

Taming Event Cameras with Bio-Inspired Architecture and Algorithm: A Case for Drone Obstacle Avoidance

Jingao Xu¹, Danyang Li¹, Zheng Yang¹✉, Yishujie Zhao¹, Hao Cao¹,
Yunhao Liu¹, Longfei Shangguan²

¹Tsinghua University ²University of Pittsburgh

{xujingao13, lidanyang1919, hmilyyz, yunhaoliu}@gmail.com
cobs14@126.com, caoh19@mails.tsinghua.edu.cn, longfei@pitt.edu

ABSTRACT

Fast and accurate obstacle avoidance is crucial to drone safety. Yet existing on-board sensor modules such as frame cameras and radars are ill-suited for doing so due to their low temporal resolution or limited field of view. This paper presents **BioDrone**, a new design paradigm for drone obstacle avoidance using stereo event cameras. At the heart of BioDrone is two simple yet effective system design inspired by the mammalian visual system, namely, a chiasm-inspired signal processing pipeline for fast event filtering and obstacle detection, and a lateral geniculate nucleus (LGN)-inspired event matching algorithm for accurate obstacle localization. To make BioDrone a practical solution, we further take significant engineering efforts to deploy the software stack on FPGA through software and hardware co-design. The performance comparison with two state-of-the-art event-based obstacle avoidance systems shows BioDrone achieves a consistently high obstacle detection rate of 96.1%. The average localization error of BioDrone is 6.8cm with a 4.7ms latency, outperforming both baselines by over 40%.

CCS CONCEPTS

• **Human-centered computing** → **Ubiquitous and mobile computing**.

✉ Zheng Yang is the corresponding author.

Jingao Xu and Danyang Li are co-primary authors.

Project repository: <https://github.com/MobiSense/BioDrone>.

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KEYWORDS

Mobile Computing; Drone-based Applications; Obstacle Avoidance; Event Camera; Bio-inspired Design

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1 INTRODUCTION

Drones are among the most disruptive inventions in the past few years, spawning many novel applications including aerial imaging[7, 35, 37], last-mile delivery[47, 68, 71], sky networking[15, 61], and industrial inspection[1, 13, 75]. Despite their huge market value, safety remains a crucial challenge for drones, particularly for those high-speed drones in industrial and urban applications. For instance, DJI's industrial drones cruise at up to 25m/s[19], and the relative speed between two Amazon delivery drones can reach 30m/s[4]. Drone collisions with obstacles (e.g., birds[48], drones[16]) will not only cause financial loss but also threaten human safety[2, 27], which sets a strong barrier for drone adoption.

Fast and accurate obstacle detection and localization plays a key role in drone obstacle avoidance – the lower the detection latency, the more time the drone could take to react; and a higher localization accuracy increases the likelihood the drone can dodge them. Existing solutions primarily rely on frame-based cameras[22, 70] and radars[33, 45]. However, the low spatial-temporal sampling resolution of these on-board sensors makes it challenging for drones to perceive obstacles timely or localize them accurately.

For instance, the sampling interval of a typical frame-based camera varies from 20ms to 50ms, during which an obstacle can move up to 40cm (given a 20m/s relative speed). As a result, we are expected to see severe motion blurring on each image (Fig.1c). Such motion blurring will fail the vision

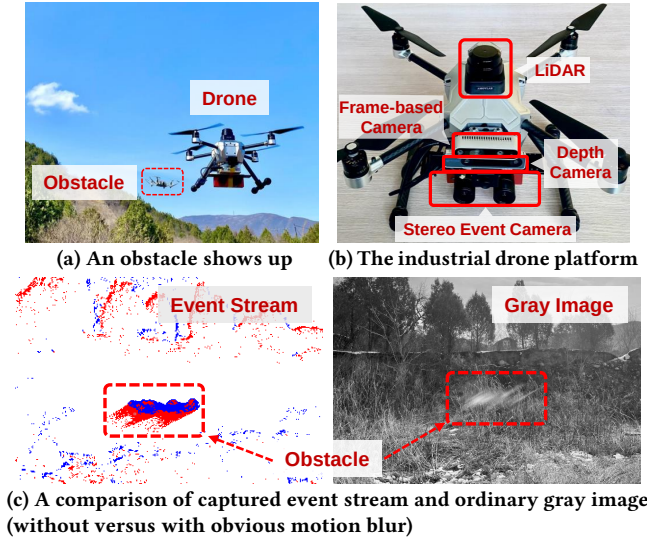


Figure 1: Snapshot of an obstacle avoidance maneuver.

algorithms, impairing both obstacle detection and localization accuracy. The radar-based solutions, on the other hand, suffer from high miss detection rates due to their limited field of view (FoV)[24, 76].

Drone obstacle avoidance with event cameras. Event cameras are novel bio-inspired sensors that report pixel-wise intensity changes asynchronously. Endowed with microsecond resolution, event cameras are able to capture high-speed motions without blurring (Fig.1c). Hence event cameras are envisioned to be an ideal solution to challenging vision tasks such as high-speed feature tracking[85], motion tracking[39], and simultaneous localization and mapping (SLAM)[26].

To better understand the potential of event cameras for obstacle avoidance, we reimplement seven state-of-the-art systems[10, 24, 29, 49, 52, 65, 84] (red circles in Fig.2, and [29, 65] require multi-modal fusion) with stereo event camera setup and evaluate their performance. Our benchmark studies (§2.3) reveal that they face fundamental challenges for high-speed drone adoption, as elaborated below.

- **Event burst impairs drone obstacle detection.** Event cameras are hyper-sensitive to environmental change. For instance, a slight change in lighting can lead to a remarkable change in pixel-wise intensity, resulting in hundreds of event reports. In practice, the scene in the camera's view changes rapidly due to drone movement; thus we will see an event burst where thousands of events are reported within a short time and those critical obstacle-triggered events are easily buried by massive numbers of environment-triggered events.

- **Event sticking delays drone obstacle localization.** Conventional vision algorithms are designed for frame-based cameras and cannot be directly applied to event streams for obstacle localization because the output of an event camera

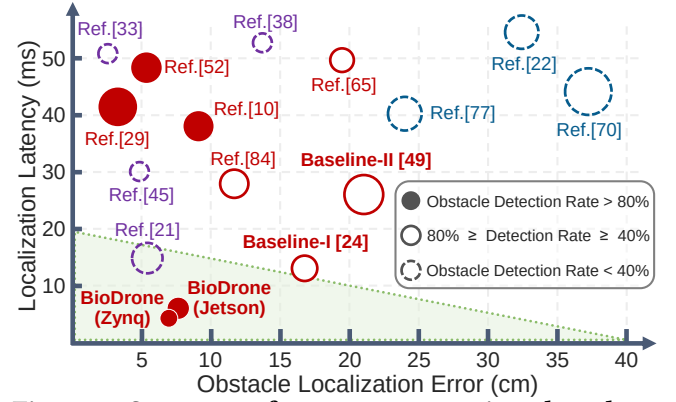


Figure 2: System performance comparison based on our field studies (§2). A smaller circle size indicates a more stable performance. The green area indicates a feasible performance range for high-speed (i.e., 20m/s) drones (§2.2). is not an image but a stream of asynchronous events. To address this issue, the current practice periodically sticks a lot of scattered events into a compact image and applies image-based algorithms (e.g., stereo triangulation[28] or deep neural networks[10, 29, 52, 65]) that are both computationally demanding. Repeating these operations would cause significant delays in obstacle localization.

Although existing solutions (e.g., Baseline-I[24]) achieve high obstacle *detection* accuracy by using a monocular event camera. The obstacle *localization* performance, however, drops significantly in high-speed scenarios (i.e., 20m/s) due to the increasing task complexity and growing data volume.

Given that the event camera is a kind of bio-inspired vision sensor, we ask a question: Could we tackle the above challenges by studying how animals process binocular visual signals for efficient obstacle localization? To answer this question, we resort to bionics and take a comprehensive study (§3.1) on (i) how binocular visual signals are transmitted from the retina to the visual cortex in the mammalian visual system; and (ii) how they are rapidly filtered, matched, and spatio-temporal corrected through the visual pathway.

Our Work. In this paper, we leverage the **Biological** lessons learned from mammalian visual system and propose BioDrone, a **Drone-oriented** obstacle avoidance system. BioDrone features three key designs to fully unleash binocular event cameras' potential for obstacle localization and is implemented on FPGA with software-hardware co-design by embracing on-chip intelligence[6, 57], as elaborated below.

- On system architecture front, we imitate how mammal's *visual pathway* processes binocular visual signals and propose a visual-pathway-inspired signal processing pipeline for binocular event streams. Unlike the current practice where event streams are processed separately and not fused until the final triangulation stage, BioDrone fuses binocular event streams at an early stage, enabling the subsequent

event filtering, matching, and localization modules to take full advantage of binocular information (§3.3).

