NEUROMORPHIC SENSING AND PROCESSING FOR SPACE DOMAIN AWARENESS

Paul Kirkland, Carmine Clemente,
Malcolm Macdonald and Gaetano Di Caterina *

Department of Electrical and Electronic Engineering
University of Strathclyde, Glasgow, UK

Gabriele Meoni

Φ-lab, ESRIN
European Space Agency
Frascati, Italy

ABSTRACT

As space debris poses substantial risks to space-based assets, the need for efficient, high-resolution monitoring and prediction methods is pressing. This paper presents the findings from the project NEU4SST, exploring Neuromorphic Engineering, specifically event-based visual sensing coupled with Spiking Neural Networks (SNNs), as a solution for enhanced Space Domain Awareness (SDA). Our research concentrates on event-based visual sensors and SNNs, offering low power consumption and precise high-resolution data capture and processing. These technologies bolster the ability to detect and track objects in space, addressing key challenges in the Space domain. Our method exceeded previous models by 15% on the informedness metric, demonstrating its potential in improving SDA, and aiding safer, more efficient space operations. Continued research and development in this area are crucial for realising the full potential of Neuromorphic engineering for future space missions.

***Index Terms*—** Neuromorphic, Event-Based Camera, Spiking Neural Network.

1. INTRODUCTION

The rapid evolution of Space Situational Awareness (SSA) coupled with the vital importance of Space Domain Awareness (SDA) necessitates efficient tools for tracking the ever-increasing number of objects in near-Earth space [1, 2]. This paper explores a cutting-edge approach that harnesses the synergy of neuromorphic event-based visual sensors [3] and Spiking Neural Networks (SNNs) [4], to provide a transformative platform for enhancing SSA and SDA capabilities.

Neuromorphic sensors, inspired by the workings of the biological retina, asynchronously capture high temporal resolution spatial data, consuming significantly less power, a paramount attribute in space applications [3]. Their unique ability to exploit non-linear signal-noise relationships [5], capturing data at optimal signal-to-noise times, optimises SSA precision and increases the efficiency of tracking objects in space.

*This work was funded by the European Space Agency through grant ID I-2021-05556 as part of the Cognitive Cloud Computing in Space campaign.

SNNs are the third generation of neural networks, mimicking human neural processes to adeptly handle the complex data from these event-based sensors [4]. This equips SNNs with enhanced learning and adaptation abilities, offering a novel solution to the SSA and SDA challenges. By enabling simultaneous detection and tracking of moving objects in low signal-to-noise environments [5], this synergy improves space debris management and collision risk mitigation, thereby safeguarding both space and terrestrial assets [6, 7].

We identify several key areas where neuromorphic engineering and SNNs can potentially enhance SSA and SDA capabilities: capturing space object motion paths with high temporal resolution; developing a cataloguing system able to handle increasing numbers of entries; ensuring accuracy sufficient for reliable conjunction warnings; and enabling object tracking during daytime. These areas align with findings from a recent UK Space Agency report [1].

In this paper, we present a novel approach to the detection and tracking of objects in space, based on the combination of event sensor data and SNN-based neuromorphic processing. The experimental results reported indicate that, on the same dataset, our novel approach can achieve better performance than the state-of-the-art, which does not employ SNN or neuromorphic processing. At the same time, the approach proposed provides a step closer to realising a complete end-to-end neuromorphic pipeline, from sensing to processing. This approach is data-efficient, meaning that it produces data only when needed, and therefore also energy-efficient. These are key elements for applications onboard spacecraft.

The rest of the paper is organised as follows. Section 2 describes the SNN developed in this work, and the data and metrics used for comparison. Section 3 reports on the experimental results obtained, while section 4 concludes the paper.

