



What's catching your eye?

Event-driven sensing and neuromorphic computing for active vision

Vision is an exploratory behaviour that emerges from the dynamic relationship between actions and sensory feedback. For any agent, whether biological or robotic, processing visual input efficiently is fundamental to understanding and interacting with the environment.

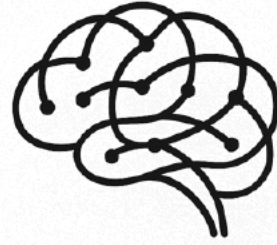
The central challenge lies in continuously recalibrating perception through sensorimotor contingencies, where what an agent sees is shaped by how it moves. Embodiment is central to this vision: perception and action are inseparable, and intelligence emerges from their continuous interaction with the physical world, shaped by the very structure of our sensors. Selective visual attention is one of the many mechanisms by which the visual cortex meets this challenge, organizing and interpreting complex visual scenes in real time.

To address these challenges, I develop brain-inspired algorithms that harness the computational principles of biological neurons and spiking neural networks, optimized for neuromorphic hardware. These algorithms enable real-time robotic perception with microsecond latency and milliwatt power consumption, bringing the efficiency of biological vision systems within reach of autonomous systems at the edge.

Giulia D'Angelo

Assistant Professor, MSCA Postdoctoral Fellow, Czech Technical University (CTU), Prague

Giulia D'Angelo is an Assistant Professor at the Czech Technical University in Prague, where she develops neuromorphic algorithms for active vision. She earned a BSc in Biomedical Engineering from the University of Genoa and an MSc (with honours) in Neuroengineering. During her Master's at King's College London, she developed a neuromorphic system for the egocentric representation of peripersonal visual space. She completed her PhD in neuromorphic algorithms at the University of Manchester, where she received the President's Doctoral Scholar Award, in collaboration with the Event-Driven Perception for Robotics Laboratory at the Italian Institute of Technology, proposing a biologically plausible model for event-driven, saliency-based visual attention. Following her PhD, she was awarded a Marie Skłodowska-Curie Postdoctoral Fellowship at the Czech Technical University in Prague, during which she explored sensorimotor contingency theories in neuromorphic active vision. After completing the fellowship, she joined the Czech Technical University in Prague as an Assistant Professor. Her current research, funded by the GACR Standard Grant from the Czech Science Foundation, bridges bio-inspired software and neuromorphic hardware to enable robust, efficient perception and control for low-power, low-latency autonomous systems.



NEURO-INSPIRED
PERCEPTION &
COGNITION

What's catching your eye?

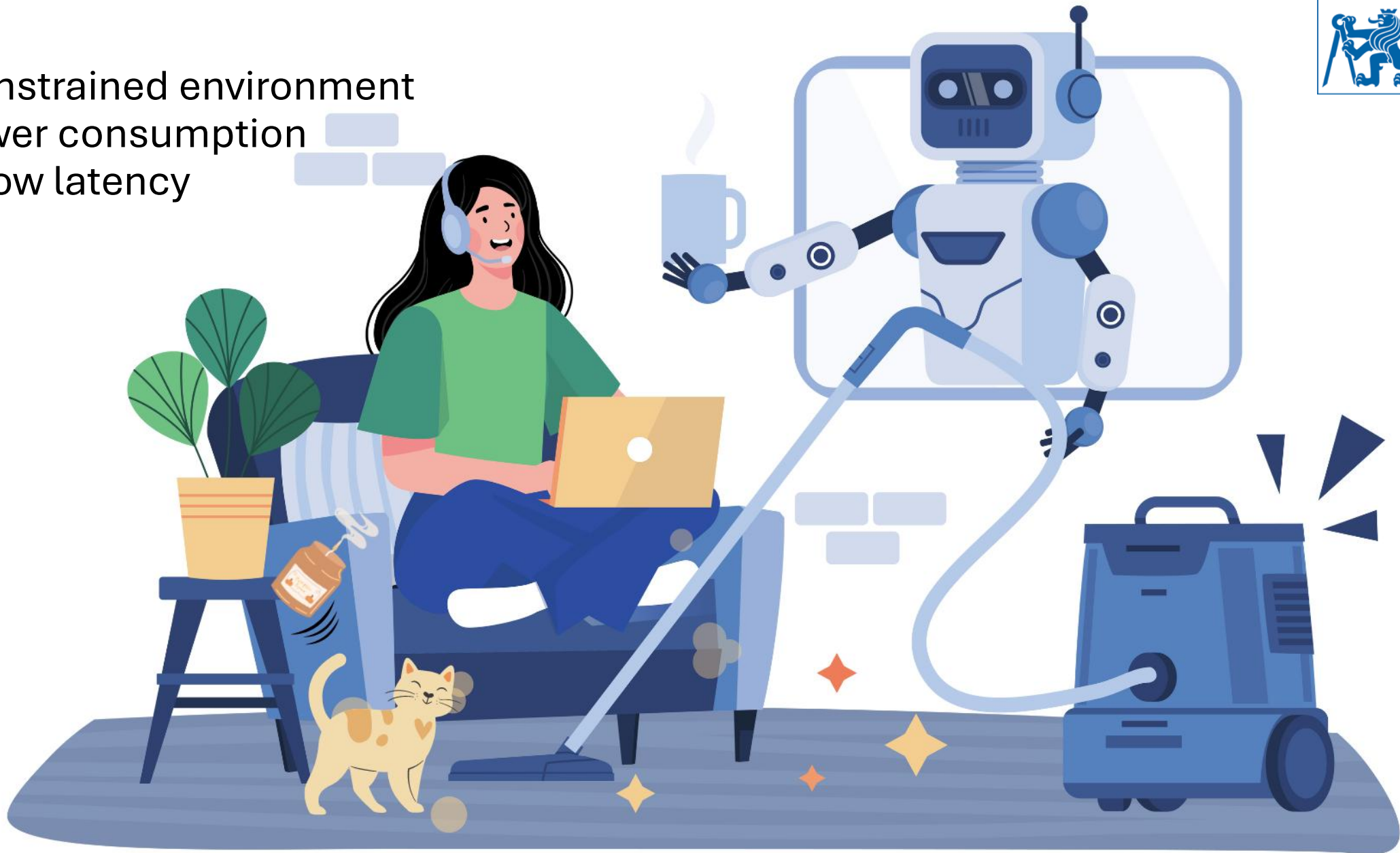
Event-driven sensing and neuromorphic computing for active vision



Giulia D'Angelo
Assistant Professor
Czech Technical University in Prague (CTU)



Unconstrained environment
Low power consumption
Low latency

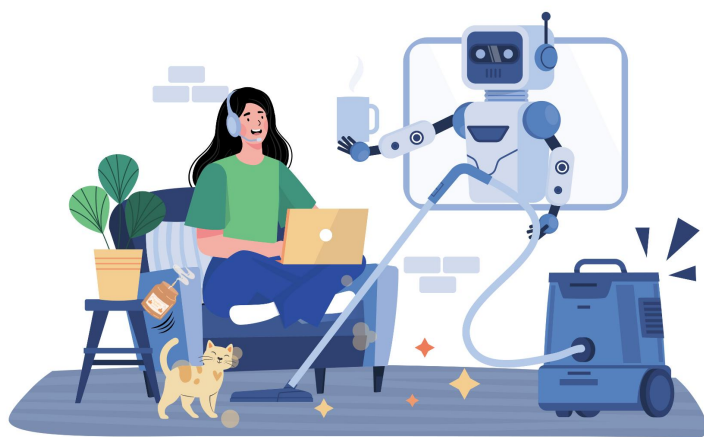


Unconstrained environment
Low power consumption
Low latency

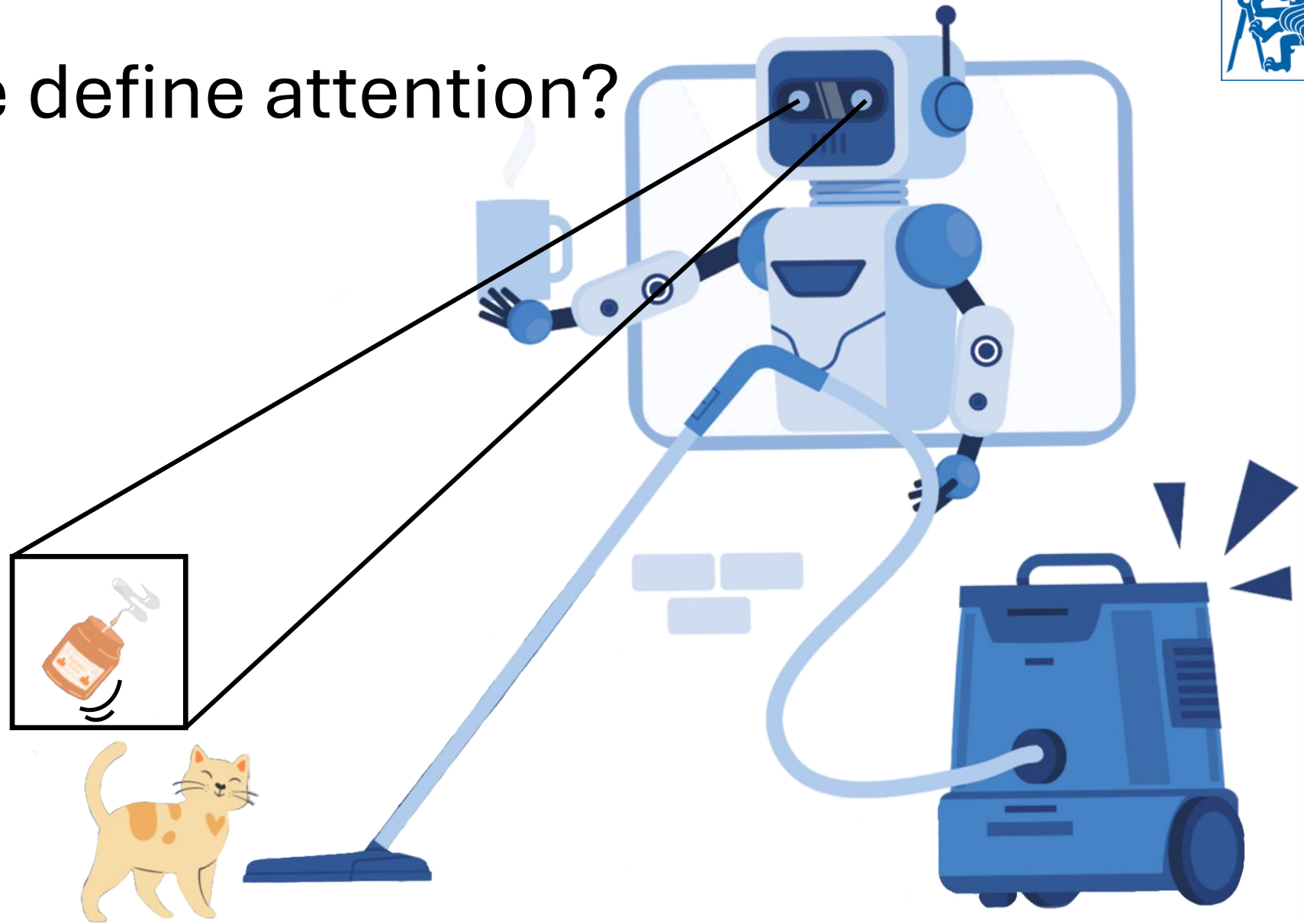
Someone has already done it!

“It consumes a paltry 20 watts, much less than a typical incandescent lightbulb”

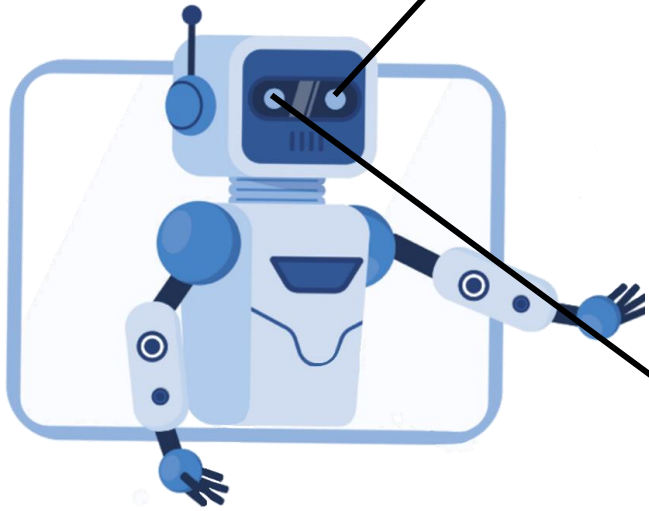
Furber, Steve. "To build a brain." *IEEE spectrum* 49.8 (2012): 44-49.



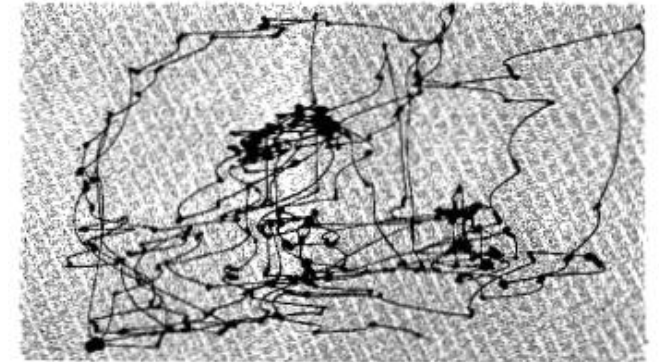
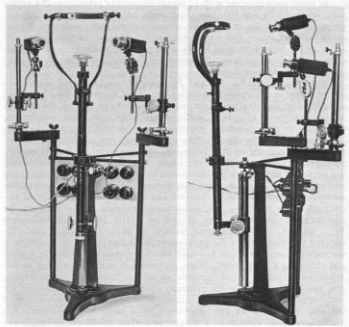
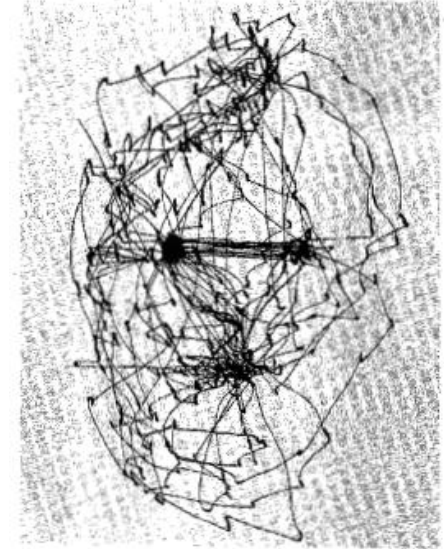
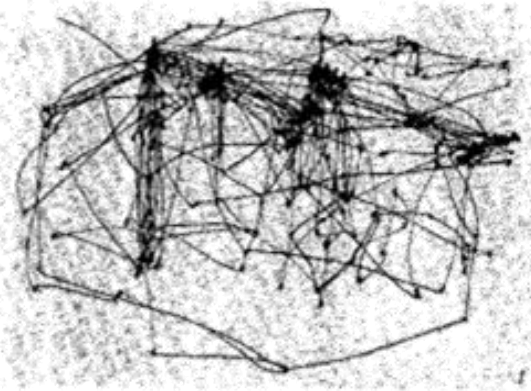
How do we define attention?



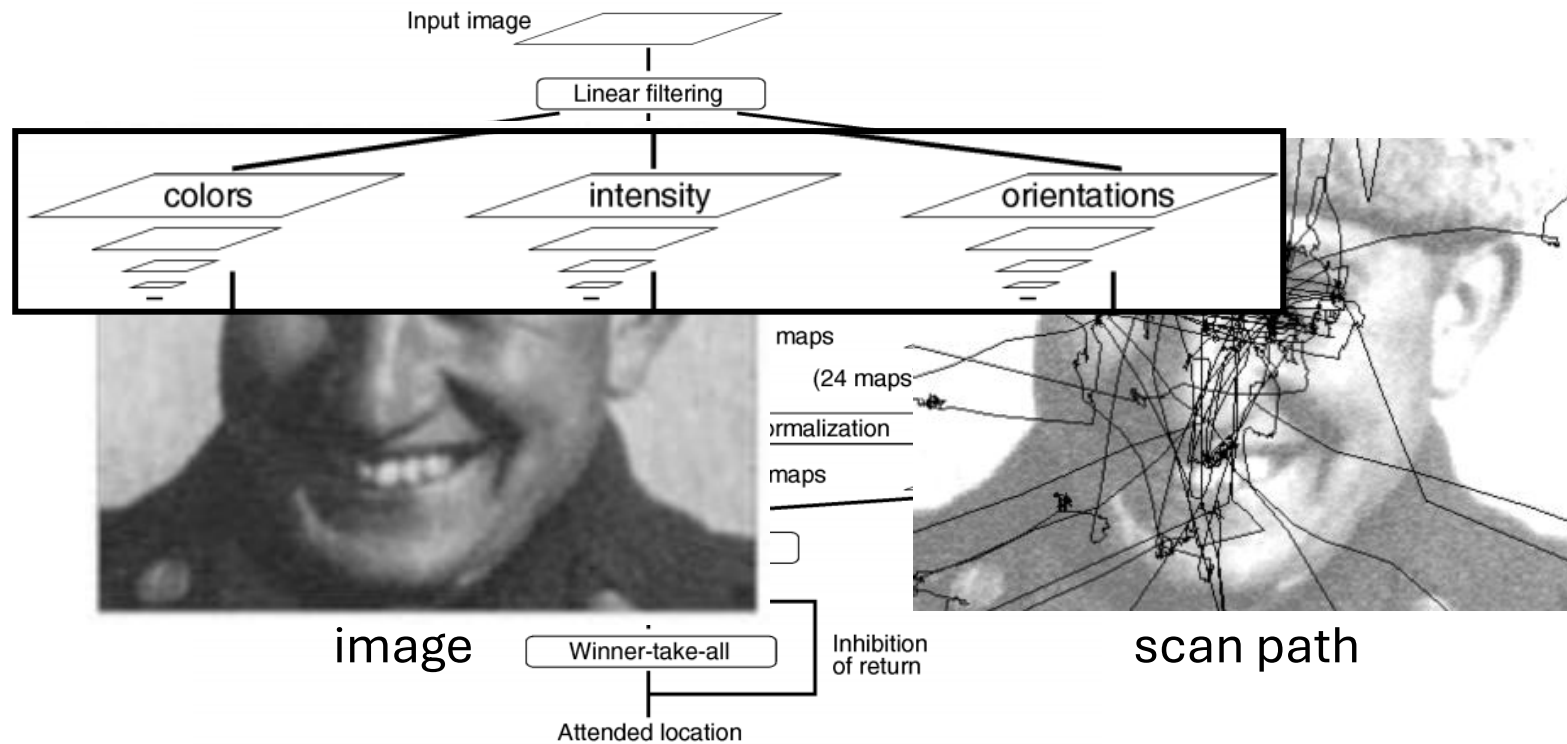
How do we define attention?



How do we define attention?



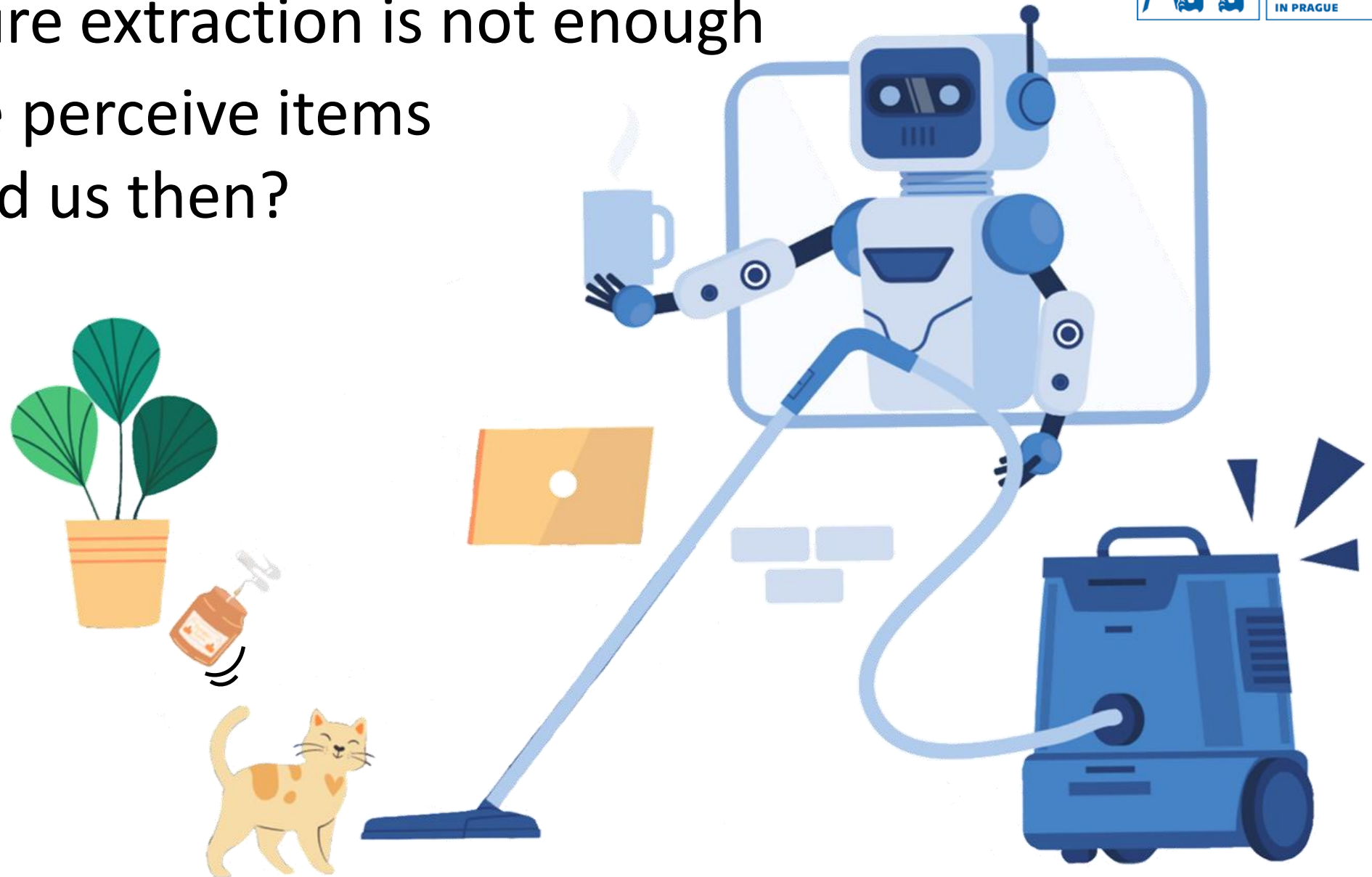
Cool, but feature extraction is not enough What is a saliency map ?

