $\alpha_f \gg \alpha_s$:

$$\theta_f \leftarrow \theta_f + \alpha_f \, r_t \, \nabla_{\theta_f} J_t - \lambda_f (\theta_f - \theta_s), \tag{7}$$

$$\theta_s \leftarrow \theta_s + \alpha_s \, r_t \, \nabla_{\theta_s} J_t, \tag{8}$$

where r_t is the self-supervised reward at time t (consistent with 4.1), J_t is the objective function combining membrane potential output and prediction error, and λ_f is a regularization coefficient that softly anchors the fast copy to the slow baseline. Through this coupling, θ_f adapts quickly to new conditions but does not drift arbitrarily, while θ_s integrates only stable trends over longer timescales.

ii. Consolidation Mechanism: The dual representation allows the system to selectively consolidate short-term adaptations into long-term memory. Specifically, when a fast parameter θ_f remains stable within a temporal window T_c, its value is gradually transferred into the corresponding slow copy θ_s. This ensures that only consistent and environmentally relevant adaptations become part of the long-term representation, while spurious fluctuations are discarded. Formally, consolidation is defined as

$$\theta_s \leftarrow \theta_s + \eta \, (\theta_f - \theta_s), \quad \text{if } \mathrm{Var}_{T_c}(\theta_f) < \epsilon, \tag{9}$$

where η is the consolidation rate and ϵ is a variance threshold controlling the stability criterion. By this mechanism, θ_s gradually integrates stable features of the environment, while θ_f remains available for rapid re-adaptation when the context changes. This prevents repetitive relearning of recurring conditions and mitigates catastrophic forgetting, as slow parameters encode long-term priors while fast parameters provide continual plasticity.

b. Novelty

> **Paper 2.** *Lifelong Learning LPLC2 Collision Perception Model with Differential Adaptive Pathway*

This work introduces a dual-timescale adaptive mechanism into an LPLC2-inspired collision perception model, combining fast plasticity with

slow consolidation. This represents an exploration toward granting lightweight, real-time bio-inspired networks unprecedented environmental adaptability.

c. Risks and feasibility

Model training stability: In the initial experiments, the number of learnable parameters will be deliberately restricted to ensure that their effects remain interpretable and controllable. Once a clear understanding is obtained regarding how each parameter contributes to adaptation under changing environments, the proportion of learnable parameters will be gradually increased. Although this strategy may limit the model's adaptability at the early stage, it guarantees stable and reliable baseline performance from the outset.

Catastrophic forgetting: A major challenge lies in catastrophic forgetting, where rapid updates to accommodate new scenarios may overwrite previously consolidated knowledge. While numerous methods have been proposed to alleviate this problem, lightweight systems must preserve computational efficiency and real-time responsiveness. Therefore, it is essential to design anti-forgetting strategies under strict resource constraints. The corresponding methods and evaluation metrics addressing this issue will be discussed in detail in later stages of the project (see Section 4.3).

Computational Trade-offs of Maintaining Dual Parameter Sets: On robot platforms with limited onboard resources (e.g., *TurtleBot3*), maintaining dual parameter sets (fast parameters θ_f and slow parameters θ_s) does introduce additional memory overhead. However, since our network is relatively small and the learnable parameters involve only the core feed-forward network, memory consumption is not expected to be a major bottleneck.

The main challenge lies in designing training and optimization schemes for these key parameters to balance rapid adaptation and long-term stability. In initial experiments, we will attempt to apply the dual-parameter mechanism to all core parameters to maximize fast learning and robust retention. If deployment reveals performance or efficiency limitations, we may consider maintaining dual parameters only for selected critical parameters, while updating others with a single fast/slow mechanism. This trade-off may have consequences: parameters without full dual-parameter representation might exhibit local instability, slower adaptation, or reduced efficiency in learning new environments.

On micro-robot platforms with extremely limited memory (e.g., *Colias*), implementing a full online dual-parameter learning scheme is infeasible. For individual units, we will explore limited learning of core feed-forward parameters or use distributed evolutionary strategies for collective adaptation,

allowing the swarm to respond to different environmental scenarios. Individual robots do not maintain full dual parameter sets, avoiding memory and computation overhead beyond hardware limits, while still allowing evaluation of the model's adaptive potential under extreme resource constraints.

d. Evaluation Metrics and Outcomes

Metrics: In this stage we focus on the model's ability to rapidly learn and achieve high accuracy in newly encountered environments; the problem of mitigating catastrophic forgetting will be addressed as the next research question. Each "task" corresponds to a different type of environment in which the model performs collision detection, and the "task success rate" refers to the "Accuracy" defined in Equation 6.

$$\Omega_{new} = \frac{1}{N-1} \sum_{i=2}^{N} \alpha_{new,i}, \tag{10}$$

where N is the total number of tasks (distinct environment types), i indexes the sequential order of environments encountered during learning ($i = 1$ is the first learned environment, $i = N$ the last), and $\alpha_{new,i}$ denotes the collision-detection accuracy achieved on the i-th new environment immediately after online learning. A higher Ω_{new} indicates and faster learning in unseen scenarios.

Outcomes: An LPLC2 neural network capable of rapid learning and adaptation in new and diverse environments.

Specifically, when trained on the initial baseline environment, the proposed model is expected to achieve collision-detection accuracy comparable to manually parameter-optimized state-of-the-art bio-inspired models (see Equation 6). When subsequently exposed to novel and unseen environments, it should surpass existing state-of-the-art bio-inspired models in terms of rapid adaptation performance (see Equation 10). The final model should be capable of continuously performing online learning in dynamically changing environments, with each new adaptation achieved using only a small number of data samples.

4.3 Regularization-based Long-Term Learning and Hardware Deployment

RQ 3. *How can lightweight bio-inspired neural networks with environmental adaptability overcome catastrophic forgetting, particularly under constrained onboard computational resources?*

a. Methodology

A central challenge in enabling the ability of lifelong learning for neural networks is the *catastrophic forgetting*[79]. Various strategies have been proposed to alleviate this problem, including regularization-based consolidation, replay-based mechanisms, generative replay, dynamically expandable architectures, and meta-learning approaches, each with distinct trade-offs in resource cost and adaptability, as summarized in Table 4.

