

Hybrid Learning for Event-Based Visual Motion Detection and Tracking of Pedestrians

Cristian Axenie
Nuremberg Institute of Technology, Germany

History, facts, and figures

A renowned patron

Proud of our roots

The university's roots (history) can be traced back to the year 1823 and the founding of the Städtische Polytechnikum (Municipal Polytechnic) – the oldest of our forerunners.

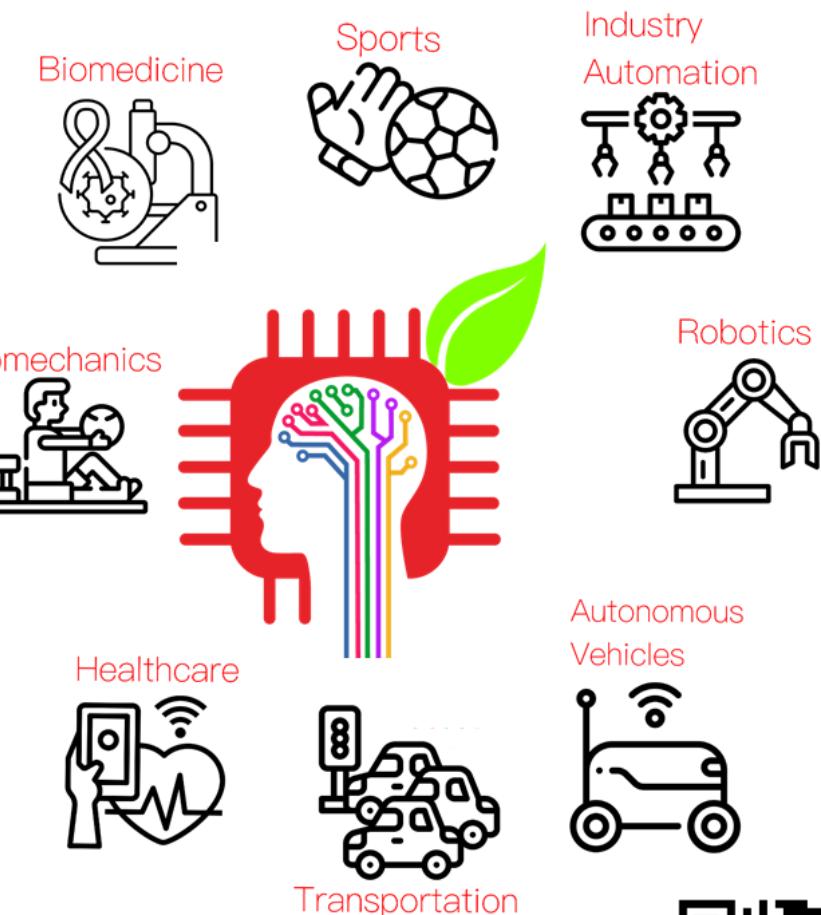


A renowned patron

The university is named after the world-renowned physicist, Georg Simon Ohm (biography), who was a physics and mathematics professor in Nuremberg between 1833 and 1849, and also fulfilled the role of rector.

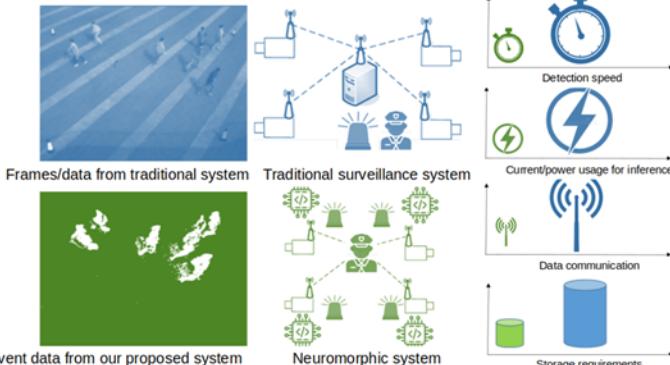
The famous omega

The Greek letter omega in the university's logo is a tribute to Georg Simon Ohm's greatest discovery – his law concerning electrical resistance.

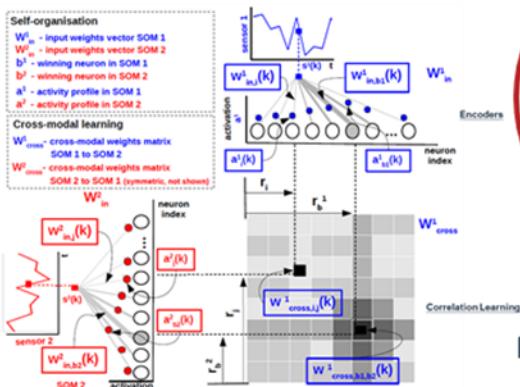


Sensorimotor Processing, Intelligence, and Control in Efficient compute Systems (SPICES) Lab

Fast, Efficient, Robust and Green Inference



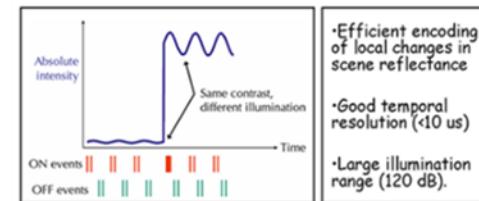
Learning algorithms



Algorithms for Spiking Neural Networks

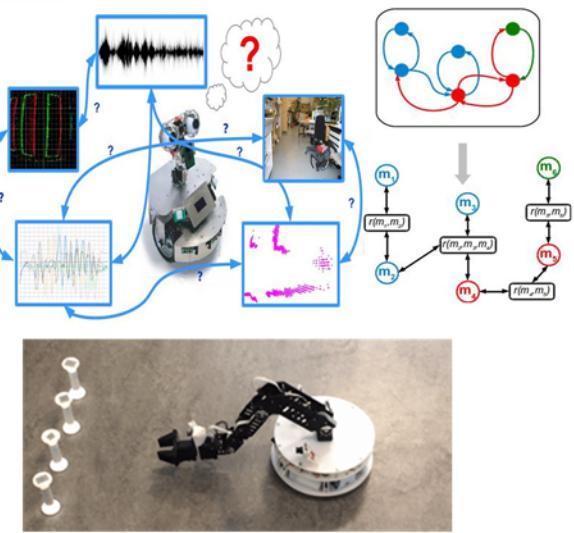


Spike-based/Event-based data representation



- Efficient encoding of local changes in scene reflectance
- Good temporal resolution (<10 us)
- Large illumination range (120 dB).

