Dataset Overview

EVENT-BASED VISION DATA

Task 1

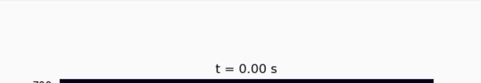
Recording Statistics

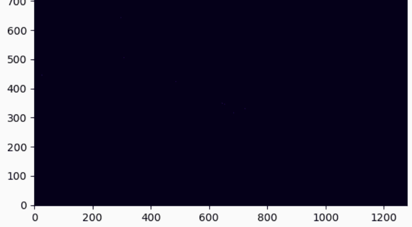
- **Recording Duration**
  12.7 seconds
- **Total Events**
  ~61 million
- **Sensor Resolution**
  1280 × 720
  Active region ~1.07 MP after dead pixels
- **Event Rate**
  ~4.8M events/s

Quality Metrics Analysis

METRIC	VALUE	IMPLICATION
Dead pixels	17.1%	"Clean" setup background
Hot pixels (bg)	1	Excellent sensor health
Background noise	1,583 evt/ms	LOW
Spatial entropy	18.38 bits	Structured & information-rich (92.8% max)

Summary: High-resolution, high-frequency event data with low noise despite significant dead pixel percentage, indicating a controlled environment suitable for algorithm validation.




700
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600
800
1000
1200

08

Event Rate Local Extremes vs. Arm Configuration

Task 1: Dataset Metrics

Background

TIMELINE, CURRENT POSITION & PHD MOTIVATION

AUG 2014 - JUN 2018
BSc Robotics and Mechatronics
Nazarbayev University

JUN 2017 - MAY 2018
Robotics Research Assistant
ALARIS (Robotics Lab in NU)

SEPT 2018 - JUL 2023
MSc AI and Robotics
Sapienza University of Rome

NOV 2020 - JUL 2021
AI and Robotics Intern
Baker Hughes R&D Team

SEPT 2022 – SEPT 2023
AI Engineer
botshelf.ai (AI Startup)

JAN 2024 – PRESENT
Research Fellow
ISTC CNR

Why PhD?

The path from practice to research

FROM FIELD TO THEORY + NATURE'S BLUEPRINT

Deploying autonomous systems exposed hard constraints: energy budgets, sensor degradation, real-time uncertainty. Traditional methods hit fundamental bounds. Optimization alone cannot overcome architectural constraints. Insects navigate complex environments with minimal power and computation, showing a different computational paradigm.

NEXT STEP

Neuromorphic computing for efficient, robust autonomy

JAN 2024 – PRESENT
Research Fellow
ISTC CNR

Multi-UAV systems for agricultural robotics. Developing perception and planning algorithms for field deployment.

KEY FOCUS

- Perception & planning for swarm systems
- Field experiment design & data pipelines
- **Hardware:** DJI Mini 3, UviFy (Jetson NX)

Data Collection & Autonomy

PREVIOUS WORK

AGRITECH

Deployment Pipeline

1. Mission Planning

Defined GPS waypoints meticulously to ensure a specific image overlap percentage for optimal photogrammetry.

2. Flight Simulation

Validated trajectory planning using **PX4 autopilot** within the Gazebo simulation environment before field testing.

3. Real World Testing

Executed autonomous flights with a custom onboard stack integrating hardware and software services.

Autonomy Architecture

HARDWARE COMMUNICATION LOOP

FCU ⇄ `MAVLink` Jetson NX `WiFi/Telemetry` GSC

Field Validated

Informative Path Planning for Agriculture

PREVIOUS WORK: ACTIVE SENSING & FIELD DEPLOYMENT

AGRITECH

Problem & Methodology

Motivation

Precision Agriculture with UAVs

- **Goal:** Early detection of wheat lodging (stem displacement) to enable timely interventions.
- **Challenge:** Altitude-Resolution Trade-off. High altitude covers more area but reduces resolution/accuracy.

Active Planning Loop

Probabilistic Mapping
Bayesian updates + CRF spatial consistency

↓

Informative Planning
Max Information Gain (IG) vs. Altitude cost

↓

Execution
Adjust altitude dynamically based on uncertainty

Sensor Models & Results

Empirical Sensor Models

Derived from classifier predictions on UAV images by sampling labeled tiles across altitudes.

`High Altitude: FN ↑, FP ↓` | `Low Altitude: Accuracy ↑`

Key Results

Adaptive vs. Lawnmower
IPP enables more efficient coverage and higher mapping accuracy than traditional lawnmower patterns by focusing on high-uncertainty areas.

Sampling Efficiency
Minimal upfront sampling (single image per altitude) suffices to calibrate the sensor model for specific field conditions.

Orthomap Validation
Tested on real wheat fields (Adria, Italy). Adaptive pairwise weighting yielded the most stable coverage despite real-world noise.