Regularization-based methods such as Elastic Weight Consolidation (EWC)[80], Synaptic Intelligence (SI)[91], and Orthogonal Gradient Descent (OGD)[92] mitigate forgetting by constraining parameter or gradient updates that are critical to previously acquired knowledge. These approaches are particularly attractive for resource-constrained platforms because they require no explicit data replay and introduce only limited computational overhead. In contrast, replay-based mechanisms maintain past knowledge through memory buffers or pseudo-sample generation[81], which can improve robustness but demand additional storage and processing power. Generative replay and dynamically expandable models provide flexibility in handling novel tasks but often increase model size and latency, conflicting with the real-time requirements of embedded robotic systems.

Considering these trade-offs and the strict computational and memory constraints of lightweight bio-inspired neural architectures, we adopt Elastic Weight Consolidation (EWC) as the primary lifelong learning mechanism in our framework. This choice achieves a balance between continual adaptability and computational efficiency, making it particularly suitable for deployment on platforms such as *TurtleBot3*.

i. Elastic Weight Consolidation within Dual-Timescale Framework: To mitigate catastrophic forgetting while preserving lightweight efficiency, we integrate Elastic Weight Consolidation (EWC)[80] into the dual-timescale learning process. Each parameter's importance is quantified via the Fisher information F_i, which constrains updates through a quadratic

Method Category	Core Idea	Pros	Cons / Resource Cost	Suitability
Regularization-based (EWC, SI, OGD)	Constrain parameter or gradient updates to preserve prior knowledge	Low storage, lightweight, easy to integrate; suitable for limited hardware	Requires gradient or Fisher information tracking; moderate computation overhead	**High**
Replay-based	Store and rehearse past samples or outputs	Effective at mitigating forgetting	Extra storage and memory access; scales poorly with many tasks	Medium
Generative Replay	Generate pseudo-samples or features using a generative model	Avoids storing raw data	Generative model adds complexity and latency	Low
Expandable Models	Dynamically increase network capacity for new tasks	Flexible and modular	Increases model size; difficult to remain lightweight	Low
Task-Agnostic Meta-Learning	Automatically infer task structure and adapt via meta-updates	Works without task labels; adaptive	High computation and memory buffer requirements	Medium

Table 4. *Comparison of Lifelong Learning Methods for Lightweight Bio-Inspired Networks. Regularization-based methods, including Elastic Weight Consolidation (EWC), Synaptic Intelligence (SI), and Orthogonal Gradient Descent (OGD), are particularly suitable for lightweight bio-inspired neural systems due to their minimal memory footprint, online adaptability, and computational efficiency.*

penalty:

$$\mathcal{L}_{EWC} = \sum_i \frac{\lambda}{2} F_i(\theta_i - \theta_{i,\text{ref}})^2, \tag{11}$$

where θ_i is the current parameter, $\theta_{i,\text{ref}}$ its consolidated reference, F_i reflects its sensitivity to past tasks, and λ controls penalty strength. For lightweight networks such as LPLC2, F_i can be efficiently approximated by averaging

squared gradients over a sliding buffer, ensuring low overhead. Thus, EWC serves as a regularization term acting jointly with the fast/slow update rules and consolidation mechanism.

ii. Algorithmic Summary:

Algorithm 1 Dual-Timescale Online Learning with EWC-Regularized Consolidation

---

1: **For each frame t:**
2:     Compute loss L_t and gradients $g_i = \partial_{\theta_i} L_t$
3:     $\delta \leftarrow r_t$ $\triangleright$ self-supervised reward signal
4: **for** each i in fast parameters **do**
5:     $\theta_i \leftarrow \theta_i + \alpha_f(\delta \cdot g_i - \lambda F_i(\theta_i - \theta_{i,\text{ref}}))$
6: **end for**
7: **for** each i in slow parameters (periodically) **do**
8:     $\theta_i \leftarrow \theta_i + \alpha_s(\delta \cdot g_i - \lambda F_i(\theta_i - \theta_{i,\text{ref}}))$
9: **end for**
10: **Every T_c frames (Consolidation):**
11:     Estimate $\hat{F}_i \leftarrow \frac{1}{N}\sum_{n=1}^{N}(g_i^{(n)})^2$ from buffer
12: **for** fast parameters satisfying stability condition **do**
13:     $\theta_{i,\text{ref}} \leftarrow (1 - \rho)\theta_{i,\text{ref}} + \rho\theta_i$
14:     $F_i \leftarrow (1 - \eta)F_i + \eta\hat{F}_i$
15: **end for**

We will first conduct offline experiments, during which the methods for mitigating catastrophic forgetting will be continuously evaluated and refined using Equation 12. Once the proposed model demonstrates the ability to rapidly learn new environments while exhibiting only minor performance degradation on previously learned scenarios (e.g., less than 20% or 10%), we will proceed to optimize and deploy the model across different robotic platforms.

    iii. Potential Robotic Platform Deployment Plan: During the whole project, we might deploy the proposed model across a range of robotic platforms with progressively increasing levels of hardware constraints:

    (1) *TurtleBot3 Waffle-Pi*,
    (2) *e-puck*[93],
    (3) *Colias*[94], and
    (4) UAVs.

    Among these, (1) and (2) are currently available at the Computational Autonomous Learning Systems Lab (CSE 128), Department of Computer Science, University of York, while (3) is available at the Machine Life and

Intelligence Research Centre, School of Mathematics and Information Science, Guangzhou University. The deployment difficulty increases gradually across the platforms, and achieving adaptive lightweight collision perception on each represents a distinct step toward practical applications:

TurtleBot3 offers relatively sufficient onboard computational resources (*Raspberry Pi 4B*, 4GB RAM). We will implement the network in Python, leveraging *PyTorch* for essential online learning updates. If *PyTorch/TensorFlow* proves impractical, we will hand-code the proposed network to ensure deployment feasibility.

e-puck[93] (*STM32F407VG*, 192KB RAM / 1MB Flash) has limited onboard memory and computation. Based on our experience of implementing crab-inspired monostratified lobula giant neurons (MLGs) for collision perception[55,95,96], running the model in Python would cause prohibitive latency, losing real-time capability. Therefore, we will implement the proposed model in C language. Despite its constraints, this platform remains suitable for swarm tasks.

