DYNAMIC SPACE OBJECT DETECTION WITH NEUROMORPHIC VISION SENSORS

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ABSTRACT

Space Situational Awareness (SSA) incorporates the detection, tracking, and prediction of the movements of objects orbiting Earth. It is critical for protecting space assets and mitigating collision risks, but it remains challenging due to the large number of objects, their high-velocity dynamics, and challenging lighting conditions. In this research, we present the use of a Neuromorphic Vision Sensor (NVS) for observing and detecting Resident Space Objects (RSOs) to enhance SSA capabilities. The NVS is a cutting-edge, bio-inspired sensor that operates asynchronously, responding to logarithmic changes in light intensity at the pixel level. This sensor is integrated with a high-performance 0.8-meter diameter Ritchey–Chrétien telescope, part of the Abu Dhabi Quantum Optical Ground Station (ADQOGS), which features a pointing accuracy of less than 4 arcseconds. This NVS event camera is activity-dependent which captures substantially less data in sparse scenes than standard cameras, optimizing data handling. Additionally, its ability to detect high-speed motion and capture fine RSO details mitigates the limitations of traditional cameras prone to motion blur and low resolution. Leveraging the unique characteristics of the NVS, we are developing a novel and robust approach for RSO detection across various scenarios and lighting conditions. The NVS offers advantages such as reduced power consumption, lower processing requirements, higher dynamic ranges, and faster data communication. These attributes make NVS exceptionally well-suited for space imaging and SSA applications. Our work involves developing an innovative deep learning algorithm designed to process the NVS event streams. This algorithm differentiates between event streams arising from sky background noise and those associated with RSOs, revealing the spatiotemporal relationships within the NVS data and producing bounding boxes for detected RSOs. Training and evaluation on the locally recorded NVS-based datasets has yielded promising preliminary results, showcasing the potential of Artificial Intelligence (AI) for processing raw NVS data in SSA fields. Key deliverables comprise equipping the NVS sensor to a ground-based telescope, developing advanced deep learning algorithms for RSO detection, tracking, and constructing a new NVS-based dataset locally collected in the United Arab Emirates (UAE). These initiatives are expected to significantly enhance the UAE's RSO monitoring capabilities, improving accuracy, operational efficiency, and strategic insights, thus advancing SSA and the management of space objects.

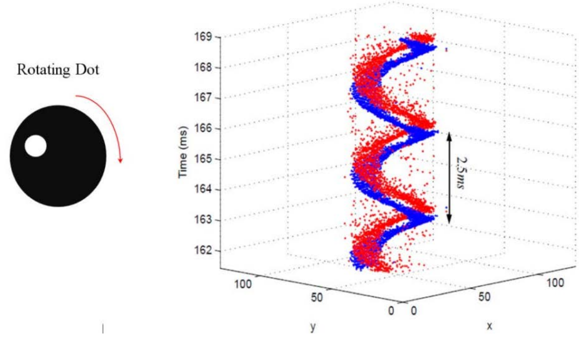


Figure 1: Visualization of event generation by a neuromorphic vision sensor when observing a rotating black disk featuring a single white dot spinning at 400 Hz [1]

Keywords: Neuromorphic Vision Sensors; Space Situational Awareness; Artificial Intelligence; Deep Learning; Resident Space Objects.

1. INTRODUCTION

Space Situational Awareness (SSA) has become increasingly vital due to the escalating risks posed by space debris, threatening the sustainability and safety of orbital operations. As Earth's orbital environment becomes more congested, precise and timely detection of debris is crucial to prevent collisions and protect critical space infrastructure. Currently, passive imaging sensors, particularly Complementary Metal-Oxide-Semiconductor (CMOS) cameras, play a significant role in SSA applications, including satellite tracking, astronomy, and Earth observation. However, conventional sensors face significant limitations, particularly in accurately detecting high-speed objects under challenging orbital lighting conditions.