- On system algorithm front, we first introduce a Chiasm-inspired Event Filtering (CEF) algorithm to quickly filter out environment-triggered events from the massive amount of events with a very low false positive rate (§4.1). We then propose a Lateral Geniculate Nucleus (LGN)-inspired Event Matching (LEM) algorithm to determine the spatial location of obstacles directly on binocular event streams thus eliminating cumbersome event sticking operations (§4.2).

- On system implementation front, we implement BioDrone on a commercial Xilinx Zynq-7020[73] chip. We design exclusive logic circuits, on FPGA, to parallelize the pixel-wise event processing, expediting the whole software stack (§5).

We deploy BioDrone on a drone testbed and further integrate it into ArduPilot[5], a widely-used open-source drone flight controller. We conduct extensive experiments with various types of obstacles and in different flying speed settings both indoors and outdoors. We compare the end-to-end obstacle localization accuracy and latency of BioDrone with two state-of-the-art (SOTA) event camera-based drone obstacle avoidance systems Baseline-I[24] (Science Robotics'20) and Baseline-II[49] (IROS'18). Evaluation results show that BioDrone achieves 96.1% obstacle detection rate, outperforming both baselines by >10%. BioDrone further achieves 6.8cm obstacle localization accuracy with 4.7ms latency, outperforming baselines by >40%.

In summary, this paper makes following contributions.

- (1) We systematically study both the conventional sensor- and event camera-based drone obstacle avoidance systems, and reveal the fundamental limitations of these solutions.
- (2) We demonstrate that bio-inspired designs can effectively improve drone obstacle detection and localization accuracy with a stereo event camera setup. As biology progresses and the future grasp of the visual system deepens, we believe this bio-inspired design will spawn new ideas in this domain.
- (3) We fully implement BioDrone through software-hardware co-design and deploy it on an industrial drone, conducting a head-to-head comparison with two SOTA systems. The evaluation results show BioDrone's efficacy.

2 BACKGROUND AND MOTIVATION

2.1 Drone Obstacle Avoidance Primer

As illustrated in Fig.3a, obstacle avoidance consists of *localization* and *action* two phases. During the *localization* phase, suppose an obstacle shows up abruptly at t_0 and is perceived by a drone at t_1 after a perception delay Δt_p . Upon detecting the obstacle, the drone takes Δt_c to localize the obstacle. Noting that the drone still follows its planned trajectory to move before localizing the obstacle at t_2 . Afterward, the on-board

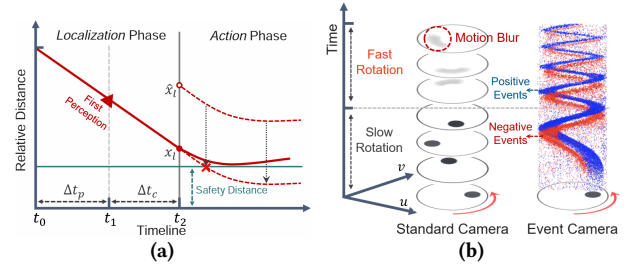


Figure 3: (a) Relative distance changes in an avoidance maneuver. (b) Illustration of the event stream.

flight controller changes the drone's trajectory to dodge the obstacle (i.e., keep a safe distance from it) in the *action* phase.

Both the localization delay ($\Delta t_l = \Delta t_p + \Delta t_c$) and localization error ($\Delta x = \hat{x}_l - x_l$) are crucial to drone obstacle avoidance. A long delay Δt_l leaves the drone very short time to react, and a large localization error Δx misleads the flight controller to execute a wrong obstacle avoidance maneuver.

2.2 Limitations of the Current Practice

Existing radar-based (e.g., LiDAR[31, 33, 43], mmWave[21, 46, 76], or ultrasound[80]) and camera-based solutions (e.g., monocular[30, 70], stereo[22, 77], or depth[60]) are ill-suited for drone obstacle avoidance due to their high perception delay (high Δt_p) or low localization accuracy (high Δx). Take DJI Matrice 200 v2, the most advanced industrial drone, as an example. Its cruising speed can reach $v_c = 20m/s$ in a wide range of applications such as urgent package delivery, emergency services, and rapid terrain mapping. Based on the manufacturer's safety guideline[20], the safety distance between the drone and obstacle should be no less than $l_s = 60cm$, with an emergency braking distance at $l_b = 50cm$.

What is a feasible solution? Let l be the distance between the drone and the obstacle. To ensure the drone can successfully evade the obstacle, the localization delay Δt_l and accuracy Δx should satisfy the following equation:

$$v_c \times \Delta t_l + l_b + \Delta x \leq l - l_s. \quad (1)$$

Now assuming an obstacle shows up 1.5m (i.e., $l = 1.5m$) away from the drone. Based on Eq.1, we can draw a feasible area (the triangle area in green) in Fig.2 where each point within this area represents an acceptable localization latency and accuracy. Any point outside this feasible area would lead to a failure in drone obstacle avoidance maneuvers.

Examining the current practice. We build a drone testbed by integrating five types of sensor units, including a LiDAR, a mmWave radar, a depth radar, a monocular camera, and a stereo camera, into an industrial drone (Fig.1b). We then re-implement seven obstacle avoidance solutions [21, 22, 33, 43, 45, 70, 77] and evaluate their performance in high-speed scenarios by conducting over 1,500 obstacle avoidance tests (§6). Fig.2 depicts their obstacle detection rate, average

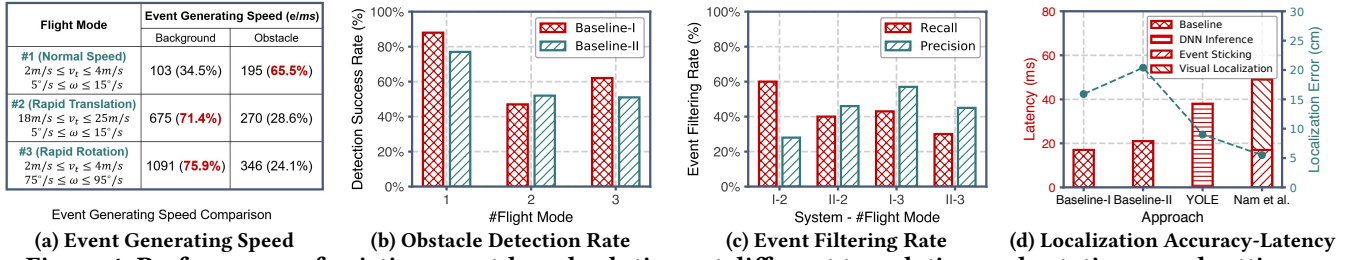


Figure 4: Performance of existing event-based solutions at different translation and rotation speed settings.

localization accuracy (Δx) and delay (Δt_l). As seen, frame camera-based solutions (i.e., blue circles) suffer from long localization delays due to their long frame exposure time (around 20ms) and excessive image processing delay (adding another 10-20ms). Worse still, the motion blurring shown in each frame would confuse the obstacle detection and localization algorithm, exacerbating both misdetection rate and localization errors. On the other hand, LiDAR and mmWave radar-based solutions (i.e., purple circles) suffer from low detection rate (i.e., $\leq 40\%$) due to their limited field of view.

2.3 Event Camera for Obstacle Avoidance: Opportunities and Challenges

Event cameras are bio-inspired sensors that work differently from frame-based cameras. Instead of capturing images at a fixed rate, an event camera measures per-pixel brightness changes asynchronously, resulting in a stream of events at *microsecond* resolution[26]. Specifically, an event camera has smart pixels (similar to the photoreceptor cells on retinas) that trigger events independently of each other: as shown in Fig.3b, once a pixel detects a change of intensity in the scene, it will instantly output an event $e_k = (x, t_k, p_k)$, encoding the occurrence time t_k (at microsecond resolution), pixel location $x = (u, v)$, and polarity p_k (blue for +1 vs. red for -1 in Fig.3b) of the intensity changes (i.e., brighter or darker).

The high temporal resolution empowers the event camera to detect environment changes promptly. However, leveraging event cameras to detect obstacles for high-speed drones is facing two fundamental challenges, as elaborated below.

• **C1: Event burst impairs drone obstacle detection.** Events captured by an event camera can be classified into two categories: environment-triggered and obstacle-triggered events. The former is generated due to the ego-motion of the event camera, while the latter is caused by the appearance of obstacles. To detect and further localize an obstacle, a system needs to identify obstacle events from massive events. To this end, existing solutions apply IMU-based ego-motion compensation algorithms to filter out environment-triggered events[24, 26, 49]. However, as shown in Fig.4a, the number of events generated per millisecond surged from around 300 to 1,500 and the new additions are mainly environment

events. Such a burst of environmental events overwhelm obstacle events and degrade existing algorithms' performance.