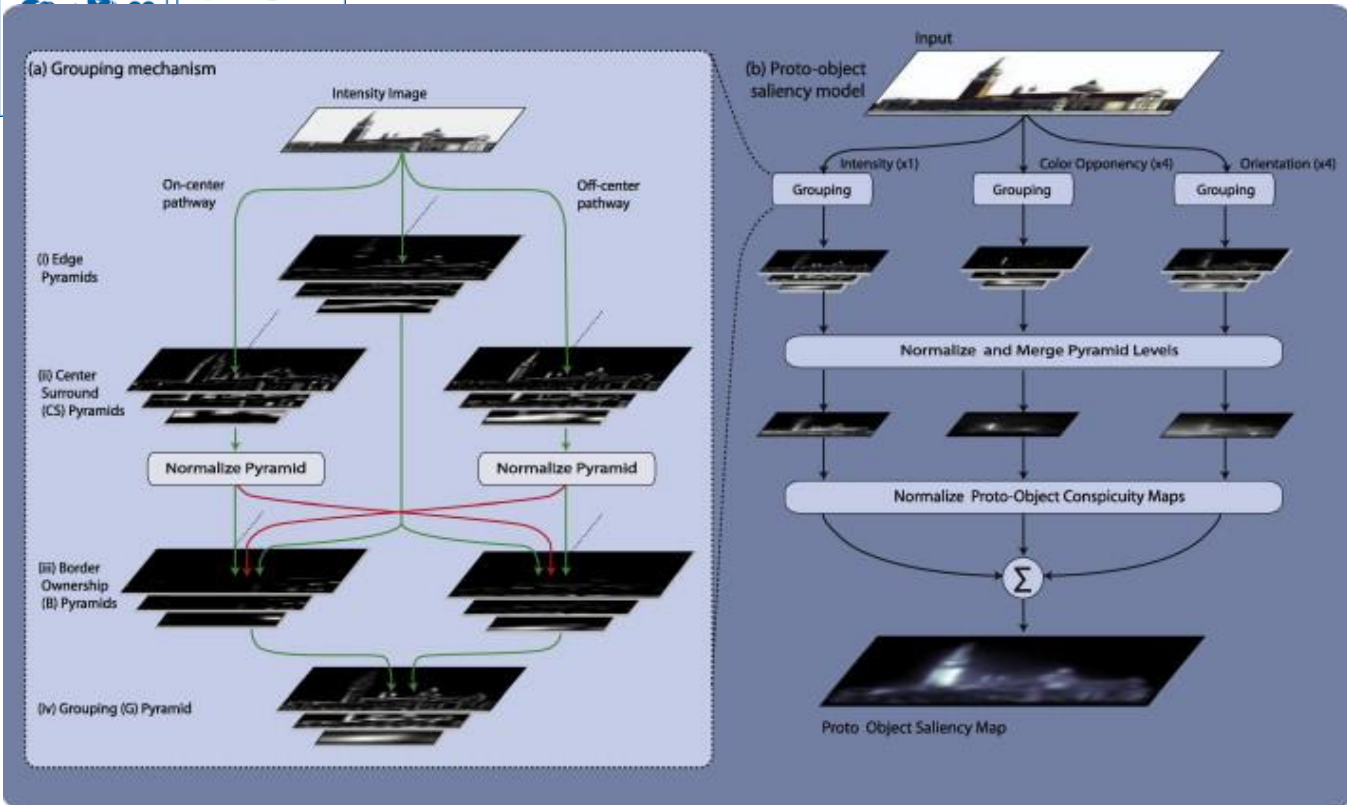


saliency map

Cool, but feature extraction is not enough

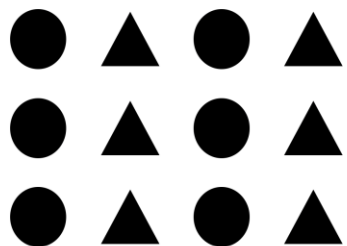
How do we perceive items
around us then?



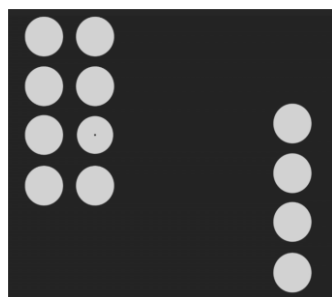


Russell, Noam, et al. "A model of proto-object based saliency." *Vision research* 94 (2014): 1-15.

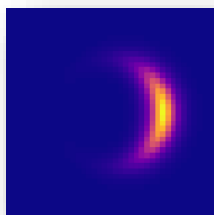
similarity



proximity

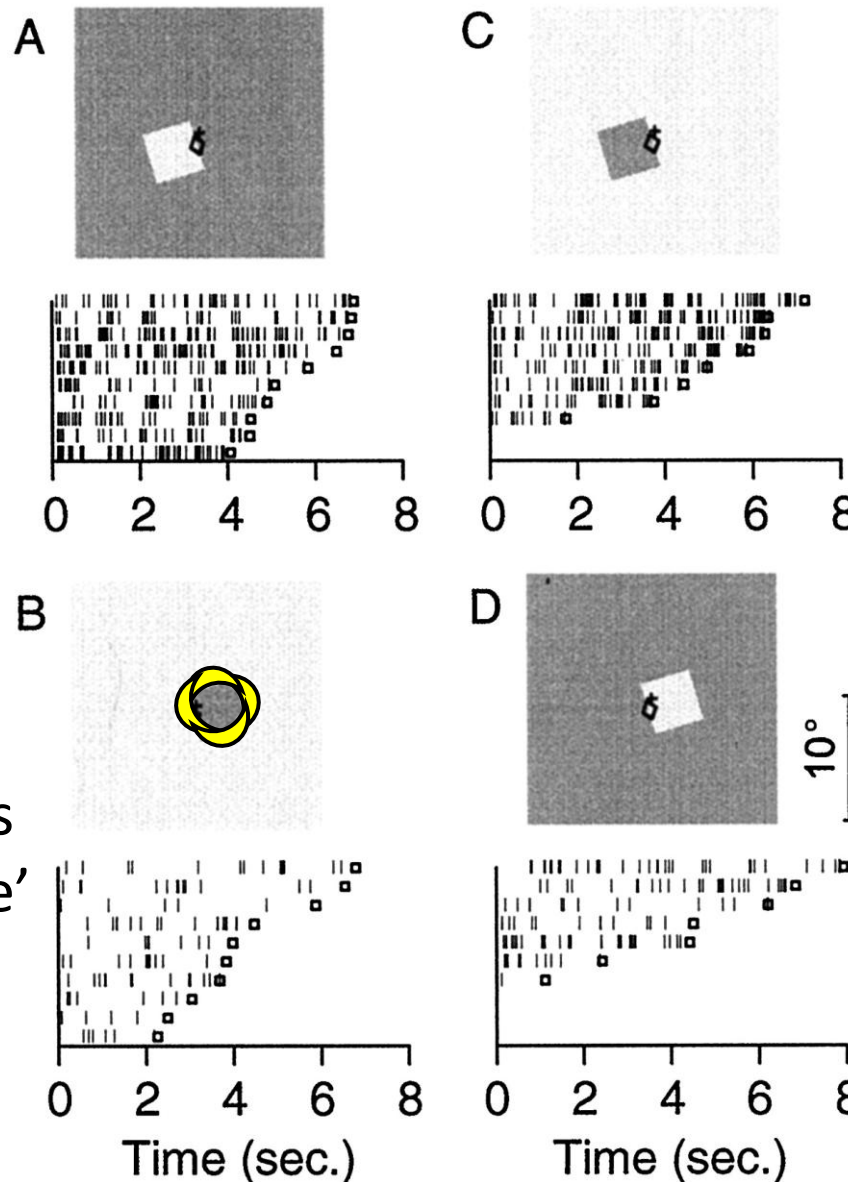


Proto-object is an 'object to be'



Border Ownership cells

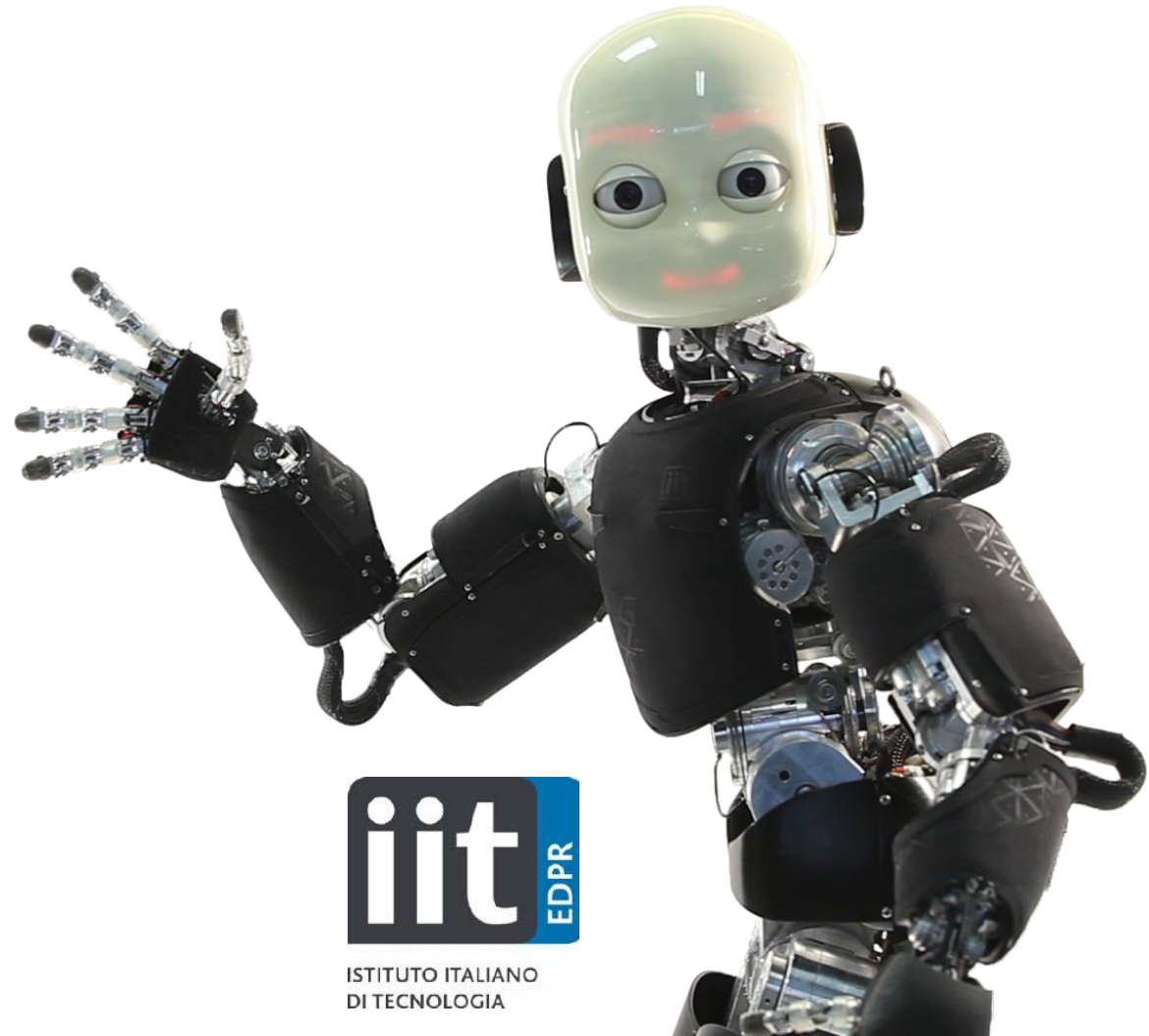
Cell 13id4 (V2)



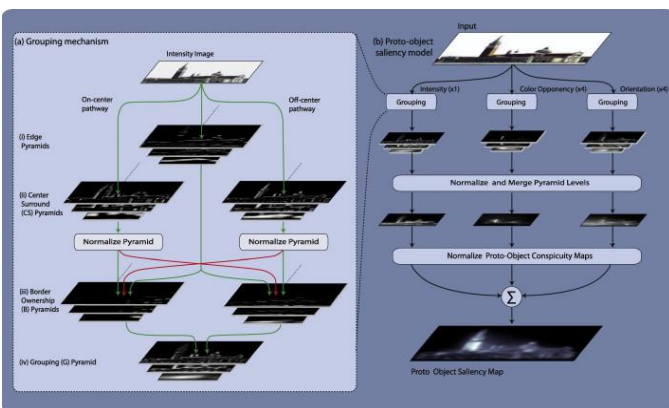
Zhou, Hong, Howard S. Friedman, and Rüdiger Von Der Heydt. "Coding of border ownership in monkey visual cortex." *Journal of Neuroscience* 20.17 (2000): 6594-6611.



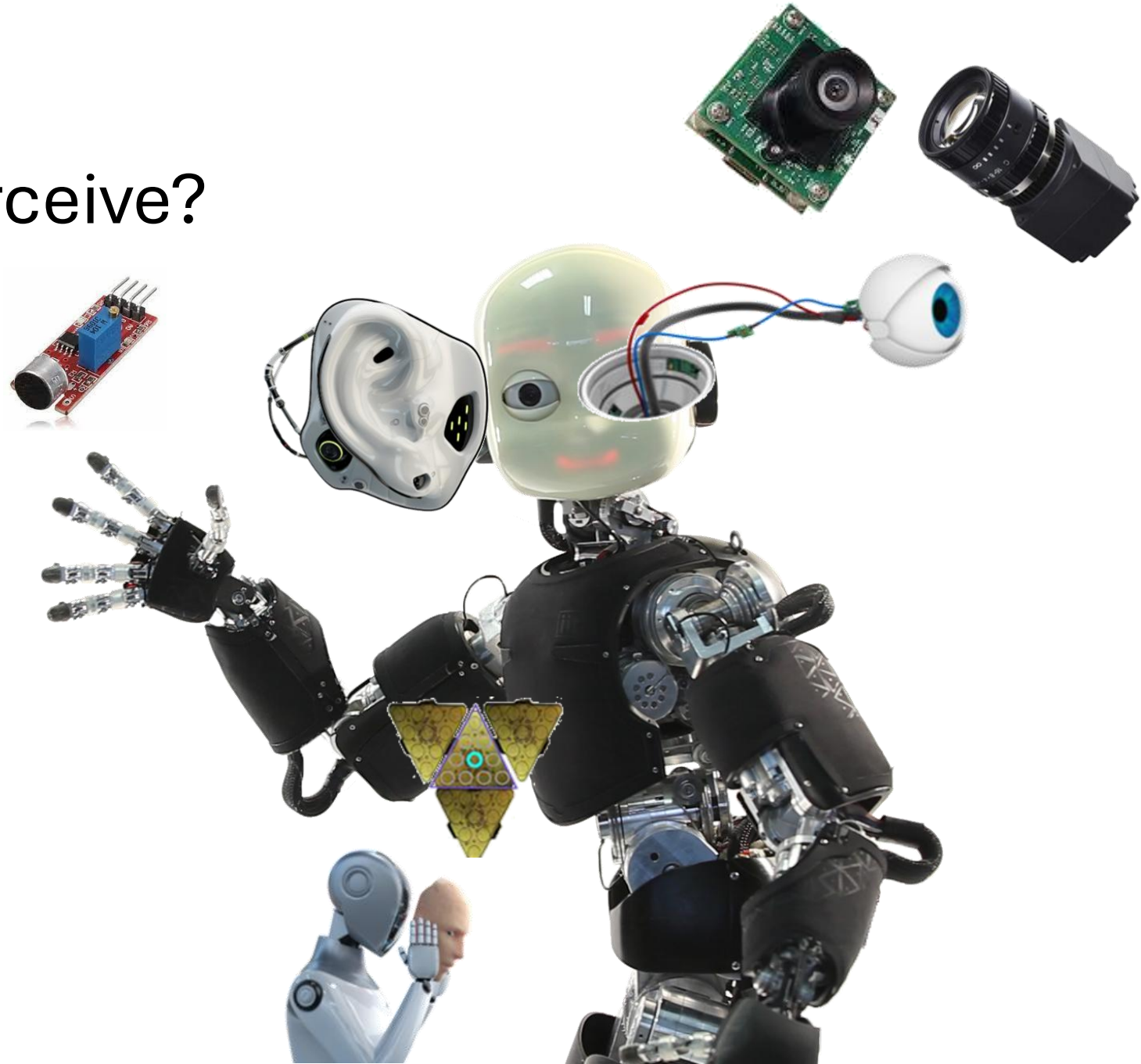
iCub

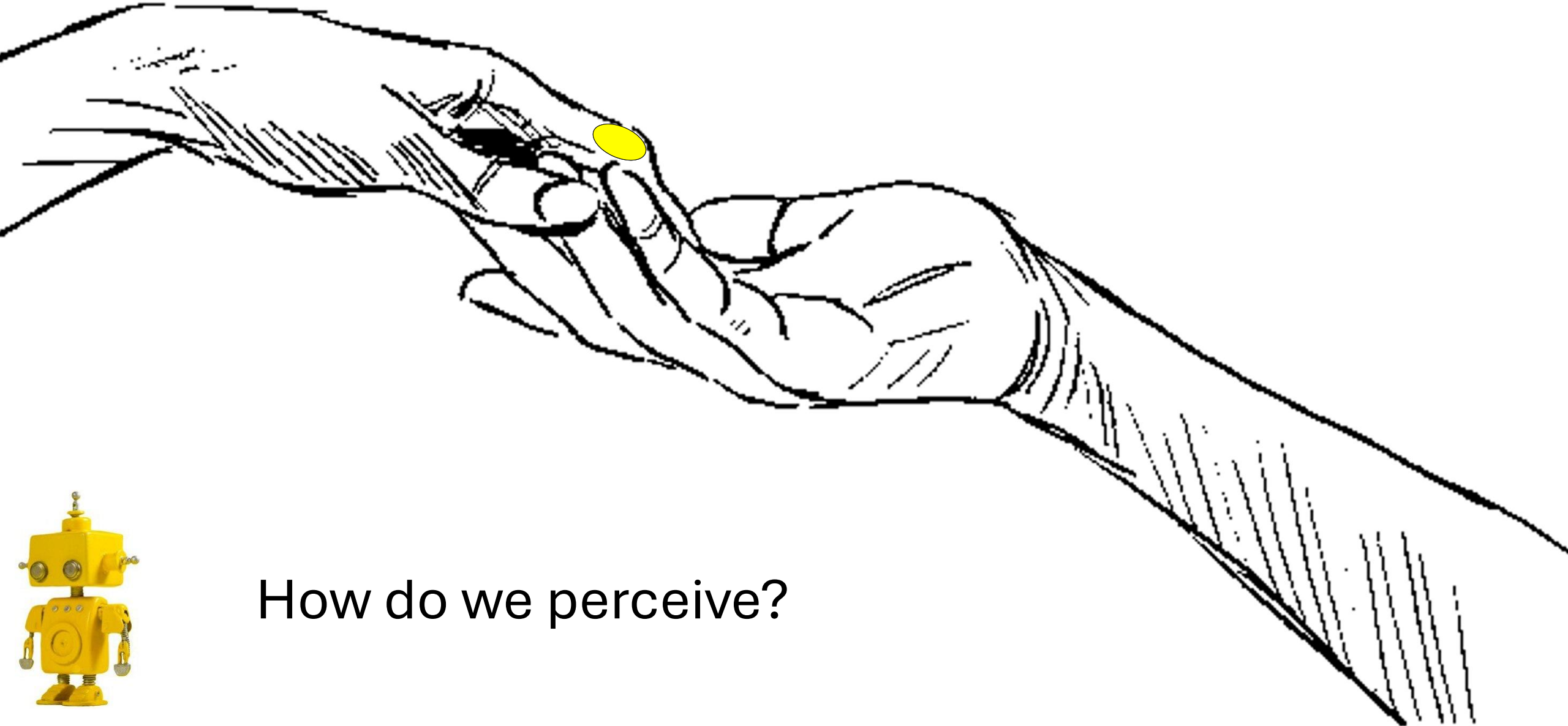
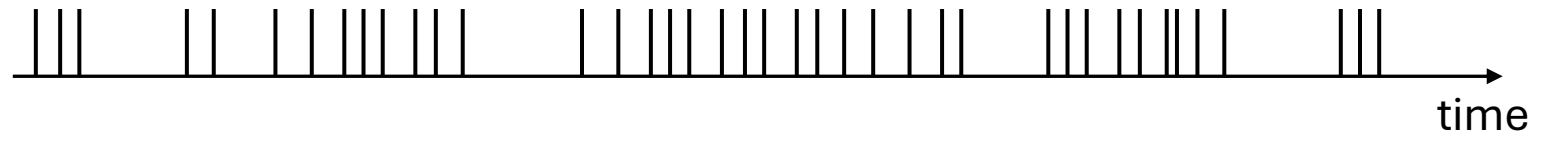


ISTITUTO ITALIANO
DI TECNOLOGIA



How does a robot perceive?