Neuromorphic Vision Sensors (NVSs), commonly known as Event Cameras, have emerged as an innovative technology capable of overcoming the limitations associated with conventional passive sensors. Unlike conventional frame-based cameras, NVSs operate asynchronously, registering pixel-level changes only upon detecting logarithmic variations in light intensity. This operational principle significantly enhances their responsiveness and adaptability, making them exceptionally suited for detecting and tracking rapidly moving space objects under challenging orbital lighting conditions.

NVSs integrate specialized pixel-level circuitry, enabling

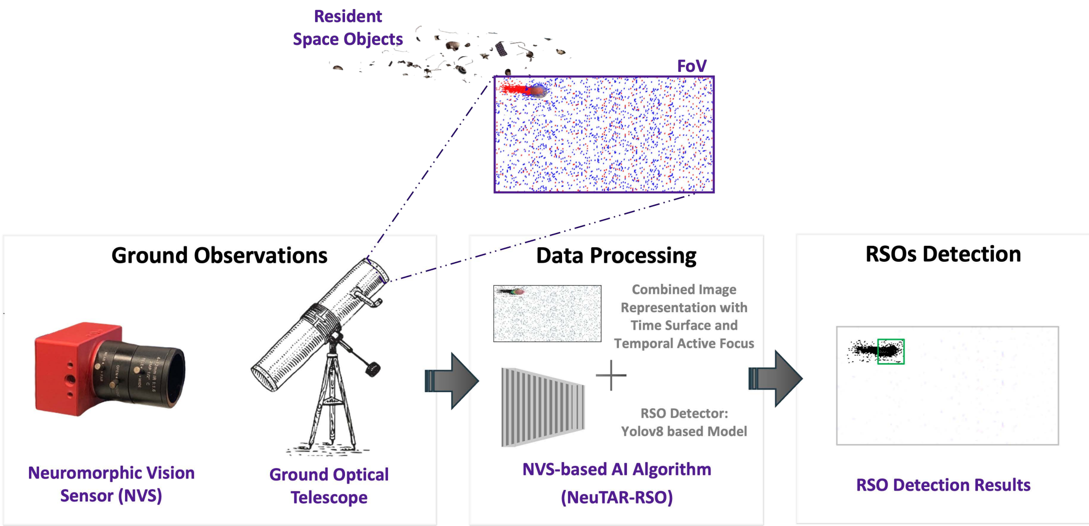


Figure 2: Framework for Space Object Detection: Neuromorphic Vision-based SSA

imaging at high speeds, low power consumption, and with a wide dynamic range. In contrast to traditional sensors that capture data in frames over fixed integration periods, NVSs operate asynchronously, generating output only when relevant changes in illumination occur. Each pixel independently detects luminance variations and produces discrete ”events,” characterized by pixel coordinates (x,y), an accurate timestamp (t) at microsecond resolution, and a binary polarity indicator (p), signaling an increase or decrease in luminance, as illustrated in Figure 1. This event-driven mechanism substantially reduces data generation, particularly in sparse observational conditions commonly encountered in space environments. Such efficient operation, combined with enhanced sensitivity and responsiveness, makes NVSs particularly advantageous for spacecraft navigation [2, 3], precise tracking of satellites and stars [4, 5, 6], and effective detection of Resident Space Objects (RSOs) [7, 8, 9, 10]—critical tasks for advancing SSA.

In this work, we propose a novel approach integrating NVS technology with advanced AI-driven methods to significantly enhance the detection capabilities of RSOs for SSA, as presented in Figure 2. Specifically, we design and implement a learning-based model, called NeuTAR-RSO, trained and evaluated using locally recorded NVS datasets collected at the Abu Dhabi Quantum Optical Ground Station (ADQOGS) in the United Arab Emirates (UAE). Through this approach, we aim to advance space imaging technology and deliver a robust, efficient, and accurate solution tailored to address critical SSA challenges.

The remainder of this paper is structured as follows: Section 2 presents the problem statement along with the key contributions of this research. In Section 3, we detail the proposed framework for utilizing NVS technology within SSA applications, covering the experimental setup for local dataset acquisition and the complete development pipeline, including the training and evaluation methods for the deep learning-based space object detection algorithm. The qualitative experimental results are provided and discussed in Section 4. Finally, Section 5 summarizes the research findings and conclusions.