To validate the above analysis, we conduct an obstacle detection experiment under different flight modes. As shown in Fig.4b, the detection rate of two SOTA solutions, Baseline-I[24] and -II[49], drops to $< 60\%$. To better understand the reasons for failure cases, we further examine the event filtering performance of these two baselines in two high-speed flight modes (i.e., mode 2 and mode 3). We observe that both systems achieve a very low event filtering rate (recall and precision $< 60\%$ in Fig.4c), which confirms our analysis.

• **C2: Event sticking delays drone obstacle localization.** Once the obstacle is detected, the drone has to localize it in 3D space. Typically, localization is more time-consuming than detection due to the additional operations involved. For instance, Baseline-I requires binocular parallax optimization, matching, and triangulation after detection, which is more computationally intensive as outlined in [24].

Moreover, conventional vision algorithms (e.g., stereo triangulation[28]) or DNNs cannot be directly applied as the output of an event camera is not fix-rate frames but a stream of asynchronous events. To solve this issue, the current practice proposes to (i) stick all generated events within a time window (e.g., $< 1ms$) into an image and then apply image-based algorithms (Fig.5c); or (ii) design event data-oriented DNNs (e.g., spiking neural networks[63]) for object localization. However, as depicted in Fig.4d, although the localization accuracy is boosted, either the sticking operations, the stereo visual algorithms, or DNN inference introduces significant delays, leaving the drone no time to react.

In summary, although event cameras hold great potential for delay-sensitive tasks such as drone obstacle avoidance, there still lack effective algorithms and system support to fully unleash their potential, especially with a stereo setup for localization tasks.

3 BIO-INSPIRED ARCHITECTURE

Our system architecture and algorithms are inspired by the *biological visual pathway*. In this section, we first introduce the biological visual pathway in mammalian visual system and describe how visual information is filtered, processed,

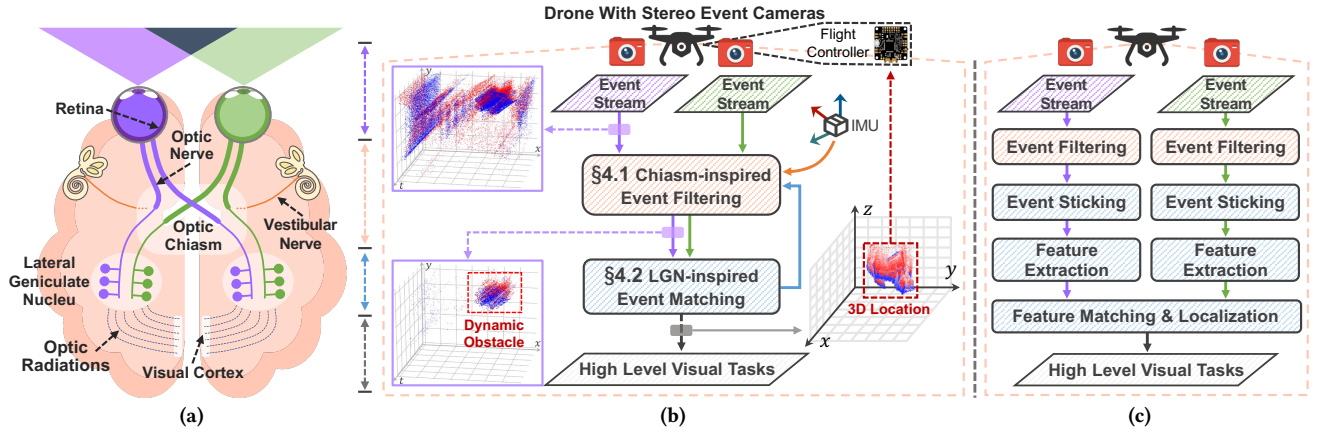


Figure 5: System architecture comparison. (a) Human binocular visual pathway. (b) BioDrone's architecture inspired by (a). (c) System architecture of conventional event-based systems[24, 49, 50], where binocular event streams are processed separately and follow traditional visual localization workflow (i.e., from feature extraction to matching and then stereo triangulation).

and transmitted from retina to brain through the pathway. We then present the lessons learned and explain how we leverage these insights to design BioDrone.

3.1 Biological Visual Pathway

As illustrated in Fig.5a, light entering eyes is refracted by the cornea and lens and then stimulates photoreceptor cells on the *retina* to produce visual signals. The *optic nerves* carrying those visual signals from both eyes cross at the *optic chiasm*, which localizes at the base of the hypothalamus of the brain[36]. Additionally, the *vestibular nerves* that transmit human motion information, interact with the optic nerves at the optic chiasm and select which necessary visual signals will be further carried forward to the thalamus for subsequent processing[17]. Afterwards, the filtered visual signals enter the *lateral geniculate nucleus* (LGN) are re-organized and spatio-temporally correlated to achieve a 3D representation of environment[62]. Finally, the correlated visual representations reach the *visual cortex* via *optic radiations*, and complex visual perception tasks will be accomplished here.

3.2 Bio-lessons

We have learned two biological lessons from visual pathway:

- **L1: Early integration of binocular visual signals.** Binocular visual signals are integrated at an early stage (i.e., at optic chiasm instead of brain). This allows visual signal filtering and matching to take full advantage of the binocular information. In contrast, current practice[24, 49] process, filter, and extract visual features from each event stream independently, as illustrated in Fig.5c.
- **L2: Fast processing of low-level visual tasks.** The low-level visual tasks (e.g., object detection and localization) are rapidly accomplished along with the signal transmission through the visual pathway (i.e., the binocular visual signals

are filtered at optical chiasm and then matched at LGN). The visual cortex, on the contrary, focuses on high-level visual tasks (e.g., object recognition or segmentation).

While the mechanisms of the optic chiasm and LGN handle visual signals are still being explored, the above early integration and collaborative signal-processing architecture inspires our design for handling binocular event streams. Our work aims to provide initial proof that bio-inspired designs can heighten the performance of corresponding bio-inspired sensors. Future designs, which rely on the latest research, are subject to evolution as new discoveries emerge.

3.3 Overview of BioDrone

BioDrone shares a similar architecture with the biological visual pathway to unleash the potential of event cameras, as shown in Fig.5b. We explain the functional units below.

- From the architecture perspective, following lesson-L1, BioDrone features a visual-pathway-inspired signal processing pipeline, fusing binocular event streams at an early stage, which allows the obstacle detection and localization tasks to combine and fully leverage the binocular event information.
- From the algorithm perspective, following lesson-L2, BioDrone attempts to mimic how *optical chiasm* and *LGN* process binocular visual signals and designs two heuristic algorithms. Specifically, BioDrone proposes a *Chiasm-inspired Event Filtering* (CEF) mechanism for event filtering and obstacle detection, and an *LGN-inspired Event Matching* (LEM) module to localize obstacles from the integrated event stream.

Finally, the obstacle localization results from LEM will be used to guide the flight controller to execute desirable evasive operations. By optimizing the algorithms to parallelize event processing, we accelerate the entire software stack on FPGA.

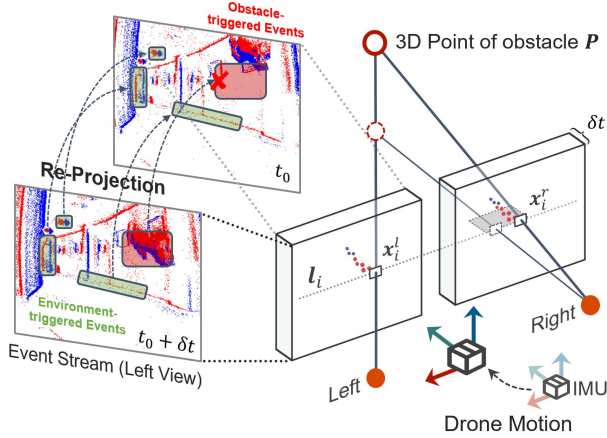


Figure 6: Illustration of the chiasm-inspired event filtering scheme. Left: the distinction between environment- and obstacle-events under ego-motion instruction; Right: the binocular constraint that an obstacle event should satisfy.

4 BIO-INSPIRED ALGORITHM DESIGN

In this section, we describe two bio-inspired algorithms for event filtering (§4.1) and obstacle localization (§4.2).

