Application of Data-driven Feature Tracking for Event Cameras in "Low Light Space Object Tracking"

Tanzeel Ahmad, Roshitha Makula, Jeevan Tubinakere Govindaraju

December 12, 2024

Abstract

GitHub

This project introduces an advanced feature tracking system optimized for low-light and dynamic space environments, using event cameras. By integrating robust low-light detection and adaptive tracking, the proposed system offers accurate tracking of objects, such as satellites and space debris, under challenging conditions. The system combines real and synthetic datasets, advanced prepossessing techniques, and an extension of the data-driven feature tracking architecture with temporal attention and predictive tracking.

1 Introduction

Tracking space objects such as debris, comets, or satellites in low-light and high-speed scenarios presents unique challenges. Current tracking systems often fail to perform effectively under extreme lighting variations and dynamic object movements. Event cameras offer a promising solution by capturing temporal and spatial changes with high fidelity. However, the lack of robust and efficient feature-tracking algorithms tailored for event data limits their application.

This project builds upon the state-of-the-art research outlined in Data driven Feature tracking. By extending their framework to simulate and analyze space-specific scenarios, we aim to propose a cost-effective and accurate approach for tracking space objects using event cameras. This work has significant implications for improving situational awareness and mitigating potential risks posed by space debris.

2 Background

Tracking objects in challenging environments, especially in space, requires robust models capable of handling extreme lighting variations, fast-moving objects, and limited computational resources. Traditional frame-based cameras struggle in such conditions due to motion blur and low frame rates. Event cameras, on the other hand, capture changes in brightness asynchronously, making them ideal for dynamic and low-light scenarios.

This project builds on the seminal work of Data-driven Feature Tracking for Event Cameras, which introduced a novel tracking framework leveraging convolutional backbones, temporal attention modules, and optical flow estimation. This framework demonstrated effective tracking for standard event camera datasets, offering a significant step forward in the field of feature tracking for event-based vision.

The key components of the original model include a convolutional backbone for spatial-temporal feature extraction, a temporal attention module (ConvLSTM) for stabilizing object tracking, and a predictive tracking mechanism for distinguishing between camera motion and object motion. While the original framework was tested on synthetic datasets and simple real-world scenes, our goal is to extend its capabilities to track objects in the unique and unpredictable context of space.

Tracking space debris, comets, and other celestial objects presents additional challenges, as lighting conditions are harsh, and object motion can be irregular. To address these challenges, we introduce a new synthetic space dataset, generated from realistic space imagery using AI-driven video synthesis. This synthetic data, combined with event-based conversion tools like V2E, provides a means to test the model's generalization and robustness. Our objective is to assess how well the pre-trained model can generalize to this new dataset and explore whether fine-tuning or re-training on synthetic data improves tracking accuracy. This project serves as a continuation of prior work, pushing the boundaries of event-based feature tracking into the realm of space applications.

3 Data Sources

To effectively evaluate the application of data-driven feature tracking for event cameras, we used two distinct datasets: the default dataset provided by the original study and a synthetic space dataset generated specifically for this project. These datasets allowed us to compare the model's performance in varied conditions, including standard event camera benchmarks and challenging, low-light, space-like environments. By leveraging both datasets, we aimed to analyze the adaptability and robustness of the feature tracking approach under different scenarios.

3.1 Default Data

The default dataset includes ec_subseq and eds_subseq. These datasets represent standard benchmarks for event camera applications, providing both event data and associated pose information. The ec_subseq data set comprises event streams captured in controlled indoor environments, while the eds_subseq dataset features dynamic scenes with variable lighting and motion patterns. Ground truth annotations, calibration files, and $pre-trained$ models are provided, enabling straightforward evaluation. This data set serves as a robust baseline for testing the performance of feature tracking under ideal and well-studied conditions.

3.2 Synthetic space data

To address the limitations of existing datasets for space object tracking, we created a synthetic dataset by simulating a low-light space environment. This dataset was generated by first utilizing actual space images, which were fed into an AI video generator to create continuous video sequences. These videos were then converted into event data using the v2e (video-to-event) converter, producing high-resolution event streams under challenging lighting conditions. The dataset also includes additional metadata such as time surfaces and pose information, assuming a stationary camera setup. This synthetic dataset captures unique dynamics such as debris movement, comet tracking, and varied lighting intensities, offering a novel testbed for evaluating the performance of event cameras in space applications.