2. PROBLEM STATEMENT AND CONTRIBUTION

This research addresses the challenge of detecting and tracking RSOs by designing and developing a specialized module utilizing NVS technology integrated with a ground-based telescope system (ADQOGS). The developed approach focuses on efficient real-time performance, optimized for use on limited processing resources. This module not only aims to strengthen the UAE’s capabilities in protecting space-based assets but also prioritizes local data collection and facilitates both national and international research collaborations. Ultimately, this effort contributes directly to enhancing technological innovation in the UAE’s space exploration initiatives and overall SSA.

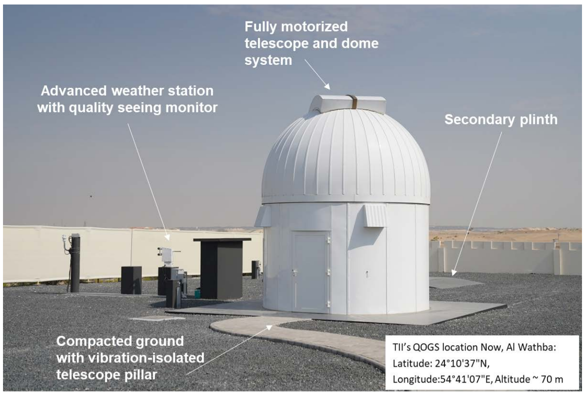
3. PROPOSED FRAMEWORK NVS FOR SSA

This section outlines the proposed framework, structured into three main stages: (1) Data Acquisition, involving ground-based observations to compile a local NVS dataset; (2) Data Processing, focusing on the design and development of the NeuTAR-RSO model for detecting space objects; and (3) Detection Output, highlighting the identification of objects of interest. The details of each stage are presented comprehensively in the subsequent subsections.

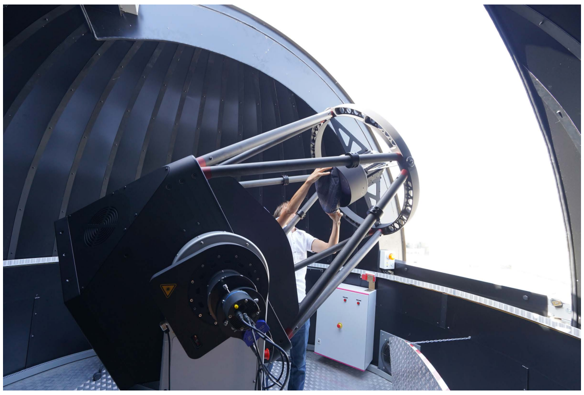
3.1. Data Acquisition - Ground Observations and Data Collection

ADQOGS is situated in Abu Dhabi at an elevation of 70 meters above sea level, with geographical coordinates of

$24°11'$ N, $54°41'$ E, as presented in Figure 3. Its primary observational instrument is an 80-cm Ritchey–Chrétien telescope with an f/6.85 focal ratio. The site's infrastructure supports fully automated telescope operation, enabling SSA data collection during the instrument's idle periods. The NVS camera, DAVIS346c, will be integrated at one of the telescope's two Nasmyth ports, using custom-designed adapters attached directly to the telescope structure.



(a) ADQOGS Site description



(b) The AltAz 800 f6.85 telescope

Figure 3: Overview of the ADQOGS site layout. ADQOGS is hosted at Al Sadeem Observatory in Al Wathba, Abu Dhabi [11]

The objective of the initial observations is to compile a preliminary local dataset using NVS recordings, ensuring the presence of RSOs, to facilitate the development and evaluation of our detection and tracking module. To achieve this, we propose a telescope pointing strategy based on known RSOs and real-time NVS stream data acquisition, as illustrated in Figure 4. Prior to the observations, candidate RSOs are identified from Two-Line Element (TLE) databases and imported into ANSYS Systems Tool Kit (STK) for pass simulations. STK provides precise Azimuth and Elevation data, which are verified using orbit propagation methods to confirm each RSO pass. This process generates a comprehensive observation schedule containing the anticipated RSOs along with corresponding telescope pointing coordinates (RA and Dec) and timing information. The resulting dataset enables rigorous analysis of the camera's operational parameters, sensitivity optimization, and facilitates the development of a robust data processing algorithm tailored specifically for effective RSO detection.