4.1 Chiasm-Inspired Event Filtering

Optic nerves carrying visual signals from eyes and vestibular nerves carrying motion signals from cochleas cross at optic chiasm. Like a busy intersection, optic chiasm is the rendezvous point where binocular visual information gets fused and filtered under the guidance of proprioceptive motion information. Typically, about 1,200,000 photoreceptors on human retina generate visual signals per second, yet merely around 1,700 of them would pass through optic chiasm[23].

Motivated by the chiasm's ultra-efficient signal filtering performance, we design a chiasm-inspired event filter that leverages the drone's IMU perception data (simulating the vestibular motion signals) to pick up obstacle events in binocular event streams. The insight behind this mechanism lies in two-fold: (i) IMU could be leveraged to infer the ego-motion of event cameras, which provides a priori knowledge to cull environment-triggered events. Just like in our daily life, when your head is turning right, your righter visual field becomes clear while the lefter blurs, and vice-versa; and (ii) the collaborative use of binocular event streams would further improve the filtering performance as the spatial relationship (i.e., pose transformation) between the stereo event cameras provides an additional constraint. For instance, a single eye is less sensitive to the depth change of a moving object compared to two eyes.

4.1.1 Event Filtering Based On Ego-motion Instruction. We first explain how we filter events based on IMU sensor readings. As illustrated in both Fig.6 and Fig.7b, suppose we collect a batch of events $\mathcal{E}$ and IMU data $\mathcal{I}$ within a short

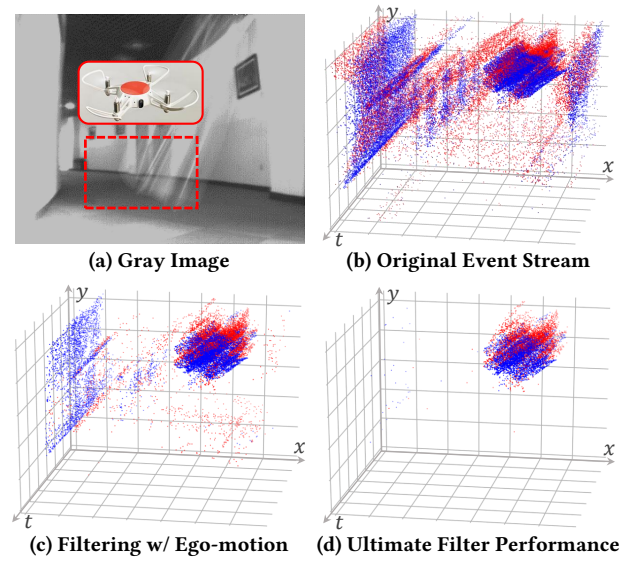


Figure 7: Step-by-step event filtering performance.

time window $[t_0, t_0 + \delta t]$, and each dot in these figures represents an event and the color of this dot shows its polarity (red for -1 while blue for +1). The high-end IMU sensors on the drone can provide motion tracking results[24, 58]. Given an arbitrary event shows up in this window, say, $e_i = (x_i, t_i, p_i)$ where x_i, p_i represents the event's pixel-wise location and polarity at timestamp t_i , we can estimate the event's past location $\hat{x}_0$ at t_0 based on drone motions. There are two cases: (i) If e_i is an environment-triggered event, its estimated location $\hat{x}_0$ at t_0 should match its real location x_0 captured at timestamp t_0 because the environment change is only caused by the drone movement. (ii) Conversely, if e_i is an obstacle-triggered event, its estimated location $\hat{x}_0$ at t_0 should not match x_0 since the obstacle moves yet our event location prediction does not take into account the obstacle movement.

Based on the above analysis, we project all events captured within the time window $[t_0, t_0 + \delta t]$ to the timestamp t_0 and obtain a 2D map, as shown in Fig.6. The environment-triggered events (denoted by green rectangles) are aligned when being projected to this 2D map, whereas the obstacle-triggered events (denoted by red rectangles) are scattered due to obstacle movement. BioDrone explores this opportunity to filter out the former. We model this process in §A.1 and present the algorithm in §4.1.3. We further design circuits on FPGA to parallelize the projection process, as the operations for each event are independent (§5).

4.1.2 Event Filtering Based On Binocular Consistency.

Over 70% of environmental events are successfully filtered out with ego-motion instruction (Fig.7c). However, there are still stubborn residues since: (i) event cameras also suffer from sampling noise, and the firing time of those noisy events

Algorithm 1: Chiasm-Inspired Event Filtering

Input: Raw Event Stream: $\mathcal{E}^l = \{e_i^l\}, \mathcal{E}^r = \{e_i^r\}$
Output: Obstacle-triggered events: $\mathcal{E}_{obstacle}^l, \mathcal{E}_{obstacle}^r$

```

1 for each  $\mathcal{E}$  in  $\{\mathcal{E}^l, \mathcal{E}^r\}$  do
2   for each  $e_i$  in  $\mathcal{E}$  do
3      $\mathbf{x} = \text{EventWarp}(e_i)$ ;
4      $D[\mathbf{x}].\text{append}(e_i)$ ;
5   end
6   for each  $\mathbf{x}$  in  $D.\text{key}()$  do
7      $\rho_{imu}(\mathbf{x}) = \text{ObstacleCheck}(D[\mathbf{x}], \mathcal{E})$ ;
8     if  $\rho_{imu}(\mathbf{x}) > \tau_{threshold}$  then
9        $\mathcal{E}_{IMU}.\text{extend}(D[\mathbf{x}])$ ;
10    end
11  end
12 end
13  $d = \text{DepthEstimate}(\mathcal{E}_{IMU}^l, \mathcal{E}_{IMU}^r)$ ;
14 for each  $e_i^l$  in  $\mathcal{E}^l$  do
15    $e_i^r = \text{EventDiscover}(e_i^l, d)$ ;
16   if  $e_i^r \neq \text{Null}$  then
17      $\mathcal{E}_{obstacle}^l.\text{append}(e_i^l)$ ;  $\mathcal{E}_{obstacle}^r.\text{append}(e_i^r)$ ;
18   end
19 end

```

is random; and (ii) due to the bias of projection view, different events may be accidentally mapped to the same pixel areas. Accordingly, it's challenging to find an optimal threshold to distinguish the different events in ego-motion instruction. This is also the reason why the current practice[24, 49] fails to achieve reliable event filtering performance.

To address this issue, we first cluster events and obtain the obstacle's counter, as shown in the top-right corner of Fig.7c. The events outside the contour can be safely filtered out. However, since the contour estimated by clustering is less accurate, we are expected to see plenty of environment-triggered events around the obstacle. To filter out these events, we are inspired by binocular consistency. As illustrated in the bottom right of Fig.6, let e_l and e_r be an event reported by the left event camera and right event camera, respectively. We first estimate a rough depth of the obstacle by triangulating the center of contour[24]. If e_l is triggered by an obstacle, then according to the Epipolar constraint[82], e_r should show up on a specific area which can be estimated by the pixel location of e_l and the depth of the obstacle (estimated by triangulation). Otherwise, if e_r is not found in this specific area, both e_r and e_l should be environment-triggered event. We model this process in §A.2.

Finally, we remove the salt-and-pepper noise using morphological algorithm[24]. Compared to the original event

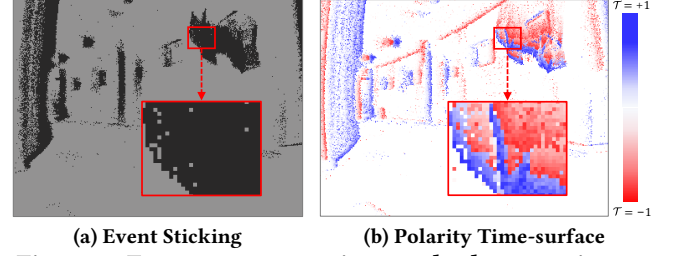


Figure 8: Event representation method comparison.

stream (Fig.7b), the obstacle is well separated after these two steps filtering, presenting a sharp and clear contour (Fig.7d).

4.1.3 Putting Them Together. Algorithm 1 shows how we practice these two steps filtering. Line 1–12 and Line 13–19 represents event filtering based on ego-motion instruction (first step) and binocular consistency (second step), respectively. Specifically, given input event streams $\mathcal{E}_l$ and $\mathcal{E}_r$ within the time window $[t_0, t_0 + \delta t]$, function `EventWarp` first predicts each event's past location at timestamp t_0 . The algorithm then runs function `ObstacleCheck` on each pixel to decide whether the events are triggered by environment or an obstacle. Only those obstacle-triggered events (termed as $\mathcal{E}_{IMU}$) are fed into the second-step where `EventDiscover` function leverages the binocular consistency to eventually obtain obstacle-triggered events $\mathcal{E}_{Obstacle}$.