EDOPT Overview

EVENT-CAMERA 6-DOF OBJECT TRACKING

Task3

ICRA 2024

EDOPT: Event-Camera 6-DoF Object Tracking for Robotic Manipulation

> *Tracking the full 6-DoF pose (position + orientation) of a moving rigid object using only an event camera, in real time and at very high frequency.*

Crucial Applications

- Grasping moving objects in dynamic environments
- Advanced manipulation beyond static pick-and-place
- High-speed collision avoidance

Key Capabilities

Event-Only

Asynchronous, low-latency, blur-free vision without RGB or depth

>300 Hz

Real-time tracking suitable for high-speed robotics

Model-Based

Uses 3D mesh rendering + event statistics (no learning required)

Generalizable

Robust and works with any known object mesh

The Algorithm

1. Raw Events → "Edge Likelihood Image"

↓

2. Object Pose → Expected Edges (Projection)

↓

3. Compare & Update Pose Estimate

Core Benefit

By comparing events directly to projections of a known 3D object model, EDOPT eliminates the need for heavy deep learning pipelines.

Robust, Lightweight & Universal

EDOPT: Sensor Processing

CORE ALGORITHM COMPONENTS

Task3

1. EROS Surface

Exponentially Reduced Ordinal Surface: A 2D map encoding the likelihood of a contrast edge at pixel $O_t(x,y) \in [0,1]$ based on all past events.

UPDATE RULE (PER EVENT)

- Decay kernel neighborhood by factor
- Set event pixel to `1.0`

Key Properties

2. Visual Expectation E(X)

Given pose X^+, where should edges appear?

State Expectation

Generate 13 pose hypotheses $\{X^+\}$ around current pose using image Jacobian (calibrated for ~1px shift).

Model Projection

Project object mesh onto image plane using calibrated camera intrinsics for candidate pose.

Gradient Extraction

Sobel + Difference-of-Gaussians filter to highlight true edges → clean map $E(X^+)$.

3. State Update

SCORING FUNCTION $\text{Score} = E(X_i^+) \cdot O_t$

- **Correlation:** Positive regions in E reinforce matching edges in O; negative regions suppress mismatches.
- **Multi-Hypothesis:** Accept several hypotheses in one iteration (e.g., x-axis

Empirical Results

PERFORMANCE COMPARISON & REAL-WORLD VALIDATION

Task3

Exp 1: Baseline Comparison (vs RGB-D-E)

Synthetic dataset (Unreal Engine) with ground-truth pose. Comparing against state-of-the-art DNN baseline.

Method	Pos Error (cm)	Rot Error (deg)	Frequency
EDOPT (Ours)	**0.70** ✓	**2.30°** ✓	**300 Hz**
RGB-D-E (Baseline)	0.73	2.44°	5 Hz

Result: Matches accuracy but runs **60x faster**.

Exp 2: Generalization Ability

Testing on objects not seen during any training phase.

EDOPT PERFORMANCE

Median Error < 1 cm, Median Angle < 6°

RGB-D-E fails completely as the DNN cannot generalize to new objects without retraining.

Exp 3: Live Online Tracking

- **Setup:** ATIS camera (640×480)
- **Target:** Hand-held toy car with free 6-DoF motion

Qualitative Results:

Visually consistent tracking with no frame jumps and smooth updates, validating real-time performance.

Comparison Summary

High Frequency + Generalization

EDOPT achieves State-of-the-Art accuracy at **>300 Hz** (vs 5Hz) while working on any object with a mesh, eliminating the need for object-specific retraining.

Critical Analysis

STRENGTHS, WEAKNESSES & FUTURE OUTLOOK

Strengths

- **First event-only solution** to a 6-DoF event-based tracking problem.
- **Simple & Interpretable:** Mesh projection + Jacobian; no blackbox learning.
- **Model-based Generalization:** Works on any object with a mesh without retraining.
- **Real-time & High-freq:** >300 Hz enables dynamic manipulation applications.
- **Decoupled Architecture:** Asynchronous loops for sensory vs. inference layers.
- **Reproducible:** Open-source code and datasets released.

Weaknesses

INTRINSIC LIMITATIONS

- **Initialization:** Only tracks once pose is known; no failure recovery.
- **Velocity Cap:** Fixed hypothesis set limits tracking of very dynamic tasks.
- **Mesh Dependency:** Degrades with inaccurate meshes, wear, or reflections.

EXPERIMENTAL GAPS

- **Limited Failure Analysis:** Sensitivity to calibration/clutter is under-characterized.
- **No Ablation Studies:** Unclear contribution of specific parameters (EROS, kernel).
- **Comparison Fairness:** RGB-D-E baseline run at 5 Hz (vs potential 30 Hz).

Why This Paper?

Context & Methodology

First pure event-only 6-DoF object pose tracker relevant to dynamic robotic grasping. It presents an elegant combination of asynchronous perception, geometric modeling, and structured hypothesis competition that outperforms trained RGB-D-E baselines.

Significance

Strong technical substance with clear, discussable limitations. EDOPT demonstrates that pure model-based tracking can be fast and generalizable, even if it currently lacks adaptability to realistic noise and occlusions.

Proposed Neuromorphic Upgrade

Adding plasticity and uncertainty handling while retaining structural elegance:

- **Learned Proposal Network:** Spiking RNN predicting ΔX from EROS (motion priors).
- **Spiking Bayesian Layer:** Posterior over pose in spike rates (uncertainty + recovery).
- **Learned Event → Gradient:** Spiking convolutions replacing Sobel+DoG.