Table 1: Observed RSOs at ADQOGS (NVS-based Dataset)

Object Name	Object Type	NORAD ID	Description
EGS-16908	Satellite	16908	Japanese geostationary satellite
NOAA-6	Satellite	11416	NOAA weather and Earth observation satellite
NOAA-15	Satellite	25338	NOAA polar-orbiting weather satellite
RESURS-DK 1	Satellite	29228	Russian Earth observation satellite
COSMOS 1933	Satellite	18958	Russian military reconnaissance satellite
SAOCOM 1B	Satellite	46265	Argentinian radar Earth observation satellite
SL-12 R/B(2)	Known Debris	15772	Upper-stage rocket body debris (Russian SL-12)
SL-16 R/B	Known Debris	26070	Upper-stage rocket body debris (Russian SL-16)
SL-16 R/B	Known Debris	20625	Upper-stage rocket body debris (Russian SL-16)
SL-8 R/B	Known Debris	N/A	Rocket body debris (Russian SL-8)

During the initial observational sessions conducted from December 2024 through January 2025 (6:00 pm to 8:00 pm UAE local time), we successfully collected NVS-based datasets capturing various known RSOs. These observations comprise operational satellites and debris objects, summarized clearly in Table 1. A representative visualization of these acquired NVS event streams is presented in Figure 4.

3.2. Data Processing - NeuTAR-RSO Algorithm for Space Objects Detection

In this section, we describe the preparation of input data, the architecture of the proposed NeuTAR-RSO model, the procedure for generating approximate ground-truth data, and the training and testing methodology employed for NeuTAR-RSO.

3.2.1. Input Data Preparations

Data acquired by the NVS camera consists of asynchronous events triggered by changes in the logarithmic intensity of the observed scene. These events occur at pixel-level resolution within a spatial array defined by dimensions $H \times W$, corresponding respectively to the height and width of the sensor's frame. Each event stream containing N events, represented as $\{e_i\}_N$, can be expressed as a sequence of four-dimensional tuples:

$$\{e_i\}_N = \{x_i, y_i, t_i, p_i\}_N, \tag{1}$$

where $(x_i,\, y_i)$ denote the spatial coordinates of the i-th event, t_i represents the event timestamp, and p_i indicates