Sensor Fusion



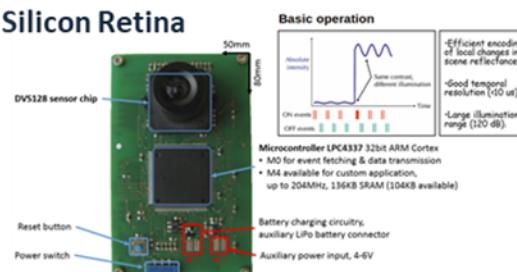
Closed-loop Sensorimotor Control



Neuromorphic Chips

Neuromorphic Sensors and Computers

Silicon Retina



Team



Ertan Halilov



Julian Main



David Weiss



Cristian Axenie



Outline

- Goal
- Solution overview
- Sensing and algorithmics
- Performance evaluation
- Deployment
- BOM



Goal

“Vision Zero” as a street safety policy that strives for the elimination of traffic fatalities for all transportation modes.



[McKee Road & Jackson Avenue](#), San Jose, California

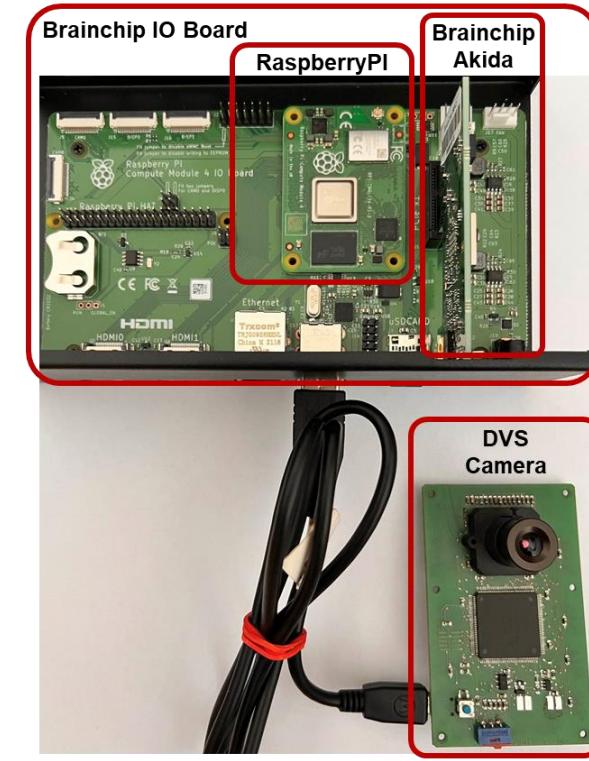
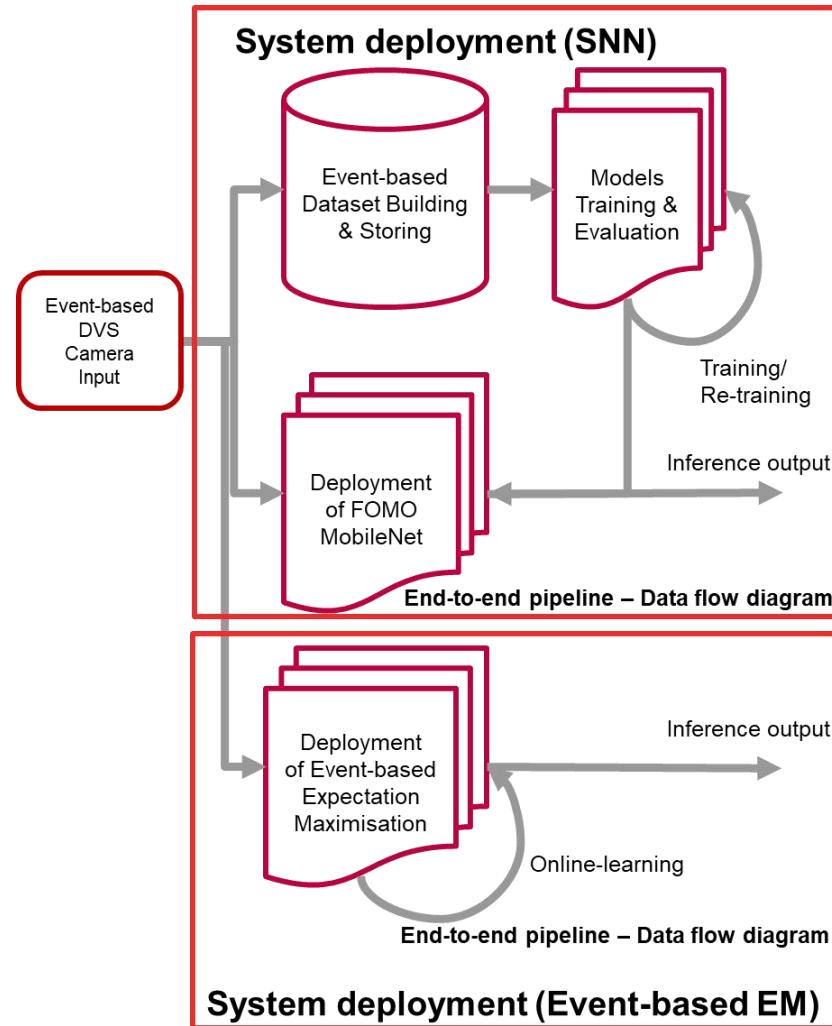


[Tully Road & La Ragione Avenue](#), San Jose, California

Cost effective and accurate solutions are needed to **detect pedestrians** during the **day** and especially at **nighttime** to implement safety measures. **Solutions** need to have a **very good energy footprint, robustness**, and a **budget** that allows scaling to city level.