Colias[94], a widely used and low-cost microrobot, presents an even greater challenge due to its highly constrained onboard resources (*STM32F427*, 256KB RAM). For this platform, the proposed network will be implemented in C language. Prior work has shown that an LPLC2-inspired feed-forward network can be deployed on *Colias*, occupying only 70KB of memory while achieving ultra-selectivity in collision detection and supporting multi-object localization[66]. This demonstrates that compact yet sophisticated neural models can indeed be optimized for such resource-limited platforms. However, enabling true online learning on microcontrollers of this scale remains a significant open challenge. For micro-robots with extreme resource limitations (e.g., *Colias*), individual lifelong adaptation may be infeasible.

To address this, we propose to exploit the swarm nature of *Colias* robots: by running distributed evolutionary algorithms across multiple agents, the swarm can collectively adapt to changing environments through mechanisms of competition, elimination, and selection. In this paradigm, each unit maintains a lightweight and static model, while long-term adaptation emerges at the swarm level, thereby alleviating the computational burden on individual robots. Communication within the swarm can be realized through the existing collective intelligence platform[97–99] available at the Machine Life and Intelligence Research Centre.

UAVs require lightweight, robust, and cross-environment adaptive collision-detection models more urgently than ground robots. In addition to constrained onboard resources, UAVs face unique challenges: operating in 3D space with more complex environments, higher speeds, and stronger motion

jitter – all of which demand higher collision selectivity. To approach this goal, we will begin in simulation using *MuJoCo* with models from the open-source Menagerie library, such as the *Skydio X2* quadrotor and *Crazyflie 2.0*, before attempting real-world deployment.

Across all platforms, the dual-timescale feed-back pathway serves as the unifying mechanism, ensuring both rapid online adjustment and stable long-term retention.

iiii. Integration with Neuromorphic Hardware: Beyond conventional robotic platforms, integrating advanced neuromorphic hardware with event cameras is expected to further leverage the high real-time capability of LPLC2-inspired neural networks, enabling the development of high-speed, low-power bio-inspired collision detection systems. We propose to process the sparse, asynchronous event streams output by the DVS through three modules: (1) event stream processing module; (2) presynaptic spiking neural network (SNN)[100,101]; and (3) LPLC2 neural network. The system aims not only for high-precision collision detection but also to exploit the microsecond-level temporal resolution of event cameras, achieving high dynamic responsiveness and environment-adaptive learning capability.

The event stream processing module converts the DVS events (x, y, t, p) into inputs suitable for neural network processing. Temporally, it applies exponential decay filtering or sliding window integration to suppress noise; spatially, it uses neighborhood event aggregation or event morphology filtering to reduce isolated pixel triggers. Processed event streams are then encoded into spike sequences or tensors acceptable to the neural network. Encoding schemes include Time Surface Encoding, Phase Encoding, Polarity Split Encoding, and Event Count Image. The specific encoding strategy will be chosen based on the downstream SNN input dimensions and hardware compute constraints.

The presynaptic SNN retains the DVS's 2D spatial topology and learns motion features from the event stream. Its scale can match the camera resolution, with multiple feature channels representing different motion directions or speeds. Neurons are modeled using LIF (Leaky Integrate-and-Fire)[102] or ALIF (Adaptive Leaky Integrate-and-Fire)[103], supporting STDP or differentiable learning via surrogate gradients. This presynaptic neural network extracts key signals such as motion patterns, foreground/background motion cue, and global illumination, providing inputs to the LPLC2 neural network.

The LPLC2 neural network acts as a postsynaptic network, integrating SNN outputs to generate ultra-selective responses to approaching objects. Previous studies have preliminarily validated the feasibility of RMO-based (Radial Motion Opponency) methods inspired by fruit fly LPLC2 structures

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for collision detection tasks[5]. Initially, only key parameters are learnable to maintain system stability, while a fast-slow parameter strategy supports environmental adaptation. Future extensions may include multi-attention mechanisms, population coding, and inter-layer feed-back modulation to build a more comprehensive and capable collision detection system.

This architecture fully exploits the high temporal resolution of event cameras and the computational efficiency of SNN and LPLC2, achieving fast, low-power collision detection with environment-adaptive capability, providing robust autonomous perception for robotic platforms in highly dynamic scenarios.

b. Novelty

> **Paper 3.** *Learn and Adapt: A Bio-Inspired Onboard Solution for Lifelong Collision Perception*

Enabling robotic systems to continuously learn and adapt their collision-detection capabilities onboard is crucial for real-world deployment. This work demonstrates that bio-inspired, lightweight neural networks can support lifelong adaptation, allowing robots to autonomously adjust to dynamic and diverse environments without relying on external computation or retraining.

c. Risks and feasibility

Online learning for robots presents unique challenges. In the first two research questions, we assumed limited data input in the form of video streams. However, in real-world scenarios, robots cannot rely on repeated trial-and-error, since a single collision may already cause system failure.

(1) *TurtleBot3.* For ground robots with relatively abundant resources, we will implement a reset mechanism[104]: after a collision occurs during trial-and-error, the robot can automatically revert to a safe pre-collision state, enabling repeated learning.

(2) *Colias/e-puck* swarm robots. For highly resource-constrained micro-robots, we will adopt swarm-level evolutionary strategies. Through collective exploration, competition, and selection, the swarm can yield individuals adapted to the environment. Successful policies can then be propagated to other agents via inter-robot communication.