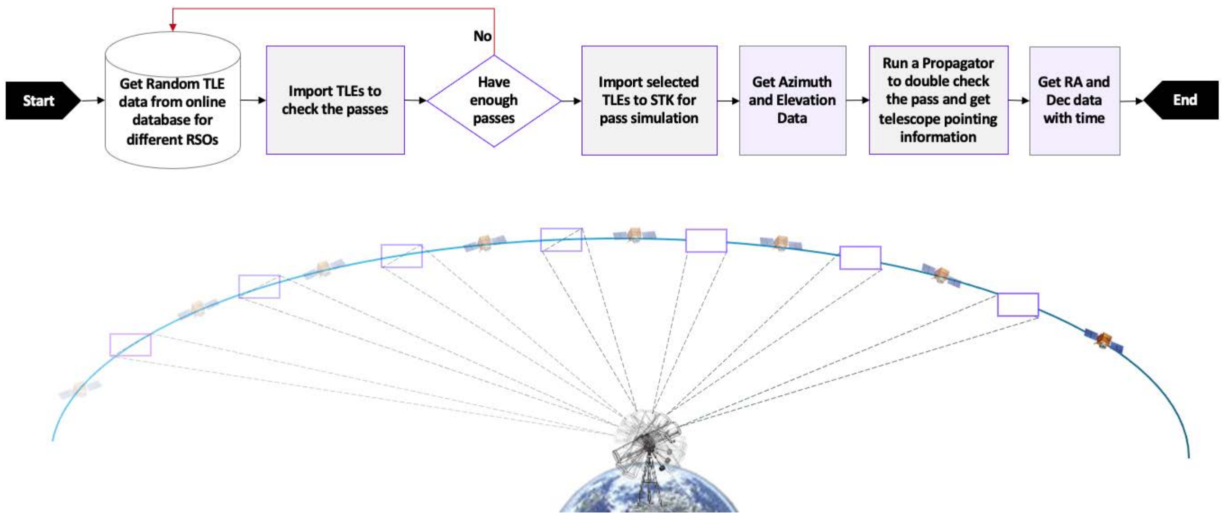


Figure 4: Telescope pointing method for RSO observation and real-time acquisition of a local NVS event stream dataset

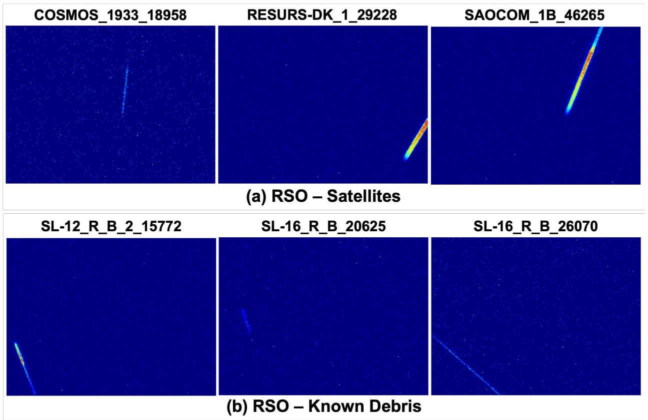


Figure 5: Sample of neuromorphic event stream data collected at the ADQOGS, capturing known RSO satellites and debris in December 2024 and January 2025

polarity. The polarity p_i is defined as +1 if the pixel's brightness increases and -1 if it decreases.

To handle these events, they are aggregated into a 4D event tensor $\{x_i, y_i, t_i, p_i\}$ over a predefined temporal window. Detecting resident space objects (RSOs), which are high-dynamic objects observed against a dark background, is particularly challenging due to a significant number of simultaneous noise events that occur alongside genuine events from the RSO. To effectively differentiate the events related to high-speed space objects within the narrow field of view from the abundant background noise (e.g., dark sky), we explore different event representations processed in real-time prior to applying the main detection model, described later in the next section. Specifically, we examine two event representations—Time Surface and Temporal Active Focus (TAF)—which leverage temporal information and the volume of generated events to distinguish dynamic object events from background noise.

The temporal characteristics of the event stream inherently reveal the velocity of dynamic objects when encoded into a 2D event-based image representation using temporal information as a feature. The Time Surface representation transforms events into a 2D image in which each pixel's intensity encodes the recency of events at that location, typically using an exponential decay function, as introduced in [12, 13]. A more recent approach, the Temporal Active Focus (TAF) method, introduced in [14], efficiently represents sparse event data as a dense tensor optimized for event-based object detection. Unlike conventional sparse event spike tensors, TAF selectively maintains only the latest temporal events at each spatial and polarity position using a First-In, First-Out (FIFO) queue structure. This approach enables TAF to efficiently capture dynamic temporal information in a dense format, substantially reducing computational complexity and storage requirements, thereby enhancing performance in dynamic object detection tasks.

In this work, we explore both representations and propose a fused event representation named Temporal Active Representation (TAR), obtained by combining the Time Surface and Temporal Active Focus representations. As shown in Figure 6, the TAR representation enhances the clarity and distinctiveness of dynamic objects compared to either the Time Surface or TAF alone. Thus, TAR is employed as the input to our proposed NeuTAR-RSO detection framework, detailed in the subsequent section.