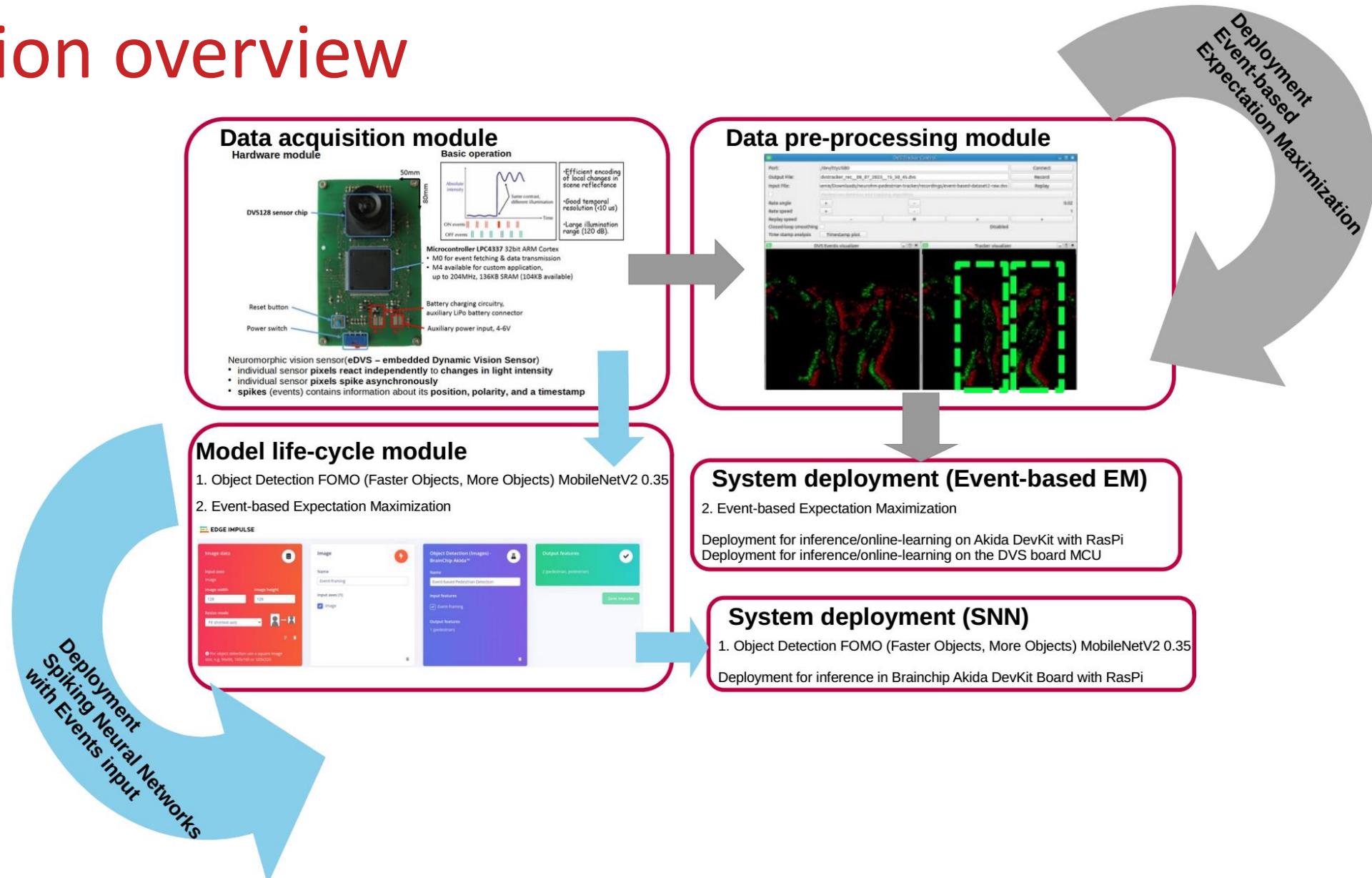
Solution overview



End-to-end pipeline – System hardware



Solution overview





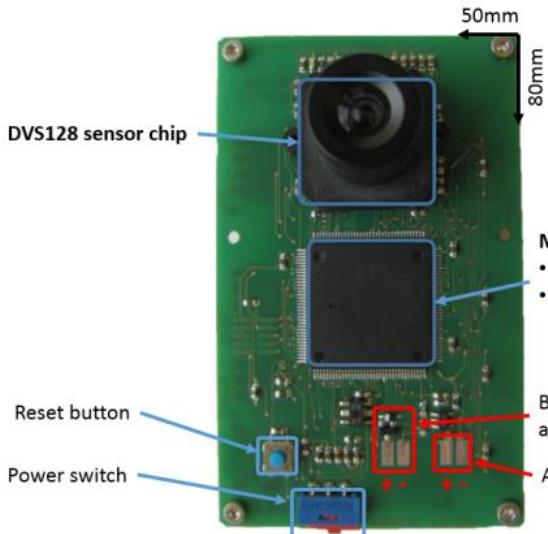
Solution development and life-cycle

The screenshot shows the Edge Impulse web interface. The left sidebar has a 'Dashboard' icon, followed by a collapsed 'Devices' section, 'Data acquisition' (with 'Create impulse', 'Image', and 'Object detection' options), 'Impulse design' (with 'EON Tuner', 'Retrain model', 'Live classification', 'Model testing', 'Versioning', and 'Deployment' sections), and 'GETTING STARTED' (with 'Documentation' and 'Forums' links). The main area shows the project 'Cristian Axenie / Project SPIDER - Team NeurOhm Brainchip Akida' with a subtitle 'SPIDER - Spiking Perception and processing for Intelligent Detection of pEdestrians on urban Roads'. It features three tabs: 'OBJECT DETECTION' (selected), 'OBJECT DETECTION X', and '+ New tag'. Below this is a 'Getting started' section with three buttons: 'Add existing data', 'Collect new data', and 'Upload your model'. A 'Sharing' sidebar on the right shows a progress bar and a 'Run this m' link with a 'Scan QR coc' button. At the bottom, there's a 'Start with a tutorial' section featuring three colored buttons with icons: a hand for 'Documentation', a camera for 'Tutorials', and a microphone for 'Samples'.

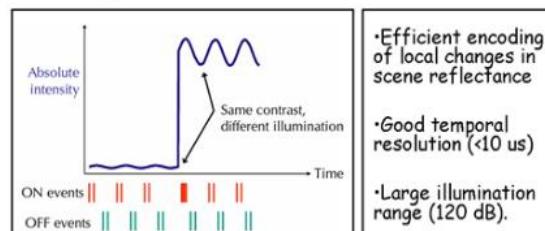
Approach

- Sensing

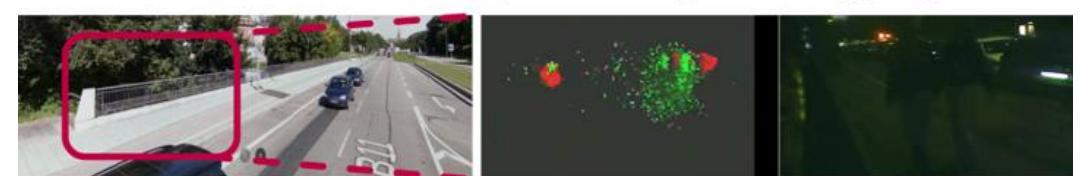
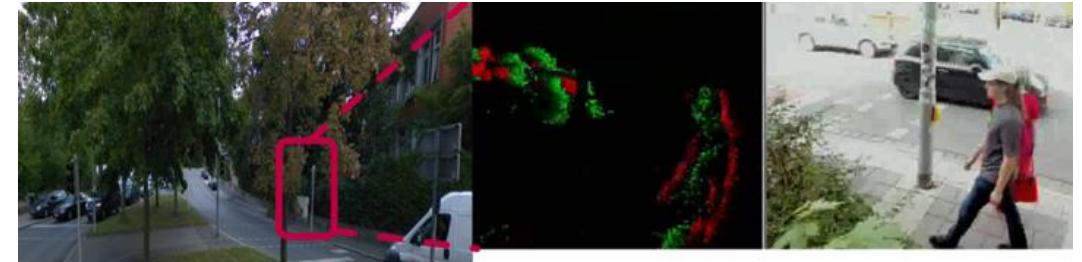
Hardware module



Basic operation



- Efficient encoding of local changes in scene reflectance
- Good temporal resolution (<10 us)
- Large illumination range (120 dB).