How do we perceive?





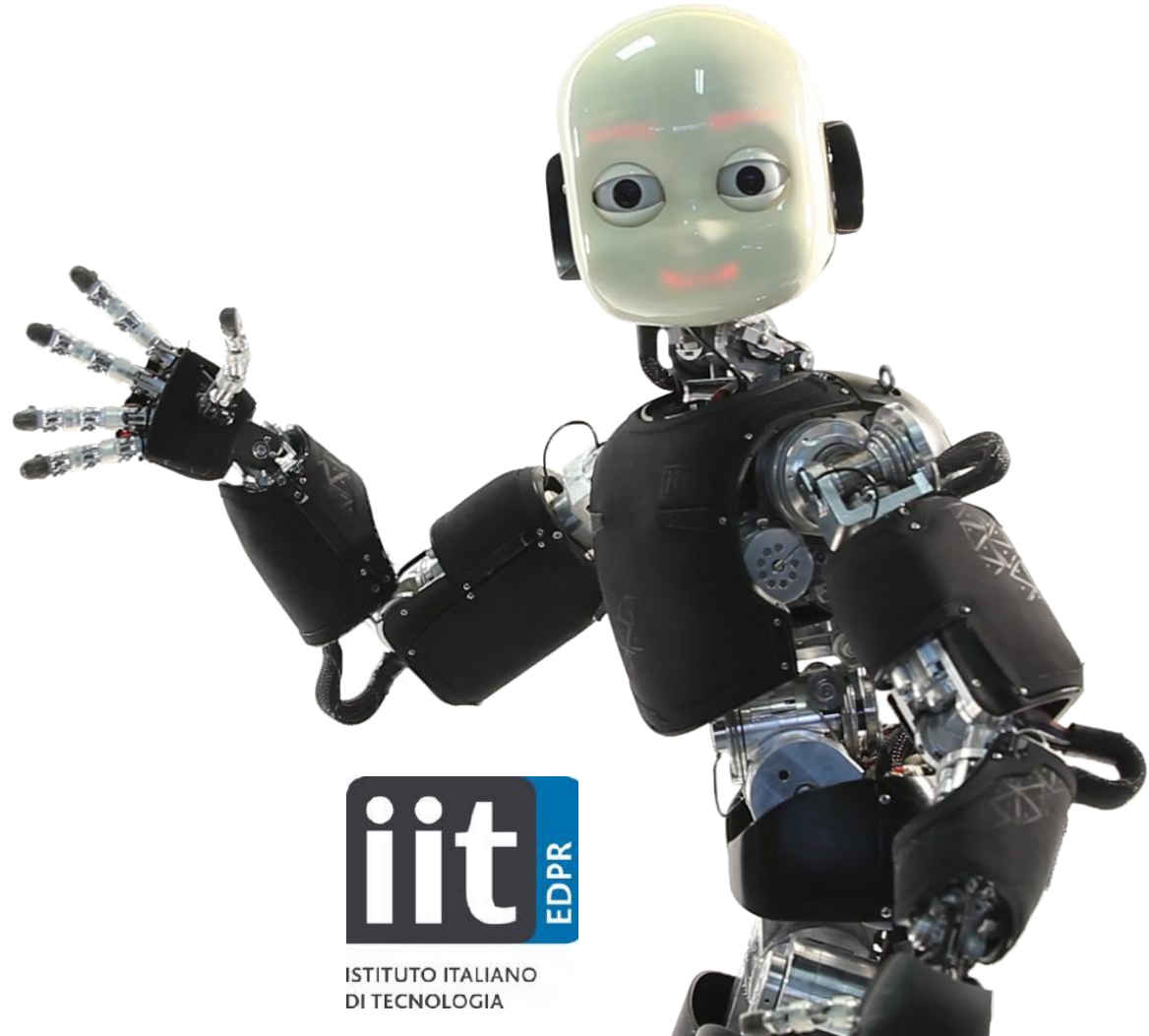
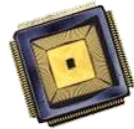
events



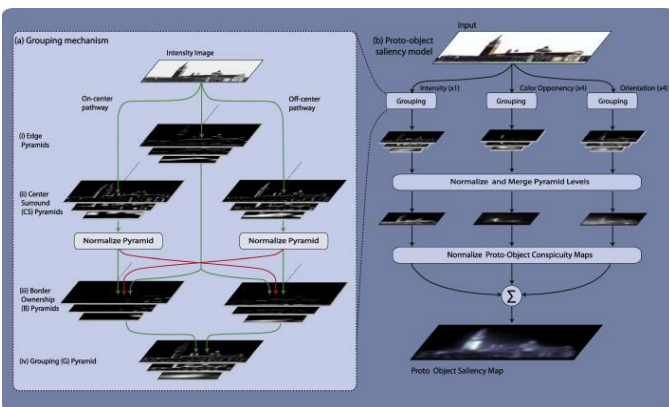
How do we perceive?



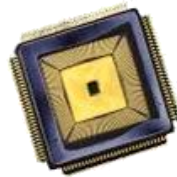
Neuromorphic iCub



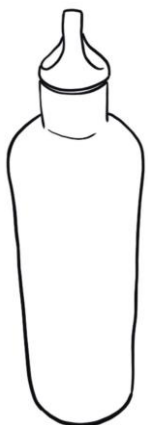
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DI TECNOLOGIA



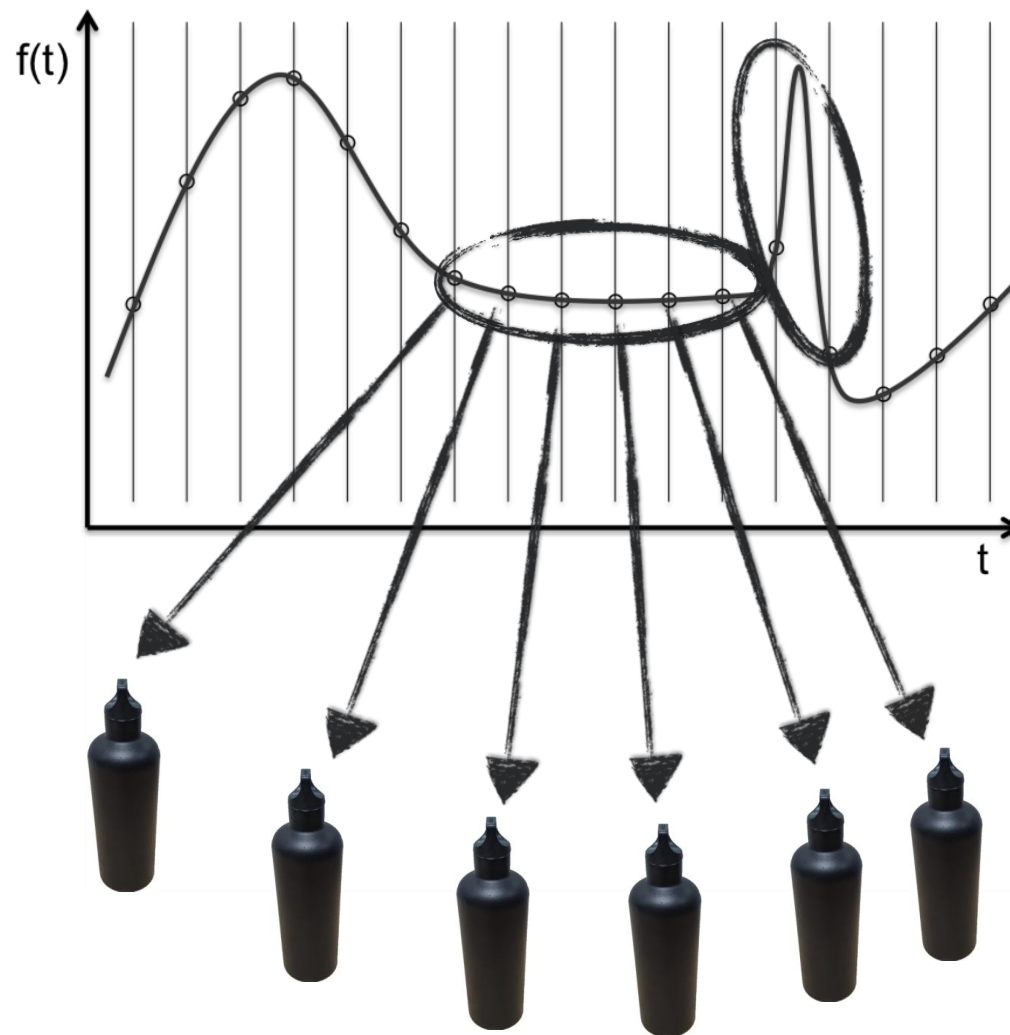
How does a neuromorphic camera work?



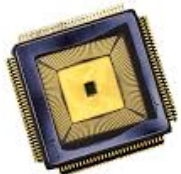
Let's start from a
frame-based camera!



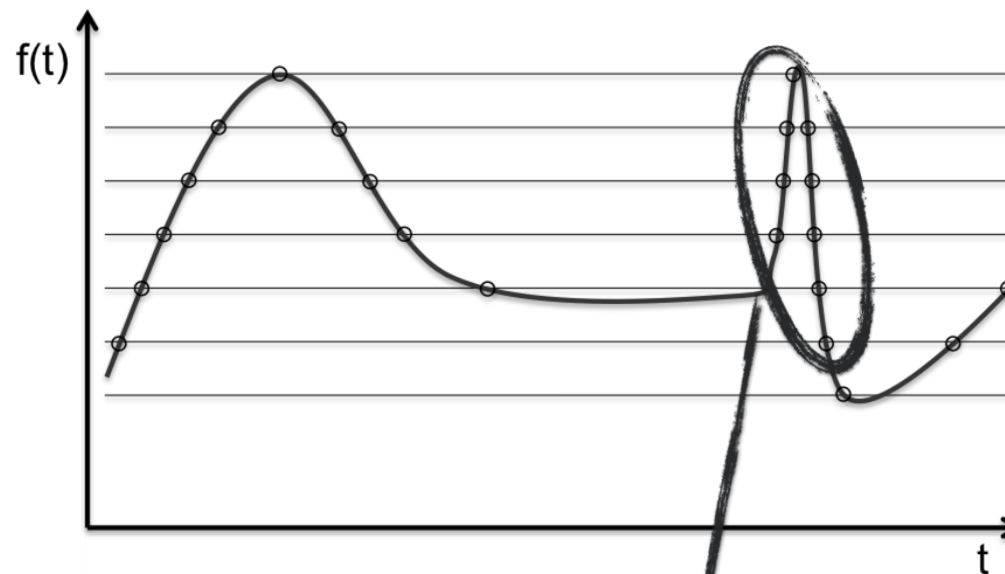
Clock-Based Sampling — fixed Δt



44 slides

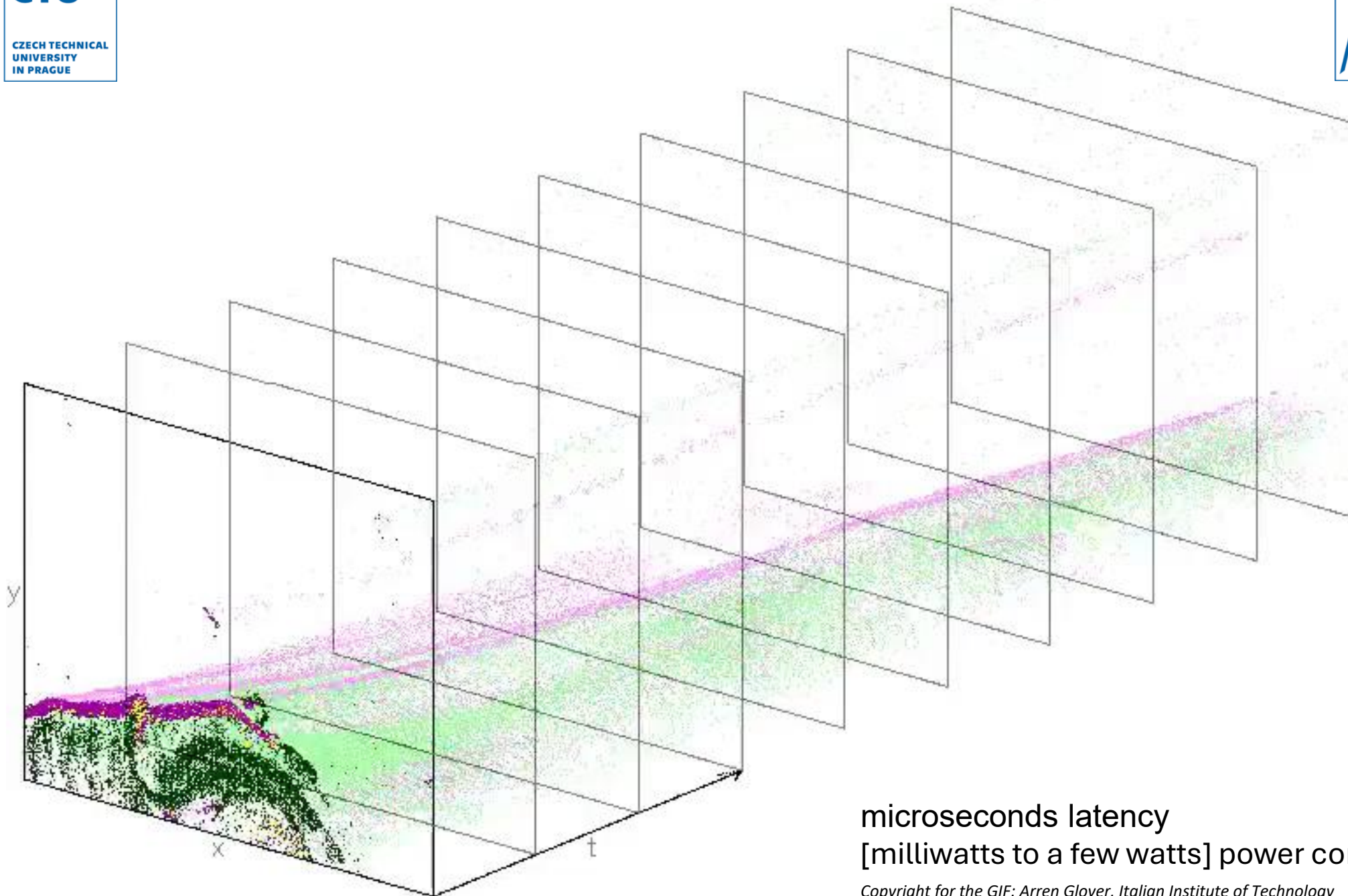


Data-Driven Sampling — fixed Δf (or $\Delta f/f$)



event = $e(x,y,t,p)$

44 slides

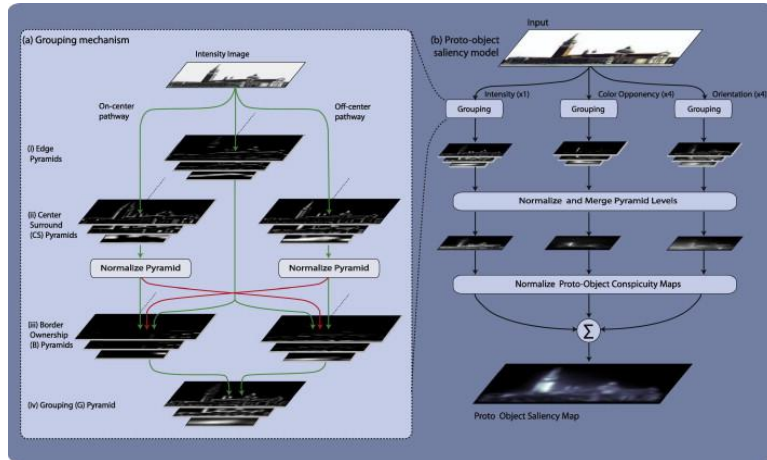


microseconds latency
[milliwatts to a few watts] power consumption

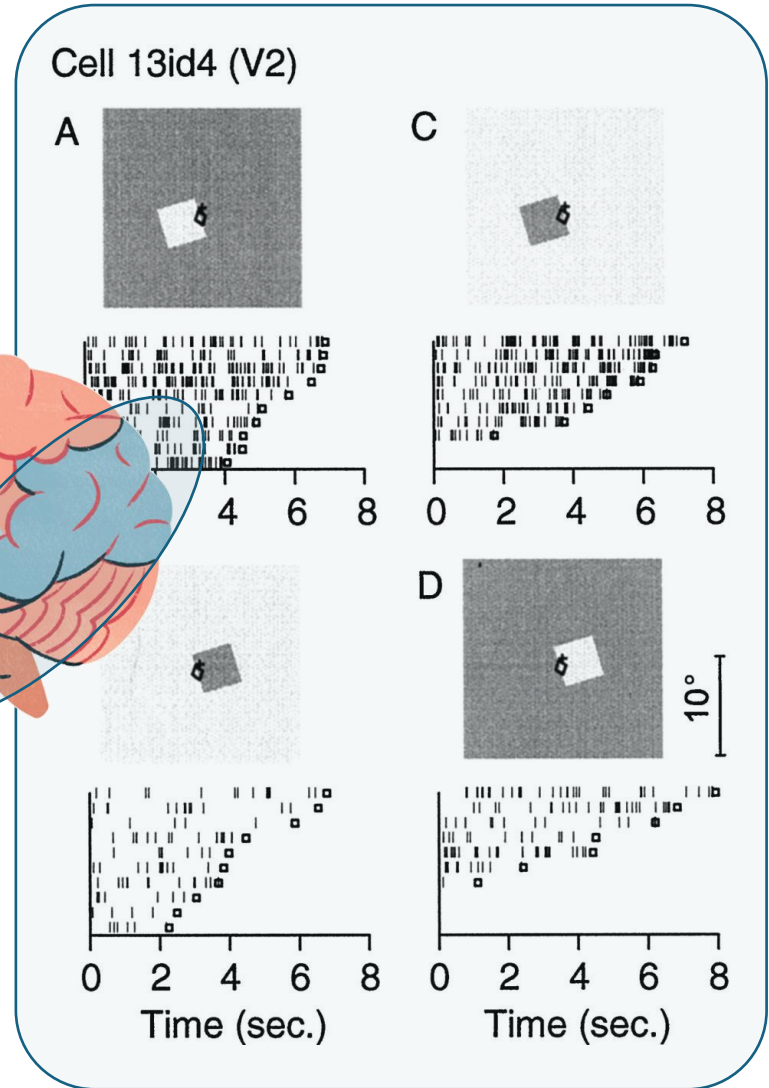
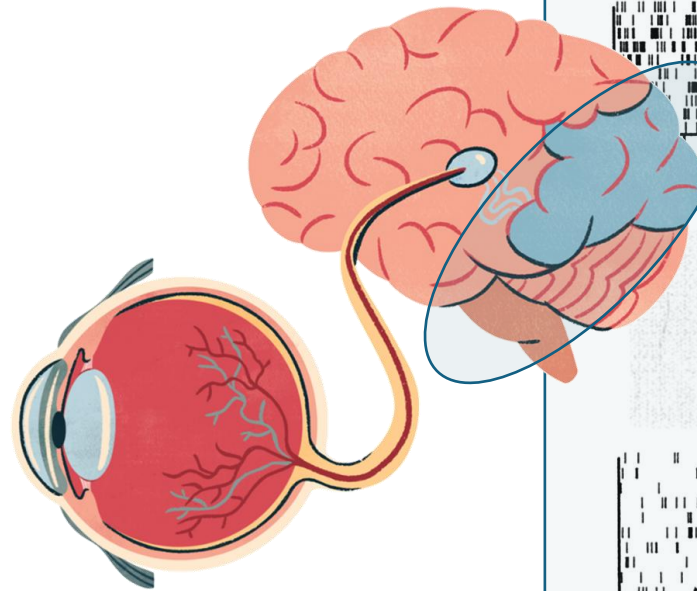
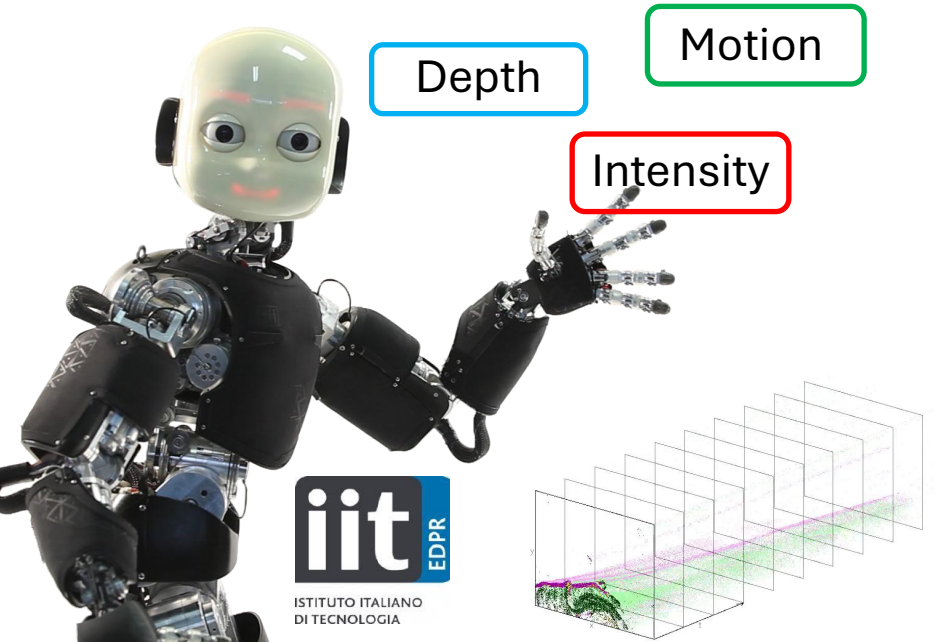
Copyright for the GIF: Arren Glover, Italian Institute of Technology

Is it just fancy bioinspiration?