2. METHODOLOGY

2.1. Event-based SSA dataset

The study employed the event-based space situational awareness (EBSSA) dataset by Afshar et al. [8] as a benchmark for testing the SNN developed in this research. This dataset,

This is a peer reviewed, accepted author manuscript of the following research contribution: Kirkland, P., Clemente, C., Macdonald, M., Di Caterina, G., & Meoni, G. (Accepted/In press - 03 April 2023). Neuromorphic sensing and processing for space domain awareness. In *2023 International Geoscience and Remote Sensing Symposium, IGARSS2023 - Proceedings IEEE.*

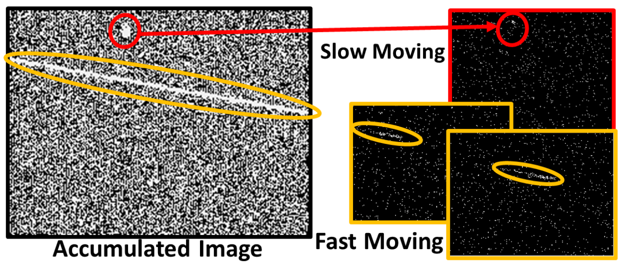

Fig. 1. An accumulated image (3.5 seconds) and breakdowns of the slow- and fast-moving objects (100ms) that need to be extracted simultaneously. (SL8RB-21938)

comprising over 8 hours of data and 377 million events, is unique in the literature as the only publicly available event-based space imaging dataset. The data was gathered from a robotic electro-optic telescope facility, using both ATIS [9] and DAVIS [10] event-based sensors, mounted alongside existing astronomy equipment. Hand-labelled ground truth is provided in the dataset, representing the expert human interpretation of the motion of objects in the field of view against the highly noisy event stream, offering a comprehensive and challenging standard for algorithm testing.

The dataset provided the opportunity to explore the dynamics of the non-linear relationship between noise and signal, and to investigate how the highest signal-to-noise ratio might be achieved through careful information accumulation. The asynchronous event-driven nature of the sensing, with a high temporal resolution allowing for the capture of one or few events, served to highlight the benefits of this approach. Further advantage could be taken of the knowledge that the signal would display a high degree of spatial locality over a short period, particularly in the case of very fast-moving objects. This is a feature that can be successfully exploited by a convolutional network.

The advantage of a high sampling rate, combined with a selective accumulation process, is illustrated in Figure 1. This set of images reveals both the overall scene and the motion within it, including two objects moving at very different speeds. In the instance of a slow-moving but bright object, a high amount of signal is present whenever the object exhibits relative motion. Capturing information at these moments, although minimal in contrast to the full accumulated images, allows this information to be accumulated, but without the noise. The fast-moving object, despite appearing as a sparse and incoherent series of events, still produces a higher number of activations in a local area compared to the noise in the background, when viewed on a small time scale. Therefore, the highest signal-to-noise opportunities within the SNN can be found in a similar way. The challenge is in learning the spatial priors required to detect and understand this as one continuous object motion path. Example trajectories from the dataset are shown in Fig. 2, illustrating the complexity and volume of object tracking through space and time.

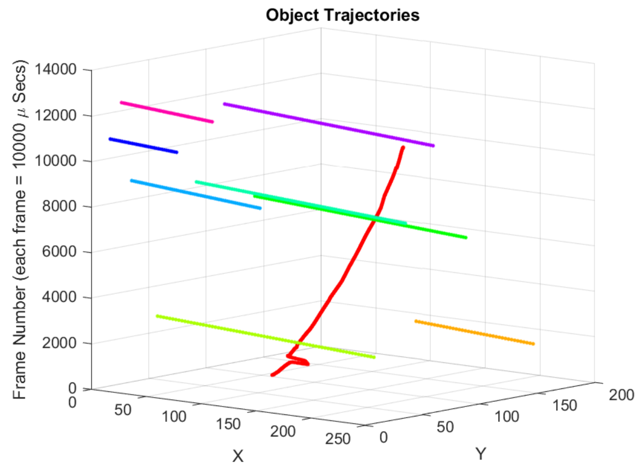

Fig. 2. Example trajectories from the SL8RB-21938 [8] .