Neuromorphic vision sensor(eDVS – embedded Dynamic Vision Sensor)

- individual sensor pixels react independently to changes in light intensity
- individual sensor pixels spike asynchronously
- spikes** (events) contains information about its position, polarity, and a timestamp



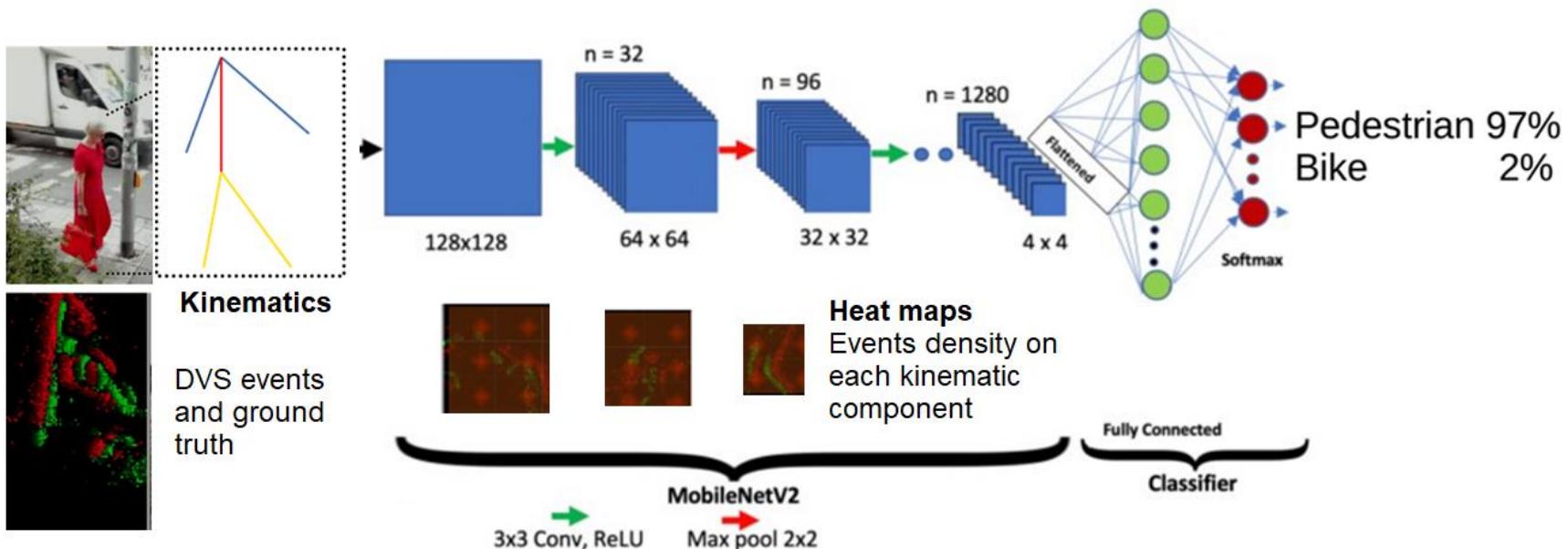
Approach

- Sensing

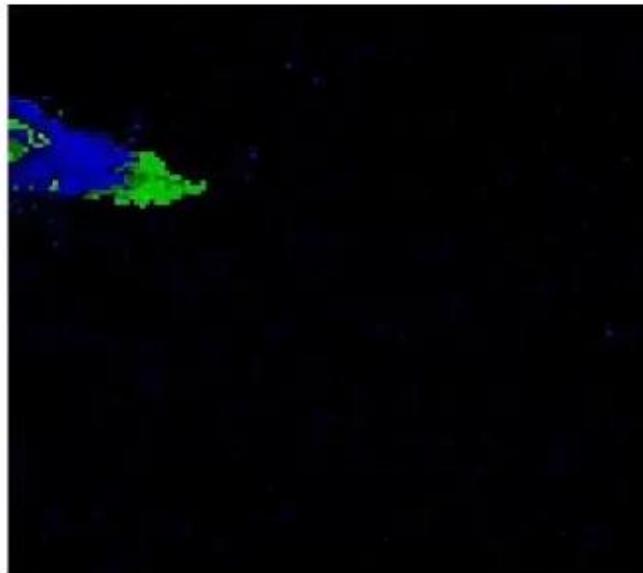


Approach

- Algorithmics – Fast Objects More Objects (FOMO) ConvNet, Spiking Neural Network (SNN)



Demo - Spiking Neural Network (SNN)



Inference speed: 24.72 ms

Power consumption/inference step: 6.06 mW

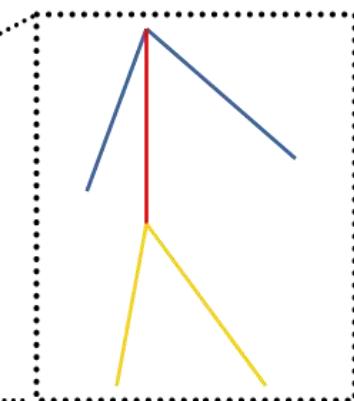
Approach

- Algorithmics – Event-based Expectation Maximization (EM)

Neuromorphic Event-based Camera Input



Skeleton Kinematics



Event-based Expectation Maximization

Adding a prediction model

$$\dot{\theta} = \frac{\Delta\theta}{\Delta t} \quad (\text{for each body segment})$$

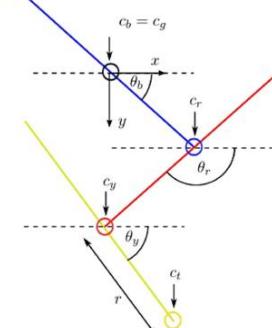
Future centers:

$$c_b(t+T) = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

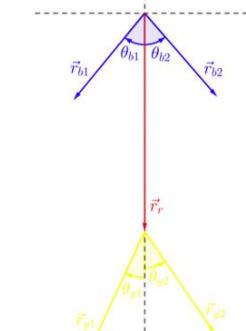
$$c_r(t+T) = c_r(t) + T \begin{bmatrix} -\dot{\theta}_b \sin(\theta_b) \\ \dot{\theta}_b \cos(\theta_b) \end{bmatrix}$$

$$c_y(t+T) = c_y(t) + T \begin{bmatrix} -\dot{\theta}_b \sin(\theta_b) - \dot{\theta}_r \sin(\theta_r) \\ \dot{\theta}_b \cos(\theta_b) + \dot{\theta}_r \cos(\theta_r) \end{bmatrix}$$

Future angles:
 $\theta(t+T) = \theta(t) + T\dot{\theta} \quad (\text{for each body segment})$



Event membership allocation

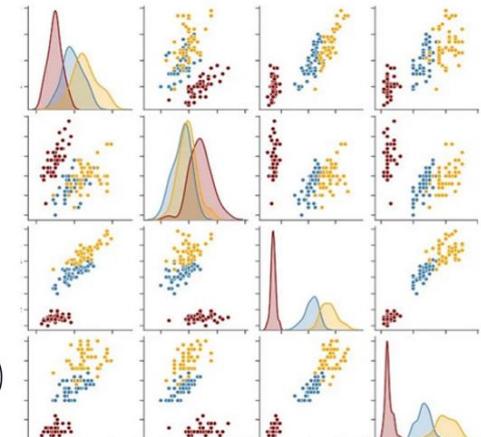


Future positions: $\vec{r}(t+T) = \vec{r}(t) + T \begin{pmatrix} -\dot{\theta} \sin(\theta) \\ \dot{\theta} \cos(\theta) \end{pmatrix}$