3.2.2. Architecture of the Proposed NeuTAR-RSO Model

Figure 7 shows the overall architecture of the NeuTAR-RSO model, where the fused TAR event frame is used as input to the network. The temporal-based features of the TAR image pixels are processed by encoding and decoding layers to detect the object of interest within the frame. The network outputs four values representing the bounding box of the detected RSO within the TAR image,

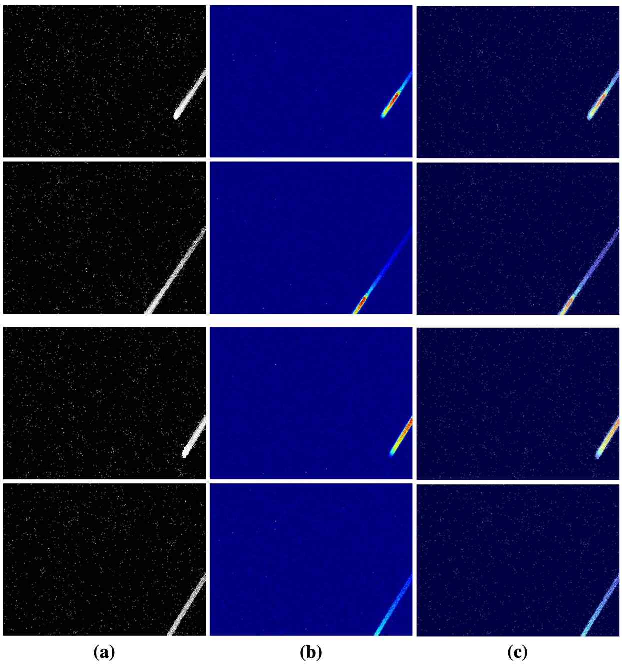


Figure 6: Input Representations of Neuromorphic stream data : (a) Time Surface, (b) Temporal Active Focus, and (c) Fusion of TS and TAF

where $(x_{\text{center}},\ y_{\text{center}},\ w,\ h)$ is the bounding box format, denoting the center coordinates, width, and height of the object.

The NeuTAR-RSO architecture is inspired by YOLOv8 and uses Cross Stage Partial (CSP) blocks to improve feature learning while keeping the model efficient. CSP blocks split and merge feature maps to preserve important information and reduce redundancy. The model also includes attention mechanisms that help it focus on the most relevant parts of the input, making it more effective at detecting small or faint RSOs in the fused TAR image. The final output layer predicts bounding box coordinates, which are passed through a sigmoid activation to normalize the values between 0 and 1, ensuring they remain within the image boundaries.

3.2.3. Approximate Ground Truth Data Preparation

The proposed NeuTAR-RSO model is developed, trained, and evaluated using our locally acquired NVS datasets. For each specified temporal window, the input to the network is a 2D TAR event image generated from all event data within that period. The corresponding output is the bounding box coordinate of the detected RSOs. To generate the approximate bounding box labels used for training, a multi-step preprocessing pipeline is applied, as summarized in Figure 8. First, a slice of events is collected every 33 ms from the event camera. From each slice, two event-based representations are created: the Time Aggregated Frame (TAF), which bins events by time and polarity, and the Time Surface, which encodes the recentness of events per pixel using an exponential decay function. Both representations are denoised with a median filter and blended into a single RGB image to enhance spatial and temporal information. This combined image is then converted to grayscale and thresholded to segment active regions. Contours are extracted from the thresholded image, and for each contour with an area above a predefined threshold (e.g., 30 pixels), an initial bounding box is generated. Finally, the bounding boxes are refined to improve localization accuracy and reduce noise, resulting in the approximate ground truth used to train the detection model.

3.2.4. Training and Testing Methodology for NeuTAR-RSO

Our approach trains the NeuTAR-RSO neural regressor on 2D TAR images—fused representations of neuromorphic vision sensor (NVS) event streams—for supervised object detection. The network outputs four values corresponding to the bounding box $(x_{\text{center}}, y_{\text{center}}, w, h)$ of the detected object. Event data, represented as (x_i, y_i, t_i, p_i), are inherently sparse and limited in spatial detail, making accurate scene interpretation and object detection—especially for fast-moving objects—challenging. However, the high temporal resolution of events enables rapid data accumulation, even in low-light conditions where noise may be present.

