

EUROPEAN CONFERENCE ON COMPUTER VISION

M I L A N O







Asynchronous Bioplausible Neuron for Spiking Neural Networks for Event-Based Vision

By Dr. Sanket Kachole

Co-authors – Hussain Sajwani, Dr. Fariborz Baghaei Naeini, Prof. Dimitrios Makris, Prof. Yahya Zweiri

Robotics & Computer Vision has endless applications

Industrial Robots



YOLO: Real-time segmentation. Surveillance



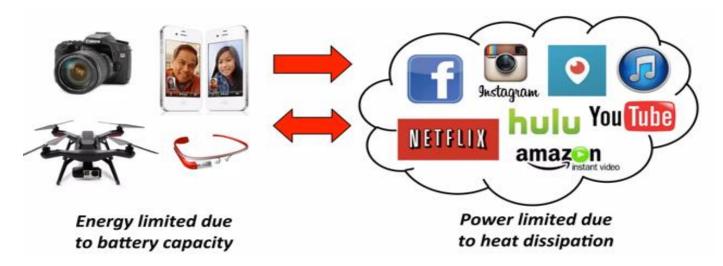
Agricultural Drones



AR/VR for surgeries



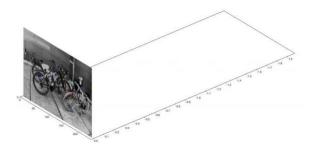
82% of all internet traffic is video. Over 500 hours of video are uploaded to YouTube every minute.



- The average battery life of a drone is 20-30 minutes per charge.
- Processing and storing video data on social media platforms generate significant heat and limit power usage.

Why are standard cameras incapable?

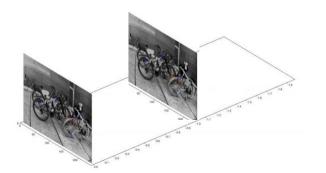
• Standard Camera Produces frames at around 30 FPS speed



Standard Camera

Why are standard cameras incapable?

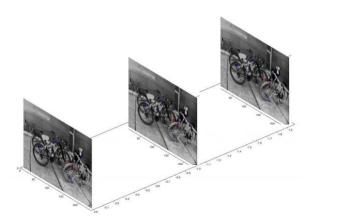
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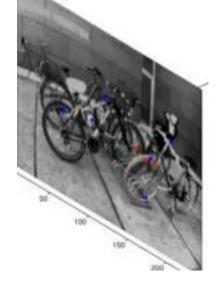


Standard Camera

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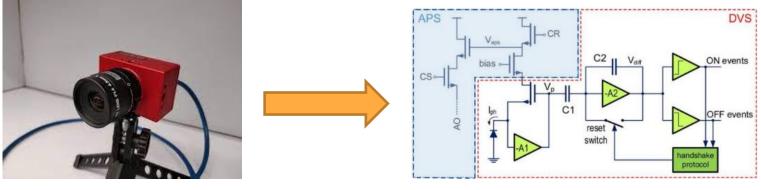




Standard Camera

Could Event Camera be the alternative solution?

- Traditional Camera captures a series of frames at a fixed frame rate
- Event camera captures individual pixels' intensity changes, asynchronously. Output is a stream of events.

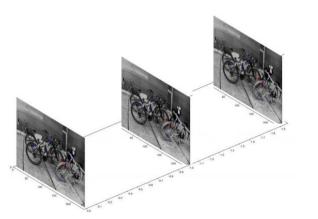


Event-Based Vision Camera

Can Event Camera tackle this problem?

RGB Camera :

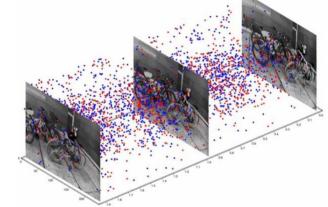
- Temporal resolution: 33000 µs or 30 FPS
- High dynamic range: 120 dB
- High Latency



Standard Camera

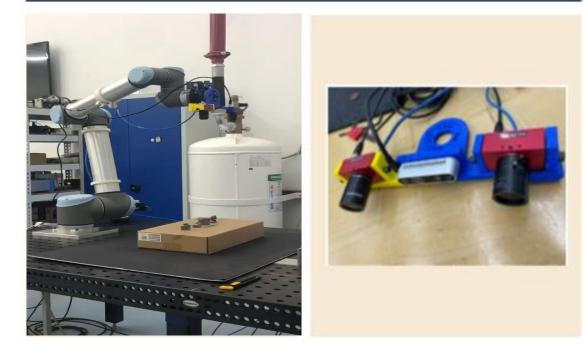
Event Camera :