Future angles: $\theta(t+T) = \theta(t) + T\dot{\theta}$

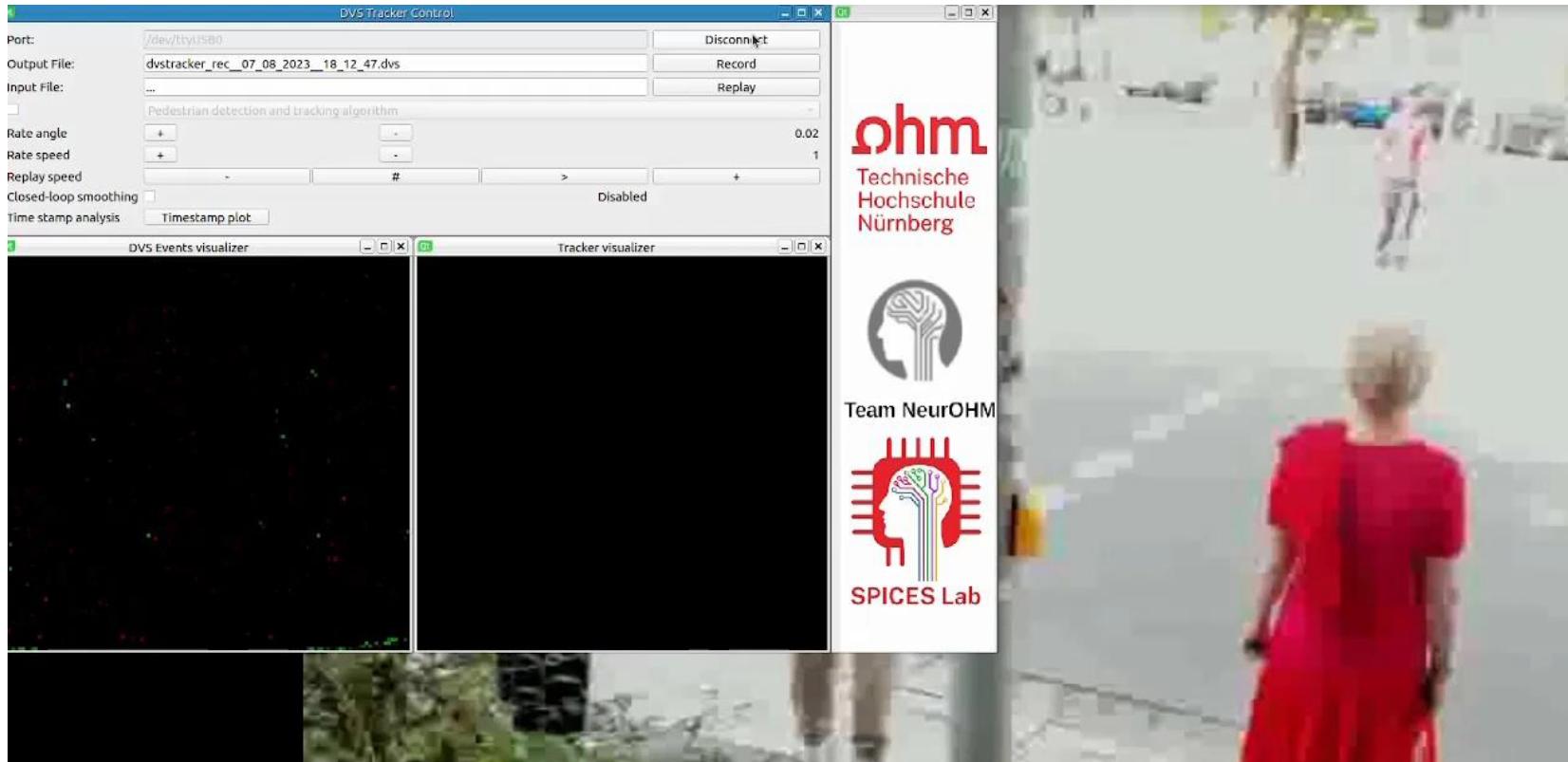
Skeleton modelling

Embedding physics in the Expectation Maximization



Likelihoods estimation

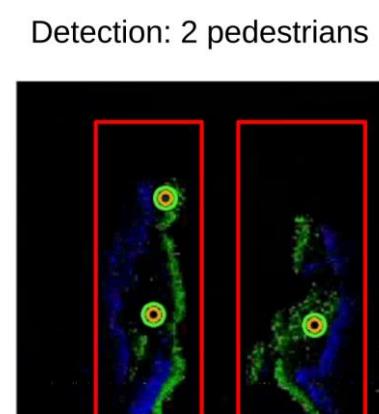
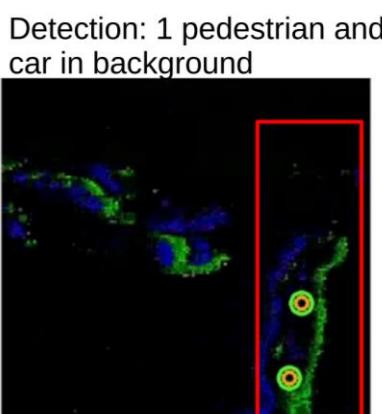
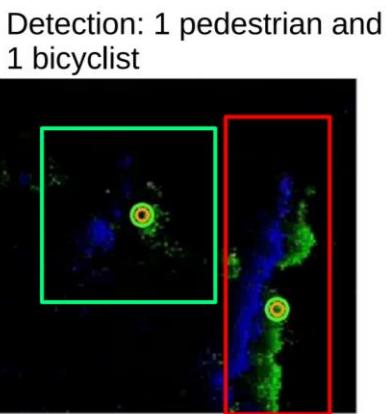
Demo - Event-based Expectation Maximization (EM)



Performance

- Spiking Neural Network

Qualitative evaluation



Quantitative evaluation

Dataset	Background %	Bicyclist %	Pedestrian %
Dataset 1 (daytime)			
Background	99.70	0.26	0.04
Bicyclist	12.10	87.90	0.00
Pedestrian	6.20	0.00	93.80
F1-Score	1.00	0.62	0.77
Dataset 2 (daytime)			
Background	97.50	2.20	0.80
Bicyclist	10.10	89.90	0.00
Pedestrian	3.20	0.00	96.80
F1-Score	1.00	0.70	0.87
Dataset 3 (night)			
Background	99.07	0.30	0.00
Bicyclist	21.10	78.00	0.90
Pedestrian	10.20	13.00	76.80
F1-Score	0.90	0.60	0.70