Visual attention

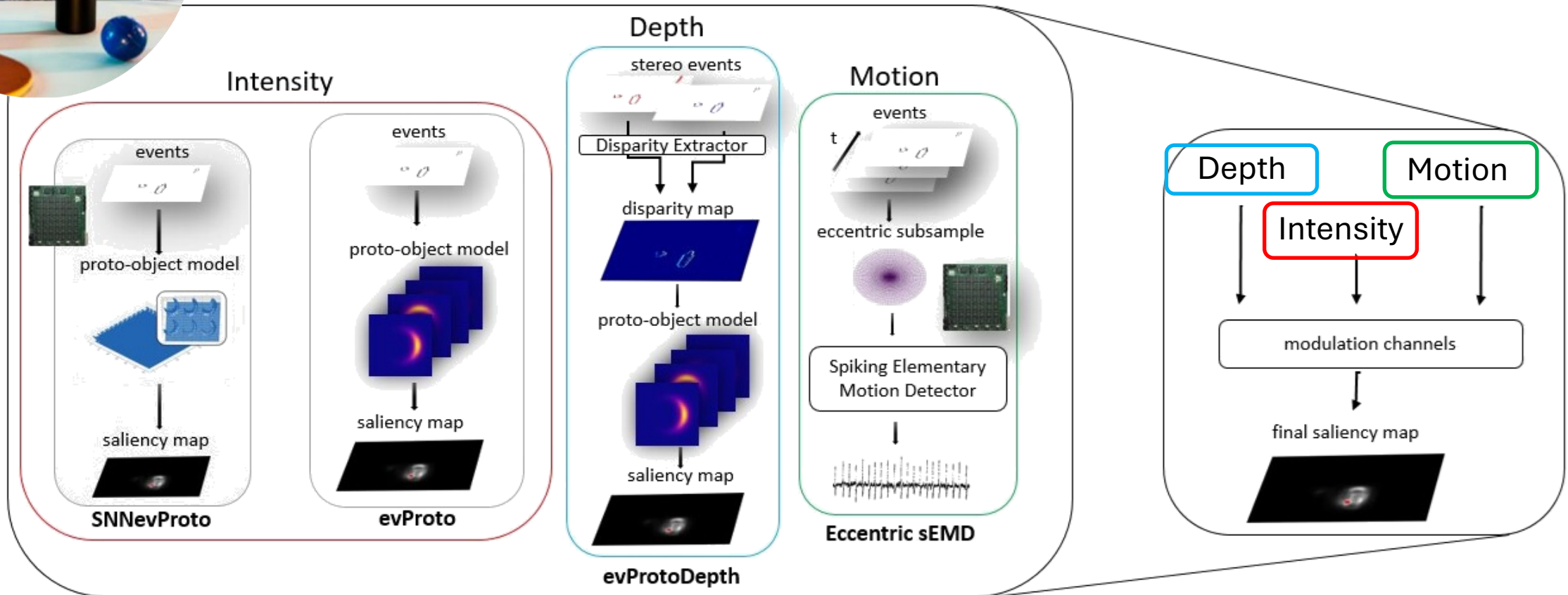


Russell, Alexander F., et al. "A model of proto-object based saliency." *Vision research* 94 (2014): 1-15.





Bioinspired saliency-based attention model



D'Angelo, G., Janotte, E., Schoepe, T., O'Keefe, J., Milde, M. B., Chicca, E., & Bartolozzi, C. (2020). Event-based eccentric motion detection exploiting time difference encoding *Front. Neuroscience*

D'Angelo, G., Perrett, A., Iacono, M., Furber, S., & Bartolozzi, C. (2022). Event driven bio-inspired attentive system for the iCub humanoid robot on SpiNNaker. *Neuromorphic Computing and Engineering*

Ghosh, S & D'Angelo, G., Glover, A., Iacono, M., Niebur, E., & Bartolozzi, C. (2022). Event-driven proto-object based saliency in 3D space to attract a robot's attention. *Scientific reports*

Iacono, M., D'Angelo, G., Glover, A., Tikhanoff, V., Niebur, E., & Bartolozzi, C. (2019, November). Proto-object based saliency for event-driven cameras. In *2019 IEEE/RSJ International IROS*

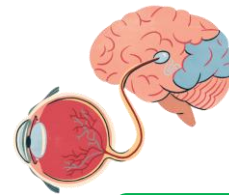
Intensity

lacono, M. et al. (2019, November). Proto-object based saliency for event-driven cameras. In 2019 IEEE/RSJ International IROS

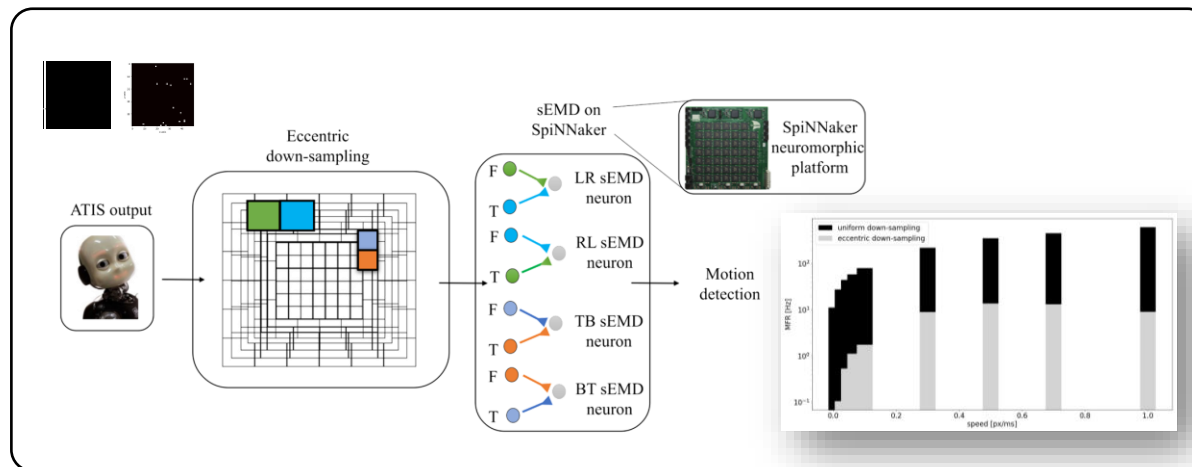
Depth

What interests a robot: Event-Driven Proto-object saliency in 3D space

Giulia D'Angelo and Suman Ghosh, Arren Glover, Massimiliano Iacono, Ernst Niebur, Chiara Bartolozzi



Motion

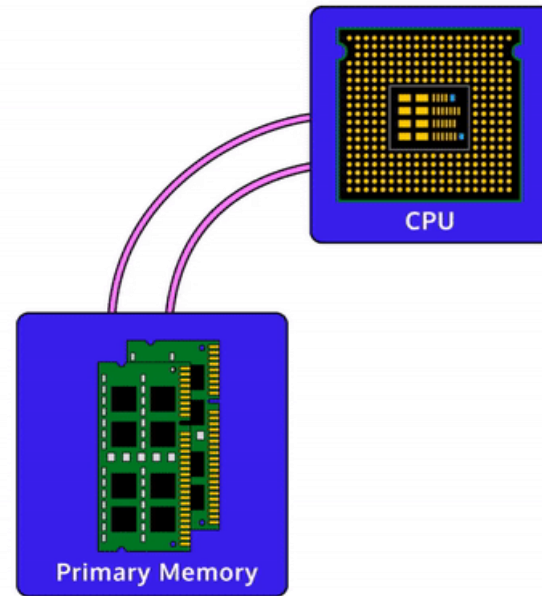


D'Angelo, G. et al. (2020). Event-based eccentric motion detection exploiting time difference encoding. *Frontiers in neuroscience*, 14, 451.

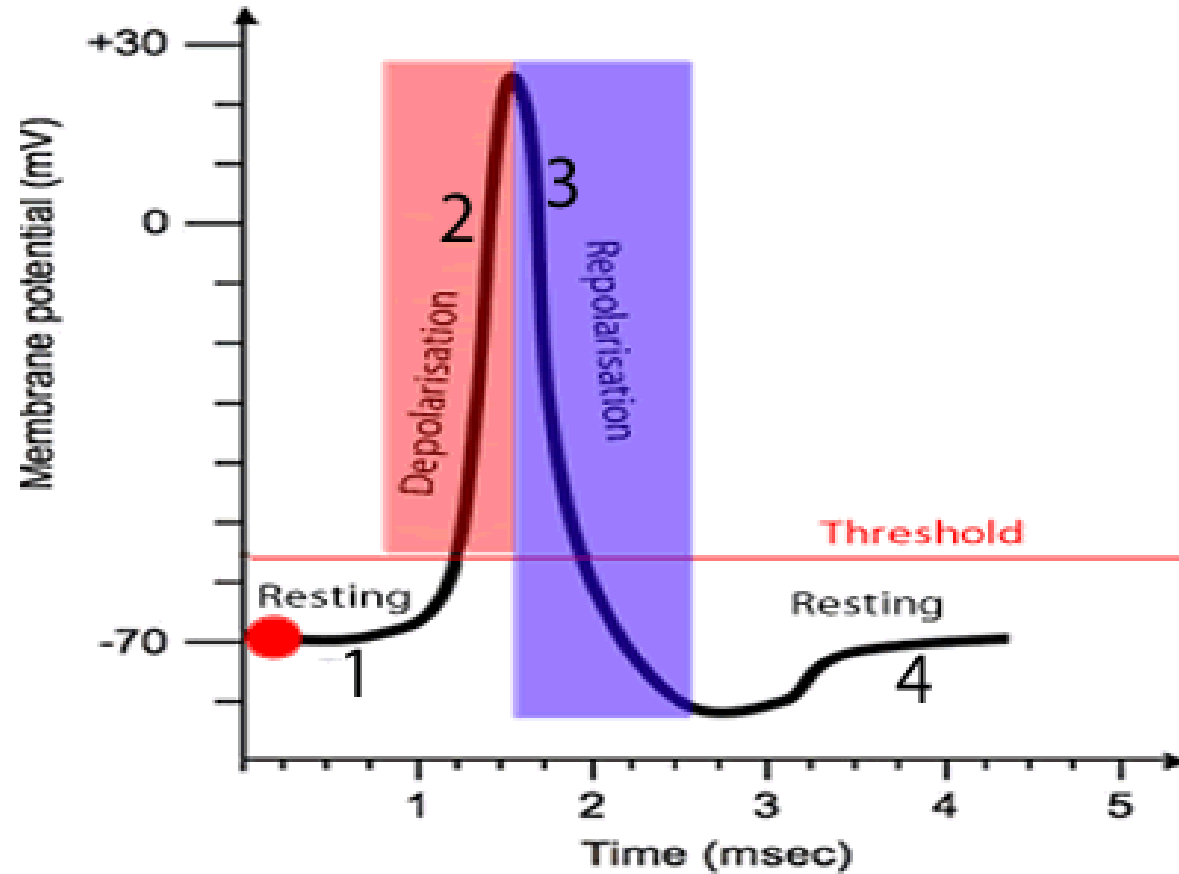
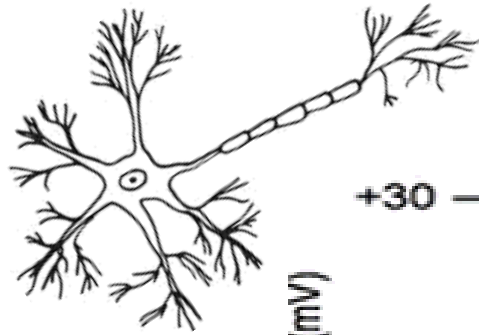
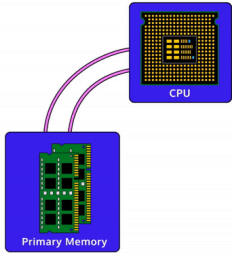
How does a neuromorphic platform work?

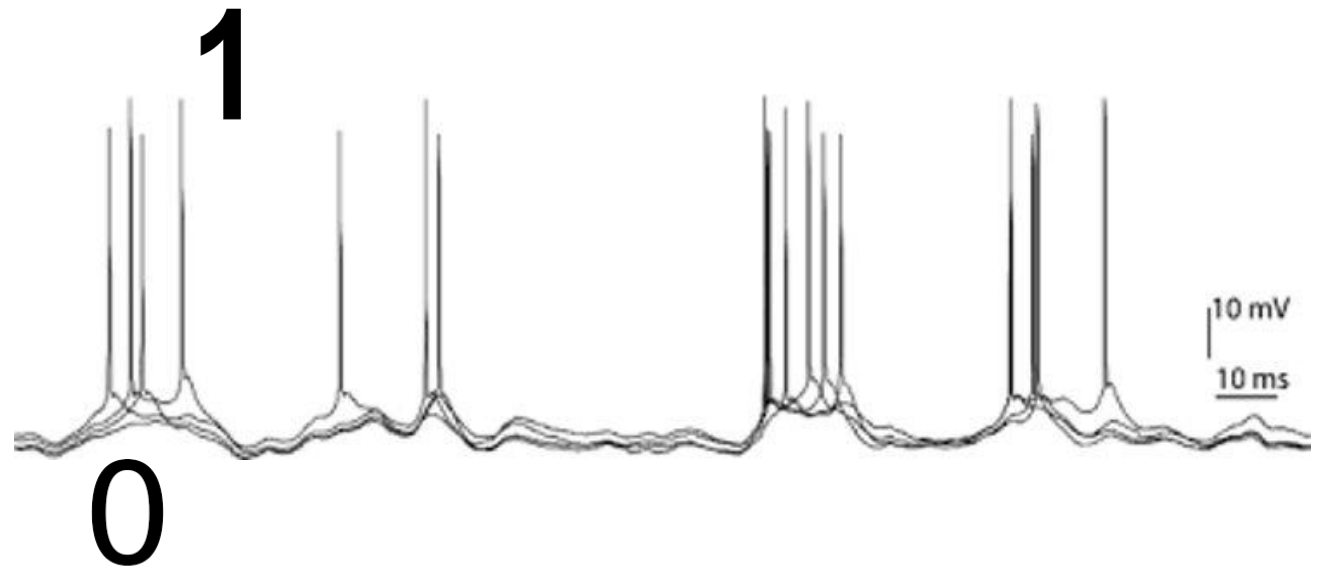
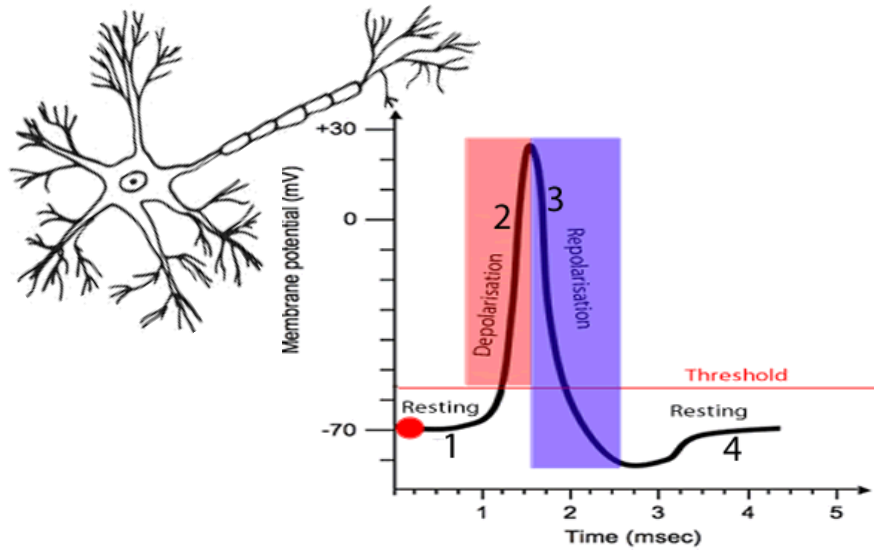


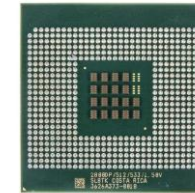
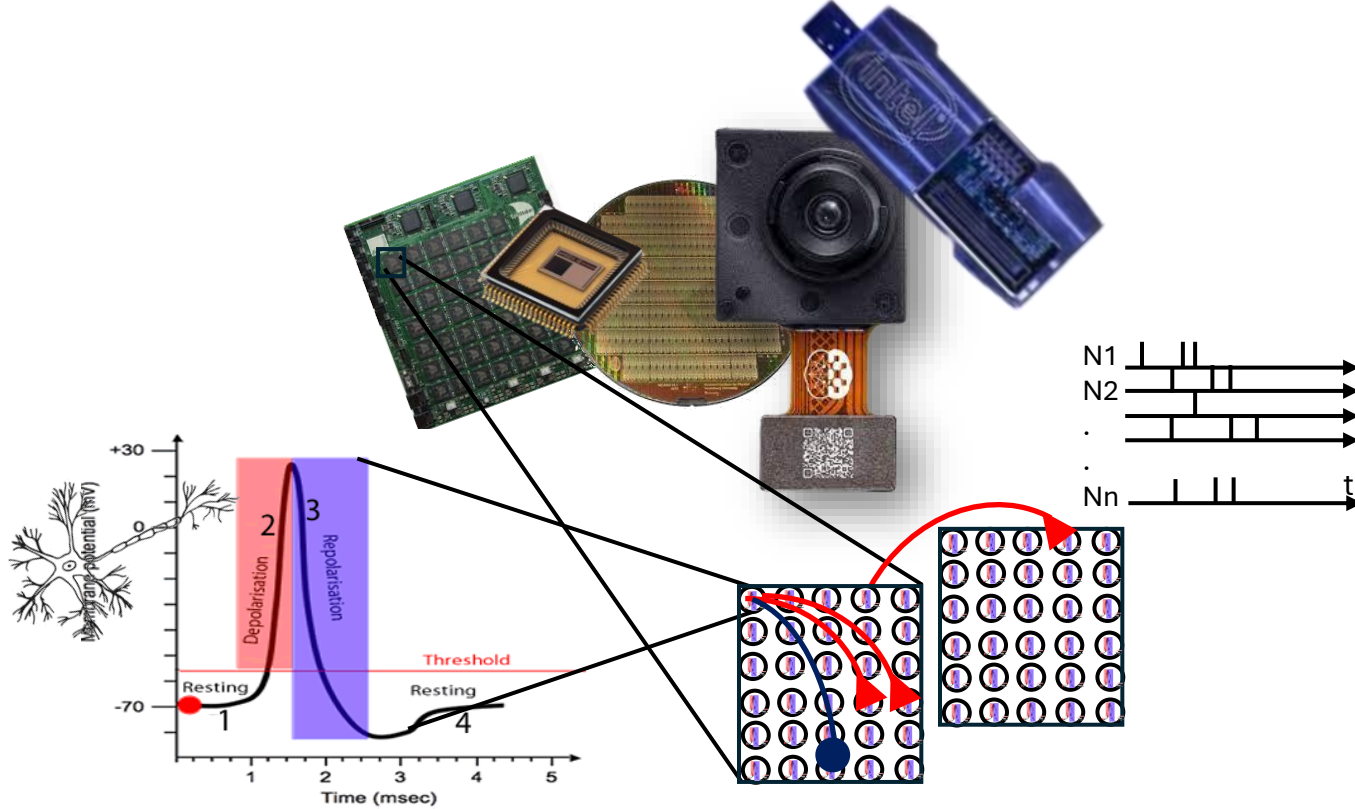
Let's start from classic CPU!



Let's start from classic CPU!