(3) UAVs. For aerial robots, collisions are prohibitively costly. Therefore, training will initially be performed in simulation (e.g., MuJoCo), followed by a sim-to-real transfer. Given that bio-inspired neural models are extremely lightweight and UAVs possess relatively richer onboard resources,

we will further explore a hybrid deployment strategy: running multiple pre-trained auxiliary models adapted to different environments alongside a main model. Once the main model has successfully adapted to the current environment, the auxiliary models can be pruned. This multi-model scheme may provide a safe surrogate for trial-and-error, offering a promising pathway toward collision-free online learning in UAVs.

d. Evaluation Metrics and Outcomes

Metrics: We adopt the commonly used metrics in continual learning proposed in[105], adapted for collision detection tasks. In this context, each "task" corresponds to a different type of environment in which the tested model must perform collision detection. The "task success rate" we use refers to the "Accuracy" defined in Equation 6.

$$
\Omega_{base} = \frac{1}{N-1} \sum_{i=2}^{N} \frac{\alpha_{base,i}}{\alpha_{ideal}},
$$

$$
\Omega_{new} = \frac{1}{N-1} \sum_{i=2}^{N} \alpha_{new,i}, \tag{12}
$$

$$
\Omega_{all} = \frac{1}{N-1} \sum_{i=2}^{N} \frac{\alpha_{all,i}}{\alpha_{ideal}}.
$$

Here, N is the total number of tasks (i.e., different environment types), and i indexes the sequential order of tasks encountered during continual learning, where $i = 1$ denotes the first learned task and $i = N$ the last one. After the model finishes learning task i, its performance is evaluated on (1) the newly learned task i ($\alpha_{new,i}$), (2) the first task to measure knowledge retention ($\alpha_{base,i}$), and (3) all tasks learned so far ($1 \dots i$) to assess overall stability and generalization ($\alpha_{all,i}$). α_{ideal} is used to normalize Ω_{base} and Ω_{all}. Ω_{base}, Ω_{new}, and Ω_{all} thus measure the model's ability to remember previous knowledge, transfer knowledge to new environments, and maintain overall performance across all tasks. Higher values indicate better continual learning performance.

Outcomes: A low-cost, bio-inspired visual collision detection solution that continuously adapts to diverse environments while mitigating catastrophic forgetting.

Specifically, in offline experiments, the proposed model is expected to maintain high accuracy across a wide range of environmental conditions, including previously encountered ones, surpassing all known feed-forward-only bio-inspired models. This performance can be further validated against stan-

dard continual learning benchmarks prior to robotic deployment. Once deployed, the lightweight model should perform online learning and adaptation using only the onboard computational resources. On robots with comparable computational capacity, the proposed model is expected to achieve collision detection success rates similar to state-of-the-art bio-inspired models, while outperforming existing feed-forward architectures under changing environmental scenarios.
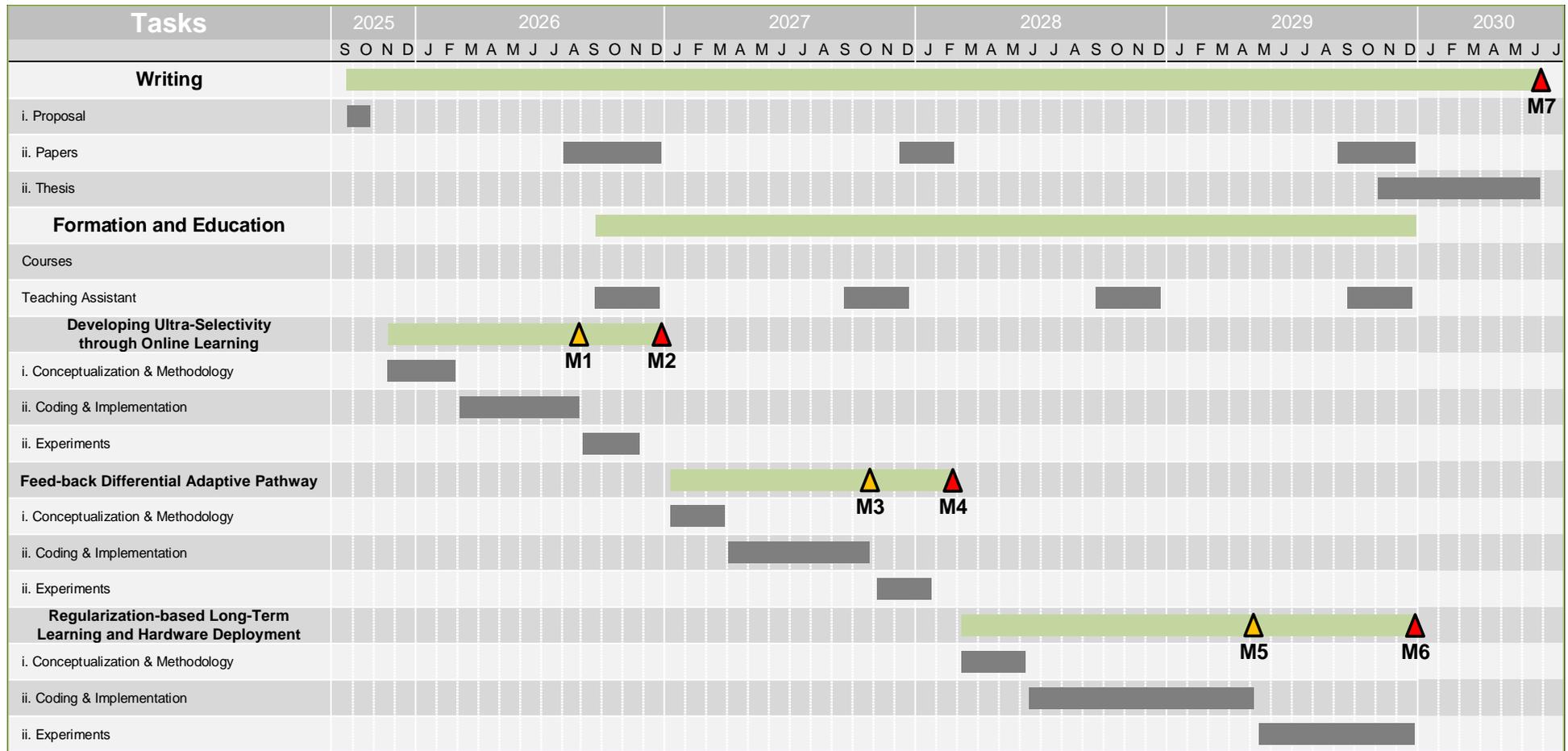
5 Timetable