4 Methodology

Our approach leverages a combination of state-of-the-art event-based feature tracking techniques and synthetic data generation tailored for low-light space environments. We began by utilizing actual space images and processed them through an AI video generator to create continuous video streams, which were then converted to event data using the v2e converter. This event data formed the basis for generating time surfaces and pose information, necessary inputs for the tracking model. The model itself incorporates a convolutional backbone for feature extraction, a temporal attention module (ConvLSTM) for stable feature tracking, and optical flow estimation for motion prediction. We evaluated the pre-trained model on both the default dataset and our synthetic space dataset, observing its performance in tracking moving objects in varied lighting conditions. The methodology ensures that both real-world and simulated scenarios are thoroughly tested, paving the way for model fine-tuning specific to space environments.

4.1 Flow Chart

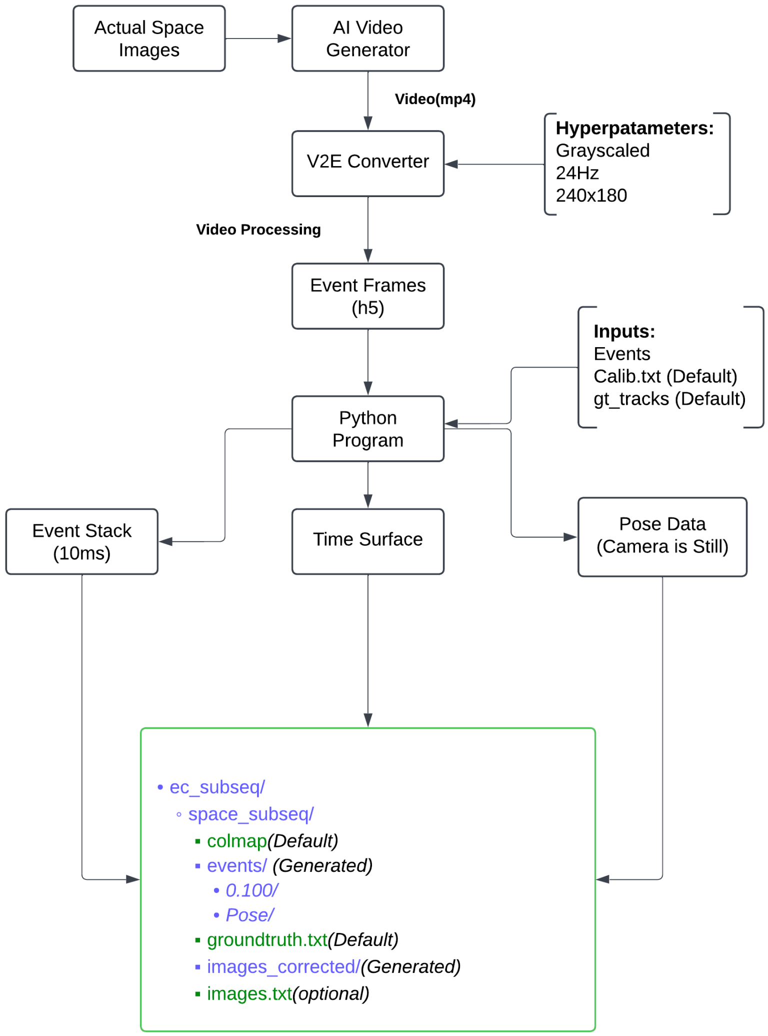

Figure 1: Caption describing the image.

4.2 Evaluation Strategy

The evaluation strategy for this project focuses on assessing the effectiveness and robustness of the data-driven feature tracking approach for event cameras in low-light conditions. Initially, we utilize the pre-trained model provided by the original research paper to evaluate the tracking performance on the default datasets ($ec_{s}ubseq$ and $eds_{s}ubseq$). Metrics such as inference latency, accuracy of object tracking, and stability of trajectories are analyzed to establish a baseline. For the synthetic space data, generated through the proposed pipeline, the same pre-trained model is used to evaluate its adaptability and generalization capability. The model's predictions are compared against ground truth data generated alongside the synthetic dataset. The evaluation includes visualizing tracking results using bounding boxes or patches on moving objects and analyzing latency from the logs. A key aspect of the evaluation is the analysis of performance degradation, highlighting the model's limitations when exposed to unseen data distributions. The insights gained from these evaluations guide recommendations for fine-tuning or retraining the model to better accommodate diverse scenarios, such as simulated low-light space environments.