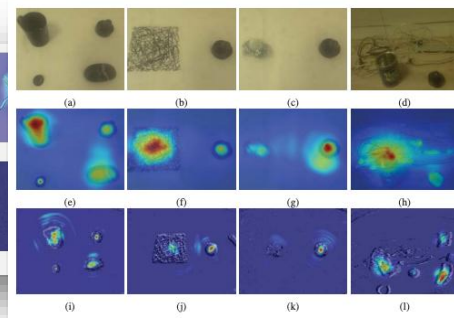
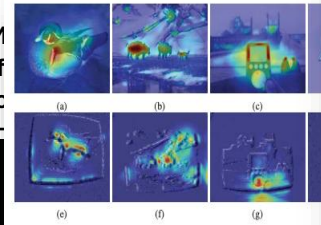


NON von Neumann architecture $e^{-\frac{\Delta T}{\tau}}$ LIF neuron
▶ Connections among neurons Excitatory and Inhibitory connections
DIGITAL: SpiNNaker (i.e. ARM cores; old 18 cores 1ms clock, new 256 Cortex M4 180 MHz; RISC)
ANALOG: DYNAP-SE (asynchronous analog circuits, NO global clock)
~mW power consumption (even less)

von Neumann architecture	NON strictly von Neumann
Single core	NO connections among cores
CISC 1 to 3 GHz	CISC 1.4 to 2.5 GHz
~125 to 250 W	~300 to 400 W

Intensity

lacono, M
saliency f
Internatic

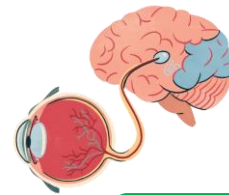


Depth

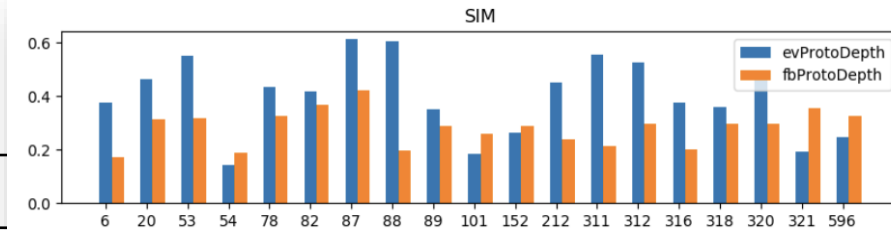
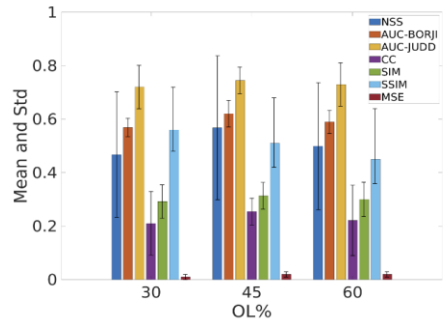
Ghosh, S & D'Angelo et al. (2022). Event-driven proto-object based saliency in 3D space to attract a robot's attention. *Scientific reports*, 12(1), 1-14.

What interests a robot: Event-Driven Proto-object saliency in 3D space

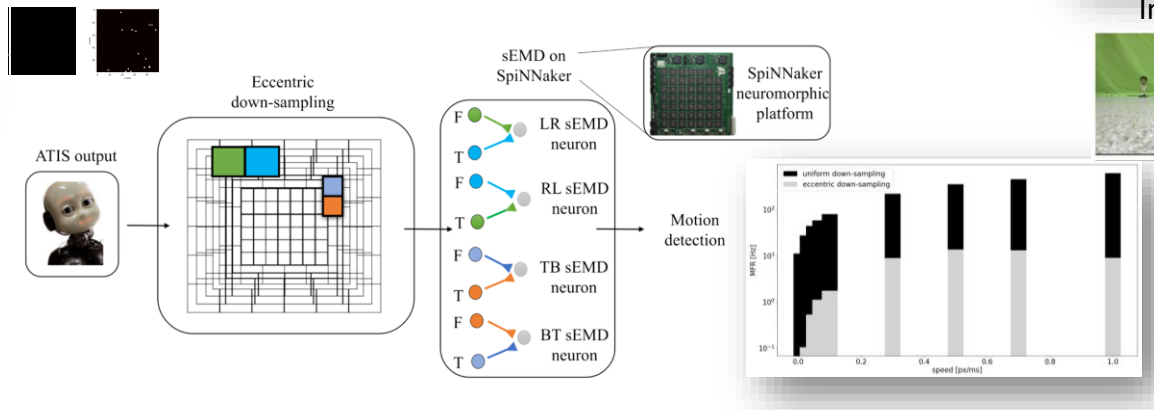
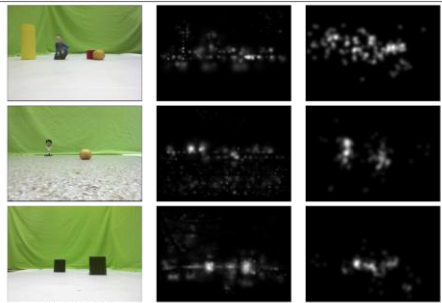
Giulia D'Angelo and Suman Ghosh, Arren Glover, Massimiliano lacono, Ernst Niebur, Chiara Bartolozzi



Motion

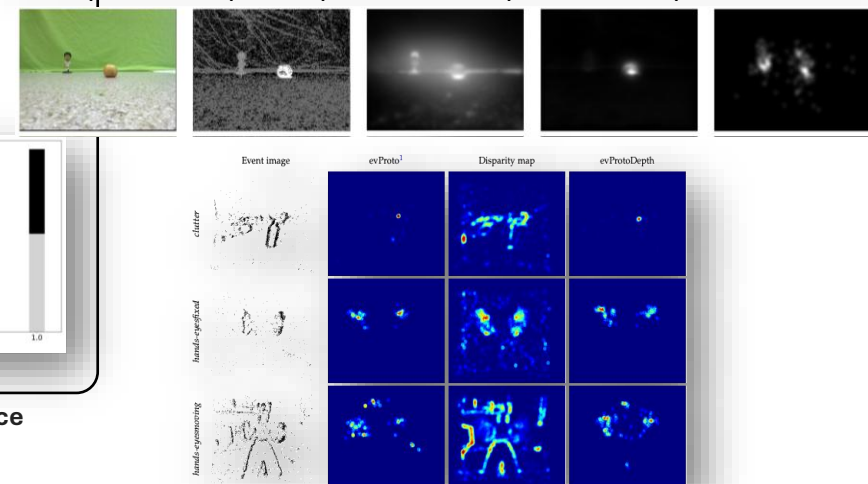


Input ED sal map 2D fixations

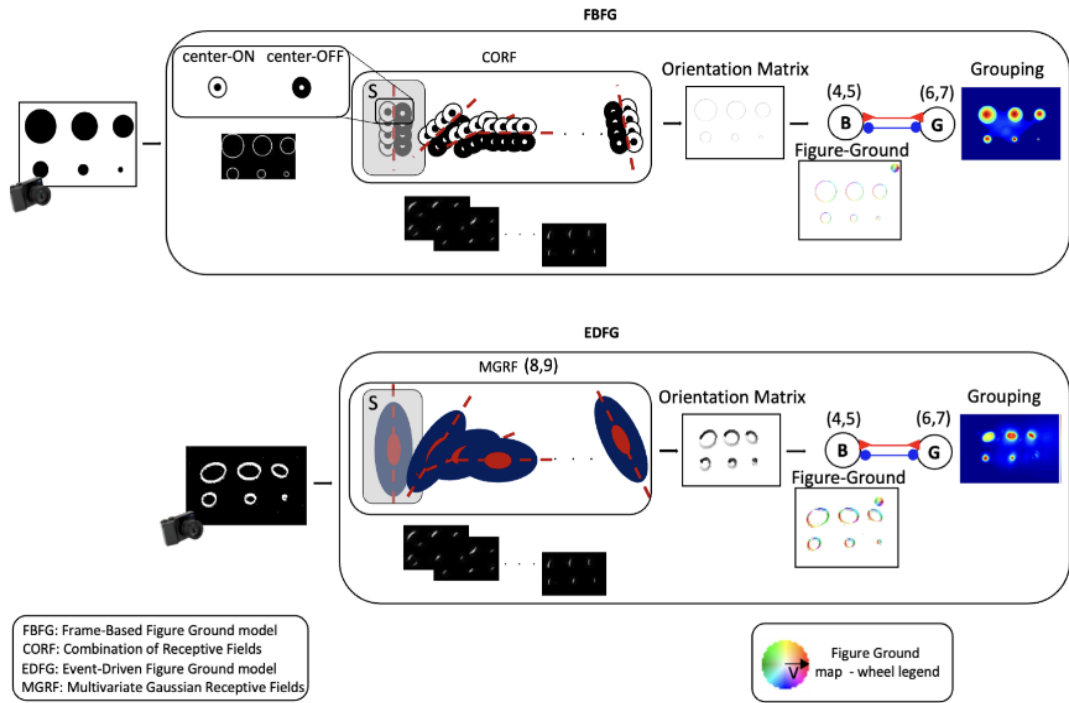


D'Angelo, G. et al. (2020). Event-based eccentric motion detection exploiting time difference encoding. *Frontiers in neuroscience*, 14, 451.

Input Depth map RGB sal map ED sal map 3D fixations



Can we segment the scene?



FB and ED Angle maps vs. Ground-Truth

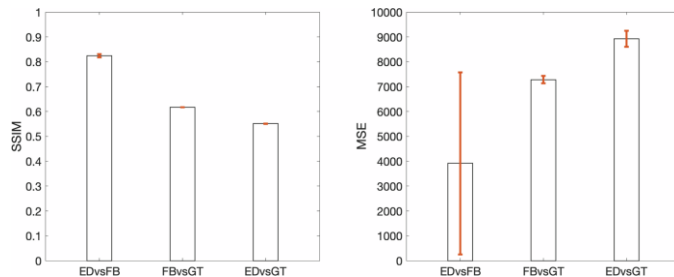
Image #	RGB Input	Ground-Truth	FB Angle map ²¹	ED Angle map
135069				
8143				
105019				
12003				
118035				
134008				

FBFG vs EDFG

Image #	RGB Input	FB Grouping [21]	ED Grouping
59078			
238011			
271031			

Means errors 5.29°

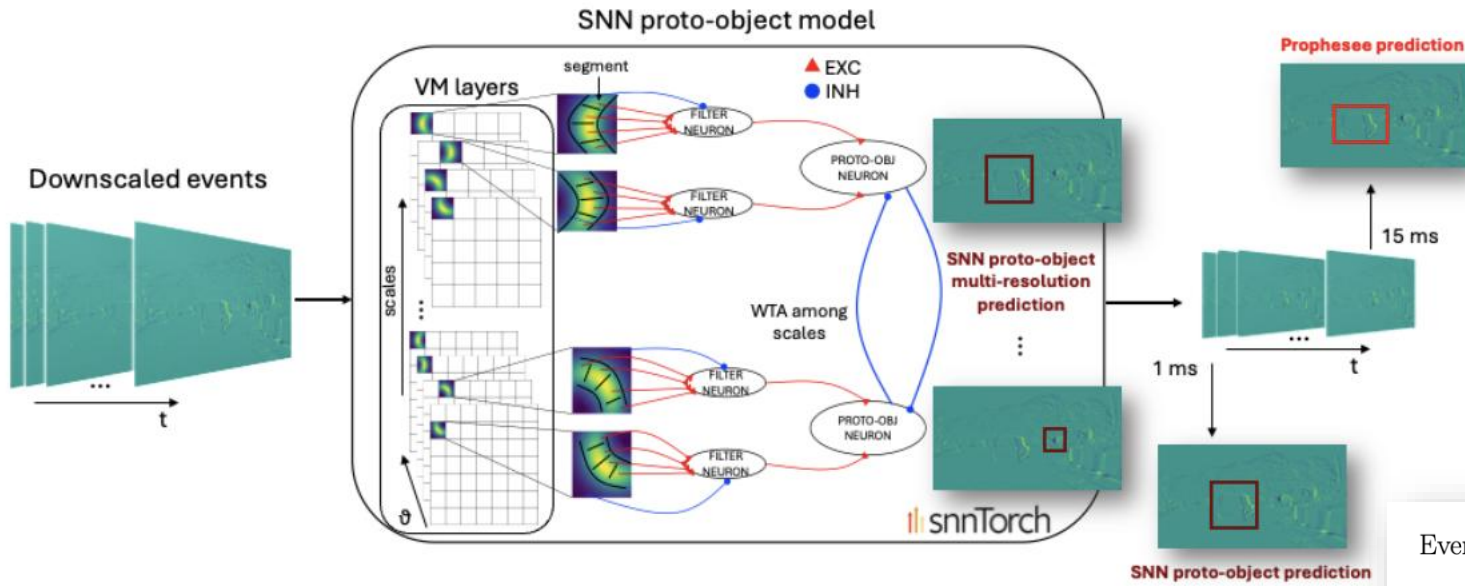
What is an object?



D'Angelo, G., Voto, S., Iacono, M., Glover, A., Niebur, E., & Bartolozzi, C. (2025). Event-driven figure-ground organisation model for the humanoid robot iCub. *Nature communications*, 16(1), 1874.

170 ms GPU

Depth



interests a robot: Event-Driven Proto-object saliency in 3D space

and Suman Ghosh, Arren Glover, Massimiliano Iacono, Ernst Niebur, Chiara Bartolozzi

Event-based Selective Attention for Multi-resolution Fast Region of Interest (ROI) Detection

Luca Peres^{*1}, Giulia D'Angelo^{2,3}, Chiara Bartolozzi³, and Oliver Rhodes¹

¹Advanced Processor Technologies Group, Department of Computer Science, The University of Manchester, Manchester, United Kingdom

²Department of Cybernetics, Faculty of Electrical Engineering, Czech Technical University in Prague, Czech Republic

³Istituto Italiano di Tecnologia, Genoa, Italy

Abstract

Neuromorphic vision systems operate under strict constraints on bandwidth, memory, and energy, particularly at the edge, motivating early mechanisms for data reduction and selective processing. In this work, we investigate a multi-scale training-free, saliency-based, bottom-up visual attention model that operates directly on low-resolution event-based input and selects regions of interest (ROIs) from the visual scene. The model is evaluated across multiple downscaling factors applied to the incoming event stream, with input resolutions reduced by up to 256× relative to full resolution. Performance is assessed on the Prophesee Automotive dataset, the largest publicly available event-based dataset, demonstrating robust ROI selection across different scales on a real-world use-case. The proposed approach is capable of detecting ROIs belonging to multiple object classes, including various vehicle types, pedestrians, traffic lights, and traffic signs, with accuracy up to 70.8%, while operating at millisecond temporal resolution, 16× finer than the temporal resolution provided by the dataset ground truth. These results highlight the potential of combining early event downscaling with saliency-based attention as an effective front-end for efficient edge neuromorphic vision systems.

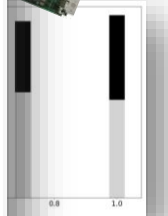
This block contains a collage of images related to the research. On the left, a 3D visualization shows a robot's field of view with a red bounding box around a region of interest. In the center, there are several SpiNNaker hardware boards. To the right, a portrait of a man is shown. Below the portrait, a diagram labeled 'NevProto' illustrates the system's components, including 'negative events', 'ATIS output' (a small image of a robot head), and a heatmap of the ROI. The text '6 SpiNNaker boards' is written at the bottom left of this collage.

geto, G. et al. (2022)

ms

6 SpiNNaker boards ☹️

EDPR





NEURO-INSPIRED
PERCEPTION &
COGNITION

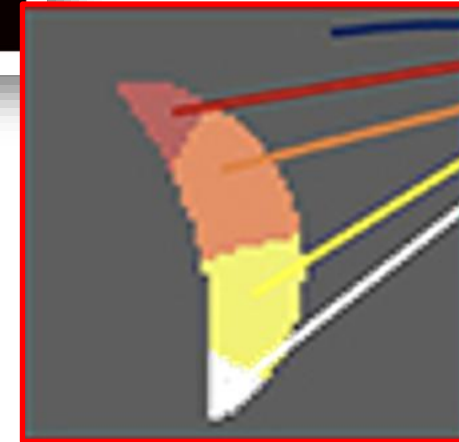
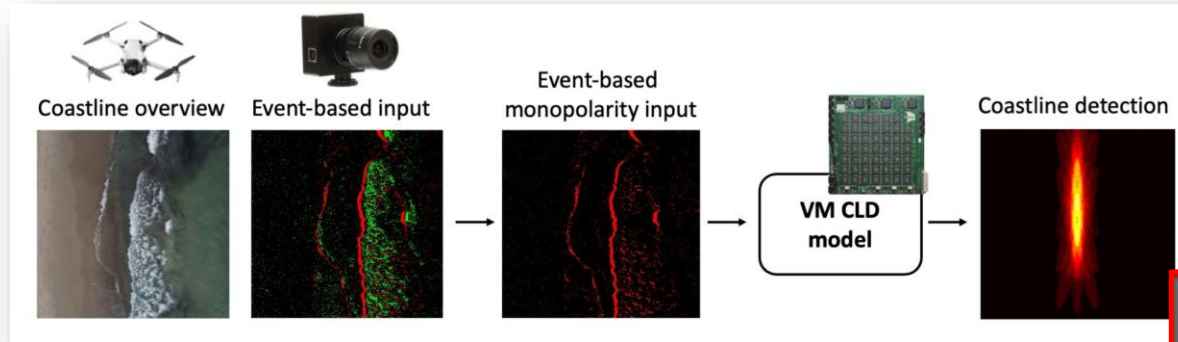


Mazdak Fatahi
PhD student
Université de Lille
Spiking Neural Networks for robotics applications



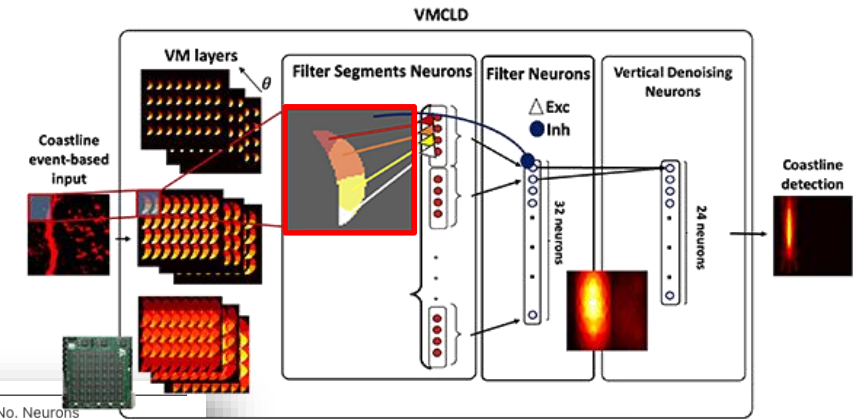
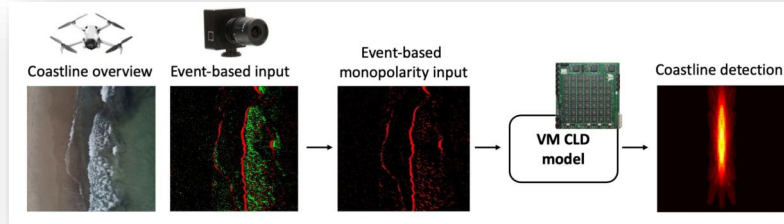


Event-driven nearshore and shoreline coastline detection on SpiNNaker neuromorphic hardware





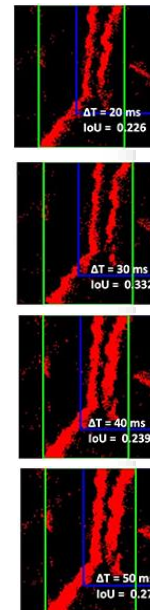
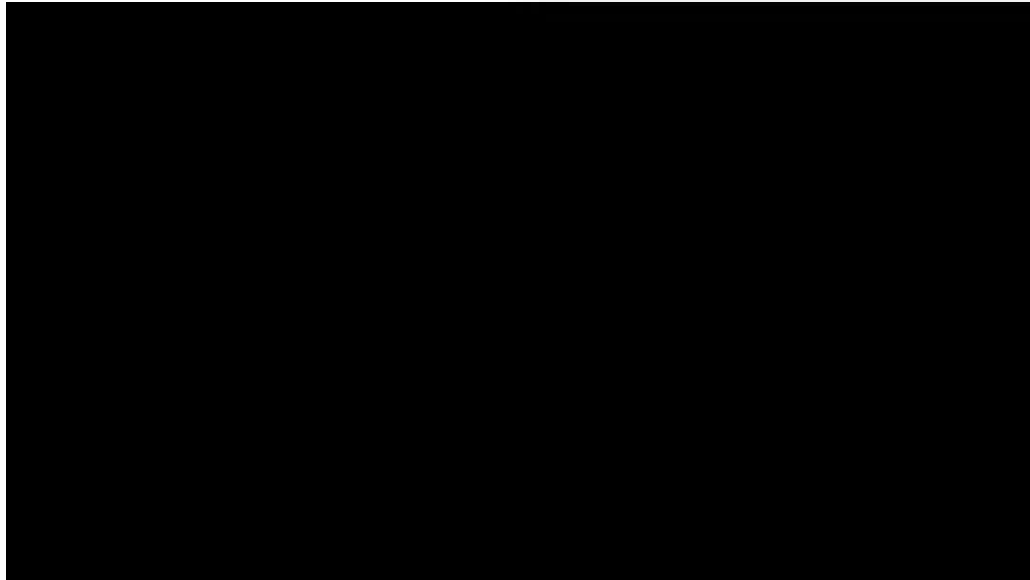
Event-driven nearshore and shoreline coastline detection on SpiNNaker neuromorphic hardware



Populations	No. Neurons
Input Population	16 384 (128x128)
Filter Segments Neurons Population	128 (32x4)
Filter Neurons Population	32
Vertical Denoising Population	24
Total	16 384 + 184 x 9 = 18 040



Average consumption $\Delta T=20$ ms is **0.3756 mW**



		Accuracy (%)	Accuracy (%)	Accuracy (%)	Accuracy (%)	Accuracy (%)	Accuracy (%)
		(Threshold = 0.80)	(Threshold = 0.70)	(Threshold = 0.60)	(Threshold = 0.50)	(Threshold = 0.40)	(Threshold = 0.30)
ΔT	Average of IoU						
20	61.68	18.69	37.88	57.07	73.23	85.35	92.93
30	65.66	22.78	49.44	67.78	78.89	90.56	98.33
40	67.06	26.35	55.69	70.66	82.04	89.82	95.81
50	69.59	24.64	57.97	78.99	87.68	93.48	96.38

Fatahi, M., Boulet, P., & D'angelo, G. (2024). Event-driven nearshore and shoreline coastline detection on SpiNNaker neuromorphic hardware. *Neuromorphic Computing and Engineering*, 4(3), 034012.