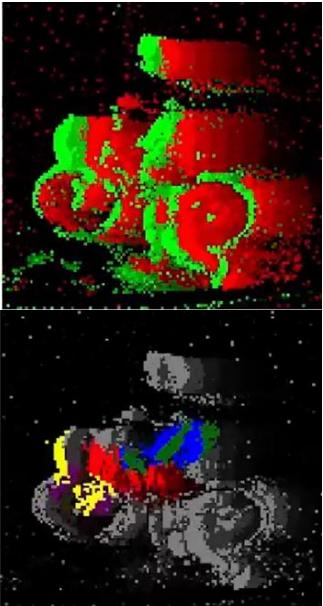
* For the accuracy evaluation of both the detection and tracking components of the system, we performed multiple experiments in order to get a statistically valid analysis. For the quantitative evaluation, we executed the following protocol: 1) Read relevant detection and tracking data from each of the experiments (i.e. N = 30 experiments); 2) Perform statistical tests (i.e., a combination of omnibus ANOVA and posthoc pairwise T-test with a significance p = 0.05) and adjust the ranking of experiments depending on significance; 3) rank subsets of relevant metrics (i.e., the metrics with a significant difference, e.g., the F1 score for detection and four others tracking specific metrics).

Performance

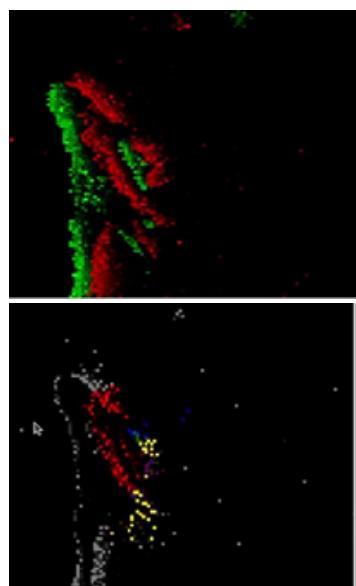
- Event-based Expectation Maximization

Qualitative evaluation

Bicyclist tracking



Pedestrian tracking



Quantitative evaluation

Dataset	Bicyclist	Pedestrian
Dataset 1 (daytime)		
Track Matching Error(%)	13.70	10.10
Tracking Time Delay(s)	0.08	0.03
Tracking Detection Rate(%)	95.00	98.00
Tracking Completeness(s)	0.38	0.25
Dataset 2 (daytime)		
Track Matching Error(%)	11.20	8.21
Tracking Time Delay(s)	0.07	0.02
Tracking Detection Rate(%)	97.00	99.00
Tracking Completeness(s)	0.38	0.25
Dataset 3 (night)		
Track Matching Error(%)	23.30	20.10
Tracking Time Delay(s)	0.09	0.08
Tracking Detection Rate(%)	76.00	79.00
Tracking Completeness(s)	0.84	0.76

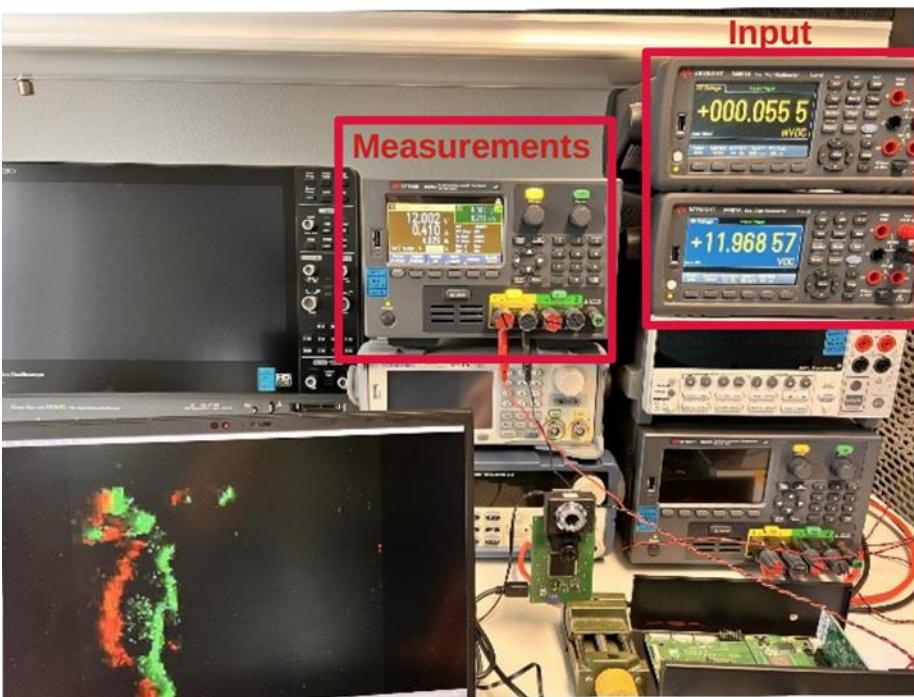
* For the accuracy evaluation of both the detection and tracking components of the system, we performed multiple experiments in order to get a statistically valid analysis. For the quantitative evaluation, we executed the following protocol: 1) Read relevant detection and tracking data from each of the experiments (i.e. N = 30 experiments); 2) Perform statistical tests (i.e., a combination of omnibus ANOVA and posthoc pairwise T-test with a significance $p = 0.05$) and adjust the ranking of experiments depending on significance; 3) rank subsets of relevant metrics (i.e., the metrics with a significant difference, e.g., the F1 score for detection and four others tracking specific metrics).

Deployment evaluation

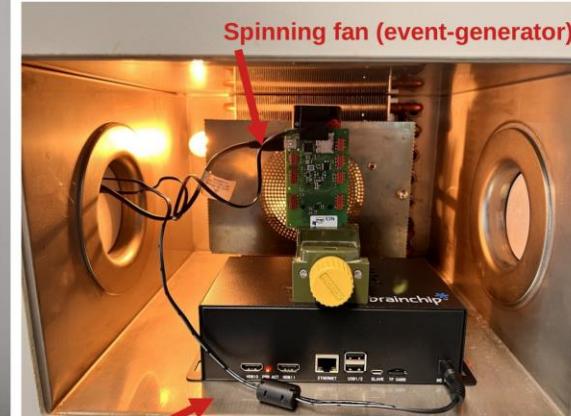
- Power consumption & weatherization analysis

Measurement setup

Camera pointing to a screen with recorded traffic data



Events visualizer on edge device



Dataset	Power(W)	Latency(ms)
Dataset 1 (daytime)	7.58	14.32
Dataset 2 (daytime)	4.92	8.21
Dataset 3 (night)	5.65	24.62

