Fully Autonomous Neuromorphic Navigation and Dynamic Obstacle Avoidance

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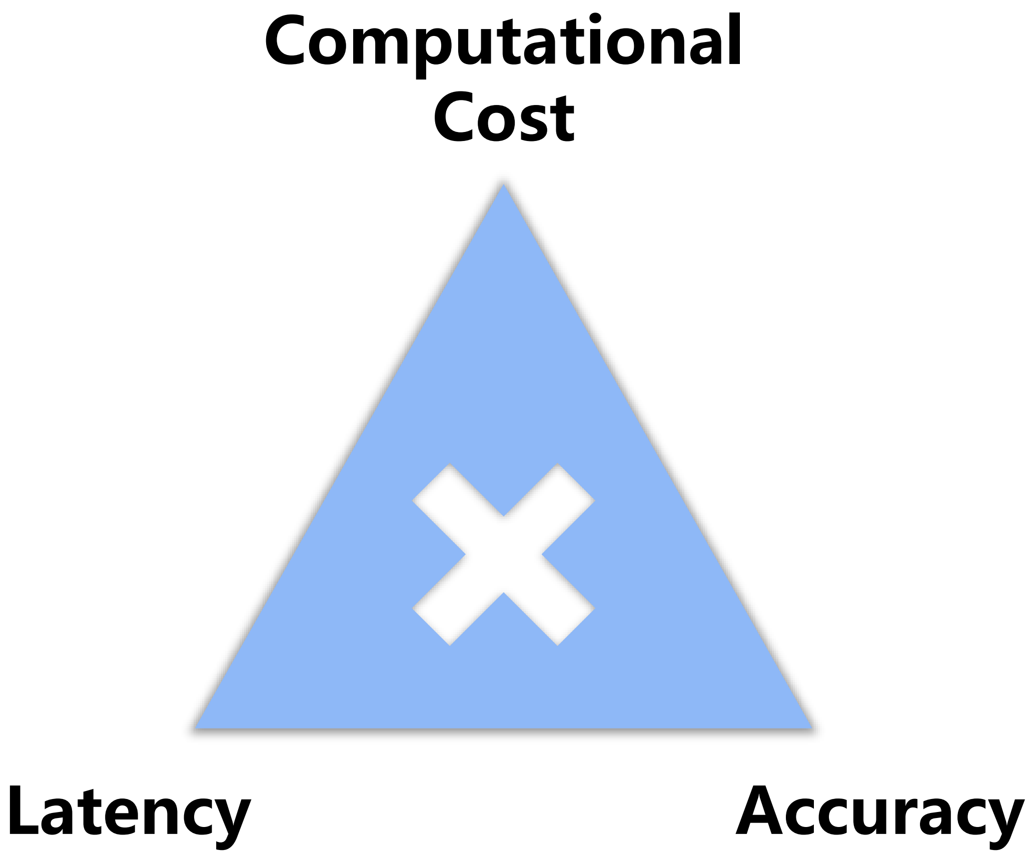
Background: Navigation and Obstacle Avoidance for Quadrotor Systems

The excellent performance of drones heavily relies on external signals.

- Positioning: GPS signals or ground station signals
- Control: Manual control or ground station commands

In signal-denied environments, most solutions are designed for larger platforms.

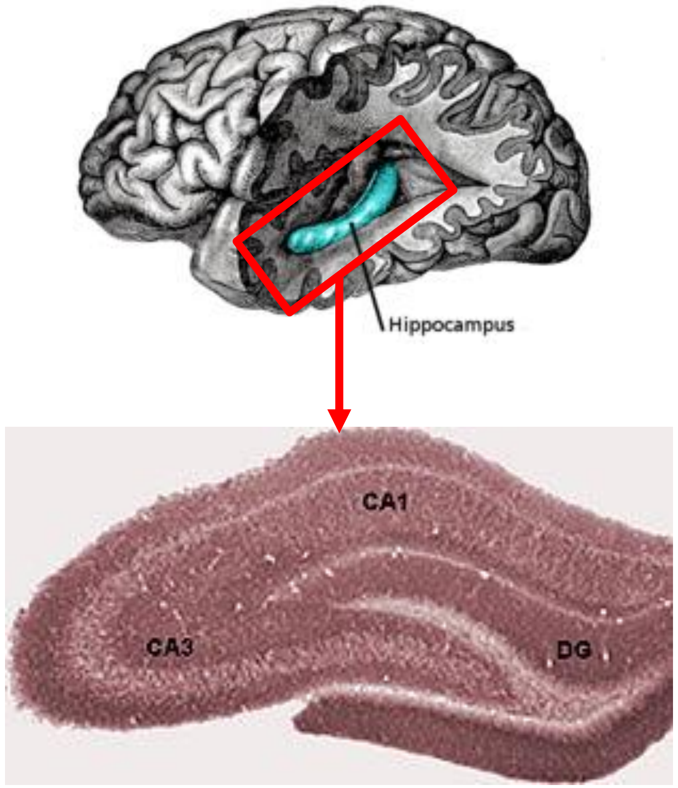
- Li-DAR system: accurate but **heavy** and **power-hungry**
- Vision system: lightweight but with **excessive computational and memory costs**