Can Spiking Neural Networks play pinball? A neuromorphic motion detector for target tracking

148 μ W

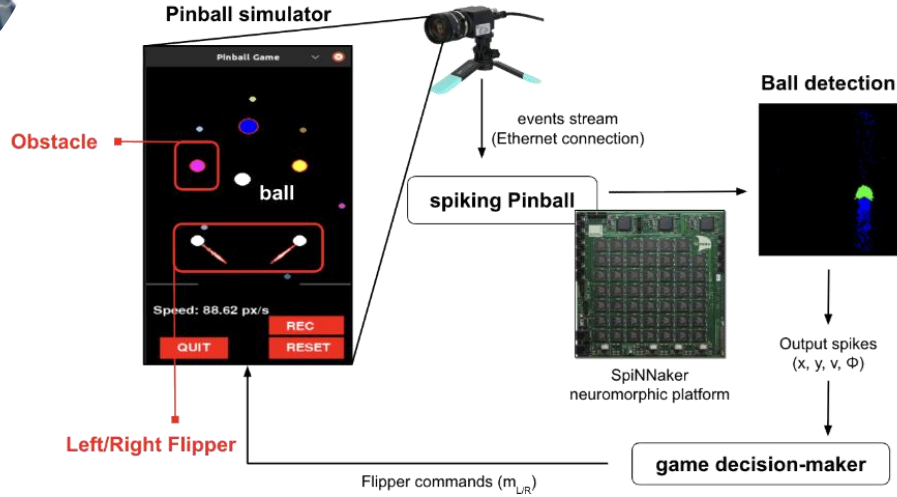


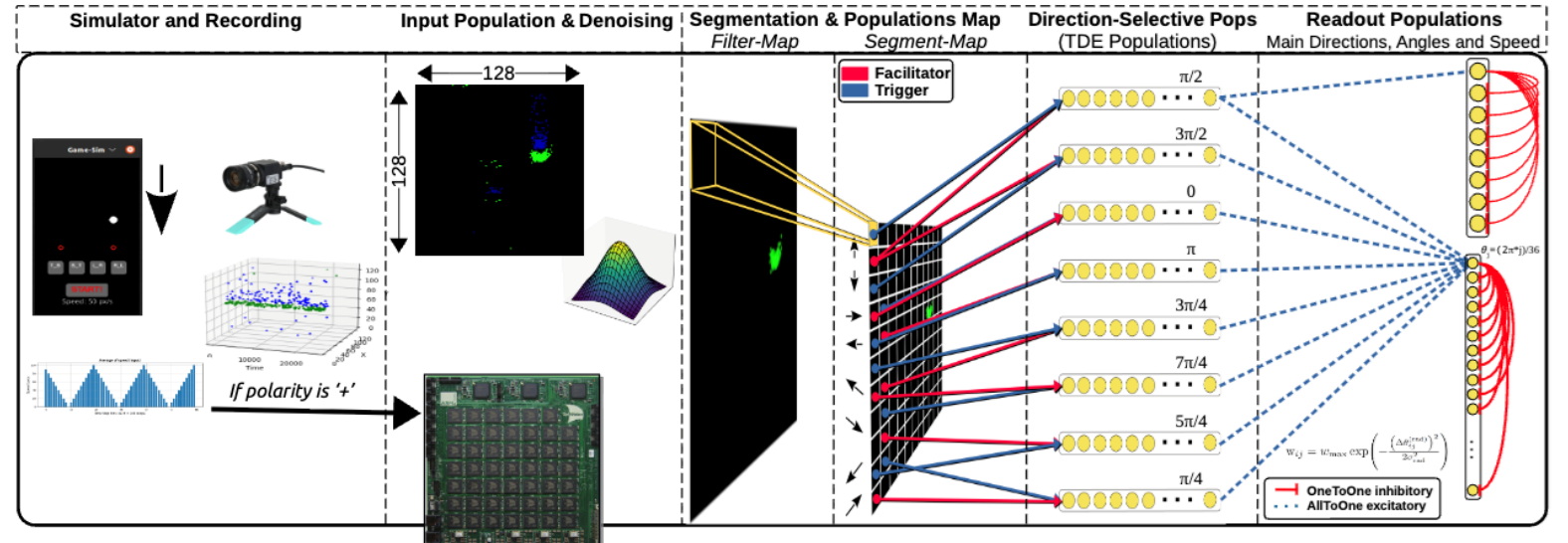
Table 4: Human baseline performance in the pinball game compared with the average game results.

Metric	Players										Min	Max	Avg	CLN*
	1	2	3	4	5	6	7	8	9	10				
Successful hits	28	34	50	49	33	40	127	112	62	48	28	127	58.3	64
Number of actions	321	56	317	422	197	88	436	394	384	206	56	436	282.1	114
Hit rate (%)	9.0	61.0	16.0	12.0	17.0	45.0	29.0	28.0	16.0	23.0	9.0	61.0	25.6	56.1
Miss rate (%)	91.0	39.0	84.0	88.0	83.0	55.0	71.0	72.0	84.0	77.0	39.0	91.0	74.4	43.9

* Closed-Loop Neuromorphic

Table 2: Upward direction detection accuracy for different receptive field sizes in the segmentation map and ΔT values, evaluated at a constant ball speed of 1000 px/s.

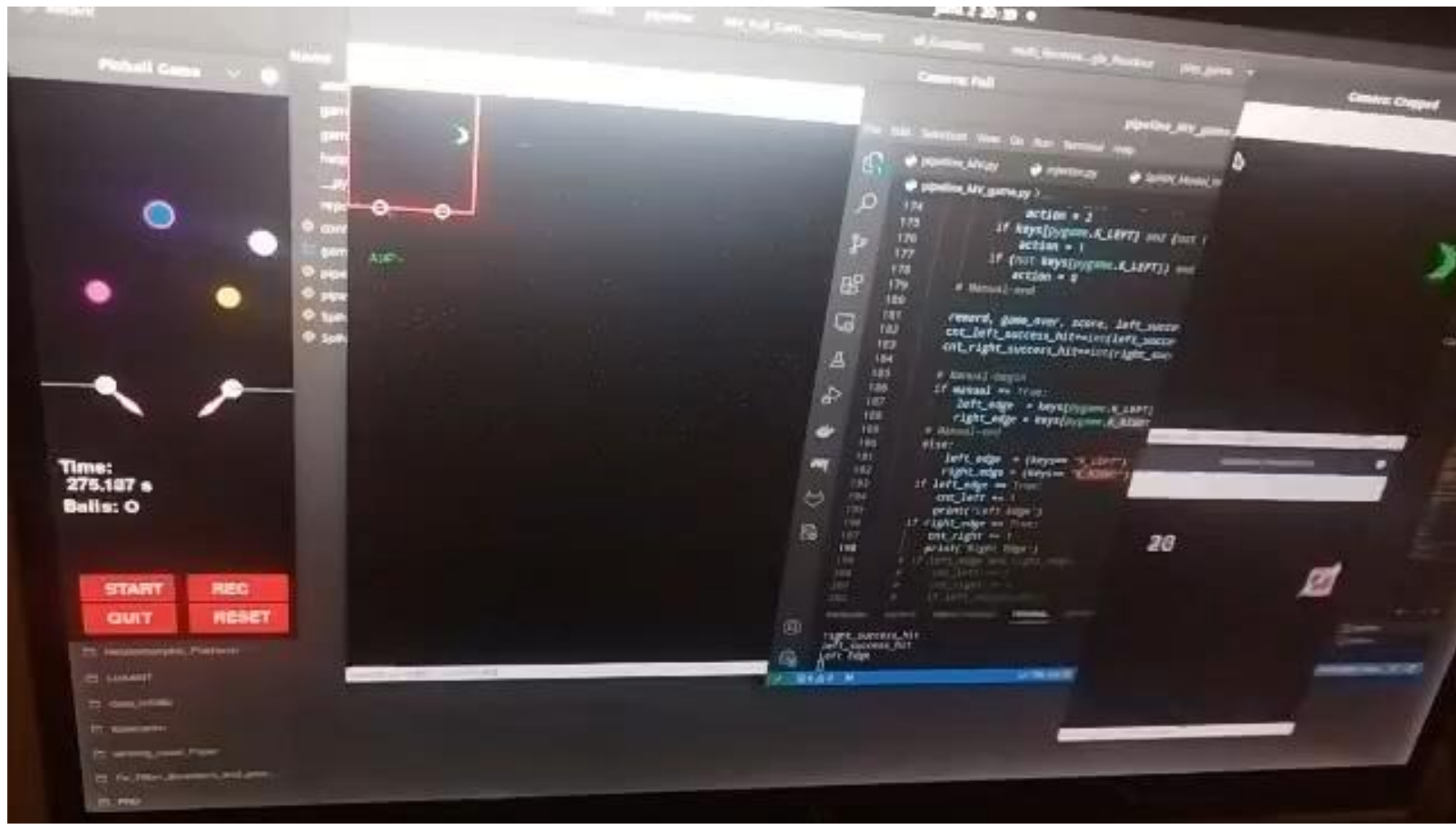
ΔT (ms)	Accuracy [%] (RF-size = 3x3)	Accuracy [%] (RF-size = 5x5)	Accuracy [%] (RF-size = 7x7)	Accuracy [%] (RF-size = 9x9)	Accuracy [%] (RF-size = 11x11)
16.7	96.15	92.31	90.38	86.54	63.46
33.4	93.10	93.10	93.10	89.66	75.86
50	100.00	95.00	95.00	85.00	75.00





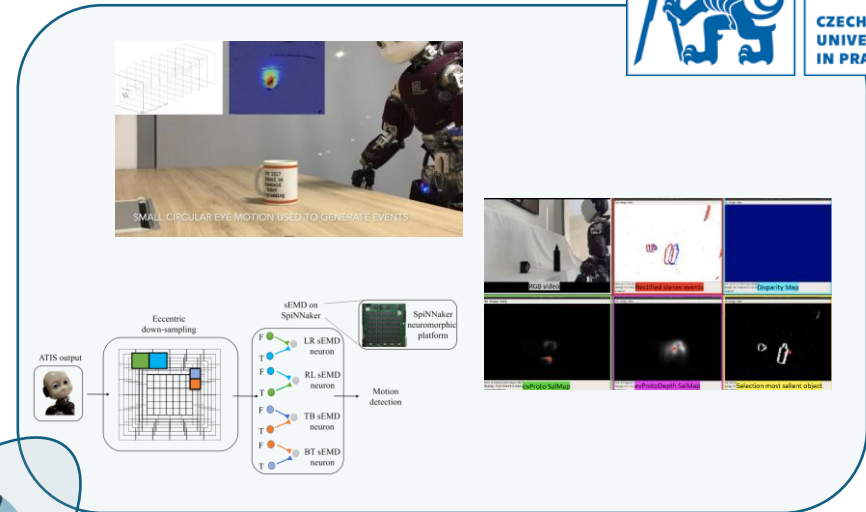
Can Spiking Neural Networks play pinball? A neuromorphic motion detector for target tracking

148 μ W

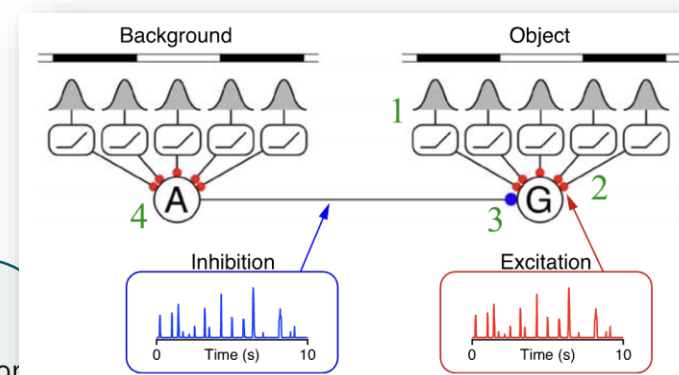
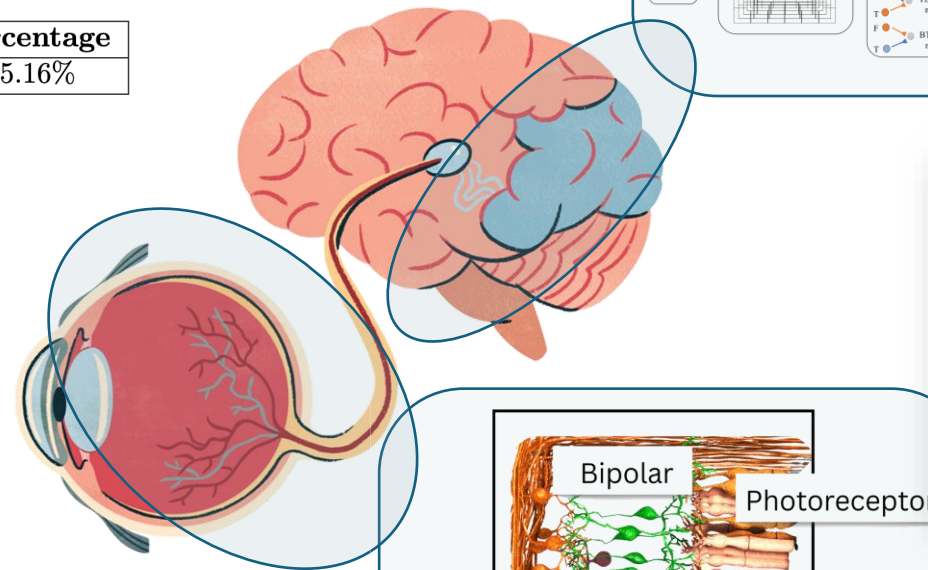


Université de Lille

Visual attention

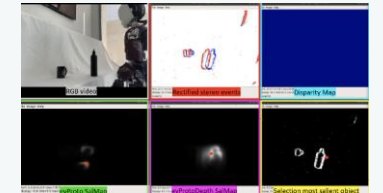
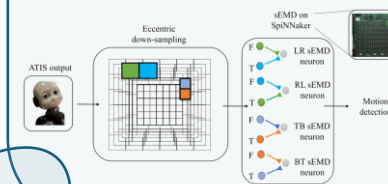


Trials	# Events	# sOMS Events	Percentage
10	14747.03 ± 2029.17	2189.15 ± 385.57	85.16%

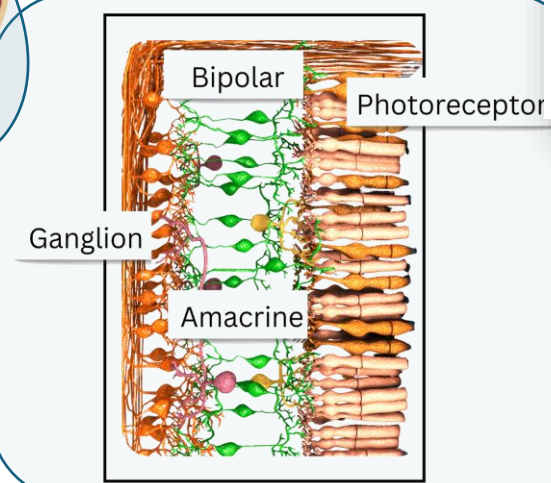
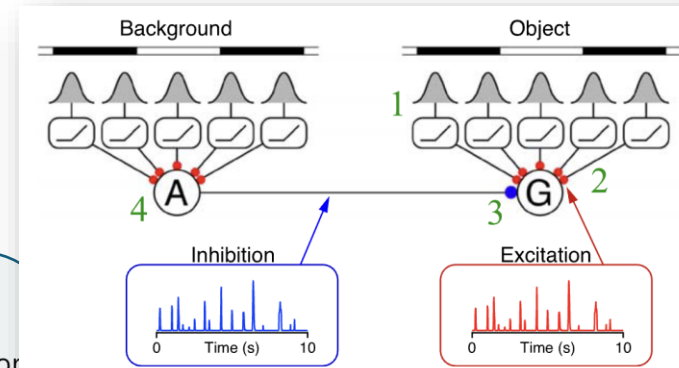
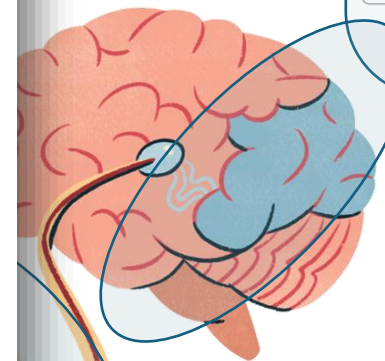


Baccus, S. A., Ölveczky, B. P., Manu, M., & Meister, M. (2008). A retinal circuit that computes object motion. *Journal of Neuroscience*, 28(27), 6807-6817.

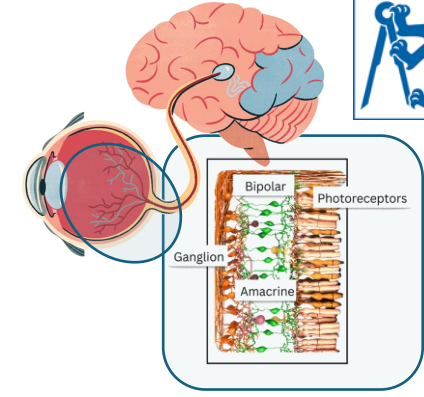
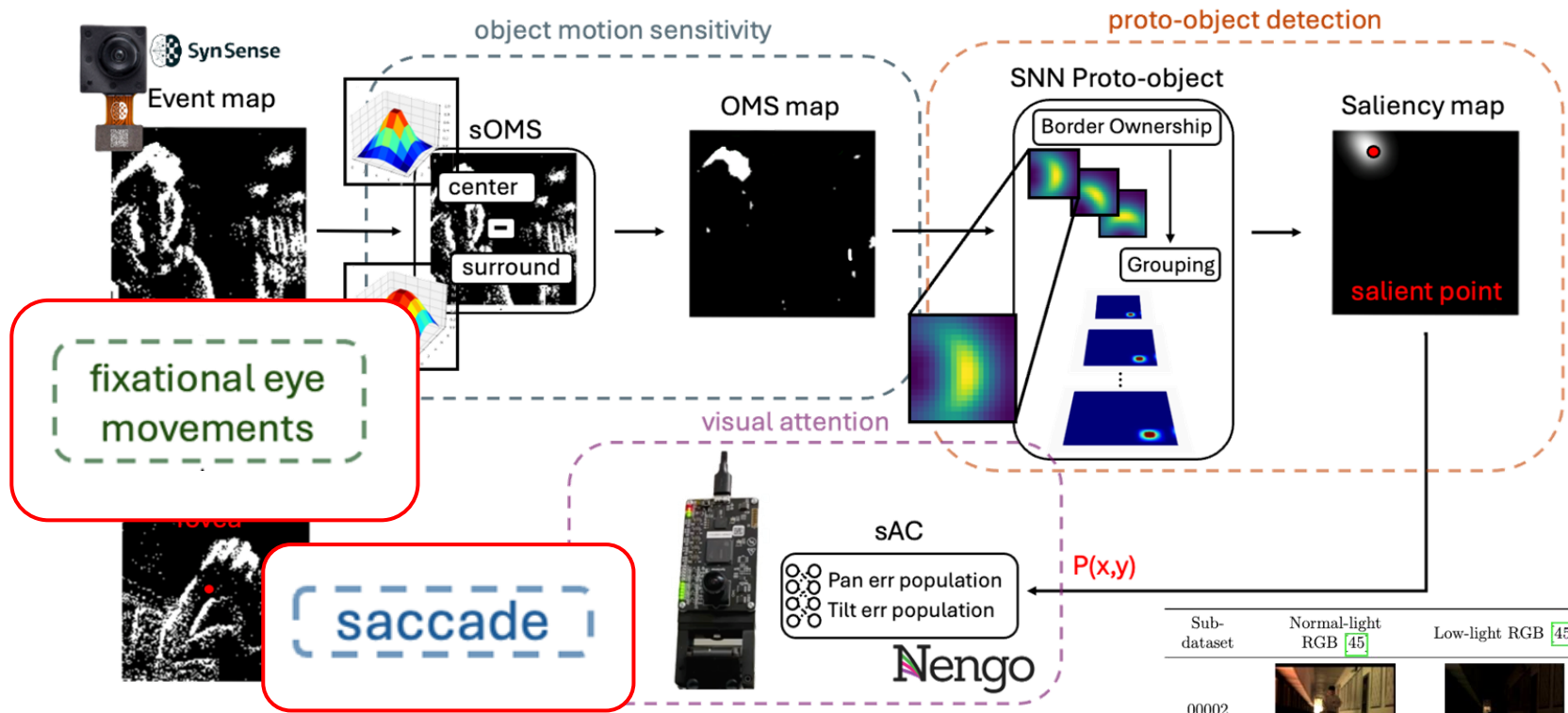
Visual attention