4.2 LGN-Inspired Event Matching

Visual signals passing through the optic chiasm are spatio-temporally correlated at LGN in order to obtain a 3D representation of the object. As shown in Fig.9, the architecture of LGN is characterized by six distinctive layers. The inner two layers are magnocellular layers that are responsible for detecting object motion and size (i.e., coarse feature), while the outer four layers are parvocellular layers for detecting the object's color and contour (i.e., fine details)[62]. Such a six-layer folding architecture supports a plethora of anatomical calculations without involving those computationally intensive spatial and temporal correlations.

Inspired by this elegant structure, we propose a neural-enhanced event matching algorithm, as elaborated below.

- First, we propose a novel event stream representation, namely polarity time-surface (§4.2.1), that maps the 3D event stream to the 2D space without sacrificing the valuable event features. Such a design can expedite feature matching without hurting the matching accuracy.
- Second, similar to LGN, we propose a six-layer hierarchical event feature extraction and matching algorithm (§4.2.2) that can localize the obstacle based on the binocular polarity time-surface timely and accurately.

4.2.1 Spatio-Temporal Representation of Events. To localize the obstacle, we have to extract reliable event features

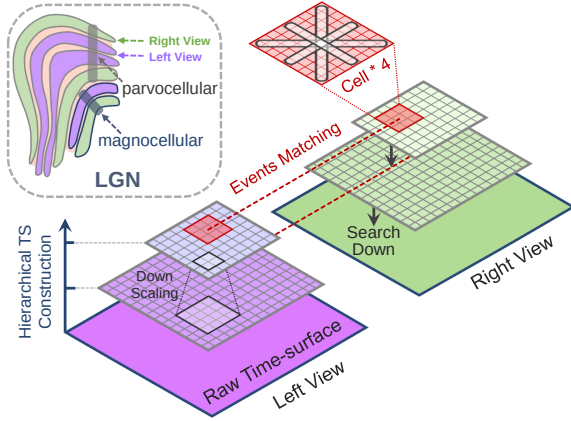


Figure 9: Illustration of our proposed LEM algorithm.

of the obstacle from the binaural event streams. Although it is viable to extract event features from the 3D meta event streams, this solution is time-consuming since there are hundreds of events stacking together within a short period.

In BioDrone, we propose a lightweight representation of event streams, namely, Polarity Time-Surface (P-TS), that can well retain rich spatio-temporal information. P-TS is a 2D map where each pixel value represents both the polarity and timestamp of the event. For instance, as shown in Fig.8b, the red and blue color indicates two different polarities of the event while the darkness of the color shows the time this event being captured. We leverage an exponential decay kernel[40] to prioritize the latest event over past events, emulating how LGN prioritizes the latest visual signals over the old ones[62]. For each pixel $\mathbf{x} = (u, v)^T$, its polarity time-surface presentation is formally defined as:

$$\mathcal{T}(\mathbf{x}, t) = \rho_{\text{last}}(\mathbf{x}) \cdot \exp\left(-\frac{t - t_{\text{last}}(\mathbf{x})}{\eta}\right), \quad (2)$$

where $t_{\text{last}}(\mathbf{x})$ and $\rho_{\text{last}}(\mathbf{x})$ are the timestamp and polarity of the event showing up at pixel $\mathbf{x}$; η is the decay rate. The parameter $\rho_{\text{last}}(\mathbf{x})$ provides an additional polarity constraint for event matching. Compared to the sticked event image (Fig.8a), the proposed P-TS presentation retains the fine-grained texture of the obstacle, making it easily distinguishable. Generating a P-TS for each event stream takes $O(n)$ time since only a one-shot traversal of events is needed. Additionally, the process will be further accelerated on FPGA (§5) as each pixel could infer Eq.2 in parallel, superior to those event sticking-based solutions[52, 65] where periodically intensive memory access is unavoidable.

4.2.2 Fast Event Feature Matching. Next, we run a feature extraction and matching on the binocular P-TS maps for obstacle localization. However, sweeping the entire P-TS maps for feature extraction and matching would consume significant amount of time. We thus resort to the lessons

learned from LGN and design a pyramidal P-TS hierarchy to expedite feature extraction and matching.

On a high level, we build two 3-layer P-TS pyramids based on the P-TS map obtained from the left event stream and right event stream, respectively, as shown in Fig.9. In the P-TS pyramid, the bottom layer $\mathcal{T}_0$ (i.e., the original P-TS map) is subsampled by a factor of k to obtain the next pyramid level $\mathcal{T}_1$. $\mathcal{T}_1$ is then filtered in the same way and subsampled to obtain $\mathcal{T}_2$. We are expected to see a sequence of reduced resolution P-TS map on the pyramidal P-TS hierarchy, with a growing reception field. Each pixel on the top layer $\mathcal{T}_2$ corresponds to a reception field of $k^2 \times k^2$. By sweeping the $\mathcal{T}_2$ map, we can essentially reduce the searching space by k^4 . **Pyramidal P-TS hierarchy generation.** Let $\mathcal{T}_0^l$ and $\mathcal{T}_0^r$ be the left and right P-TS map, respectively. Without losing generality, we take the left P-TS map for algorithm description. We down-sample $\mathcal{T}_0$ by a factor of k :

$$\mathcal{T}_{i+1}(\mathbf{x}, t) = \mathcal{T}_i(k\mathbf{x} - \frac{k}{2}[1, 1]^T, t), \quad (3)$$

where $\mathcal{T}_{i+1}$ ($i \in \{0, 1\}$) is the down-sampled P-TS. Each pixel in $\mathcal{T}_{i+1}$ represents a $k \times k$ region in previous P-TS. The pixel value is defined as that of the center pixel in the region.

Feature matching. We run feature matching on $\mathcal{T}_2$. For instance, given an event e^l in the left view, we leverage the following constraints to find its matched event e^r :

$$\sigma_e = |(\mathbf{x}^l)^T F \mathbf{x}^r| < \epsilon_e, \quad (4)$$

$$\sigma_p = |\mathcal{T}_2^r(\mathbf{x}^r, t) - \mathcal{T}_2^l(\mathbf{x}^l, t)| < \epsilon_p, \quad (5)$$

where Eq.4 is the epipolar constraint (i.e., similar to §4.1.2, the matched events should on the same epipolar line[41]) and F is the fundamental matrix obtained from camera calibration. Eq.5 indicates the timestamp and polarity of these two events should be the same (i.e., difference within threshold ϵ_p). If no events on $\mathcal{T}_2^r$ satisfy Eq.4-5, we will down search the $k \times k$ region on $\mathcal{T}_1^r$, associated to the event with minimal σ_e and σ_p , to find the matched event; and further repeat the procedure on $\mathcal{T}_0^r$ if required. Once we find the matched e^l and e^r , the spatial location of the event with depth d is:

$$d = \frac{f * b}{\|\mathbf{x}^l - \mathbf{x}^r\|}, \quad (6)$$

where f is the focal length and b is the baseline distance between two optical centers.

We further propose a cell-matching operator to enhance Eq.4-5. As shown in Fig.9, each cell is a segment of pixels centered at the candidate pixel with a certain direction. We apply a horizontal, a vertical, and two diagonal cells, as LGN does, for aggregating scores (i.e., σ_e and σ_p). That is, the matching relationship of two events is not only determined by themselves, but also by their neighboring events. The operator makes the algorithm more sensitive to moving edges,

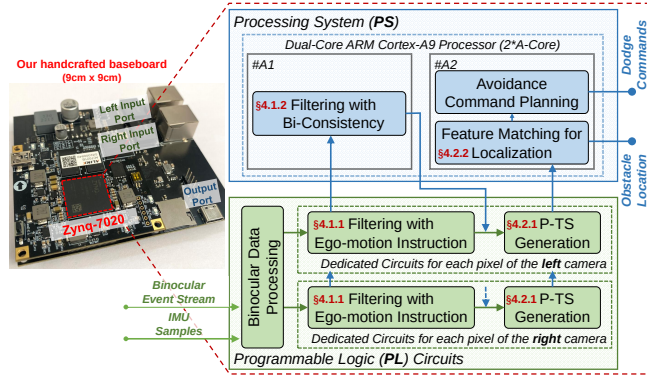


Figure 10: Implementation of BioDrone on a Zynq chip. which fits the nature of event camera. Finally, the average 3D location of all events on the obstacle’s contour is the result.

5 IMPLEMENTATION

We fully implement BioDrone on a Xilinx Zynq-7020 (the highlighted chip in Fig.10) through software-hardware co-design. It consists of a processing system (PS) and a programmable logic (PL) two modules. The PS features a dual-core ARM Cortex-A9 processor (i.e., #A1 and #A2), while PL is for hardware acceleration through FPGA. We also manufacture a baseboard for data input/output and voltage adaption.