2.2. Spiking Neural Network

This work leverages an SNN for processing event-based data derived from visual sensors. In contrast to traditional neural networks, SNNs employ binary spikes for encoding and transmitting information, thereby enhancing their compatibility with high-speed, event-based data. SNNs not only excel in data efficiency but also in energy conservation [11], thereby bolstering their suitability for deployment in space.

This project builds on the foundational work of a spiking instance segmentation network [12], employing the same architectural blueprint and methodology. To address the complex challenge of SSA and motion segmentation, which demands simultaneous recognition of various spatio-temporal features, we have transitioned from the Integrate and Fire (IF) neuron model [5] to a set of Leak Integrate-and-Fire (LIF) neurons, with layer-wise leak variation.

In this model, we utilise a simplified version of the LIF neuron, whose leak factor extends the range of temporal coincidence detection. The equation of the LIF neuron model is:

$$V_i(t) = V_i(t-1) + \sum_j w_{j,i} S_j(t-1) - \lambda_i \qquad (1)$$

where V_i, $w_{j,i}$, and S_j represent neuron membrane potential, synaptic weight, and spike train of the neuron, respectively, while λ_i is the leak factor and t is time. For this work, the SNN is simulated with discrete input steps of t =100ms, although the data is still fed to the SNN event by event, as spike-timing/sequence is important for learning. λ is also set

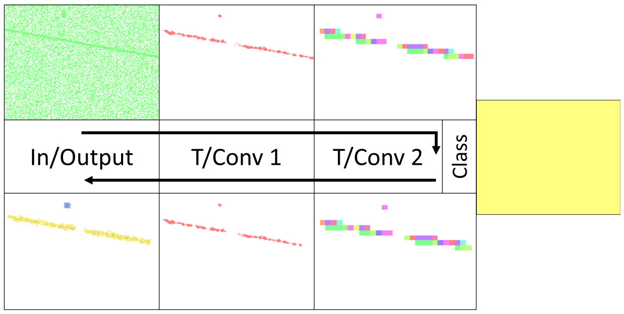

Fig. 3. Visual representation of the features being activated throughout the network, transforming input events into output events segmented with instance labels. (SL8RB-21938)

Table 1. Numerical comparison of the proposed SNN approach with previous results from Afshar et al. [8].

Algorithm	Informedness		Sensitivity		Specificity	
	mean	std	mean	std	mean	std
Raw Events	0.324	0.301	0.690	0.340	0.634	0.148
Hough D	0.244	0.343	0.552	0.408	0.692	0.224
Hough D+T	0.417	0.478	0.442	0.488	0.975	0.073
GMD D	0.609	0.323	0.756	0.284	0.853	0.117
GMD D+T	0.664	0.374	0.813	0.314	0.851	0.223
max (GMD, Hough) D	0.617	0.309	0.754	0.286	0.863	0.103
max (GMD, Hough) D+T	0.753	0.344	0.804	0.331	0.950	0.096
Feat. D.	0.564	0.443	0.580	0.430	0.984	0.041
Feat. D+T	0.775	0.348	0.782	0.349	0.992	0.019
SNN (Prop.)	**0.891**	**0.154**	**0.895**	**0.153**	**0.996**	**0.010**

to 90% and 10% of the neuron threshold in layers 1 and 2 respectively, using a 5x5 convolution kernel and a 7x7 final classification kernel with no leakage. This output is then coupled with the instance segmentation method in Kirkland et al. [12] to better handle the segmentation task.

The introduction of a layer-wise network leak parameter allows neurons to handle inputs with both short-term and long-term temporal dependencies. When integrated with the convolutional hierarchical spatial dependency, this model effectively encodes the output of an event-based sensor. Alongside conventional SNN methodologies like homeostasis and adaptive thresholding, the network undergoes unsupervised Spike-Timing Dependent Plasticity (STDP) training [13], a proven coincidence detection method for event-based data, particularly when paired with convolution kernels [14]. Within this work, the learning parameters are $\alpha^+ = 0.04$, $\alpha^- = 0.03$ with a weight initialisation of 0.8 ± 0.01. As there are not many spatio-temporal features, they converge within 1 epoch.