- Temporal resolution: 1 µs
- High dynamic range: 84 dB
- Low power: 20mW
- Low transmission bandwidth: 200 kb/s



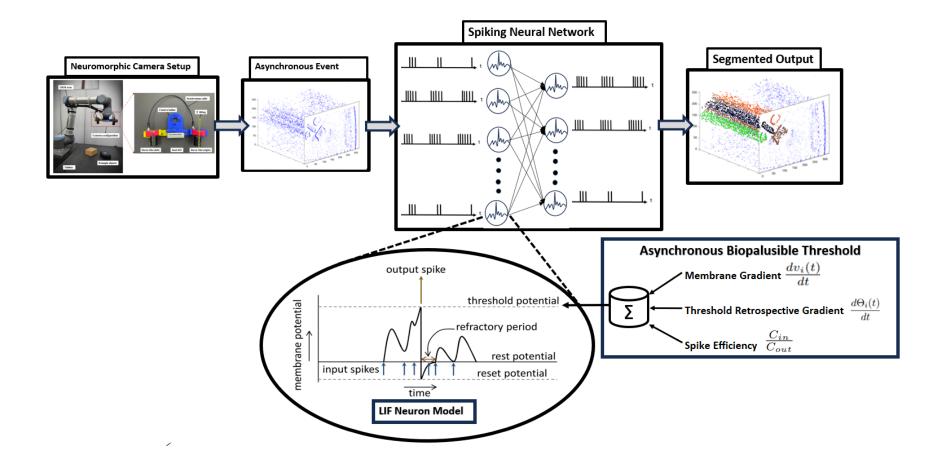
Event-Based Vision Camera

Experimental Set Up

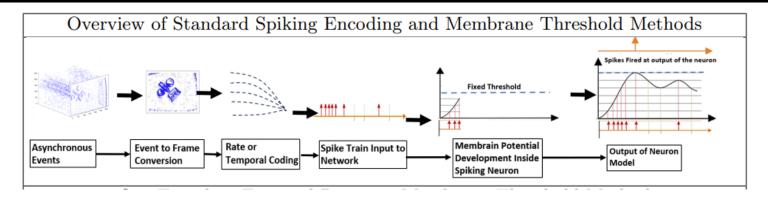


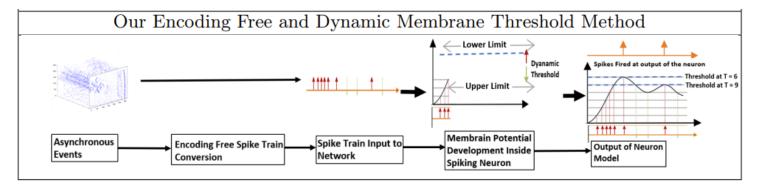
Two event cameras
(Davies346) separated
by depth camera (Intel
D435) structure
mounted on Robotic
arm (UR10).

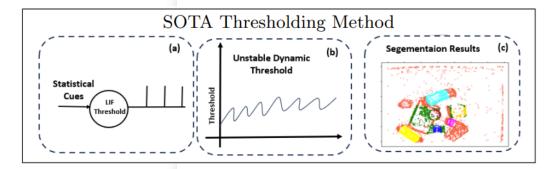
Objects cluttered on the flat wooden platform in low and bright light conditions.



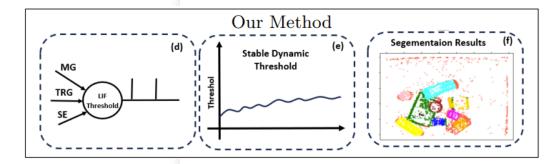
Comparative Visualization of SNNs approaches







Comparative Visualization of Thresholding Method



Generalisation Capabilities (using LIF and SRM)

• Classification and Event-wise Segmentation Accuracy across Various Datasets and Models