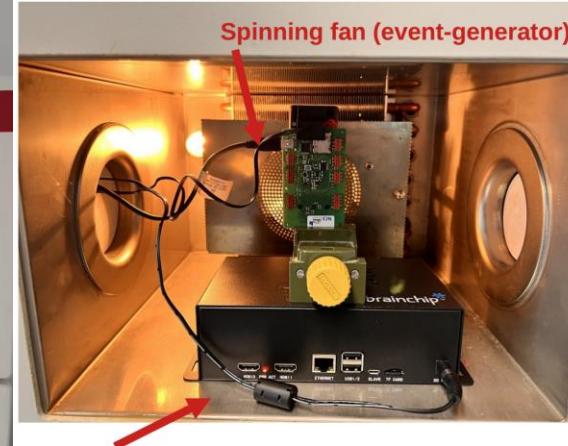
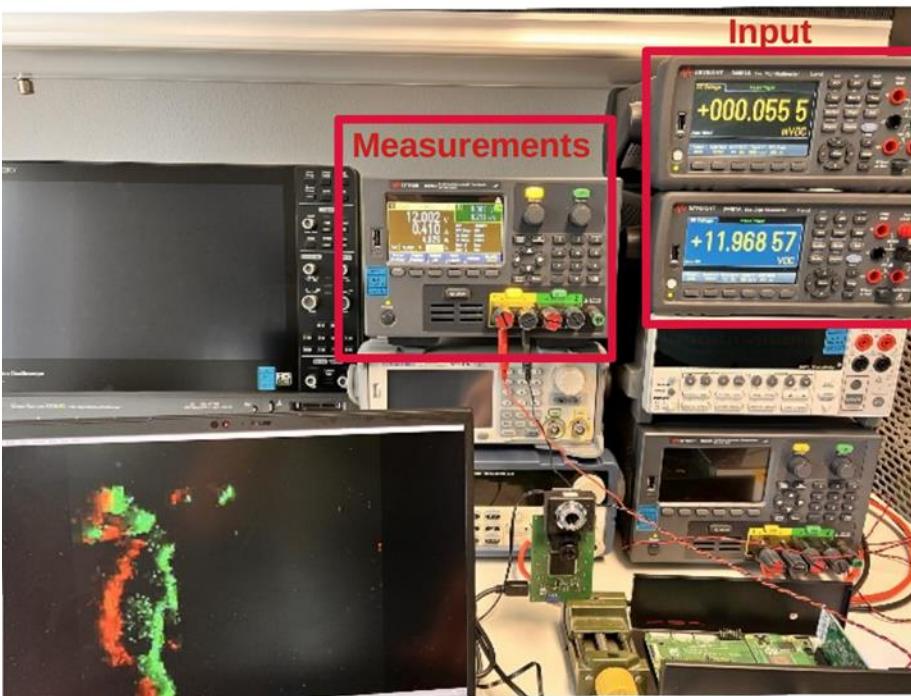
* For the accuracy evaluation of both the detection and tracking components of the system, we performed multiple experiments in order to get a statistically valid analysis. For the quantitative evaluation, we executed the following protocol: 1) Read relevant detection and tracking data from each of the experiments (i.e. N = 30 experiments); 2) Perform statistical tests (i.e., a combination of omnibus ANOVA and posthoc pairwise T-test with a significance p = 0.05) and adjust the ranking of experiments depending on significance; 3) rank subsets of relevant metrics (i.e., the metrics with a significant difference, e.g., the F1 score for detection and four others tracking specific metrics).

Deployment evaluation

- Power consumption & weatherization analysis

Measurement setup

Camera pointing to a screen with recorded traffic data



Dataset	Power(W)	Latency(ms)
Dataset 1 (daytime)	7.58	14.32
Dataset 2 (daytime)	4.92	8.21
Dataset 3 (night)	5.65	24.62

* For the accuracy evaluation of both the detection and tracking components of the system, we performed multiple experiments in order to get a statistically valid analysis. For the quantitative evaluation, we executed the following protocol: 1) Read relevant detection and tracking data from each of the experiments (i.e. N = 30 experiments); 2) Perform statistical tests (i.e., a combination of omnibus ANOVA and posthoc pairwise T-test with a significance p = 0.05) and adjust the ranking of experiments depending on significance; 3) rank subsets of relevant metrics (i.e., the metrics with a significant difference, e.g., the F1 score for detection and four others tracking specific metrics).

Complete BOM and costs

Bill of Materials (BOM) Single unit & suggested price for large quantities		
Component	Price	Notes
Raspberry PI Compute Module 4 IO Board with RPI CM4Lite	50 \$	Price pro unit sold independently from the Brainschip Akida PClexpress board (see below). https://www.reichelt.de/de/de/de/raspberry-pi-compute-modul-4-io-board-rpi-cm4-io-board-p290556.html
Brainchip Akida AKD1000 PClexpress Board	499 \$	Price pro unit sold independently from the IO board/carried board. https://shop.brainchipinc.com/products/akida%E2%84%A2-development-kit-pcie-board
IniVation Dynamic Vision Sensor	2500 \$	Price per unit, with up to 50 \$ if large quantities purchased. https://shop.inivation.com/collections/dvxplorer-lite-1/products/dvxplorer-lite-commercial-rate
USB to miniUSB cable	1 \$ (1m long USB cable) – 26 \$ (5m long USB cable with signal amplifier)	Length of the cable depends on the gantry layout, we have tried with 1m long USB cable and also with signal amplification 5m long USB cable. https://www.conrad.de/de/p/delock-usb-kabel-usb-3-2-gen1-usb-3-0-usb-3-1-gen1-usb-a-stecker-usb-a-buchse-5-00-m-rot-schwarz-vergoldete-steckkontakte-ul-zertifiziert-82755-649883.html
Total	3076 \$	Price per unit. When more units are bought a total price of approx. 226 \$ for a price per unit 100 \$ for Akida Chip , 50 \$ for RaspberryPI boards , 50 \$ for DVS camera , and long USB cable 26 \$.

-44%



Samsung SmartThings Vision

Motion sensor, wireless, 2.4 GHz. A security feature that registers movements without infringing on your private life. The movements are only recorded as silhouettes. It uses AI to identify human movements so that the alarm is not triggered by pets or moving curtains. The AI can also detect if someone is falling over, and this detection can be connected to an alarm to enable quick assistance.