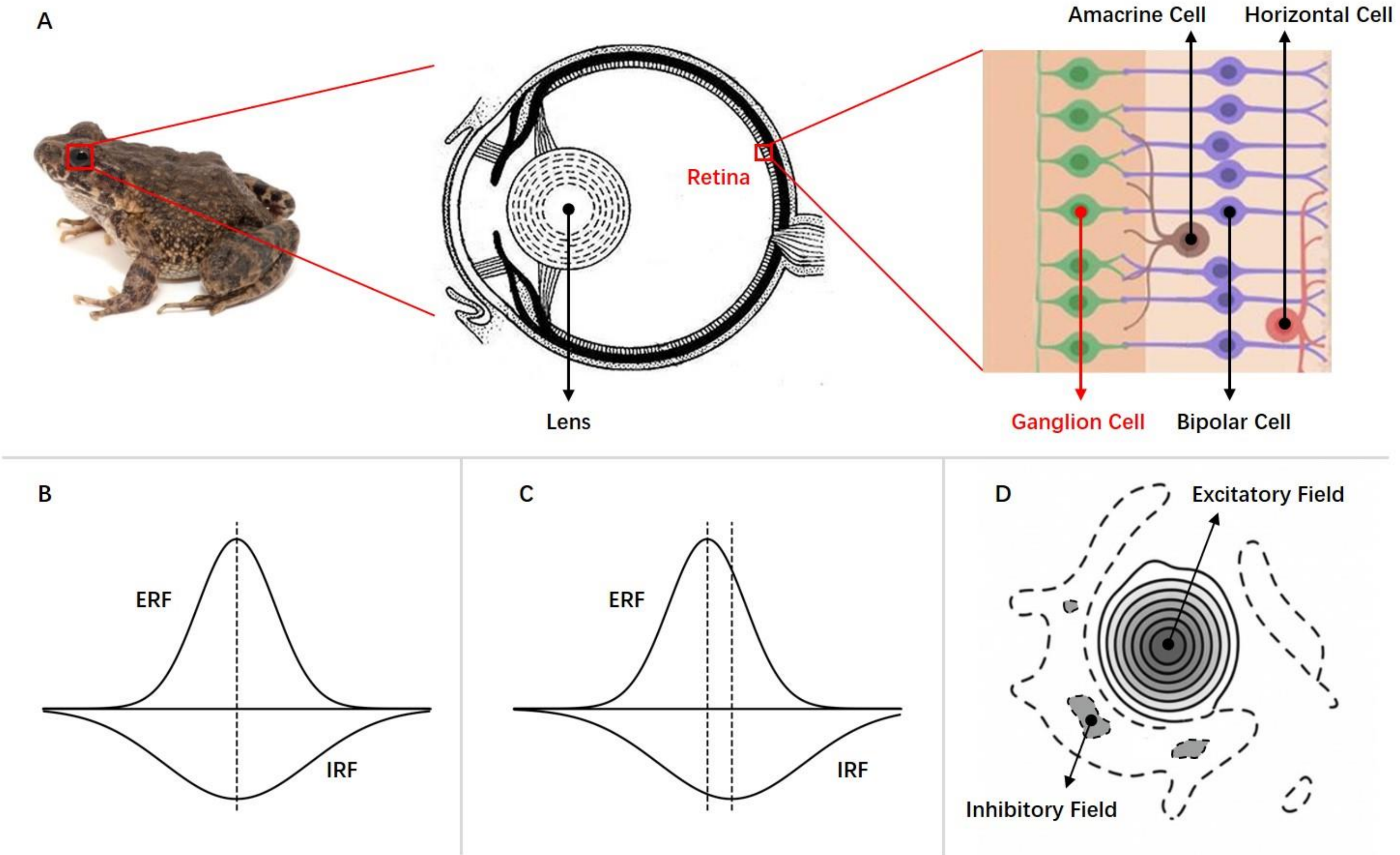


Background: Neuromorphic Intelligence

	Data intelligence driven by model learning		Cognitive bio-inspired neuromorphic intelligence
×	Massive data, High quality labeling	✓	**Few-shot learning, labeling**
×	Low adaptive ability, highly dependency on model.	✓	**Unsupervised learning, adaptive ability**
×	High computational costs, Power hungry	✓	**Low computational resources costs, Low Power**
×	Weak dependency on temporal sequence	✓	**Strong temporal sequence dependency, general solution to classical application scenario.**