Figure 1. *The Gantt chart presents the preliminary PhD project plan formulated at the end of September 2025, with conservative time estimates for each task. Triangles indicate key milestones (M): M1 – implementation of the initial online LPLC2 single-neuron model with baseline offline testing; M2 – submission of the first conference paper summarizing initial online learning results; M3 – development of a dual-timescale feed-back pathway for rapid environmental adaptation and evaluation under continuous tasks; M4 – submission of the second conference paper demonstrating the dual-timescale online adaptation framework; M5 – integration of regularization-based lifelong learning mechanisms and deployment on robotic platforms for adaptive collision detection; M6 – submission of the third conference/journal paper reporting lifelong online adaptation on robotic platforms; M7 – completion of the PhD thesis, integrating all experimental results and methods. These milestones correspond to the timeline in the chart and will be continuously monitored and adjusted as the project progresses.*

6   Collaborations

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7   Data Management Plan

This project will primarily employ video data for collision perception research. The datasets will come from three main sources:

(1) computer-generated simulation videos,

(2) real-world recordings collected in diverse indoor and outdoor environments, and

(3) publicly available open-source video datasets.

All data will focus on scenarios related to dynamic collision detection. Both raw and processed data, as well as the source code developed in this project, will be stored on secure university servers with regular backup. To ensure reproducibility and accessibility, code and curated datasets will also be maintained on the GitHub repository of the doctoral researcher (`https://github.com/Ryannnice`). Open formats – such as MP4 for video, CSV or JSON for annotations, and .aedat/.aedat4 for event camera data – will be adopted to ensure long-term usability.

After publication, non-sensitive parts of the data and the corresponding analysis code will be released openly on GitHub or institutional repositories, in line with FAIR principles (Findable, Accessible, Interoperable, Reusable)[106]. Sensitive or unpublished data will only be shared upon request.

References

[1] Lu, L. *et al.* A comprehensive survey on non-cooperative collision avoidance for micro aerial vehicles: Sensing and obstacle detection. *Journal of Field Robotics* **40**, 1697–1720 (2023).

[2] Perumal, P. S. *et al.* An insight into crash avoidance and overtaking advice systems for autonomous vehicles: A review, challenges and solutions. *Engineering applications of artificial intelligence* **104**, 104406 (2021).

[3] Strickland, M., Fainekos, G. & Amor, H. B. Deep predictive models for collision risk assessment in autonomous driving. In *2018 IEEE International Conference on Robotics and Automation (ICRA)*, 4685–4692 (IEEE, 2018).

[4] Ben Miled, M., Liu, W. & Liu, Y. Bioinspired framework for real-time collision detection with dynamic obstacles in cluttered outdoor environments using event cameras. *IET Cyber-Systems and Robotics* **7**, e70006 (2025).

[5] Schubert, F., Knight, J., Philippides, A. & Nowotny, T. Bio-inspired event-based looming object detection for automotive collision avoidance. *Neuromorphic Computing and Engineering* **5**, 024016 (2025).

[6] Zhao, J., Hu, C., Zhang, C., Wang, Z. & Yue, S. A bio-inspired collision detector for small quadcopter. In *2018 International Joint Conference on Neural Networks (IJCNN)*, 1–7 (IEEE, 2018).

[7] Zhao, J., Ma, X., Fu, Q., Hu, C. & Yue, S. An lgmd based competitive collision avoidance strategy for uav. In *IFIP international conference on artificial intelligence applications and innovations*, 80–91 (Springer, 2019).

[8] Xie, Y., Li, Z., Song, L. & Zhao, J. A bio-inspired looming detection for stable landing in unmanned aerial vehicles. *Bioinspiration & Biomimetics* **20**, 016007 (2024).

[9] Cho, E., Kim, H., Kim, P. & Lee, H. Obstacle avoidance of a uav using fast monocular depth estimation for a wide stereo camera. *IEEE Transactions on Industrial Electronics* (2024).

[10] Falanga, D., Kleber, K. & Scaramuzza, D. Dynamic obstacle avoidance for quadrotors with event cameras. *Science Robotics* **5**, eaaz9712 (2020).

[11] Park, J. & Kim, Y. Collision avoidance for quadrotor using stereo vision depth maps. *IEEE Transactions on Aerospace and Electronic Systems* **51**, 3226–3241 (2015).

[12] Li, W., Hu, Y., Zhou, Y. & Pham, D. T. Safe human–robot collaboration for industrial settings: a survey. *Journal of Intelligent Manufacturing* **35**, 2235–2261 (2024).

[13] Rill, R.-A. & Faragó, K. B. Collision avoidance using deep learning-based monocular vision. *SN Computer Science* **2**, 375 (2021).

[14] Gabbiani, F., Krapp, H. G. & Laurent, G. Computation of object approach by a wide-field, motion-sensitive neuron. *Journal of Neuroscience* **19**, 1122–1141 (1999).

[15] Yue, S. & Rind, F. C. Collision detection in complex dynamic scenes using an lgmd-based visual neural network with feature enhancement. *IEEE transactions on neural networks* **17**, 705–716 (2006).

[16] Fu, Q., Hu, C., Liu, P. & Yue, S. Towards computational models of insect motion detectors for robot vision (2022).

[17] Hu, C., Arvin, F., Xiong, C. & Yue, S. Bio-inspired embedded vision system for autonomous micro-robots: The lgmd case. *IEEE transactions on cognitive and developmental systems* **9**, 241–254 (2016).