[read more](#)

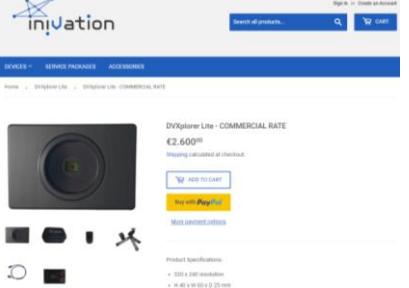
OUTLET

Normal price €129.00
€71.74
€59.29 excl. VAT

+15 pcs in stock - 2-3 working days delivery time
Cheapest private shipping €6.99

[Purchase](#)

Source: <https://www.proshop.nl/Smart-Home/Samsung-SmartThings-Vision/2786571>



DVXplorer Lite - COMMERCIAL RATE
€2.6000*
Shipping calculated at checkout

[ADD TO CART](#)
[Buy with PayPal](#)

Product specifications:
• 1080p resolution
• H.460 x W.300 x D.25 mm

Source: <https://shop.inivation.com/collections/dvxplorer-lite-1>

Best price ~226\$

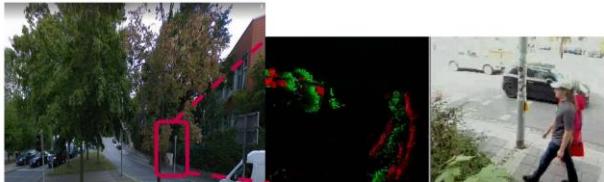
Worst price ~3000\$

ohm Deliverables

• Datasets release

Dataset location 1

- 8 lanes (4 per direction) wide street
- Location: <https://goo.gl/maps/JaYGwaTaBHj5H6SL9>
- 50 kmh (urban) speed limit
- Near university campus with Pedestrians (people walking), Bicyclists (people biking, scooting, rolling, etc.)
- Ideal Operating Environment



Dataset location 2

- 8 lanes (4 per direction) wide street
- Location: <https://goo.gl/maps/jar6AjysZIM2LP57>
- 50 kmh (urban) speed limit
- Near main train stations of the city and a location with Pedestrians (people walking/running/jogging), Bicyclists (people biking, scooting, rolling, etc.)



Dataset location 3

- 6 lanes (3 per direction) wide street on bridge
- Location: <https://goo.gl/maps/SFEsmpgmlPcD8fG7A>
- 50 kmh (urban) speed limit
- Near ring street of Munich and a location with Pedestrians (people walking/running/jogging), Bicyclists (people biking, scooting, rolling, etc.)
- Night time data acquisition



• Code release

Model life-cycle and data analysis

Accurate TinyML algorithms



• Solution release

Minimal energy footprint

Deployment

Akida Spiking Neural Networks in Event data



Deployment

RaspberryPi Event-based Expectation Maximization



Feasible deployment

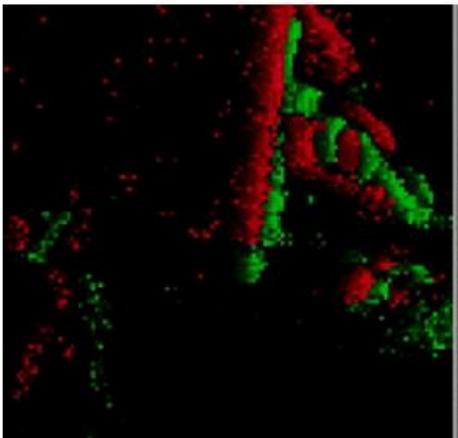


Wrap-up

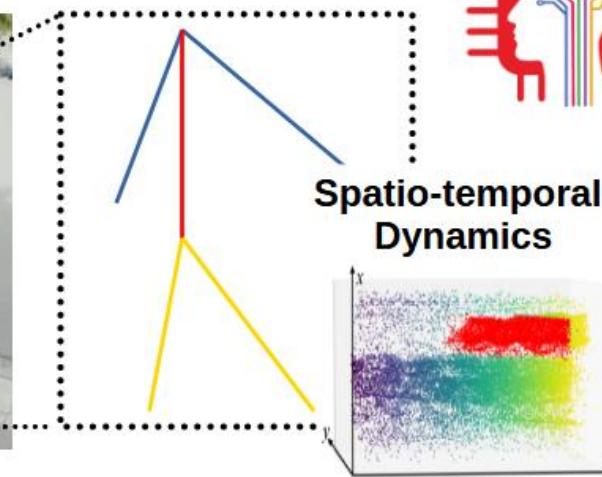
TinyML solution for supporting **VisionZero** pedestrian detection

- uses **low-power neuromorphic sensing and processing**
- employs **only local processing (at the edge)**
- provides **good accuracy for robust visual detection under varying conditions**
- **Current development:**
 - HD Event-based camera (Prophesee EVK3)
 - Explore new computing platforms (Synsense Speck)
 - Deployment at city-scale (Stadt Schwabach)

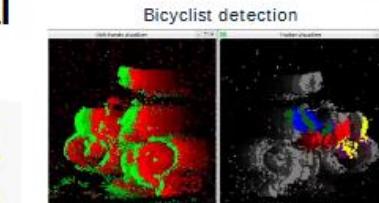
Neuromorphic Event-based Camera Input



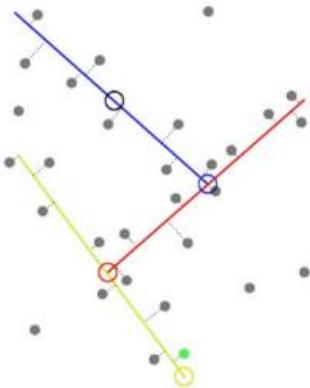
Skeleton Kinematics



Detection and tracking



Event-based Real-time Physics-informed Expectation Maximization



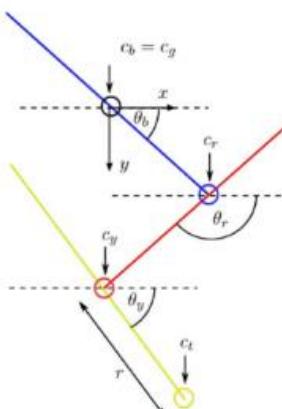
Adding a prediction model

- $\dot{\theta} = \frac{\Delta\theta}{\Delta t}$ (for each body segment)
- Future centers:
$$c_b(t+T) = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

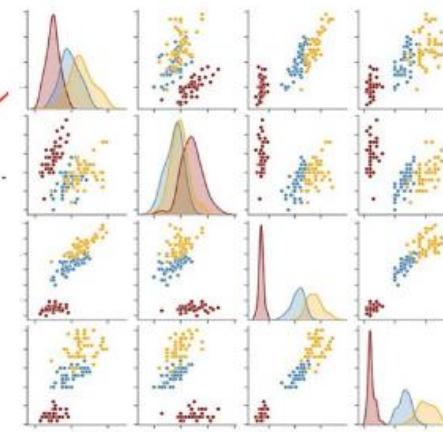
$$c_r(t+T) = c_r(t) + T \begin{bmatrix} -\dot{\theta}_b \sin(\theta_b) \\ \dot{\theta}_b \cos(\theta_b) \end{bmatrix}$$

$$c_y(t+T) = c_y(t) + T \begin{bmatrix} -\dot{\theta}_b \sin(\theta_b) - \dot{\theta}_r \sin(\theta_r) \\ \dot{\theta}_b \cos(\theta_b) + \dot{\theta}_r \cos(\theta_r) \end{bmatrix}$$
- Future angles:
$$\theta(t+T) = \theta(t) + T\dot{\theta}$$
 (for each body segment)

Event membership allocation



Embedding physics in the Expectation Maximization



Performance

	Traditional system 10 ms	Neuromorphic system 1 ms
	Traditional system 300 – 400 W	Neuromorphic system 4.9 – 7.3 W
	Traditional system 30 MB/s	Neuromorphic system 300 B/s
	Traditional system Data communication	Neuromorphic system Data communication