Motivation: Bio-inspired Neuromorphic Solution for Edge Computing Platforms

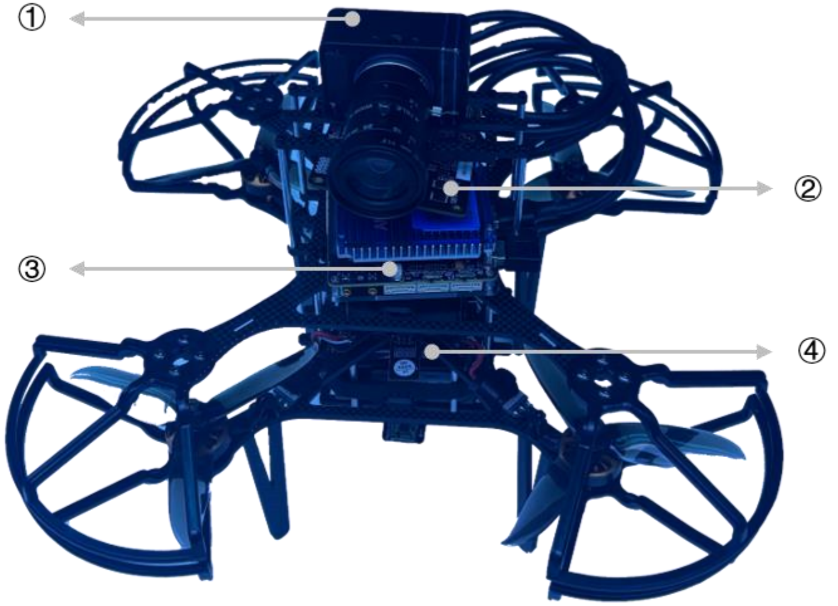


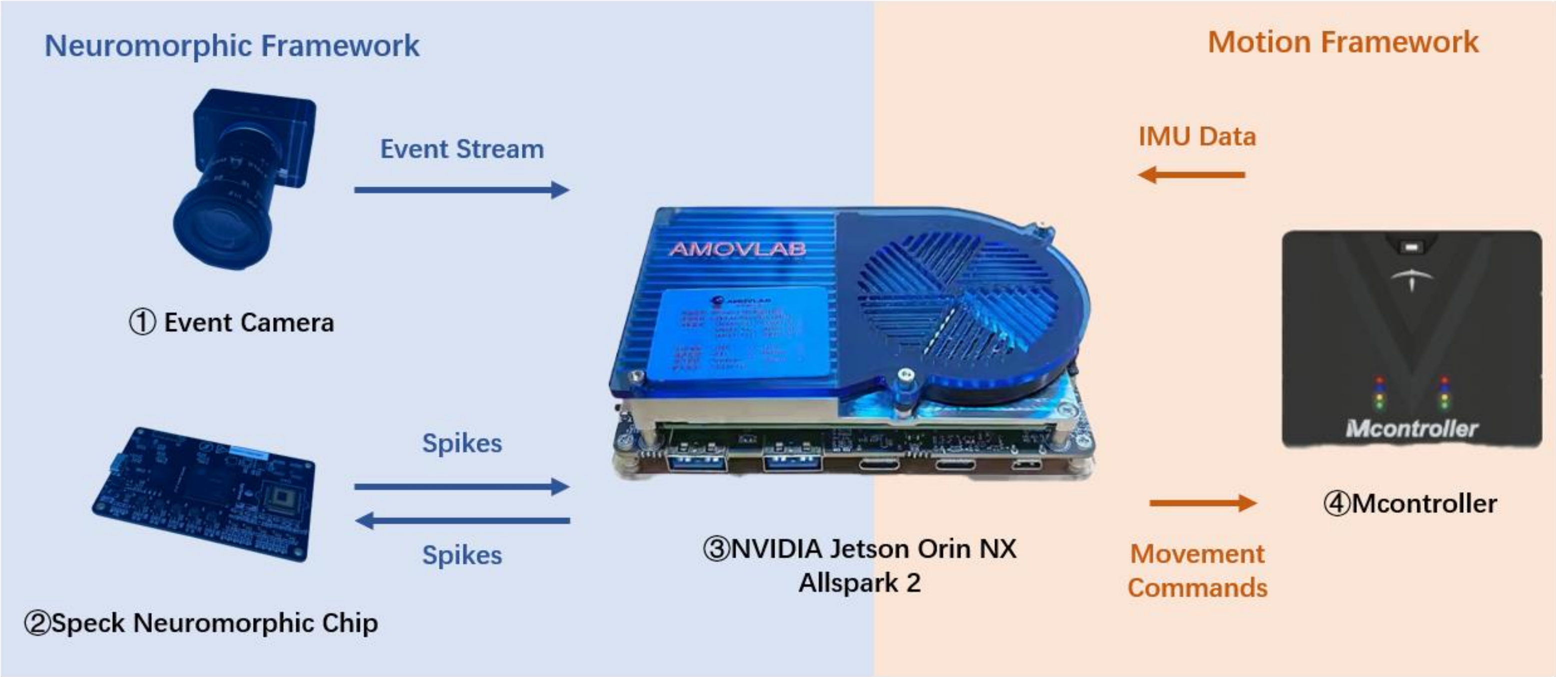


In nature, organisms (like anurans) can easily navigate and capture fast-moving objects.

Even With Tiny Brains!

Hardware Introduction





Total weight of the quadrotor: 856 g

Tip-to-tip diameter: 240 mm

Due to the constraints of the Speck chip, the computational process carried out in the neuromorphic chip still relies on an x86-based onboard computer for fundamental support.

Methods: Overview

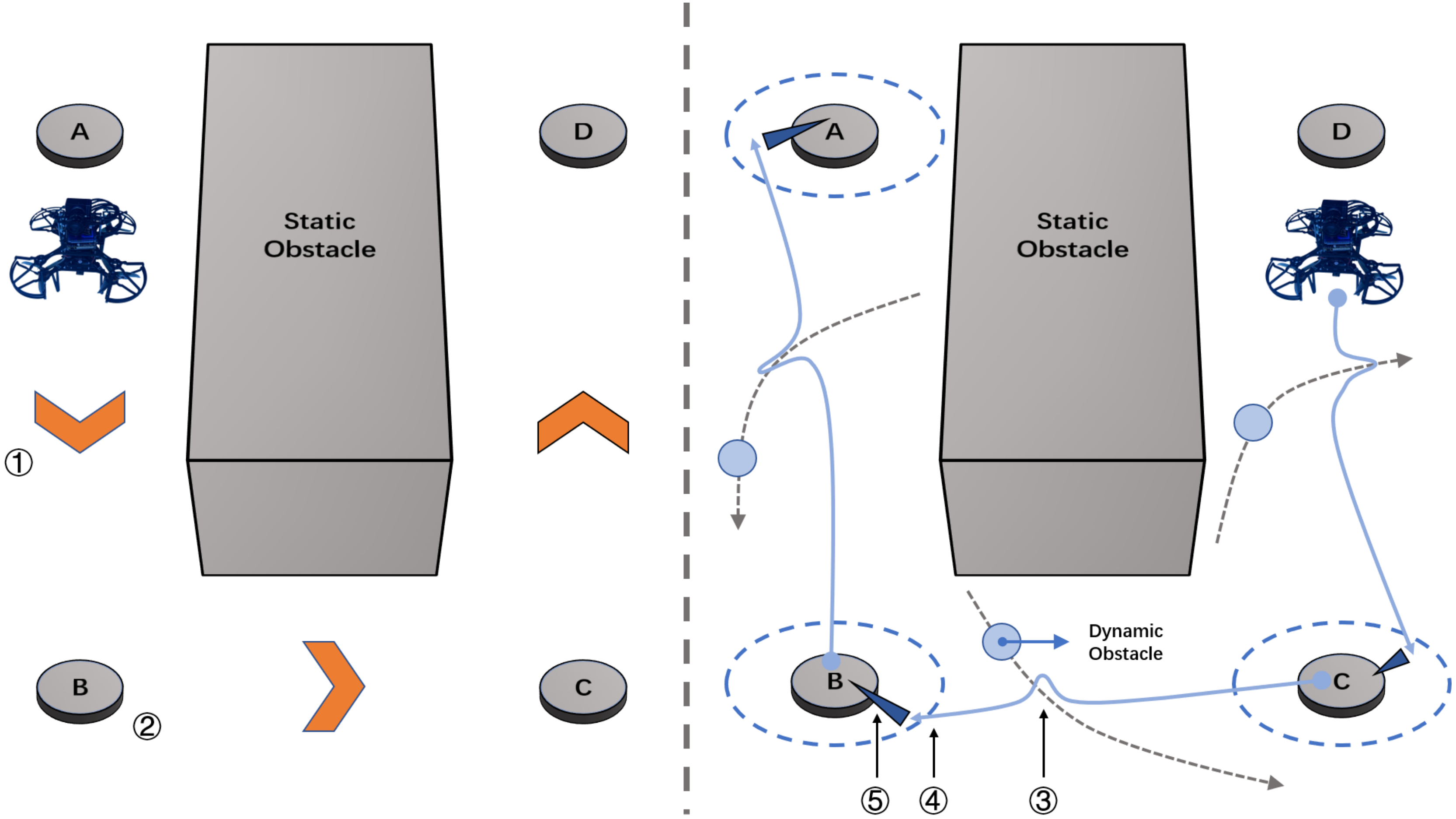
① The quadrotor performs an outbound flight