Sub-dataset	Event map ^[51]	Ground Truth ^[51]	OMS map	mean IoU % ^[12]	mean IoU %	mean SSIM %
Box				72 ± 16	64.79 ± 0.02	89 ± 0.08
Fast				69 ± 3	69.85 ± 0.15	90 ± 0.06
Floor				94	63.21 ± 0.22	94 ± 0.22
Table				88 ± 10	73.59 ± 0.22	89 ± 0.11
Tabletop				72 ± 14	82.24 ± 0.18	96 ± 0.06
Wall				82 ± 6	64.49 ± 0.07	84 ± 0.04



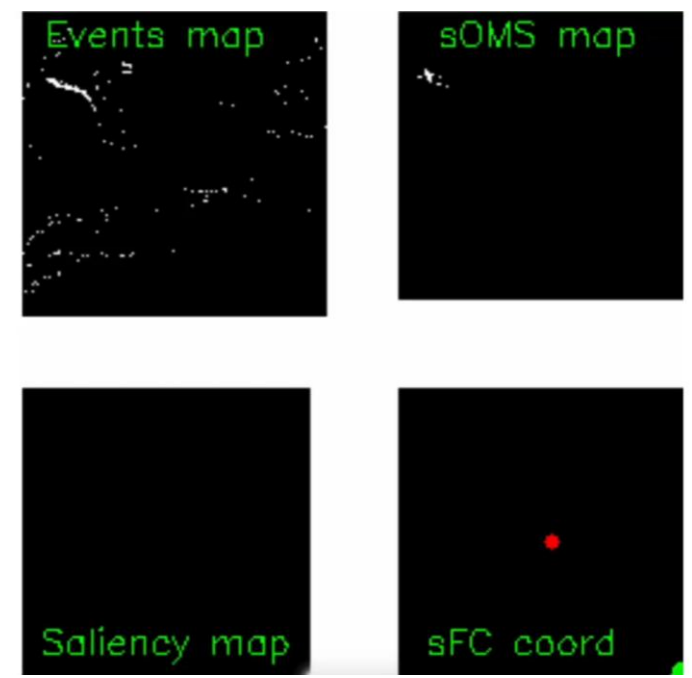
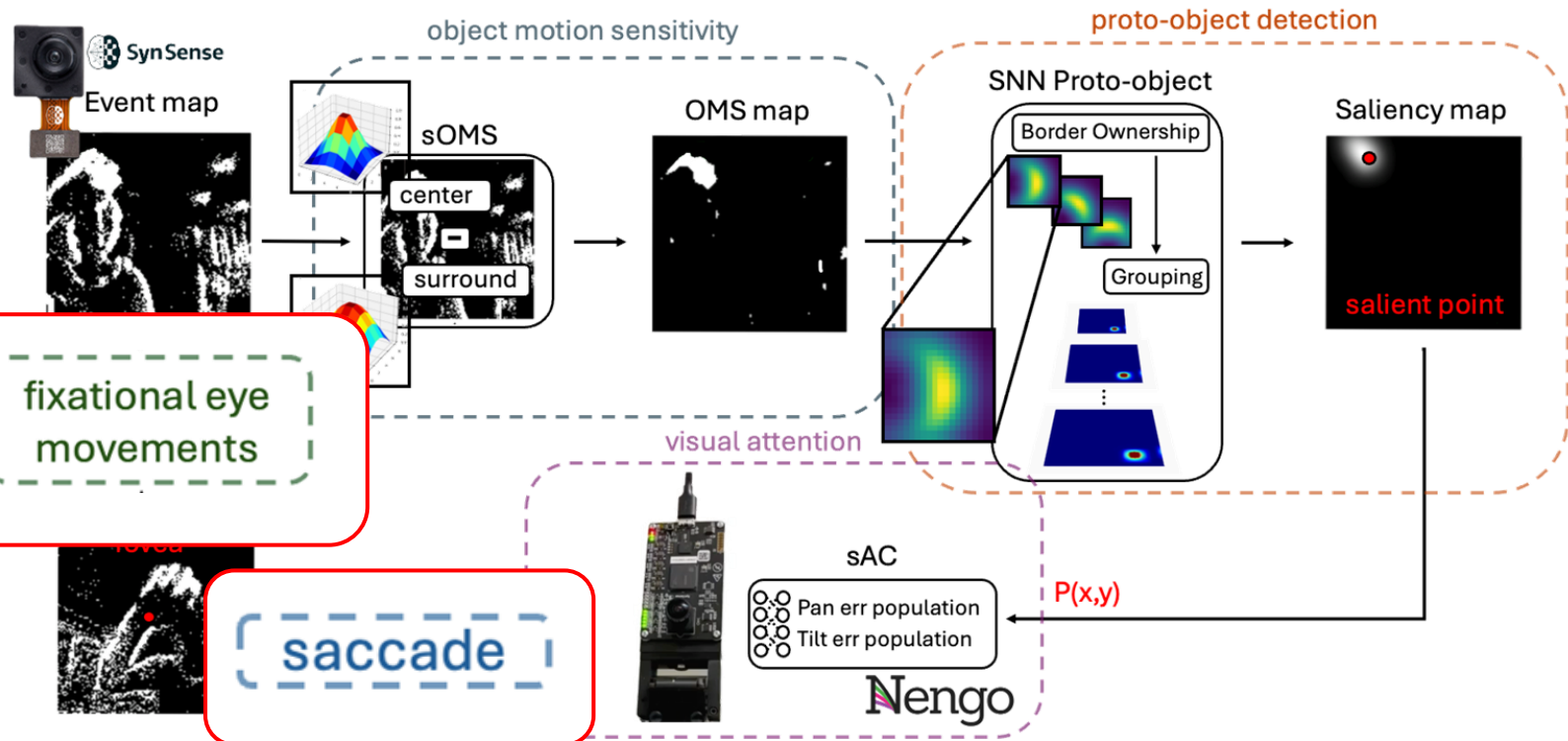
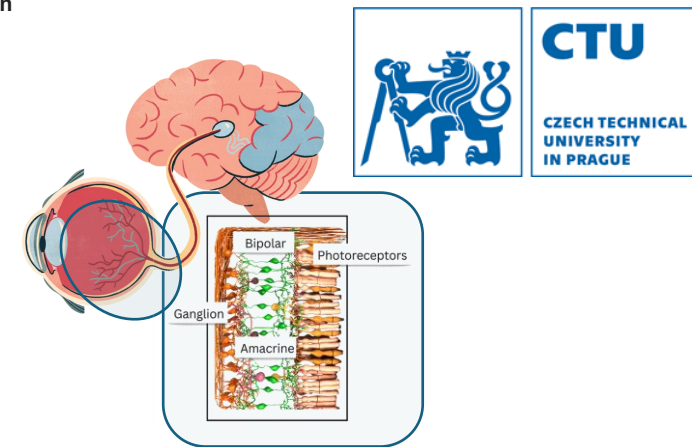
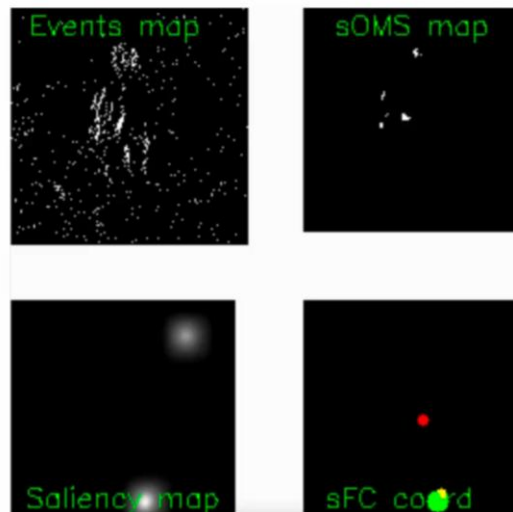
Baccus, S. A., Ölveczky, B. P., Manu, M., & Meister, M. (2008). A retinal circuit that computes object motion. *Journal of Neuroscience*, 28(27), 6807-6817.



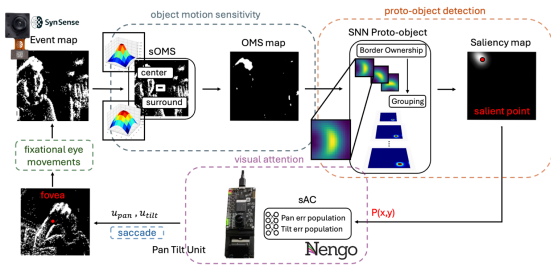
Embodiment refers to the concept of experiencing the world through a physical body or form.

Sub-dataset	Normal-light RGB [45]	Low-light RGB [45]	Event map [45]	Annotation [45]	OMS map	Saliency map	Accuracy %
00002							84.13
00011							89.88
00064							87.47
00033							72.96
00031							55.55
00025							47.84

~120 ms M2
 ~1 ms Speck
 << 1 W



Neuromorphic working in progress...

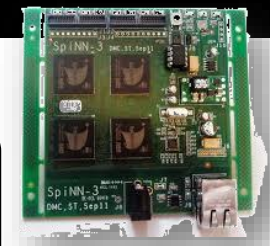
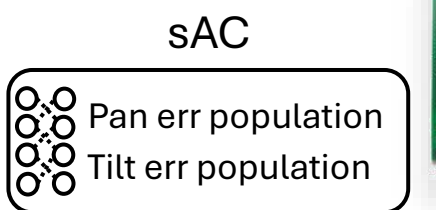
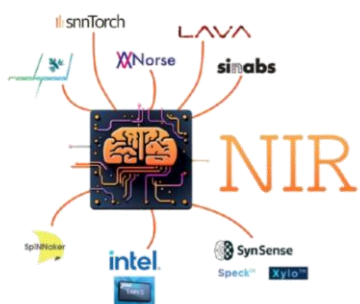


Attention System Overview

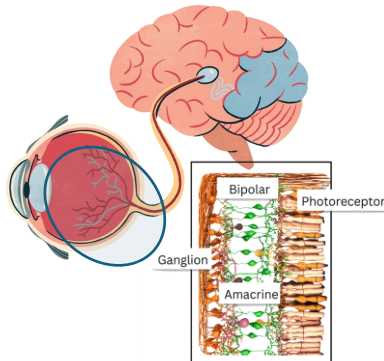
DVS Input

OMS Map

Attention Map

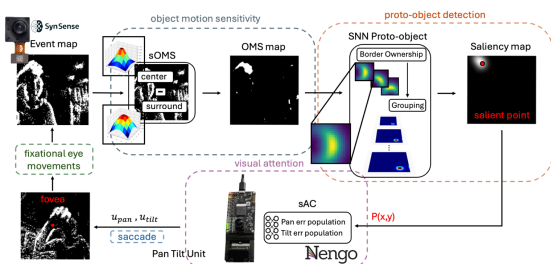


Nengo





JOHNS HOPKINS
UNIVERSITY

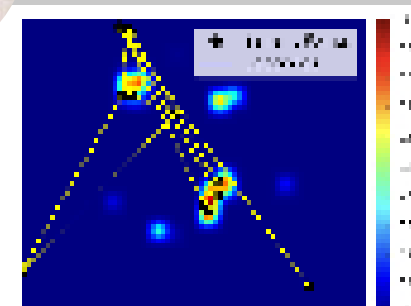
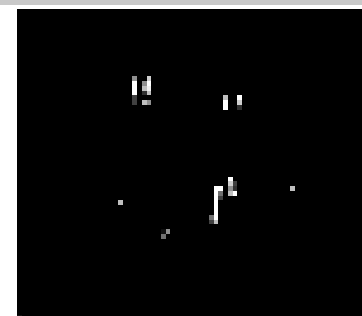


Event map

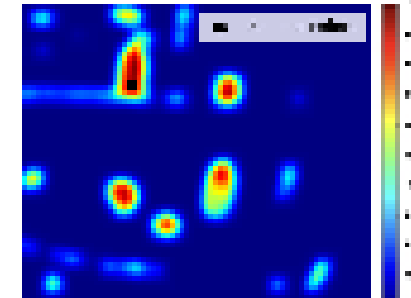
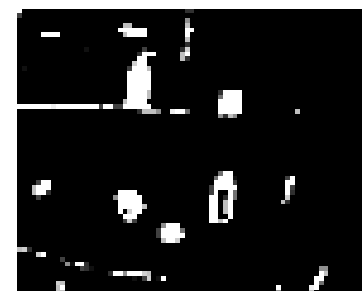
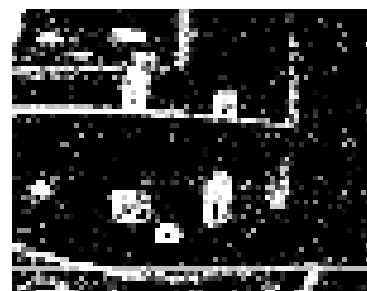
OMS map

Saliency map

Saccades:
 $t_{on} = 10 \text{ ms}$; $St_{on} = 124 \text{ ms}$



Fixational eye movements:
 $t_{on} = 124 \text{ ms}$; $St_{on} = 124 \text{ ms}$



Politecnico
di Torino



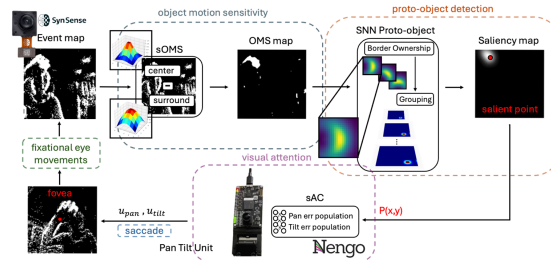
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OF SUSSEX



NEURO-INSPIRED
PERCEPTION &
COGNITION



Riccardo Pignari
PhD student - visiting 2025
Politecnico di Torino
SNNs visual attention & motion detection

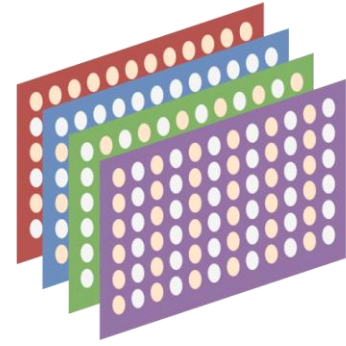
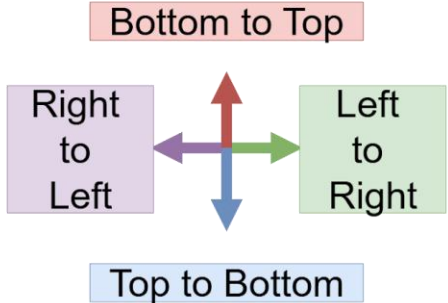
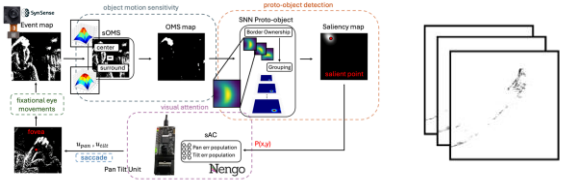




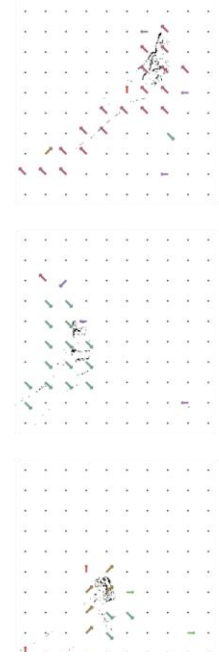
Motion direction detection through object motion segmentation



sOMS Map

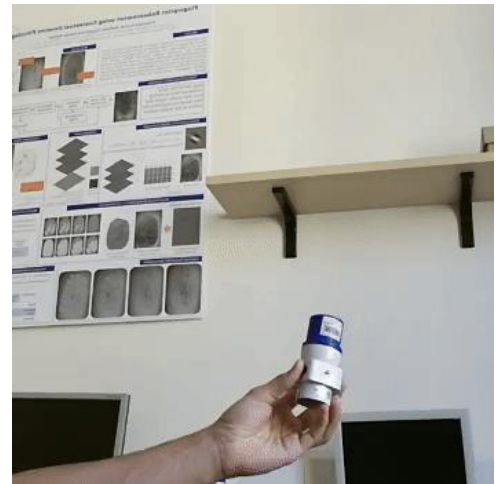


Facilitator (grey dot)
Trigger (orange dot)

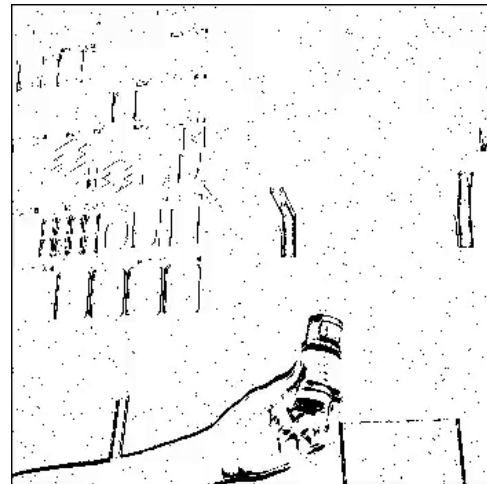


SEMD Direction Map

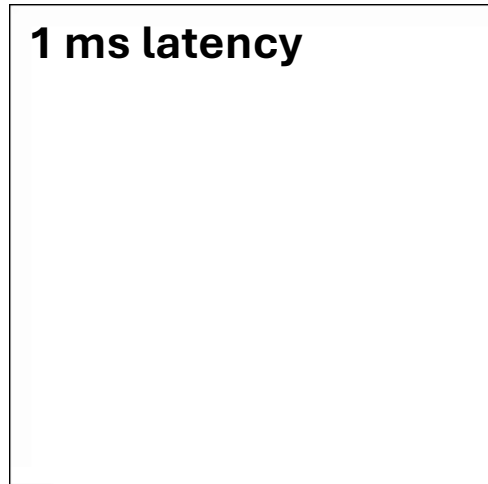
Video RGB



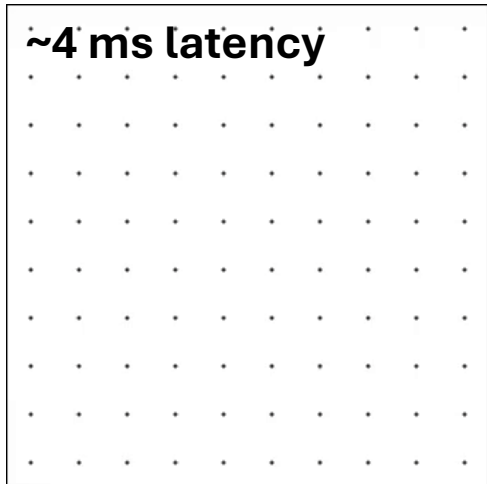
Event-camera



spiking OMS



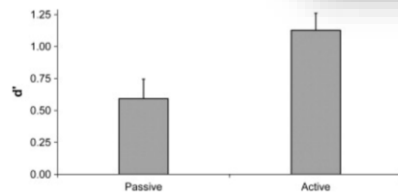
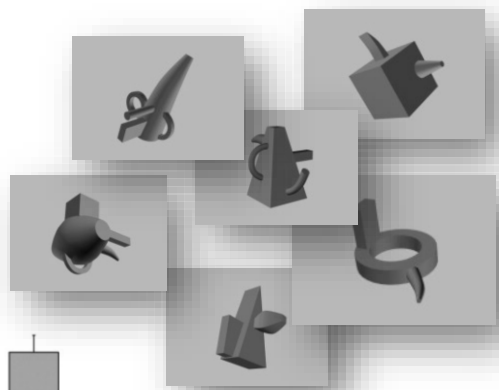
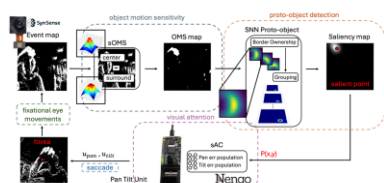
spiking EMD



“Often you do not need to store a complete internal model of the world”

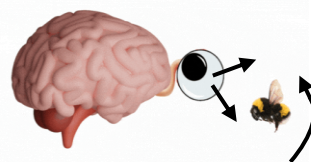
Ballard, Dana H., et al. "Deictic codes for the embodiment of cognition." *Behavioral and brain sciences* 20.4 (1997): 723-742.

We use the world as a kind of external memory



Meijer, Frank, and Rob HJ Van der Lubbe. "Active exploration improves perceptual sensitivity for virtual 3D objects in visual recognition tasks." *Vision Research* 51.23-24 (2011): 2431-2439.