- **PL:** We design exclusive logic circuits on FPGA to accelerate those event operations suitable for parallel and pipeline execution, i.e., data denoising, ego-motion-based filtering (§4.1.1), and P-TS generation (§4.2.1), on PL.

- **PS:** Before loading specific tasks, we first exploit a core-isolation strategy to isolate the computing resources of #A1 from PS, reducing the impact of CPU scheduling on task execution to better match the PL pipelines. We realize it by building a Linux OS with boot parameter `isolcpus=<cpu #A1>`. We execute the binocular-based filtering (§4.1.2) which requires frequent memory access and cannot be easily implemented through FPGA, on #A1. The final obstacle localization and command planning tasks are executed on #A2.

- **Data flow in-between:** We further leverage the physical-level direct memory access (DMA) technique[72] to transmit intermediate data among PL, #A1, and #A2. Compared with network-level solutions such as PL-PS ethernet interface[34] and OpenAMP[55], DMA ensures data interaction processes would not be interrupted by CPU scheduling.

We integrate BioDrone into an ArduPilot APM flight controller and deploy it on an AMOVLAB P450-NX drone. Implementation details can be found at the project repository.

6 EVALUATION

6.1 Experimental Methodology

Field studies. We conduct field studies both indoors and outdoors as shown in Fig.11. The performance is evaluated

Table 1: Different Drone Flight Mode Configurations

Flight Mode* (Trajectory)	Speed		Event Generating Speed (e/ms)
	Translation (m/s)	Rotation (°/s)	
1 ($A \rightarrow B \rightarrow C_1 \rightarrow D_1$)	2.0–6.0	0–10.0	100–400
2 ($A \rightarrow B \rightarrow C_1 \rightarrow D_1$)	15.0–26.5	0–10.0	350–1200
3 ($A \rightarrow B \rightarrow C_2 \rightarrow D_2$)	2.0–6.0	20–100	900–2100

* $\rightarrow$: acceleration; $\rightarrow$: uniformity; $\rightarrow$: deceleration.

in three flight modes, as defined in Table 1. The drone follows planned trajectories to move; Four volunteers throw six different types of obstacles toward the drone during the drone’s movement.

Repeatability. Before conducting experiments under each flight mode, we program a series of pre-determined flight commands into the on-board APM flight controller, enabling the drone to follow the planned trajectory, speed, and acceleration, to make our experiments repeatable.

Metrics and Ground truth. The drone logs its localization results with timestamps. We download these logs and evaluate end-to-end (E2E) localization latency Δt_l and error Δx (defined in §2). Indoors, an OptiTrack motion capture system could provide $<1mm$ localization ground truth. Outdoors, since we cannot deploy OptiTrack to obtain ground truth, we collect event streams and run an advanced yet heavy event-based object localization and segmentation neural network[3] offline. The results are taken as ground truth. We also log event classification results reported by it to examine BioDrone’s event filtering performance.

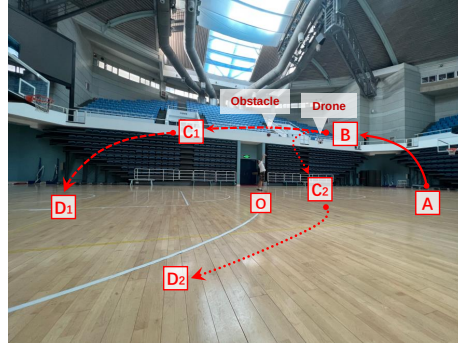
Baselines. We compare the accuracy and latency of BioDrone with Baseline-I[24] and -II[49]. We also compare the LEM module in BioDrone with ESVO[84]. As these baselines are not implemented on FPGA, we thus implement BioDrone on the drone’s onboard Nvidia Jetson TX2 for a fair comparison with them.

6.2 Overall Performance

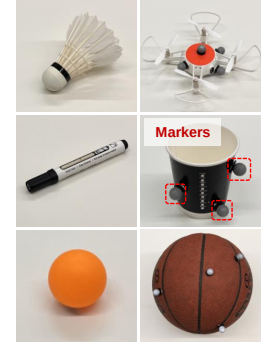
Obstacle detection and localization. Fig.12a depicts the localization performance of BioDrone and two comparative systems. The average E2E location error of BioDrone is 7.5cm, outperforming Baseline-I and Baseline-II, of which the average location errors are 15.9cm and 20.4cm, respectively. We then compare the three systems under different flight modes. Fig.12b shows that BioDrone achieves the lowest average location error across all three flight modes, outperforming both baselines by $>60\%$ in all flight modes. Moreover, as shown in Fig.12c, the obstacle detection rate of BioDrone under three flight modes are 96.1%, 87.9% and 92.6%, outperforming baselines by over 10% in low-speed (mode 1) and over 40% in high-speed scenarios (flight mode 2 & 3), respectively. Unlike the two related works that depend solely on ego-motion instruction for event filtering, BioDrone incorporates a binocular constraint to upgrade the framework, improving obstacle



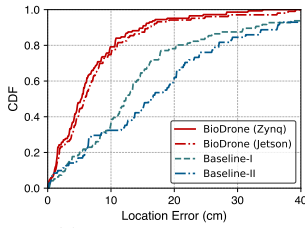
(a) Outdoor experiments



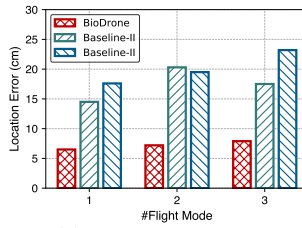
(b) Indoor experiments



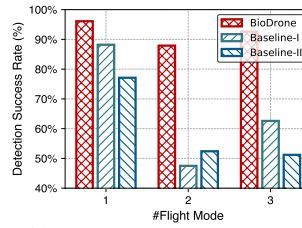
(c) Different Obstacles

Figure 11: Experimental scenarios of BioDrone. The red lines show the drone's movement trajectory.

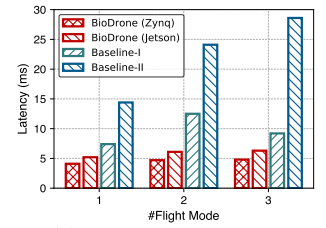
(a) Localization Error



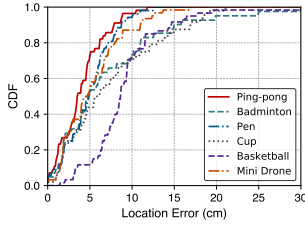
(b) Localization Error



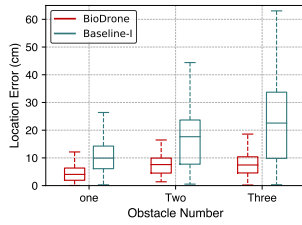
(c) Objection Detection Rate



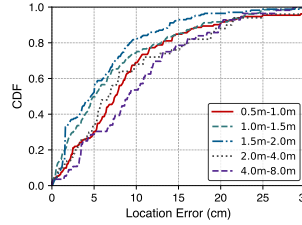
(d) Localization Latency

Figure 12: Overall Performance Comparison

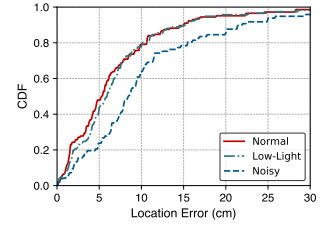
(a) Impact of Obstacle Type



(b) Impact of Obstacle Number



(c) Impact of Obstacle Distance



(d) Impact of Scene Dynamic

Figure 13: System Robustness Evaluation

detection performance. Additionally, BioDrone's LEM module optimizes stereo event matching, resulting in increased spatial localization accuracy.

End-to-end latency. We further evaluate the E2E latency, including the obstacle detection and localization two phases. As depicted in Fig.12d, the E2E latency of BioDrone is 5.2ms in flight mode 1, outperforming both baselines (6.1ms and 6.3ms, respectively). As the flight speed grows (i.e., mode 2&3), the E2E latency of Baseline-I and -II grows rapidly, making these two solutions fail in obstacle avoidance. In contrast, BioDrone maintains the lowest E2E latency (i.e., within 6ms) in all scenarios. Typically, related works encounter an inherent increase in system latency due to the simultaneous processing of binocular event streams. The subsequent steps – binocular parallax optimization, matching, and triangulation – for obstacle localization post-detection further delay the system. In contrast, BioDrone introduces the LEM module, which directly localizes objects from event streams, thereby reducing end-to-end latency.