② Periodically records event streams at Snapshot points

③ Using Bio-inspired Event RF model to perform dynamic obstacle avoidance

④ Continuously calibrates itself in the catchment area

⑤ Reaches Snapshot area

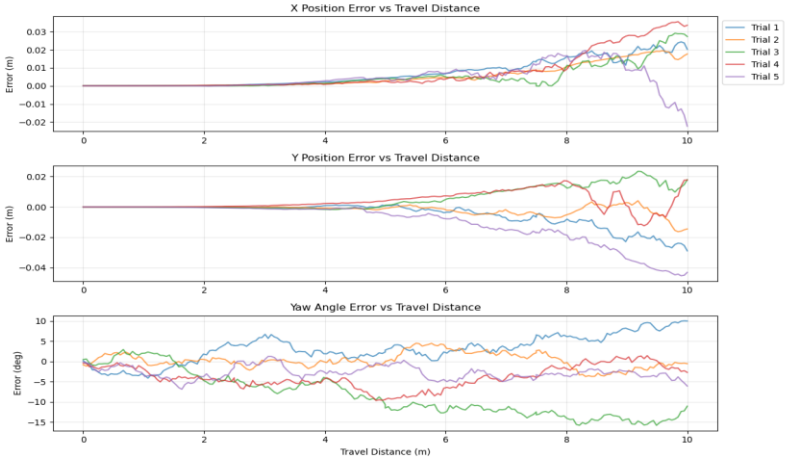


Methods: Event Visual-homing

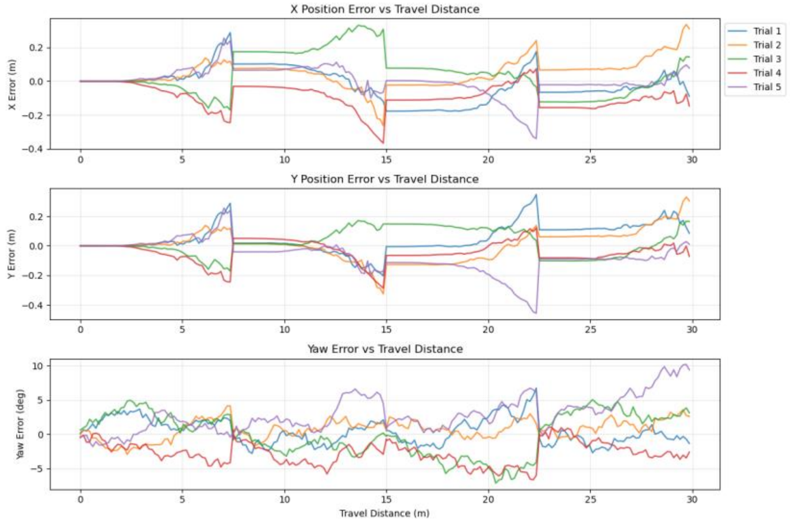
Simplified stack-over-time IMU error:

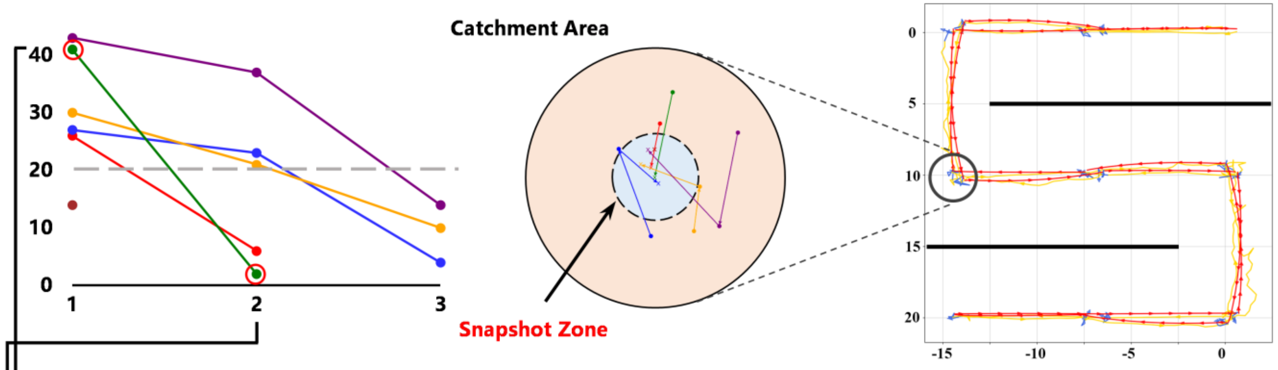
$$\delta r_N = \delta r_{N,0} + \delta v_{N,0,t} + \frac{1}{2}(g \cdot \delta\Theta_0 + b_{\alpha N})t^2 + \frac{1}{6}(g \cdot b_{gE})t^3$$