5 Results

5.1 Default dataset results

We successfully set up the code base and ran the model using the pre trained weights provided by the original authors on the default dataset. The data set included a variety of scenarios such as shapes translation, boxes rotation, and $shapes_6dof$, which allowed us to assess the performance of the model in various settings. During these evaluations, we were able to generate accurate tracking outputs and visualize the results in the form of GIF, as intended by the original implementation. These outputs effectively demonstrated the model's ability to identify and track objects under varying lighting conditions and motion patterns. The generated GIF illustrates the object trajectories tracked by the model, emphasizing the smoothness and accuracy of predictions even in challenging scenarios. Figures below showcase these visualizations, further validating the robustness of the pre trained network and the reproducibility of results on the provided datasets.

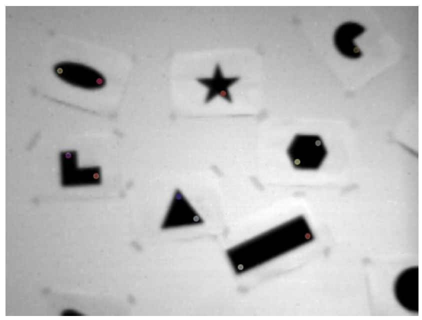

Figure 2: Tracking output from the default dataset: shapes translation.

Figure 3: Tracking output from the default dataset: boxes rotation.

5.2 Synthetic space dataset result

We extended the evaluation by introducing a synthetic space dataset, generated using actual space images processed through an AI video generator and a V2E converter. This data set simulated low-light and varied lighting conditions, closely resembling the challenges of real-world space object tracking scenarios. The synthetic data set aimed to test the model's ability to generalize to unseen and complex input data.

However, the results on this dataset were less satisfactory. While, the model produced tracking outputs, the accuracy and reliability of these outputs were significantly lower compared to the default dataset. The generated GIF revealed stationary patches, where the model failed to capture meaningful object movements or trajectories. This highlights a limitation in the model's ability to generalize well to datasets with drastically different characteristics than those seen during training.

The lack of satisfactory results suggests that the model requires further fine-tuning or retraining on simulated datasets like the synthetic space dataset. By incorporating such data into the training pipeline, the model can learn to adapt to the unique patterns and lighting conditions encountered in space tracking scenarios, ultimately improving its performance. These findings open the door for future research in enhancing the robustness and adaptability of event-based tracking models.

Figure 4: Tracking output from the synthetic space dataset.

6 Conclusion

This project aimed to explore a data-driven approach for feature tracking in event cameras, specifically targeting the challenge of tracking space objects under low-light and variable lighting conditions. Building on the foundation of an existing open-source implementation, we successfully set up the code base, executed the pre-trained model on the provided default datasets, and achieved accurate tracking results as demonstrated by the generated GIF. These results validated the effectiveness of the pre-trained model in controlled scenarios.

To push the boundaries of the model's generalization capability, we introduced a synthetic space dataset. This dataset, created by transforming space images into continuous video sequences and generating event data via the $V2E$ converter, presented a more challenging and diverse set of tracking scenarios. Unlike the default dataset, tracking performance on the synthetic space dataset was less effective. The model struggled to maintain consistent tracking, indicating that the pre-trained network could not generalize effectively to unseen and more complex datasets.

This outcome highlights the importance of fine-tuning and retraining on datasets that more closely match the target domain. The addition of synthetic space data in the training process may significantly enhance the model's ability to track debris, comets, and other space objects. Future work will focus on incorporating these datasets into the training pipeline, as well as exploring techniques like domain adaptation and contrastive learning to improve model robustness. Our findings underscore the potential of data-driven tracking approaches in space applications and pave the way for more generalizable and robust tracking solutions in challenging real-world conditions.