FPGA acceleration. As shown in Fig.12a and Fig.12d, compared to a pure software implementation on Jetson, the software-hardware co-design of BioDrone on Zynq further reduces the localization bias by 9.3% (6.8cm vs. 7.5cm) and latency by 22.9% (4.7ms vs. 6.1ms). Our hardware design on FPGA (i) realizes the parallel and pipeline execution among operations for different events, reducing the E2E latency; and (ii) enables the system to select a shorter time window Δt (§4.1), which improves the event filtering performance for better localization accuracy.

6.3 System Robustness Evaluation

Impact of obstacle type. We evaluate the impact of different types of obstacles (Fig.11c, in terms of form factor and miscellaneous texture). The results are shown in Fig.13a. As seen, textured obstacles like badminton, pen and cup have lower average localization errors of 7.2cm, 5.0cm and 7.5cm, respectively. In contrast, obstacles with relatively large size and weak texture (e.g., basketball) lead to larger localization errors. Further scrutiny reveals that the event cameras are

likely to generate more events for larger obstacles, and these events are on the vicinity of the obstacle and thus are likely to distort the obstacle localization. Nevertheless, the localization error is still within the acceptable range, which makes BioDrone a feasible solution for drone obstacle avoidance.

Impact of obstacle quantity. In this experiment, two volunteers are asked to throw multiple (2-3) obstacles toward the drone; we examine the detection and localization results for each obstacle individually. As depicted in Fig.14b, BioDrone outperforms Baseline-I by $> 40\%$ in all settings. As the number of obstacles grows, we observe a slight increase (around $3cm$) in BioDrone's localization error. In contrast, the localization error of Baseline-I grows dramatically to $24.68 cm$. The results demonstrate that the LEM module could effectively extract spatio-temporal features of different obstacles and thus distinguish them from each other. On the contrary, Baseline-I simply clusters events for triangulation, making it difficult to separate obstacles close to each other.

Impact of obstacle distance As shown in Fig.13c, when the obstacle appears at around $1.0\text{-}2.0m$, BioDrone achieves the highest localization accuracy where the average location error is $6.58cm$, and the average location error will slightly increase (within $9.5cm$ though) as the distance increases. Generally, a longer distance fails to generate sufficient events, making the feature matching more challenging.

Impact of environmental dynamic. We further evaluate BioDrone's effectiveness in low-light (i.e., dark) and noisy environments (i.e., with high background dynamics), respectively. The results are shown in Fig.13d. As seen, even in low-light conditions, the average localization accuracy remains consistent (a minor decrease within 10%), due to the HDR of event camera that still manages to capture sufficient events in dark environments. However, in noisy environments, there is a noticeable 33% decrease in average localization accuracy because BioDrone sometimes interprets dynamic background objects as foreground obstacles. A potential solution to this problem could be the integration of depth-based filtering algorithms, which is left as a future work.

6.4 Ablation Study

Contributions of each module. We examine how CEF and LEM contribute to BioDrone. We gradually embed CEF and LEM into the baseline system (i.e., Baseline-I) and repeatedly examine the localization accuracy and end-to-end latency. As shown in Fig.15a, without applying these two modules, Baseline-I achieves a localization error and latency of $15.9cm$ and $10.4ms$. As we integrate CEF module into Baseline-I, we observe the localization error declines to $12.1cm$ and the latency drops to $6.3ms$. We then integrate LEM into Baseline-I and observe that the localization error drops remarkably to $8.8cm$. However, the delay grows due to the lack of an efficient event-filtering mechanism. Finally, we integrate

both CEF and LEM into Baseline-I. As expected, both the localization error and latency reach the minimum.

Performance of CEF. We compare CEF with the filtering module of Baseline-I in high-speed mode (flight modes 2 and 3). We denote CEF in mode 2 and mode 3 as B-2 and B-3, respectively. Likewise, the filtering module of Baseline-I as I-2 and I-3, respectively. In Fig.14b, a higher recall means more obstacle-triggered events are preserved while a higher precision indicates more background events are removed. As seen, the recall of CEF is $\geq 81\%$ and its precision is $\geq 82\%$. In contrast, the filter module of Baseline-I achieves an inferior recall of 43% under flight mode 3. Even worse, the precision further drops to 28% under flight mode 2. This result demonstrates the efficacy of CEF in event filtering.

Performance of LEM. We also evaluate the performance of LEM by comparing it with the localization module in ESVO[84] and Baseline-I. As shown in Fig.14c, LEM reduces localization error by 23.8% compared to ESVO where event features are matched using naive block-matching operations. Besides, compared with Baseline-I, which exploits event clustering and triangulates the spatial location of an object at cluster-level, LEM reduces the localization error by 55.1% .

6.5 System Efficiency Study

We select a typical $120ms$ obstacle avoidance example and log the system latency, CPU workload, and memory usage in Fig.15. The drone perceives the obstacle at $24ms$, followed instantly by performing an avoidance maneuver. After $110ms$, the obstacle disappears from the drone's view.

- At the beginning $24ms$, LEM is not triggered, and the latency of CEF stays $< 0.07ms$ with CPU workload $< 9\%$.
- Then, during the $24\text{-}110ms$, the drone detects an obstacle and adjusts its own trajectory. CEF introduces a relatively higher computing latency and more CPU workload due to the larger number of events. However, the computing latency of CEF maintains at a low level (i.e., $2.73ms$) with occupying the CPU workload below 14% . Meanwhile, LEM continuously localizes the obstacle, introducing an additional $2.45ms$ computing latency and around 27% CPU workload.
- Finally, after $110ms$ when the drone has successfully fled away from the obstacle, states of the two modules return to the way it was before $24ms$ in terms of latency and CPU workload. Throughout the obstacle avoidance process, the memory resources occupied by the CEF and LEM are within $5.8 MB$ and $4.9 MB$, respectively.

During the whole avoidance procedure, BioDrone reserves $> 60\%$ CPU computational resources for upper-layer tasks.

7 RELATED WORK

Object/Obstacle localization. Object localization and tracking attract broad interest within the mobile computing community, with various systems designed around diverse sensors like WiFi [42, 79], CSI [14], acoustic signals [44], RFID [54,

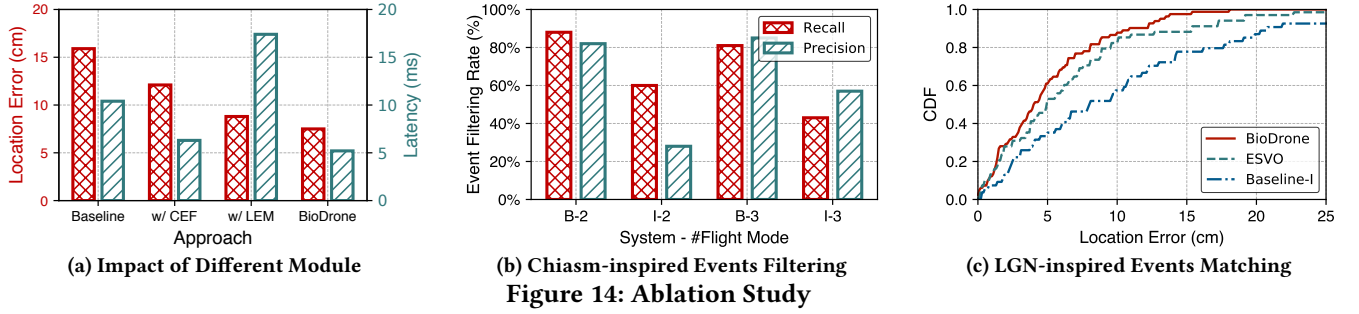


Figure 14: Ablation Study

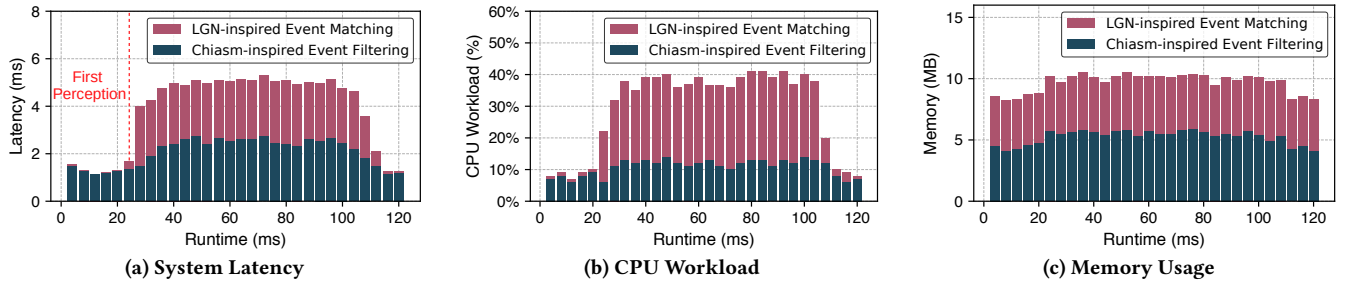


Figure 15: System Efficiency on the Drone

67], IMU [11, 74], camera [75], radar [43], etc.. For the drone obstacle localization task, camera- and radar-based solutions are often preferred in both academia and industry due to their accuracy and widespread implementation[25, 32].