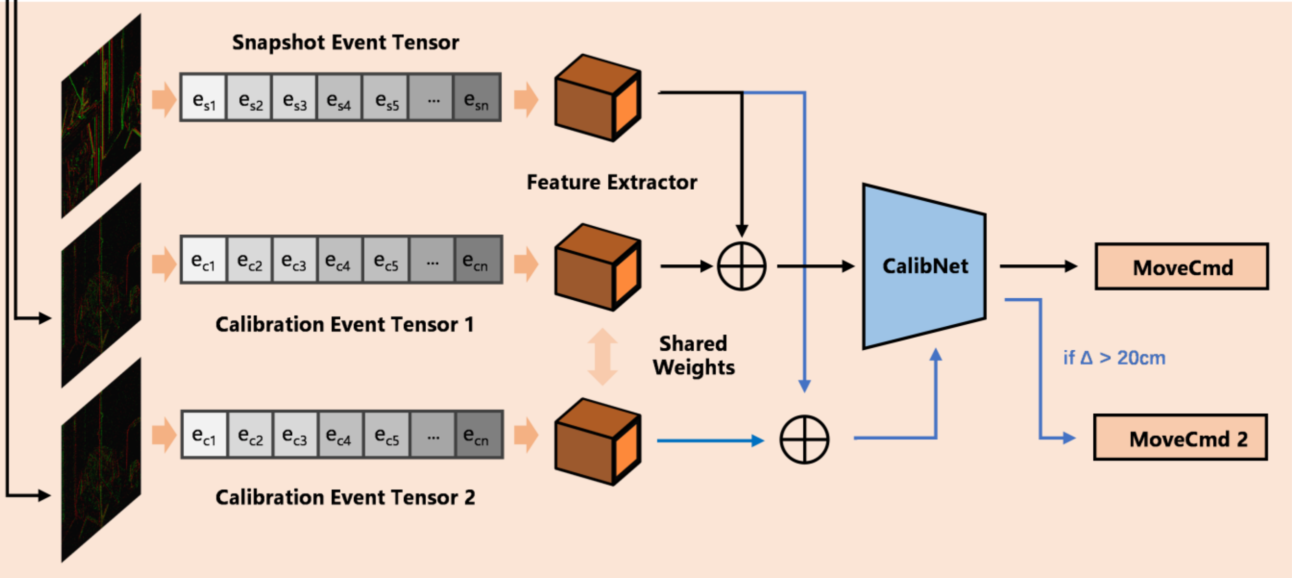
Error w.r.t. Time



Error w.r.t. Time w/ calibration





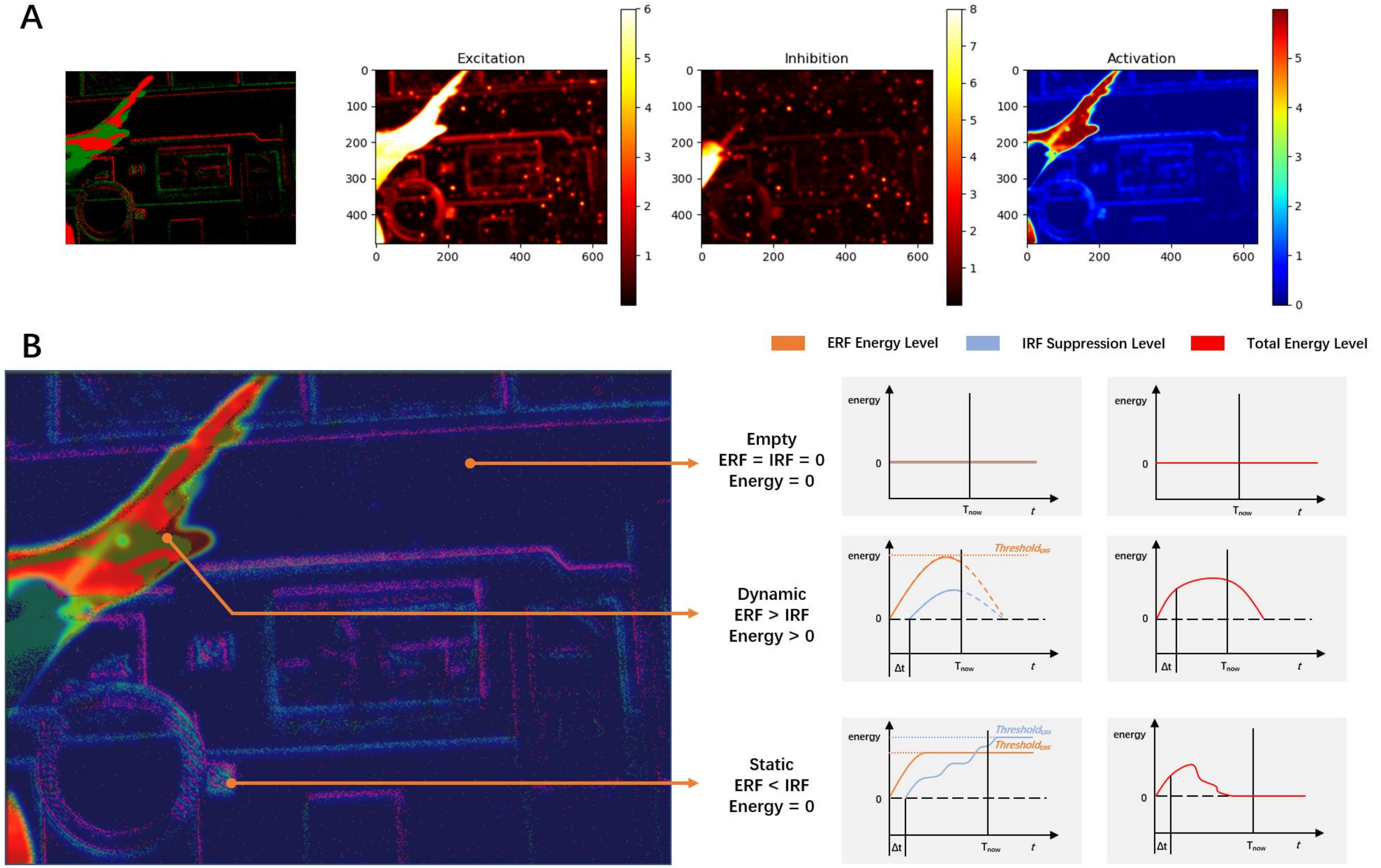


Methods: Bio-inspired Dynamic Obstacle Avoidance

Event RF Model:

The mechanism by which anurans capture highly dynamic insects is the superimposition of **ERF** (excitatory receptive field) and **IRF** (inhibitory receptive field) to **suppress the perception of static objects** and maintain sensitivity only to dynamic ones.