2.3. Performance metrics

In accordance with prior studies utilising the EBSSA dataset, we assessed the effectiveness of our model using sensitivity, specificity, and informedness metrics [8]. For consistency, a one-pixel boundary, as outlined in [8], was implemented for spatial domain classification, forming an evaluative volume when extended to the temporal domain.

Sensitivity and specificity are binary classification model measures, signifying the proportions of true positives and negatives respectively. Instead informedness combines sensitivity and specificity into a singular performance measure. Both the sensitivity and specificity are dependent on the hyperparameter choices, which is a crucial element given the dynamic nature of the SNN parameters leakage and threshold. These show an inverse correlation with sensitivity, which could lead to an increased false positives count. However, due to the hierarchical structure of the network, initial layers can exhibit high sensitivity while subsequent layers demonstrate high specificity, leading to enhanced pixel-level sensitivity and feature-level specificity.

3. RESULTS

Through the innovative addition of LIF neurons in the convolutional spiking process, the model can assign different leakage time constants per layer and threshold values on a per-neuron basis, which significantly enhances both learning and inference. This allows the network to simultaneously detect and track short-time/fast-moving and long-time/slow-moving objects.

It is particularly noteworthy how efficiently the network handles noise filtering and the detection of spatio-temporal features. The application of the initial 5x5 convolutional kernel alongside dynamic thresholds and leakage provides a robust mechanism to capture features, even in situations of sparse event occurrence, fast-moving objects and inconsistent track paths (tumbling objects).

This study also introduces a novel approach to illustrate how the learned features map onto the input signal to represent the outputs of the network. Figure 3 offers a visual demonstration of this process: from the input stage where a time-accumulated image is presented with fast and slow-moving objects (along with the associated noise), through the initial noise filtering and feature mapping stages, to the final instance segmentation output.

This work demonstrates the superior performance of an SNN applied to the SSA problem, and its marked improvement over the state-of-the-art reported in [8]. The LIF neurons and convolution kernels within the network enable efficient noise filtering, resulting in high levels of sensitivity and specificity for instance segmentation. Table 1 summarises the performance of the proposed SNN, indicating notable improvements in specificity (99.6%), sensitivity (89.5%), and informedness (89.1%). The superior specificity of the SNN is due to its direct mapping to the input spiking activation,

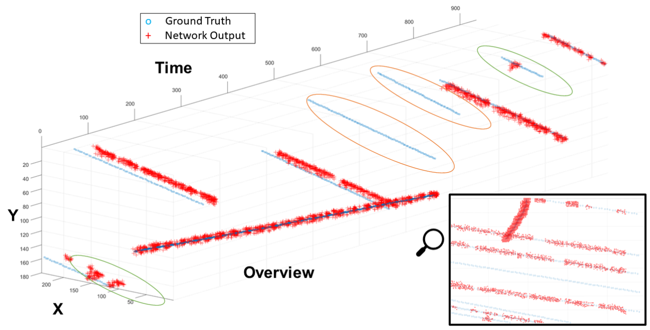

Fig. 4. Example from a difficult scene with fast and slow moving objects present. This figure shows the ground truth lines (blue) and detected objects (red). (SL8RB-21938)

ensuring precise segmentation outputs.

Furthermore, the high sensitivity achieved by the network underpins its ability to accumulate information within the spiking neurons. This, along with the inherent ability of leaky integrate and fire neurons and convolution kernels to filter noise allow for signal detection even amidst high levels of noise. These features of the SNN are advantageous in the second layer, where the network is designed to capture both long and short-term signals, again exploiting the accumulative nature of the neurons.