[18] Wang, H. *et al.* Attention and prediction-guided motion detection for low-contrast small moving targets. *IEEE Transactions on Cybernetics* **53**, 6340–6352 (2022).

[19] Zhou, B., Li, Z., Kim, S., Lafferty, J. & Clark, D. A. Shallow neural networks trained to detect collisions recover features of visual loom-selective neurons. *Elife* **11**, e72067 (2022).

[20] Zhao, J., Xi, S., Li, Y., Guo, A. & Wu, Z. A fly inspired solution to looming detection for collision avoidance. *IScience* **26** (2023).

[21] Fu, Q., Wang, H., Hu, C. & Yue, S. Towards computational models and applications of insect visual systems for motion perception: A review. *Artificial life* **25**, 263–311 (2019).

[22] Qin, Z., Peng, J., Yue, S. & Fu, Q. A bio-inspired research paradigm of collision perception neurons enabling neuro-robotic integration: The lgmd case. *arXiv preprint arXiv:2501.02982* (2025).

[23] Rind, F. C. & Bramwell, D. Neural network based on the input organization of an identified neuron signaling impending collision. *Journal of neurophysiology* **75**, 967–985 (1996).

[24] Wang, H., Dewell, R. B., Zhu, Y. & Gabbiani, F. Feedforward inhibition conveys time-varying stimulus information in a collision detection circuit. *Current Biology* **28**, 1509–1521 (2018).

[25] Fried, S. I., Münch, T. A. & Werblin, F. S. Mechanisms and circuitry underlying directional selectivity in the retina. *Nature* **420**, 411–414 (2002).

[26] Baird, E., Srinivasan, M. V., Zhang, S., Lamont, R. & Cowling, A. Visual control of flight speed and height in the honeybee. In *International conference on simulation of adaptive behavior*, 40–51 (Springer, 2006).

[27] Srinivasan, M. & Zhang, S. Visual control of honeybee flight. *Orientation and communication in arthropods* 95–113 (1997).

[28] Borst, A. & Haag, J. Neural networks in the cockpit of the fly. *Journal of Comparative Physiology A* **188**, 419–437 (2002).

[29] Maisak, M. S. *et al.* A directional tuning map of drosophila elementary motion detectors. *Nature* **500**, 212–216 (2013).

[30] Shinomiya, K., Nern, A., Meinertzhagen, I. A., Plaza, S. M. & Reiser, M. B. Neuronal circuits integrating visual motion information in drosophila melanogaster. *Current Biology* **32**, 3529–3544 (2022).

[31] Klapoetke, N. C. *et al.* Ultra-selective looming detection from radial motion opponency. *Nature* **551**, 237–241 (2017).

[32] Zhou, B., Gao, F., Pan, J. & Shen, S. Robust real-time uav replanning using guided gradient-based optimization and topological paths. In *2020 IEEE International Conference on Robotics and Automation (ICRA)*, 1208–1214 (IEEE, 2020).

[33] Yu, H., Zhang, F., Huang, P., Wang, C. & Yuanhao, L. Autonomous obstacle avoidance for uav based on fusion of radar and monocular

camera. In *2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 5954–5961 (IEEE, 2020).

[34] Schleich, D., Beul, M., Quenzel, J. & Behnke, S. Autonomous flight in unknown gnss-denied environments for disaster examination. In *2021 International Conference on Unmanned Aircraft Systems (ICUAS)*, 950–957 (IEEE, 2021).

[35] Calkins, L. *et al.* Distance estimation using self-induced noise of an aerial vehicle. *IEEE Robotics and Automation Letters* **6**, 2807–2813 (2021).

[36] Park, J. & Cho, N. Collision avoidance of hexacopter uav based on lidar data in dynamic environment. *Remote Sensing* **12**, 975 (2020).

[37] Wessendorp, N., Dinaux, R., Dupeyroux, J. & de Croon, G. C. Obstacle avoidance onboard mavs using a fmcw radar. In *2021 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 117–122 (IEEE, 2021).

[38] Lin, J., Zhu, H. & Alonso-Mora, J. Robust vision-based obstacle avoidance for micro aerial vehicles in dynamic environments. In *2020 IEEE International Conference on Robotics and Automation (ICRA)*, 2682–2688 (IEEE, 2020).

[39] Tordesillas, J., Lopez, B. T., Everett, M. & How, J. P. Faster: Fast and safe trajectory planner for navigation in unknown environments. *IEEE Transactions on Robotics* **38**, 922–938 (2021).

[40] Lu, H., Zong, Q., Lai, S., Tian, B. & Xie, L. Flight with limited field of view: A parallel and gradient-free strategy for micro aerial vehicle. *IEEE Transactions on Industrial Electronics* **69**, 9258–9267 (2021).

[41] Carrio, A. *et al.* Onboard detection and localization of drones using depth maps. *IEEE Access* **8**, 30480–30490 (2020).

[42] Hatch, K., Mern, J. M. & Kochenderfer, M. J. Obstacle avoidance using a monocular camera. In *AIAA Scitech 2021 Forum*, 0269 (2021).

[43] Wang, Y., Ji, J., Wang, Q., Xu, C. & Gao, F. Autonomous flights in dynamic environments with onboard vision. In *2021 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 1966–1973 (IEEE, 2021).

38

[44] Kong, F., Xu, W., Cai, Y. & Zhang, F. Avoiding dynamic small obstacles with onboard sensing and computation on aerial robots. *IEEE Robotics and Automation Letters* **6**, 7869–7876 (2021).

[45] Davies, M. *et al.* Loihi: A neuromorphic manycore processor with on-chip learning. *Ieee Micro* **38**, 82–99 (2018).

[46] Orchard, G. *et al.* Efficient neuromorphic signal processing with loihi 2. In *2021 IEEE Workshop on Signal Processing Systems (SiPS)*, 254–259 (IEEE, 2021).