R3 ganglion cells respond to stimuli to **ON-OFF brightness changes**, which are highly identical to event changes



Methods: Bio-inspired Dynamic Obstacle Avoidance

Event RF Model:

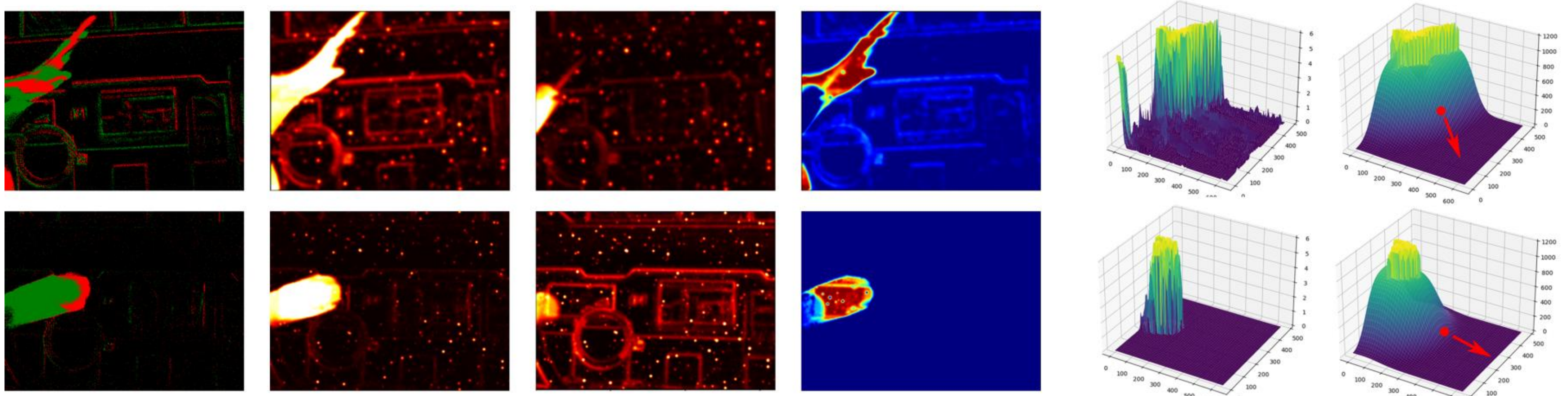
$$F(x,y,e_n,t) = min(A_1 K(t,\tau_e)G(x,y,e_n),E_{th}) - min(A_2 K(t-\Delta t,\tau_i)G(x,y,e_n),I_{th})$$

Time Kernel:

$$K(t,\tau) = \begin{cases} e^{-t/\tau} & t \geq 0 \\ 0 & t < 0 \end{cases}$$

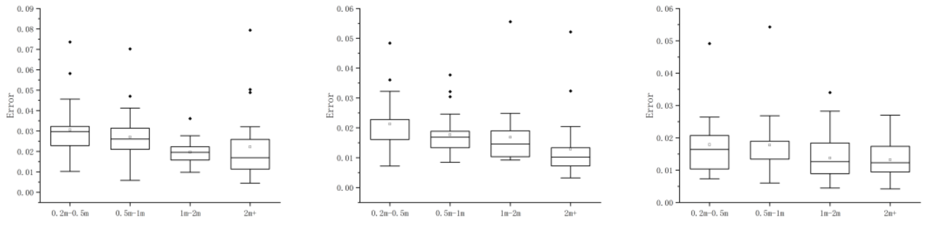
Gaussian Kernel:

$$G(x,y,e_n) = \frac{1}{2\pi\sigma_x\sigma_y} exp(-\frac{(x-x_n)^2}{2\sigma_x^2} - \frac{(y-y_n)^2}{2\sigma_y^2})$$



Raw Event | ERF | IRF | Event RF Model | Raw Potential Field | Diffused Potential Field

Experiments: Simulation



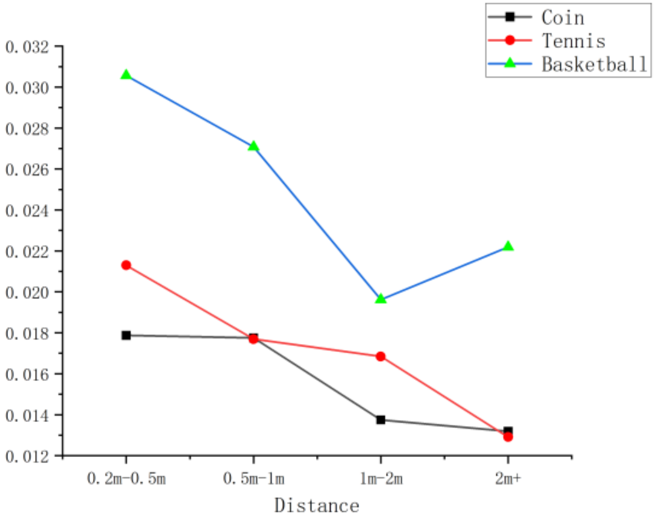
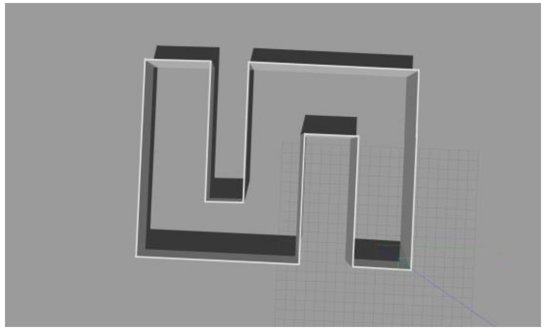