The performance of AI models is closely tied to the quality and diversity of the training dataset. A broad and well-annotated dataset is essential both for refining model parameters and enhancing generalization to unseen scenarios. Yet, collecting and labeling such datasets remains resource-intensive in certain applications. The training and evaluation data used in this work are obtained from our recorded NVS-based dataset, as described in Section 3.1. The dataset is split into 70% for training, 15% for validation, and 15% for testing. To ensure randomness and reduce bias, the dataset is shuffled before training. The NeuTAR-RSO network is implemented in PyTorch for both training and inference, using the Adam optimizer with a learning rate of 0.001. Training is guided by the SmoothL1 (Huber) loss function. Figure 9 illustrates the loss curves, showing effective model convergence during training, validation, and testing.

4. EXPERIMENTAL EVALUATIONS

This section presents the experimental evaluation of the proposed NeuTAR-RSO model, detailing the evaluation metric used and analyzing the results both quantitatively and qualitatively.

4.1. Evaluation Metric

To quantitatively evaluate the bounding box prediction accuracy of the proposed model, we utilize the *Intersection over Union (IoU)* metric, which is widely adopted in object detection tasks.

- *Intersection over Union (IoU)*: IoU measures the de-

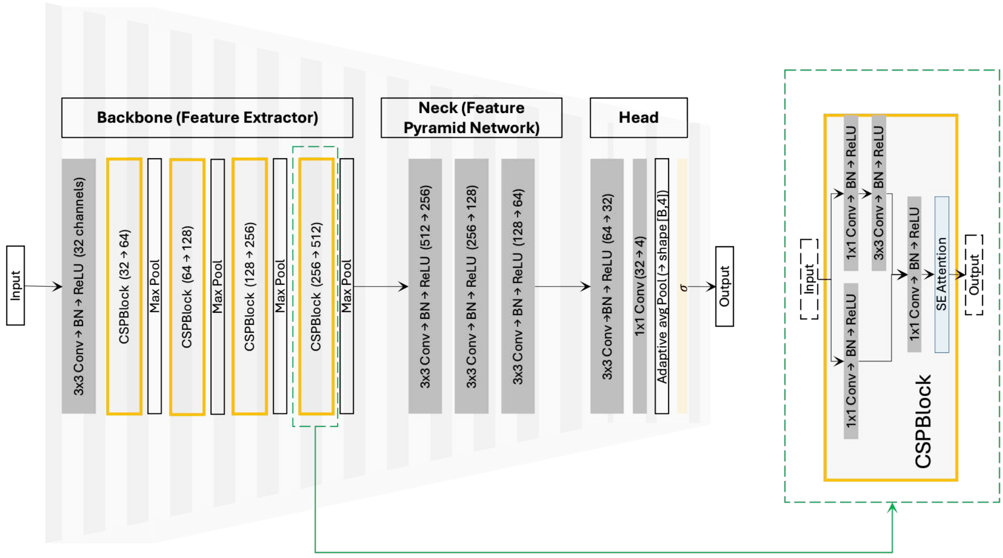


Figure 7: Architecture of the proposed NeuTAR-RSO neural network

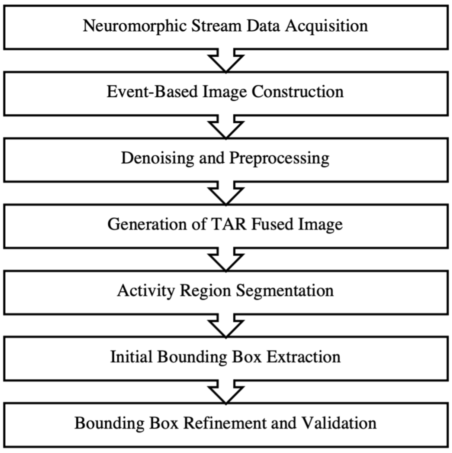


Figure 8: Approach for generating approximate ground truth bounding boxes for NVS-based RSO detection