Figure 4 provides qualitative insights, illustrating a 3D plot of the ground truth (blue dots) versus network output (red stars). Some instances of the ground truth have no corresponding network output (highlighted in orange circles), confirmed by manual inspection to lack visible features in the event streams. Smaller ground truth motion paths with limited network output are due to restricted visual data when compared to the ground truth (highlighted in green circles).

4. CONCLUSION

The event-camera technology shows promising potential in the field of Space Situational Awareness and Space Domain Awareness, providing valuable event-based data for analysis. Our study extends the capabilities of the event-camera by leveraging the SNN model, demonstrating its effectiveness and efficiency in processing spatio-temporal context data.

The SNN model exhibits superior performance in instance segmentation tasks, surpassing previous models by 15% and further enhancing the capabilities of the event-based sensor. By exploiting the input spiking activation and effectively discerning patterns amidst noise, the SNN model achieves improved specificity, sensitivity, and informedness.

The integration of the event-camera with the SNN model presents a compelling approach for efficient and effective SSA and SDA work. This combination leverages the unique data acquisition properties of the event-based camera, and the robust noise reduction and pattern recognition capabilities of the SNN model, to enhance the analysis of space-related phenomena.

Future research should focus on refining this integrated approach, exploring the full potential of event camera data, and optimising the dynamics and parameters of the SNN model for different SSA and SDA scenarios. Continued improvements in this field hold the promise of advancing our understanding of space dynamics and supporting timely decision-making in space-related operations.

5. REFERENCES

[1] CGI, "Space domain awareness study 2022,"Tech. Rep., UK Space Agency, 2022 [Online].

[2] European Space Agency, "Space debris by the numbers," Dec. 22, 2022 [Online].

[3] G. Gallego et al., "Event-based vision: A survey," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 2020.

[4] Wolfgang Maass, "Networks of spiking neurons: the third generation of neural network models," *Neural networks*, vol. 10, no. 9, pp. 1659–1671, 1997.

[5] Paul Kirkland and Gaetano Di Caterina, "Movement classification and segmentation using event-based sensing and spiking neural networks," in *2022 Sensor Signal Processing for Defence Conference (SSPD)*. IEEE, 2022, pp. 1–5.

[6] Luigi Scatteia, "Space situational awareness," PwC, Accessed Jan. 10, 2023 [Online].

[7] European Space Agency, "When debris disaster strikes," Nov. 18 2021 [Online].

[8] Saeed Afshar et al., "Event-based object detection and tracking for space situational awareness," *IEEE Sensors Journal*, vol. 20, no. 24, pp. 15117–15132, 2020.

[9] Christoph Posch et al., "A QVGA 143 dB Dynamic Range Frame-Free PWM Image Sensor With Lossless Pixel-Level Video Compression and Time-Domain CDS," *IEEE J. Solid-State Circuits*, vol. 46, no. 1, pp. 259, 2011.

[10] Christian Brandli et al., "A 240 x 180 130 dB 3 μs Latency Global Shutter Spatiotemporal Vision Sensor," *IEEE Journal of Solid-State Circuits*, vol. 49, no. 10, pp. 2333–2341, oct 2014.

[11] Mike Davies et al., "Loihi: A Neuromorphic Manycore Processor with On-Chip Learning,"*IEEE Micro*, vol. 38, no. 1, pp. 82–99, jan 2018.

[12] Paul Kirkland et al., "Unsupervised spiking instance segmentation on event data using stdp features," *IEEE Transactions on Computers*, pp. 1–12, 2022.

[13] Wulfram Gerstner et al., "A neuronal learning rule for sub-millisecond temporal coding," *Nature*, vol. 383, no. 6595, pp. 76–78, 1996.

[14] Timothée Masquelier and Simon J Thorpe, "Unsupervised learning of visual features through spike timing dependent plasticity," *PLoS computational biology*, vol. 3, no. 2, 2007.