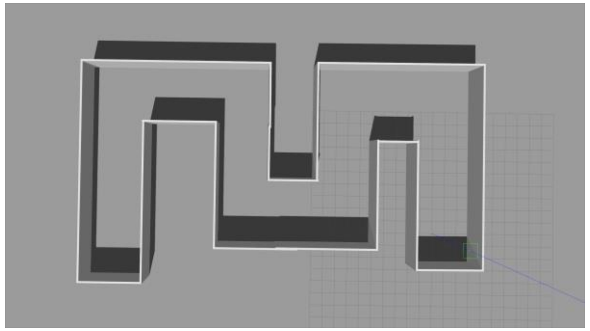
Table 1: **Centroid Difference Between RF Model and GT (m)**

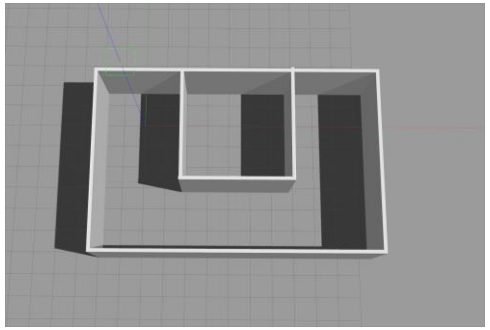
Obstacle Type	Distance	Mean	Median	Std. Dev.	M.A.D	SR
Coin-sized	0.2m - 0.5m	0.0179	0.0164	0.0089	0.0015	94%
	0.5m - 1m	0.0177	0.0134	0.0094	0.0008	92%
	1m - 2m	0.0138	0.0126	0.0077	0.0202	90%
	2m+	0.0132	0.0123	0.0053	0.0042	86%
Tennis-sized	0.2m - 0.5m	0.0213	0.0228	0.0093	0.0052	92%
	0.5m - 1m	0.0180	0.0169	0.0072	0.0093	98%
	1m - 2m	0.0168	0.0146	0.0095	0.0002	100%
	2m+	0.0129	0.0102	0.0103	0.0057	96%
Basketball-sized	0.2m - 0.5m	0.0306	0.0297	0.0141	0.0017	84%
	0.5m - 1m	0.0271	0.0261	0.0135	0.0026	96%
	1m - 2m	0.0196	0.0196	0.0059	0.0081	100%
	2m+	0.0222	0.0169	0.0166	0.0109	100%

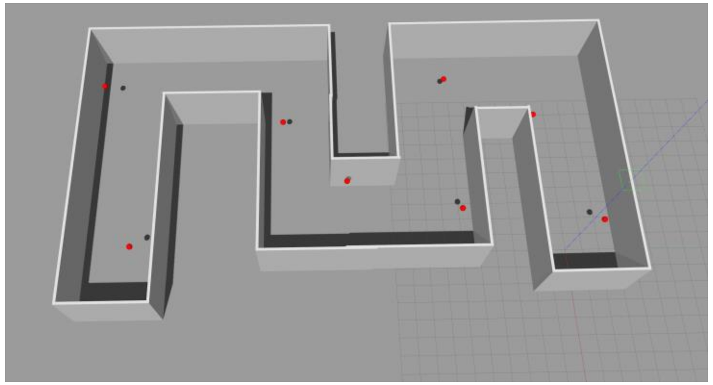
The Event RF Model could accurately capture **events produced by dynamic objects** and generate avoidance movements