[47] Chakravarthi, B., Verma, A. A., Daniilidis, K., Fermuller, C. & Yang, Y. Recent event camera innovations: A survey. In *European Conference on Computer Vision*, 342–376 (Springer, 2024).

[48] Gao, G., Liu, R., Wang, M. & Fu, Q. A computationally efficient neuronal model for collision detection with contrast polarity-specific feed-forward inhibition. *Biomimetics* **9**, 650 (2024).

[49] Fu, Q., Hu, C., Peng, J., Rind, F. C. & Yue, S. A robust collision perception visual neural network with specific selectivity to darker objects. *IEEE transactions on cybernetics* **50**, 5074–5088 (2019).

[50] He, B. *et al.* Fast-dynamic-vision: Detection and tracking dynamic objects with event and depth sensing. In *2021 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 3071–3078 (IEEE, 2021).

[51] Rodríguez-Gómez, J. P., Tapia, R., Garcia, M. d. M. G., Martínez-de Dios, J. R. & Ollero, A. Free as a bird: Event-based dynamic sense-and-avoid for ornithopter robot flight. *IEEE Robotics and Automation Letters* **7**, 5413–5420 (2022).

[52] Wang, H., Peng, J., Zheng, X. & Yue, S. A robust visual system for small target motion detection against cluttered moving backgrounds. *IEEE transactions on neural networks and learning systems* **31**, 839–853 (2019).

[53] Fu, Q., Hu, C. & Yue, S. Bio-inspired collision detector with enhanced selectivity for ground robotic vision system (2016).

[54] Li, L., Zhang, Z. & Lu, J. Artificial fly visual joint perception neural network inspired by multiple-regional collision detection. *Neural Networks* **135**, 13–28 (2021).

[55] Luan, H. *et al.* A looming spatial localization neural network inspired by mlg1 neurons in the crab neohelice. *Frontiers in neuroscience* **15**, 787256 (2022).

[56] Gu, B., Feng, J. & Song, Z. Looming detection in complex dynamic visual scenes by interneuronal coordination of motion and feature pathways. *Advanced Intelligent Systems* **6**, 2400198 (2024).

[57] Yue, S. & Rind, F. C. Postsynaptic organisations of directional selective visual neural networks for collision detection. *Neurocomputing* **103**, 50–62 (2013).

[58] Yue, S. & Rind, F. C. Redundant neural vision systems—competing for collision recognition roles. *IEEE Transactions on Autonomous Mental Development* **5**, 173–186 (2013).

[59] Fu, Q., Bellotto, N., Hu, C. & Yue, S. Performance of a visual fixation model in an autonomous micro robot inspired by drosophila physiology. In *2018 IEEE International Conference on Robotics and Biomimetics (ROBIO)*, 1802–1808 (IEEE, 2018).

[60] Wang, H., Fu, Q., Wang, H., Peng, J. & Yue, S. Constant angular velocity regulation for visually guided terrain following. In *IFIP international conference on artificial intelligence applications and innovations*, 597–608 (Springer, 2019).

[61] Wang, H. *et al.* A bioinspired angular velocity decoding neural network model for visually guided flights. *Neural Networks* **136**, 180–193 (2021).

[62] Lu, Y., Cen, J., Alkhoury Maroun, R. & Webb, B. Insect-inspired embodied visual route following. *Journal of Bionic Engineering* 1–27 (2025).

[63] Chen, T., Sun, X., Fu, Q., Qin, Z. & Peng, J. A bio-inspired and solely vision-based model for autonomous navigation. In *2024 International Joint Conference on Neural Networks (IJCNN)*, 1–8 (IEEE, 2024).

[64] Bertrand, O. J., Lindemann, J. P. & Egelhaaf, M. A bio-inspired collision avoidance model based on spatial information derived from motion detectors leads to common routes. *PLoS computational biology* **11**, e1004339 (2015).

[65] D'Angelo, G. *et al.* Wandering around: A bioinspired approach to visual attention through object motion sensitivity. *Neuromorphic Computing and Engineering* **5**, 024019 (2025).

40

[66] Liu, R., Zhou, H., Fang, C. & Fu, Q. How fly neural perception mechanisms enhance visuomotor control of micro robots (2025). URL https://arxiv.org/abs/2509.13827. 2509.13827.

[67] O'Shea, M. & Williams, J. The anatomy and output connection of a locust visual interneurone; the lobular giant movement detector (lgmd) neurone. *Journal of comparative physiology* **91**, 257–266 (1974).

[68] Sztarker, J. & Rind, F. C. A look into the cockpit of the developing locust: looming detectors and predator avoidance. *Developmental neurobiology* **74**, 1078–1095 (2014).

[69] Wang, M. *et al.* A composite neuronal model as miniaturized visual modality for collision perception. In *International Conference on Robot Intelligence Technology and Applications*, 3–16 (Springer, 2024).

[70] Zheng, Y., Wang, Y., Wu, G., Li, H. & Peng, J. Enhancing lgmd-based model for collision prediction via binocular structure. *Frontiers in Neuroscience* **17**, 1247227 (2023).

[71] Chang, Z., Chen, H., Hua, M., Fu, Q. & Peng, J. A bio-inspired visual collision detection network integrated with dynamic temporal variance feedback regulated by scalable functional countering jitter streaming. *Neural Networks* **182**, 106882 (2025).

[72] Klapoetke, N. C. *et al.* A functionally ordered visual feature map in the drosophila brain. *Neuron* **110**, 1700–1711 (2022).

[73] Hua, M., Fu, Q., Peng, J., Yue, S. & Luan, H. Shaping the ultra-selectivity of a looming detection neural network from non-linear correlation of radial motion. In *2022 International Joint Conference on Neural Networks (IJCNN)*, 1–8 (IEEE, 2022).

[74] Shuang, F. *et al.* Opplod: the opponency based looming detector, model extension of looming sensitivity from lgmd to lplc2. *arXiv preprint arXiv:2302.10284* (2023).