gree of overlap between the predicted bounding box and the ground truth bounding box, quantifying how accurately the predicted box aligns with the actual object location. It is formally defined as:

$$IoU = \frac{\text{Area of Overlap}}{\text{Area of Union}} \tag{2}$$

Typically, IoU is employed to determine if a bounding box prediction qualifies as a true positive by comparing it against a predefined threshold (commonly 0.5 or 0.7, depending on evaluation criteria). In our case, we selected 0.5 as our evaluation criteria.

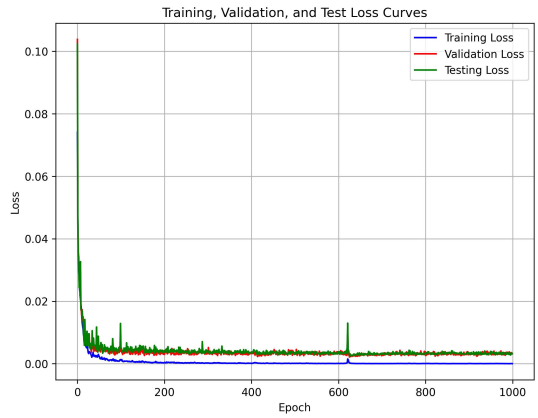


Figure 9: Loss curves generated during the training, validation, and testing of the NeuTAR-RSO model

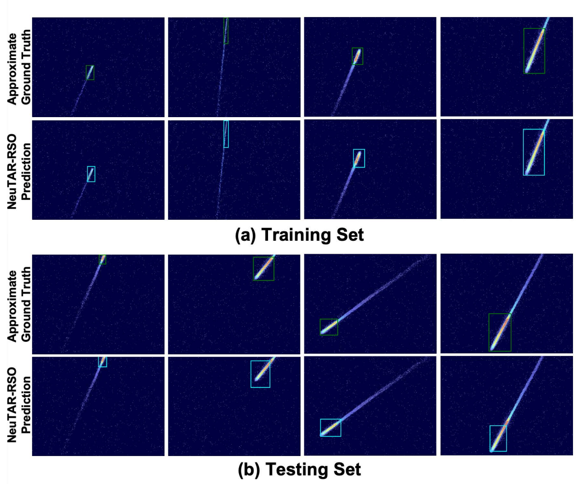


Figure 10: RSO detection results using the proposed NeuTAR-RSO algorithm on locally acquired NVS event streams for both training and testing sets

4.2. Quantitative and Qualitative Analyses

The proposed bounding box regression model achieved a mean IoU of 78.2% on the training set and 64.0% on the test set, indicating good localization accuracy and generalization to unseen data. Qualitative visualizations, shown in Figure 10, further support the quantitative results, revealing high spatial correspondence between predicted and ground truth bounding boxes across diverse scenarios. This alignment highlights the model's effectiveness in learning precise object boundaries, even under the sparse and asynchronous conditions of event-based input. These findings affirm the model's potential for space object detection and reinforce its suitability for NVS-driven RSOs' detection and tracking applications.

5. CONCLUSIONS

In this work, we presented the capability of NVS Sensors combined with an AI-based algorithm to enhance SSA. We demonstrated the experimental setup for capturing NVS observations at the Abu Dhabi Quantum Optical Ground Station (ADQOGS) and developed a dedicated algorithm for real-time detection and tracking of RSOs, showing promising preliminary results. Moving forward, we plan to expand the locally recorded NVS dataset in the United Arab Emirates (UAE), presenting the raw NVS-based observational data alongside detection and tracking results. This advancement is expected to significantly enhance the UAE's SSA capabilities by improving accuracy, efficiency, and understanding of the space environment. Ultimately, this work contributes to the advancement of space imaging technologies, laying the foundation for safer and more informed space operations.

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