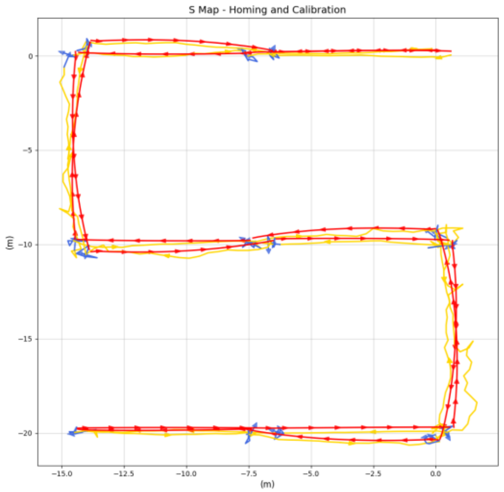
Experiments: Simulation

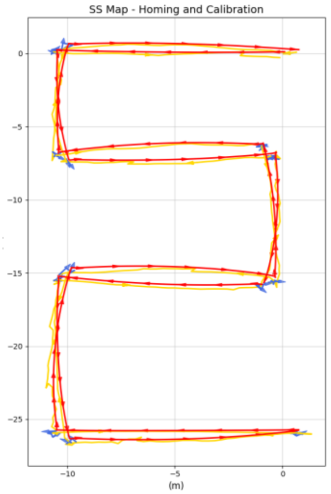


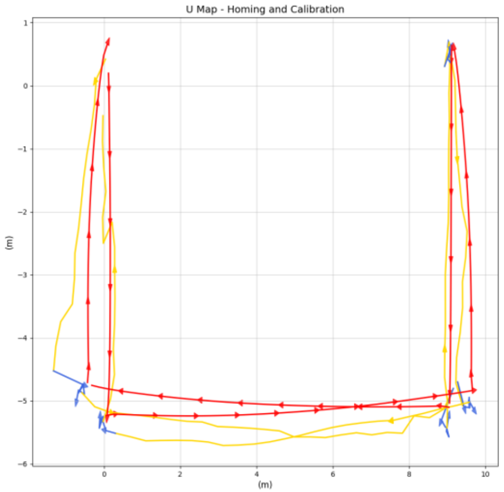


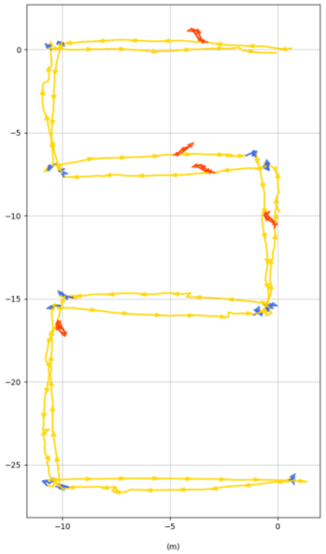




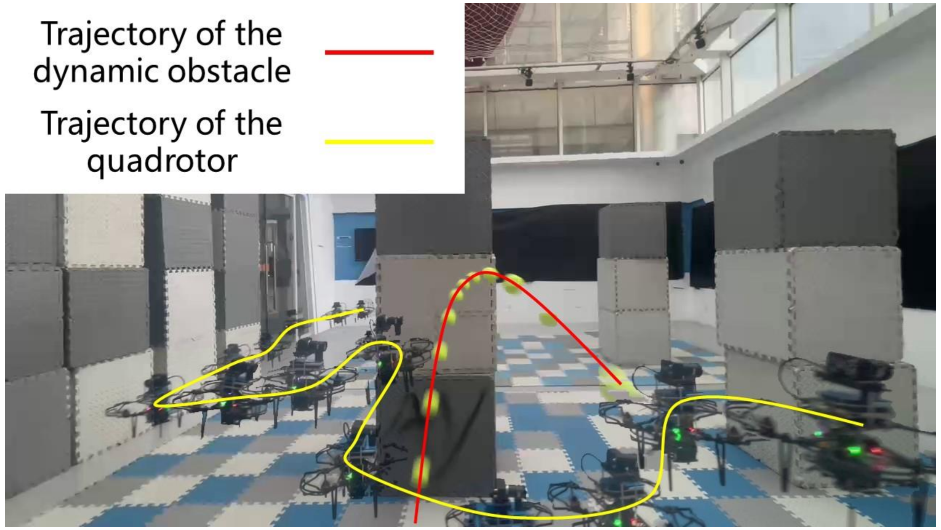






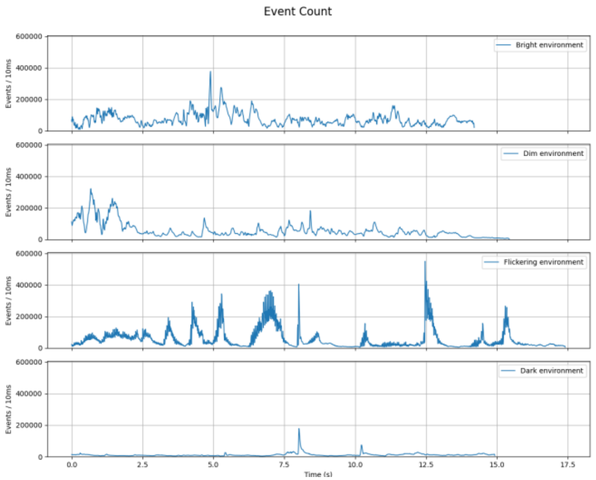


Experiments: Real-world – Indoor Experiment



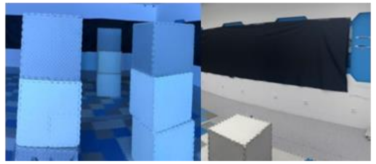
Method	Latency	Pos. Err.	SR
Method 1 [64]	19.12 ms	0.11 m	**96.3**
Method 2 [13]	39.49 ms	0.11 m	89.1
Method 3 [26]	3.56 ms	0.09 m	86.7
Method 4 (GTX 4090) [65]	14 ms	LiDAR	95.75
Method 4 (onboard) [65]	27 ms	LiDAR	86.5
Ours	**2.34 ms**	**0.02 m**	94.5

Quantitative Evaluation



Light (10 – 100 lux)

Flicker (1 – 100 lux)



Dim (1 – 10 lux)

Dark (0 – 1 lux)

Flight Arena in Various Light Conditions

Experiments: Energy Consumption and Computational Cost

Device	Idle Power (W)	Running Power (W)	Delta (W)	Latency (ms)
Speck	4.2×10^{-4}	1.56×10^{-2}	1.518×10^{-2}	-
Jetson Orin NX + Speck (10W)	3.68	4.64	0.96	2.3
Jetson Orin NX + SNN (10W) without Speck	3.71	9.52	5.81	6.8
Jetson Orin NX + ANN (10W)	3.72	-	-	-
Jetson Orin NX + ANN (25W)	3.72	22.4	18.68	12.5

Step	μ [ms]	σ [ms]	Perc. [%]
Event RF Model	0.64	0.22	27.35%
Energy Decay Update	1.09	0.34	46.58%
Potential Field	0.61	0.03	26.07%
Total	2.34	0.51	100%

Comparisons are made between the **Speck neuromorphic chip** and an **Nvidia Jetson Orin NX** for running the whole pipeline. Due to the device limit, **only SNN is performed on the Speck neuromorphic chip**, while both SNN and equivalent ANN are performed on the Nvidia Jetson Orin NX platform. The SNN ran in hardware on Speck and in software on Jetson Orin NX.

95% energy reduction of computation (down to 5% of original levels) in the neuromorphic structure and the total system energy consumption decreases to 21% of baseline values.

Conclusion

Our contributions to the community include:

- A **fully neuromorphic framework** enabling tiny UAVs to rely solely on **onboard computation and sensing** for real-time navigation and dynamic obstacle avoidance.
- A **bio-inspired** approach enabling tiny UAVs to accurately avoid dynamic obstacles at **speeds up to 10 m/s with a latency of 2.3 milliseconds**.
- An open-sourced **monocular event-based pose correction dataset** with over 50,234 paired and labeled event streams. (not mentioned in this slide due to time limit)

Code

Xiaochen Shang’s Homepage