[75] Liu, R. & Fu, Q. Attention-driven lplc2 neural ensemble model for multi-target looming detection and localization. *arXiv preprint arXiv:2504.04477* (2025).

[76] Fang, C., Zhou, H., Liu, R. & Fu, Q. A neuromorphic binocular framework fusing directional and depth motion cues towards precise collision prediction. *Available at SSRN 5245992* .

[77] Thrun, S. Lifelong learning algorithms. In *Learning to learn*, 181–209 (Springer, 1998).

[78] Kudithipudi, D. *et al.* Biological underpinnings for lifelong learning machines. *Nature Machine Intelligence* **4**, 196–210 (2022).

[79] French, R. M. Catastrophic forgetting in connectionist networks. *Trends in cognitive sciences* **3**, 128–135 (1999).

[80] Kirkpatrick, J. *et al.* Overcoming catastrophic forgetting in neural networks. *Proceedings of the national academy of sciences* **114**, 3521–3526 (2017).

[81] Chaudhry, A. *et al.* On tiny episodic memories in continual learning. *arXiv preprint arXiv:1902.10486* (2019).

[82] Yoon, J., Yang, E., Lee, J. & Hwang, S. J. Lifelong learning with dynamically expandable networks. *arXiv preprint arXiv:1708.01547* (2017).

[83] Hung, C.-Y. *et al.* Compacting, picking and growing for unforgetting continual learning. *Advances in neural information processing systems* **32** (2019).

[84] Ramesh, R. & Chaudhari, P. Model zoo: A growing" brain" that learns continually. *arXiv preprint arXiv:2106.03027* (2021).

[85] Javed, K. & White, M. Meta-learning representations for continual learning. *Advances in neural information processing systems* **32** (2019).

[86] Qin, Z., Fu, Q. & Peng, J. A computationally efficient and robust looming perception model based on dynamic neural field. *Neural Networks* **179**, 106502 (2024).

[87] Hassenstein, B. & Reichardt, W. Systemtheoretische analyse der zeit-, reihenfolgen-und vorzeichenauswertung bei der bewegungsperzeption des rüsselkäfers chlorophanus. *Zeitschrift für Naturforschung B* **11**, 513–524 (1956).

[88] Eichner, H., Joesch, M., Schnell, B., Reiff, D. F. & Borst, A. Internal structure of the fly elementary motion detector. *Neuron* **70**, 1155–1164 (2011).

[89] Borst, A. & Groschner, L. N. How flies see motion. *Annual review of neuroscience* **46**, 17–37 (2023).

[90] Fu, Q., Wang, H., Peng, J. & Yue, S. Improved collision perception neuronal system model with adaptive inhibition mechanism and evolutionary learning. *IEEE Access* **8**, 108896–108912 (2020).

[91] Zenke, F., Poole, B. & Ganguli, S. Continual learning through synaptic intelligence. In *International conference on machine learning*, 3987–3995 (PMLR, 2017).

[92] Farajtabar, M., Azizan, N., Mott, A. & Li, A. Orthogonal gradient descent for continual learning. In *International conference on artificial intelligence and statistics*, 3762–3773 (PMLR, 2020).

[93] Mondada, F. *et al.* The e-puck, a robot designed for education in engineering. In *Proceedings of the 9th conference on autonomous robot systems and competitions*, vol. 1, 59–65 (Castelo Branco: IPCB, Instituto Politécnico de Castelo Branco, 2009).

[94] Hu, C., Fu, Q. & Yue, S. Colias iv: The affordable micro robot platform with bio-inspired vision. In *Annual Conference Towards Autonomous Robotic Systems*, 197–208 (Springer, 2018).

[95] Sztarker, J., Strausfeld, N. J. & Tomsic, D. Organization of optic lobes that support motion detection in a semiterrestrial crab. *Journal of Comparative Neurology* **493**, 396–411 (2005).

[96] Luan, H. *et al.* Accelerating motion perception model mimics the visual neuronal ensemble of crab. In *2022 International Joint Conference on Neural Networks (IJCNN)*, 1–8 (IEEE, 2022).

[97] Sun, X., Liu, T., Hu, C., Fu, Q. & Yue, S. Colcos φ: A multiple pheromone communication system for swarm robotics and social insects research. In *2019 IEEE 4th international conference on advanced robotics and mechatronics (ICARM)*, 59–66 (IEEE, 2019).

[98] Liu, T., Sun, X., Hu, C., Fu, Q. & Yue, S. A versatile vision-pheromone-communication platform for swarm robotics. In *2021 IEEE International Conference on Robotics and Automation (ICRA)*, 7261–7266 (IEEE, 2021).

[99] Liu, T., Sun, X., Hu, C., Fu, Q. & Yue, S. A multiple pheromone communication system for swarm intelligence. *IEEE Access* **9**, 148721–148737 (2021).

[100] Ghosh-Dastidar, S. & Adeli, H. Spiking neural networks. *International journal of neural systems* **19**, 295–308 (2009).

[101] Yamazaki, K., Vo-Ho, V.-K., Bulsara, D. & Le, N. Spiking neural networks and their applications: A review. *Brain sciences* **12**, 863 (2022).

[102] Diehl, P. U. & Cook, M. Unsupervised learning of digit recognition using spike-timing-dependent plasticity. *Frontiers in computational neuroscience* **9**, 99 (2015).

[103] Qiu, X., Luan, Z., Wang, Z. & Zhu, R.-J. When spiking neural networks meet temporal attention image decoding and adaptive spiking neuron. *arXiv preprint arXiv:2406.03046* (2024).

[104] Sun, C. *et al.* Fully autonomous real-world reinforcement learning with applications to mobile manipulation. In *Conference on Robot Learning*, 308–319 (PMLR, 2022).

[105] Kemker, R., McClure, M., Abitino, A., Hayes, T. & Kanan, C. Measuring catastrophic forgetting in neural networks. In *Proceedings of the AAAI conference on artificial intelligence*, vol. 32 (2018).

[106] Jacobsen, A. *et al.* Fair principles: interpretations and implementation considerations (2020).