The existing literature relies on frame-based cameras (e.g., monocular [83], stereo [38]), depth cameras [66], millimeter-wave radar [81], LiDAR [8], or VIO [64, 78]. However, these works require the obstacles to be either static or quasistatic. According to our measurements (§2.2), existing solutions are not competent for high-speed drones (i.e., relative speed $>20\text{m/s}$). The limitation comes from the sensors' physical nature and cannot be easily solved with algorithms.

Event-based algorithms and systems. Event cameras offer numerous potential advantages over conventional frame-based cameras, including high temporal resolution, low latency, and high dynamic range[10, 26, 29, 52, 65]. Recent systems use them for scene reconstruction [84], SLAM[59], object tracking[24, 49], and HDR image reconstruction [51].

Among these systems, Baseline-I[24] presents a notable obstacle avoidance solution for drones. It utilizes IMU readings to filter out background events, further assisting in obstacle detection, and is most closely related to our work. However, Baseline-I is primarily oriented towards obstacle detection tasks using a monocular event camera setup, whereas our system, BioDrone, aims at obstacle localization leveraging a binocular configuration. This shift in task focus, from detection to localization, combined with the change in hardware configuration, introduces new challenges to fully harness event camera's potential for drone obstacle avoidance, as

elaborated in §2.3. In this work, we introduce a novel binocular signal processing pipeline, inspired by the visual pathway, featuring two new modules, CEF and LEM. Our design aims to enhance the accuracy and efficiency of event-based systems, with particular benefits for high-speed drones.

Bio-inspired design for event-based vision. Biological principles drive the design of event camera pixels and some event processing algorithms, such as spiking neural networks (SNN[63]), spatiotemporal oriented filters (STOF[56]), and spike-timing dependent plasticity (STDP[12]). In general, current innovations mainly mimic the working principles of the human visual cortex and design sophisticated algorithms for high-level object recognition[53], segmentation[50], and understanding[9]. Albeit inspiring, these bio-inspired systems are not the optimal solution for obstacle avoidance-related tasks due to the large computational overhead. In BioDrone, we find those delay-sensitive tasks are not executed at the visual cortex but exactly at the earlier *binocular visual pathway*. We take the bio-lessons learned from it and design BioDrone for fast obstacle detection and localization.

8 LIMITATION AND FUTURE WORK

• **Bio-inspired design.** In this study, we leverage biological concepts from the visual pathway to architect a unique signal-processing pipeline for binocular event cameras. We extrapolate the mechanisms of Chiasm and LGN to devise corresponding event filtering and localization algorithms. Note that the understanding of physiological visual perception, including stereoscopic vision, is an ongoing issue, with future findings potentially reshaping our current knowledge. Future designs will evolve based on new research progress.

• **Software-hardware co-design.** In this work, we deploy BioDrone on a commercial Zynq computing platform. By jointly scheduling computational resources of both PL and PS, we manage to boost system accuracy and real-time performance as related works[57, 69]. However, due to implementation complexities, operations related to binocular matching – which require frequent memory access – are still processed in software on the PS, and cannot yet be accelerated by the FPGA. This leaves room for future enhancements.

• **Event camera upgrade.** Event cameras, while promising, are still in their early stages of development and have certain limitations. For instance, their resolution is lower compared to standard cameras (QVGA *vs.* 1080p), restricting the usable FoV and effective observation distance for obstacle avoidance. Also, current event cameras do not support dynamic adjustment of aperture and focus. This limitation necessitates manual calibration during transitions between various work environments to avoid event sampling failure from overexposure or insufficient lighting. However, we expect these issues will be mitigated as event cameras continue to evolve and become integrated into next-generation devices.

9 CONCLUSIONS

We have presented the design and implementation of BioDrone, a software solution to support fast and accurate drone obstacle detection and localization using event cameras. BioDrone exploits biological knowledge behind human visual systems and designs a visual pathway-inspired architecture, a chiasm-inspired event filtering module, and an LGN-inspired event matching mechanism to unleash the full potential of event cameras. Extensive evaluations conducted on an industrial drone demonstrate its superior performance. Through BioDrone, we present that the bio-inspired design paradigm produces simple yet effective solutions to potentially replace heavy-weight ones, adding a new solution dimension for sensing problems with strict restrictions on accuracy, time delay, computation, and energy.

10 ACKNOWLEDGMENTS

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A APPENDIX

A.1 Modeling of Ego-motion Instruction

Generally, a camera's rotation produces a major number of events than translation in a very short time period δt [24]. Therefore, we focus on estimating the ego-rotation as IMU average angular velocities, $\bar{\omega} = \sum_{\delta t} \omega t / \delta t$. Event e_i could be

warped into the frame coordinate at t_0 by $\phi : \mathbb{R}^3 \rightarrow \mathbb{R}^3$:

$$\phi(\mathbf{x}, t) = \mathbf{K} \mathbf{R}_t \mathbf{K}^{-1} \mathbf{x}, \mathbf{x} = [u, v]^T, \quad (7)$$

where $\mathbf{K}$ is the camera's intrinsic matrix and $\mathbf{R}_t$ is the rotation matrix corresponding to $\bar{\omega} t$ given by Rodrigues' rotation formula[18]. We further exploit a projection $\Pi : \mathbb{R}^3 \rightarrow \mathbb{R}^2$ to project events onto image coordinates and define the set of warped events at t_0 as:

$$\mathcal{E}' = \{(\Pi(\phi(\mathbf{x}, t_i - t_0)), t_i, p_i) : (\mathbf{x}, t_i, p_i) \in \mathcal{E}\}. \quad (8)$$

Those corresponding events re-projected at pixel (u, v) are:

$$\mathcal{E}'_{uv} = \{(\mathbf{x}, t, p) \in \mathcal{E}' : \mathbf{x} = (u, v)\}. \quad (9)$$

We further examine the event distribution to distinguish different types of events using a time-based solution. Specifically, the more uniformly the generation time of all events in $\mathcal{E}'_{uv}$, the more likely these events are environment-triggered events, as only moving obstacles will bring an additional time-cluttered event burst on specific pixels. We calculate:

$$T_{uv} = \frac{1}{|\mathcal{E}'_{uv}|} \sum t, (\mathbf{x}, t, p) \in \mathcal{E}'_{uv}, \quad (10)$$

To eventually separate environment and obstacle events, for each pixel $\mathbf{x} = (u, v)$, we calculate a score for it as:

$$\rho_{imu}(\mathbf{x}) = \frac{T_{uv} - \bar{T}}{\delta t} \in [-1, 1], \quad (11)$$

where $\bar{T}$ is the average time of all events in $\mathcal{E}$. A higher score indicates a more misaligned generation time of $\mathcal{E}'_{uv}$, and hence the more likely associated events are from an obstacle.

A.2 Modeling of Binocular Constraint

Given an event $e^l = (\mathbf{x}^l, t^l, p^l)$ from the left event stream, if it is triggered by the movement of P on the obstacle, there must be a twin event e^r in the right stream with $\mathbf{x}^r$:

$$\mathbf{x}^r = \pi(T_{rl}, P), P = Z \mathbf{K}^{-1} \mathbf{x}^l, \quad (12)$$

where Z is the estimated depth of the obstacle, T_{rl} is the transformation from left to right camera (obtained by calibration), and $\pi(\cdot, \cdot)$ is the 3D-2D projection model.

As the estimation of Z by clustering and triangulation is inaccurate, we have to examine a few more pixels centered at $\mathbf{x}^r$ and along the epipolar line[82]. The candidate region C (the gray dotted area in the right event stream of Fig.6) is:

$$C = \{(\mathbf{x}, t, p) : \mathbf{x} \in \mathbf{x}^r \pm [\delta x, 0]^T, t \in [t_0, t_0 + \delta t]\}. \quad (13)$$

where δx denotes is set as 5 pixels in practice. We examine all events in C and define the matching score of e^l as:

$$\rho_b(\mathbf{x}_l) = \min_{e^r \in C} |t^l - e^r(t)|, \quad (14)$$

where $e^r(t)$ is the timestamp of an event in the right stream, and $\rho_b(\mathbf{x}_l)$ is set as ∞ if C is empty. Therein, a small $\rho_b(\mathbf{x}_l)$ indicates we could find a matched event associated to P and thus e^l is more likely to be an obstacle-triggered event.

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