	Classification							Segmentation				
Method	N-MNIST		DVS128		CIFAR10		N-ImageNet		ESD-1		ESD-2	
	SRM	LIF	SRM	LIF	SRM	LIF	SRM	LIF	SRM	LIF	SRM	LIF
Spiking RBM [30]	92.1	93.16	87.38	90.21	83.04	86.25	39.47	40.19	48.95	51.05	45.2	50.31
Spiking MLP (BP) [31]	94.52	97.66	90.72	93.4	86.23	90.06	41.15	43.36	49.53	54	45.5	52.42
Spiking MLP (STDP) [13]	93.47	95	90.8	92.01	87.5	91.7	44.53	45.55	52.63	58.84	46.7	49.44
Spiking MLP (STBP) [38]	97.13	98.89	92.54	93.64	86.23	91.73	46.12	47.16	55.82	63.09	49.07	51.37
DT1 [18]	99.05	99.4	95.01	96.88	89.17	92.65	48.52	47.73	57.55	61.45	50.13	54.59
DT2 [21]	98.13	98.24	92.54	95.54	89.38	91.47	47.02	48.83	58.28	64.3	53.49	56.5
BDETT [11]	99.15	99.45	94.09	96.05	91.61	93.5	48.93	49.51	61.02	65.39	51.36	55.46
ABN (Ours)	99.23	99.48	95.64	98.74	93.5	94.74	56.73	57.04	61.56	67.29	56.23	58.04

Power Consumption Comparison

Method	Model	MAC	AC	Power (W)
Calabrese [8]	CNN	285	0	0.541
Baldwin [4]	CNN	963	0	1.56
Asude [3]	Hybrid	235	81	0.404
Asude [3]	SNN	0.6	123	0.053
BDETT [3]	SNN	0.7	115	0.046
Ours	SNN	0.4	105	0.038

• We evaluate SNNs' energy efficiency by calculating the total number of accumulate (AC) operations, which are mainly sparse due to the binary nature of spikes. Using 7 nm CMOS technology data, one 32-bit AC operation consumes 0.38 pJ. We use this to estimate power usage across different SNN methods. AC operations are quantified by multiplying the architecture-based count by the average spiking activity, giving us a ratio of total spikes to total neurons in each layer.

Conclusion

- The Asynchronous Bioplausible Neuron (ABN) method introduces innovative components that enhance neuron model functionality: Membrane Gradient (MG) for directional control of membrane potential, Threshold Retrospective Gradient (TRG) for independent and controlled spike burst suppression, and Spike Efficiency (SE) for improved processing efficiency using asynchronous event data.
- Validation Across Conditions: ABN has been effectively tested on various datasets including N-MNIST, ESD-1, ESD-2, DVS128-Gesture, N-ImageNet, and CIFAR-10 DVS, proving its versatility in object segmentation and image classification.
- Efficiency Studies: ABN includes studies on neuron firing stability and efficiency, along with a comparison of its power consumption against leading methods, highlighting its potential for energy-efficient applications.





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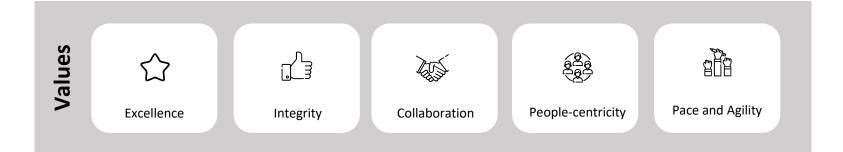
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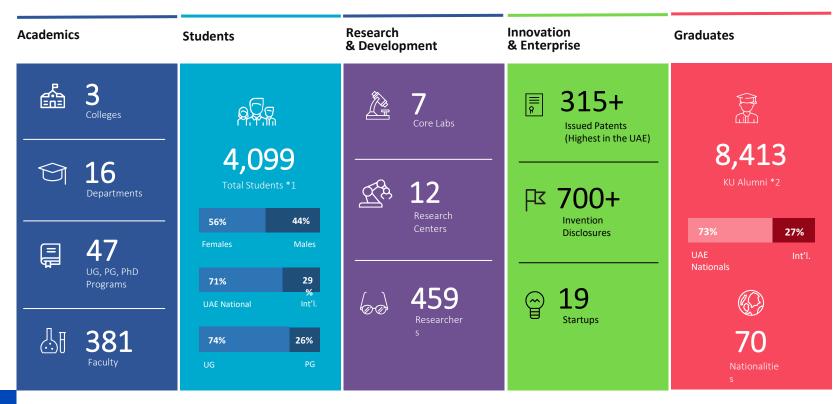
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*1 Data as for academic year 2023/24 *2 graduates of 2018-2024

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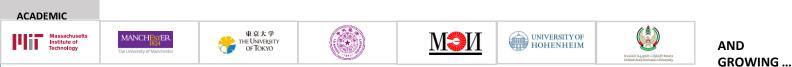




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