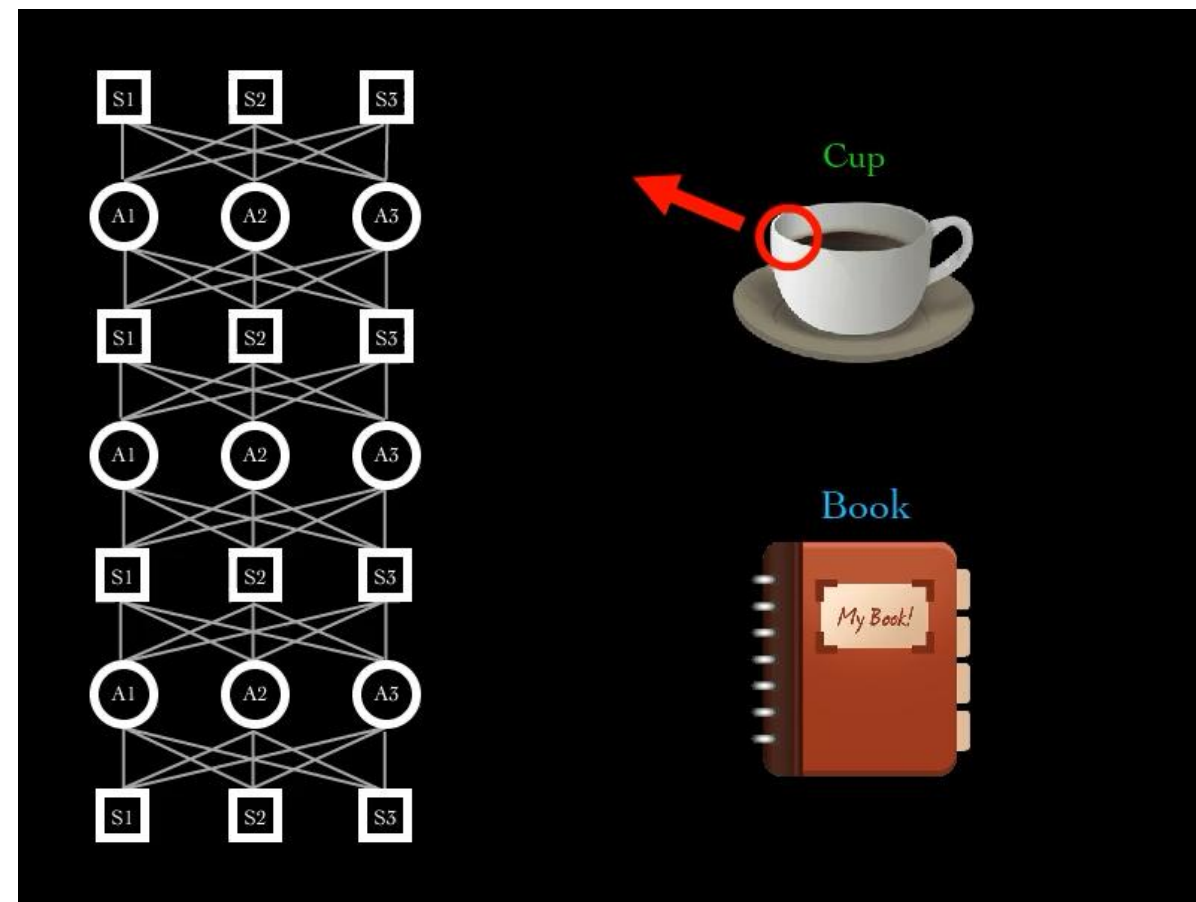
sensorimotor view



O'regan, J. Kevin, and Alva Noë. "A sensorimotor account of vision and visual consciousness." *Behavioral and brain sciences* 24.5 (2001): 939-973.

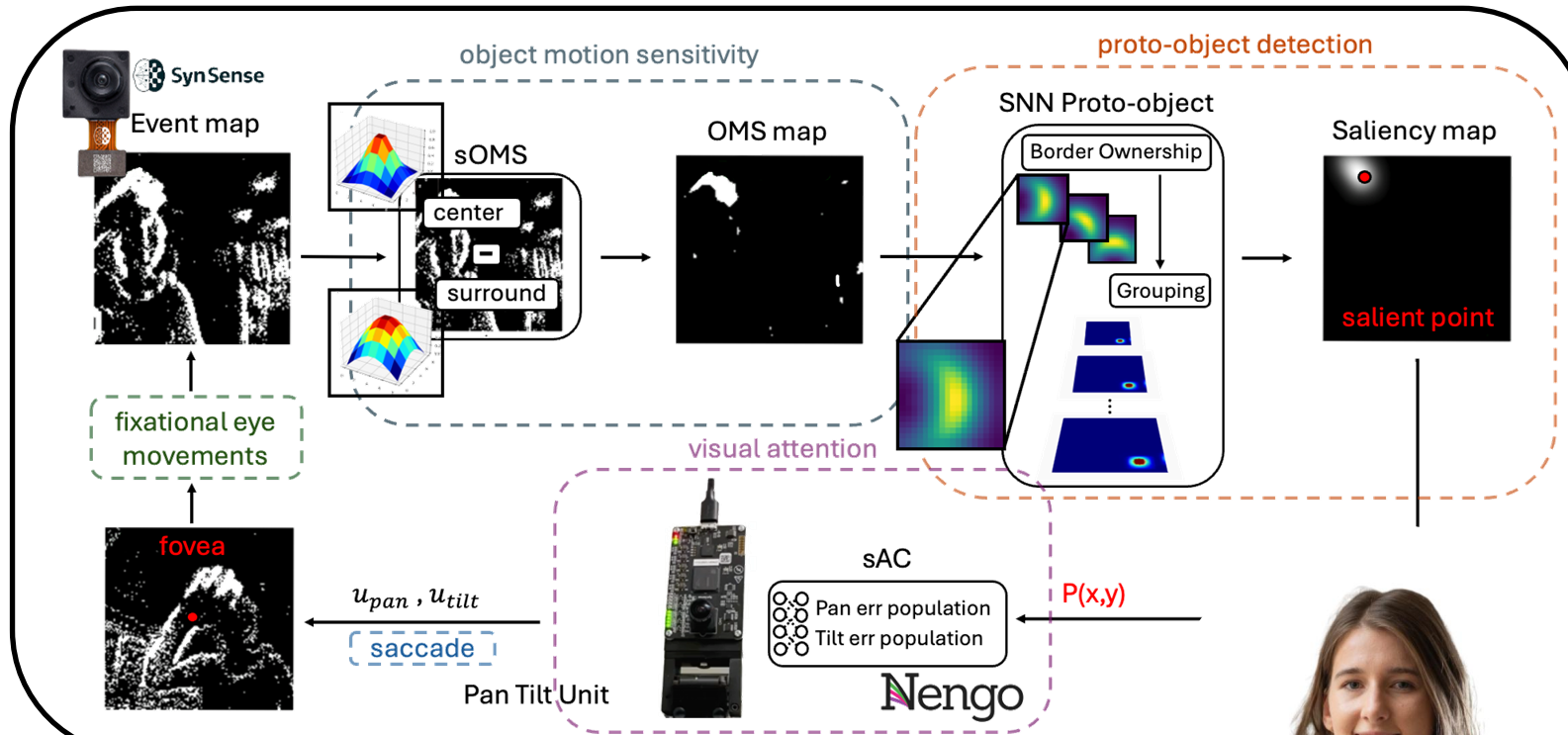


McQuillan, Maureen E., et al. "Parents influence the visual learning environment through children's manual actions." *Child development* 91.3 (2020): e701-e720.

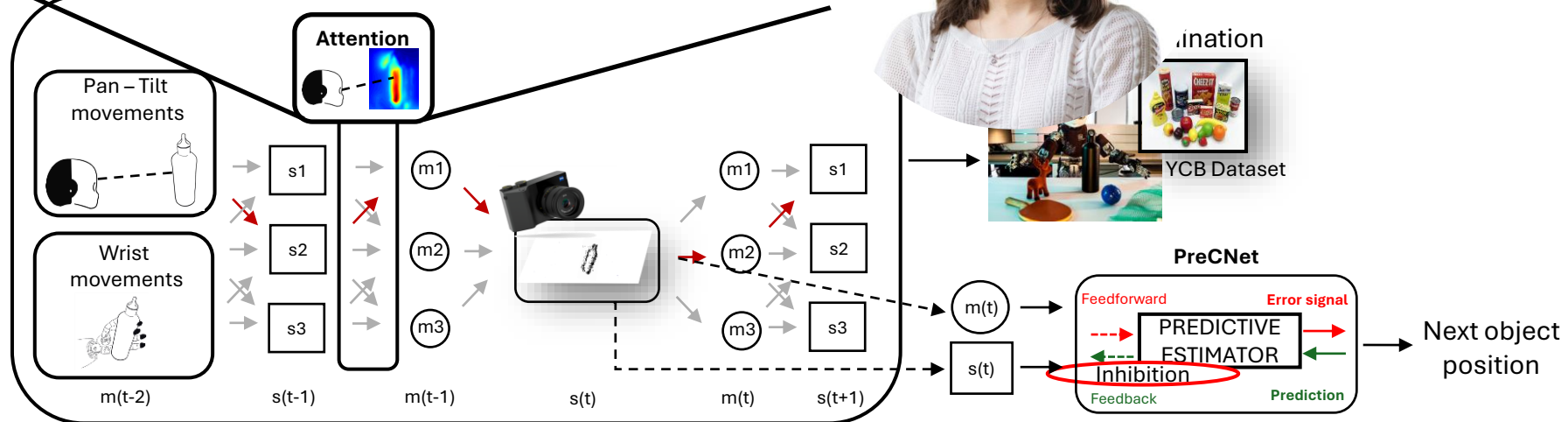
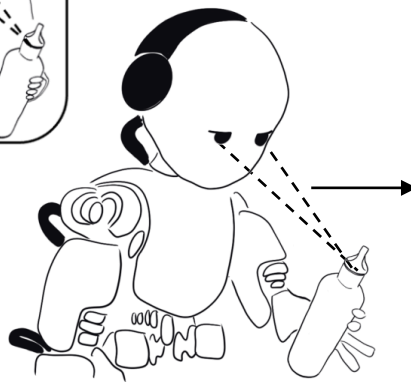


Engel, Andreas K., et al. *Trends in cognitive sciences* 17.5 (2013): 202-209.
Maye, Alexander, and Andreas K. Engel. *IEEE International Conference on Robotics and Automation*. IEEE, 2011.

Attention



Sensorimotor Contingencies (SMCT) for object percep

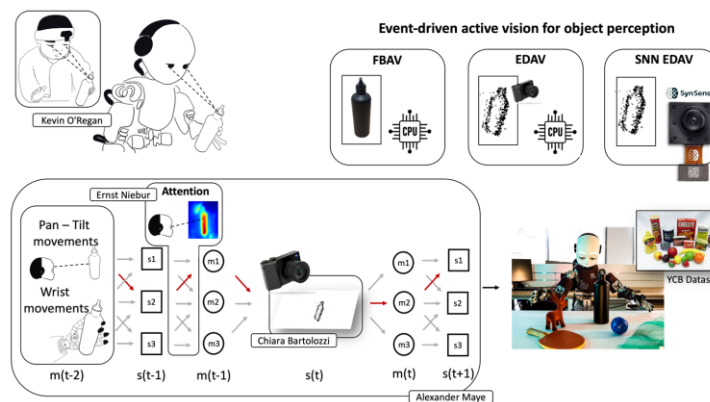




NEURO-INSPIRED
PERCEPTION &
COGNITION

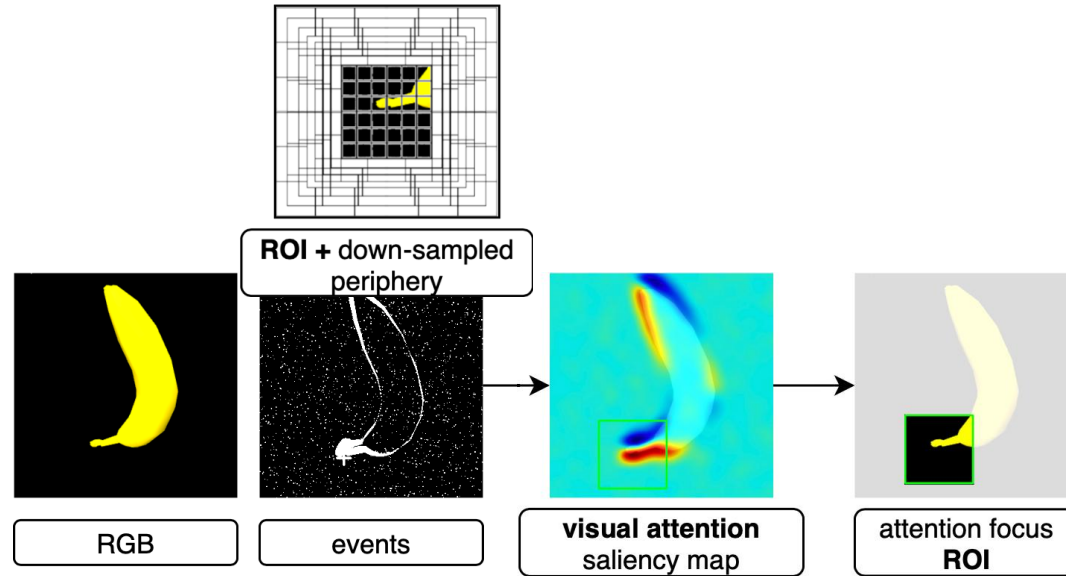


Šárka Lísková
PhD student
Czech Technical University in Prague
Computational Physics working on SNN for object learning



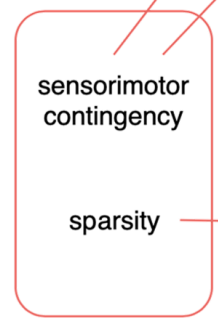
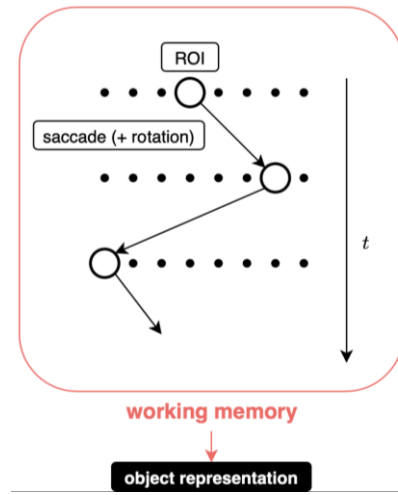
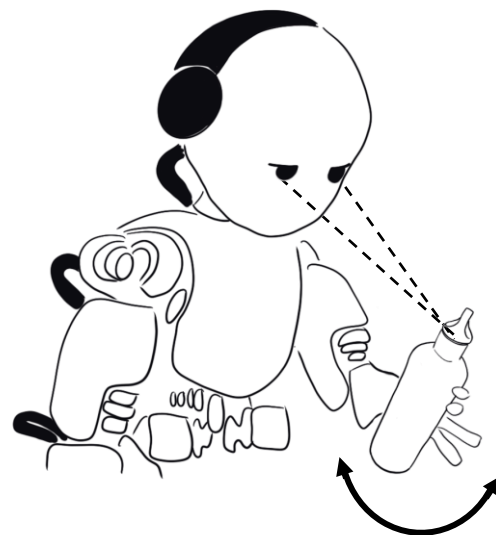


Bioinspired active vision: learning through exploration

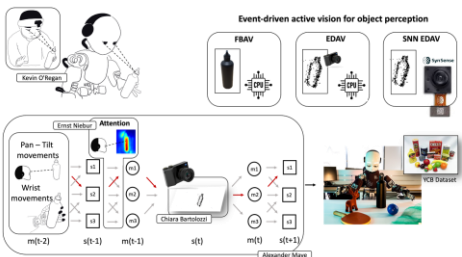


Vector Symbolic Algebra (VSA)

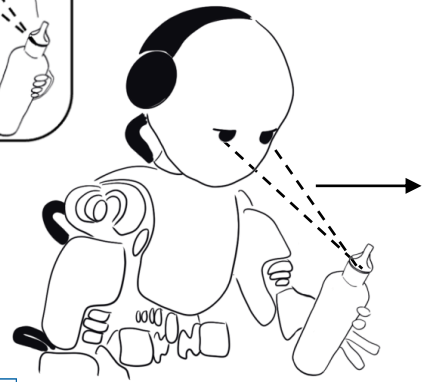
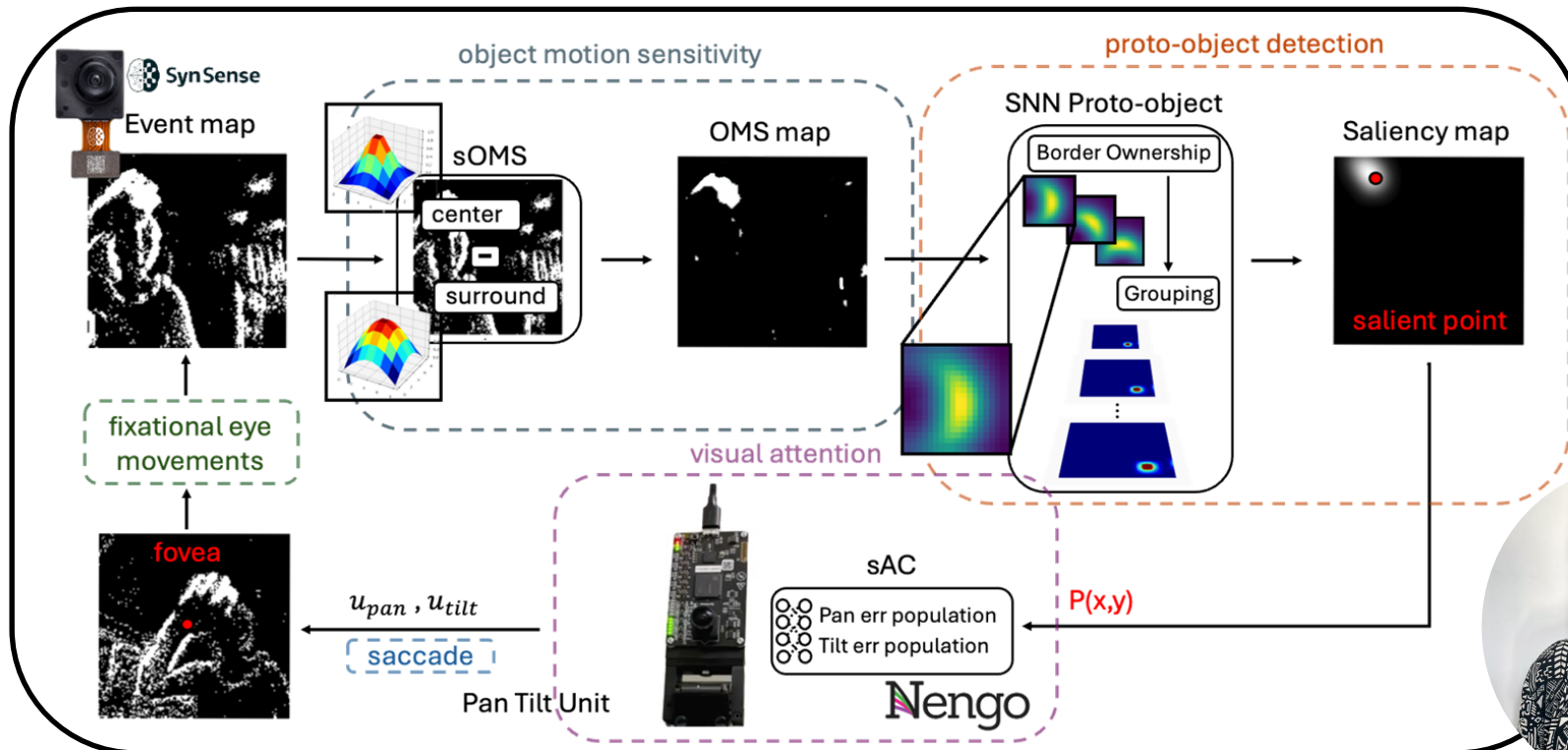
Contrastive Learning through Time



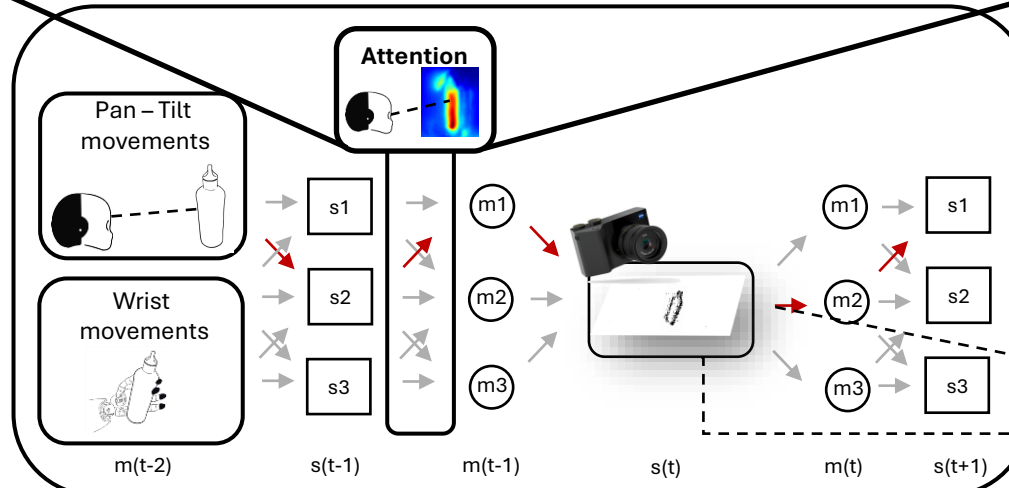
Masked Autoencoders: working memory reconstruction



Attention



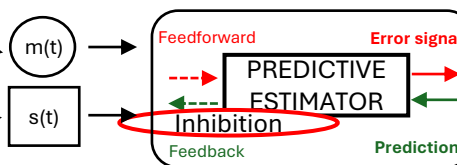
Sensorimotor Contingencies (SMCT) for object perception



Object discrimination



PreCNet



Next object position



**NEURO-INSPIRED
PERCEPTION &
COGNITION**

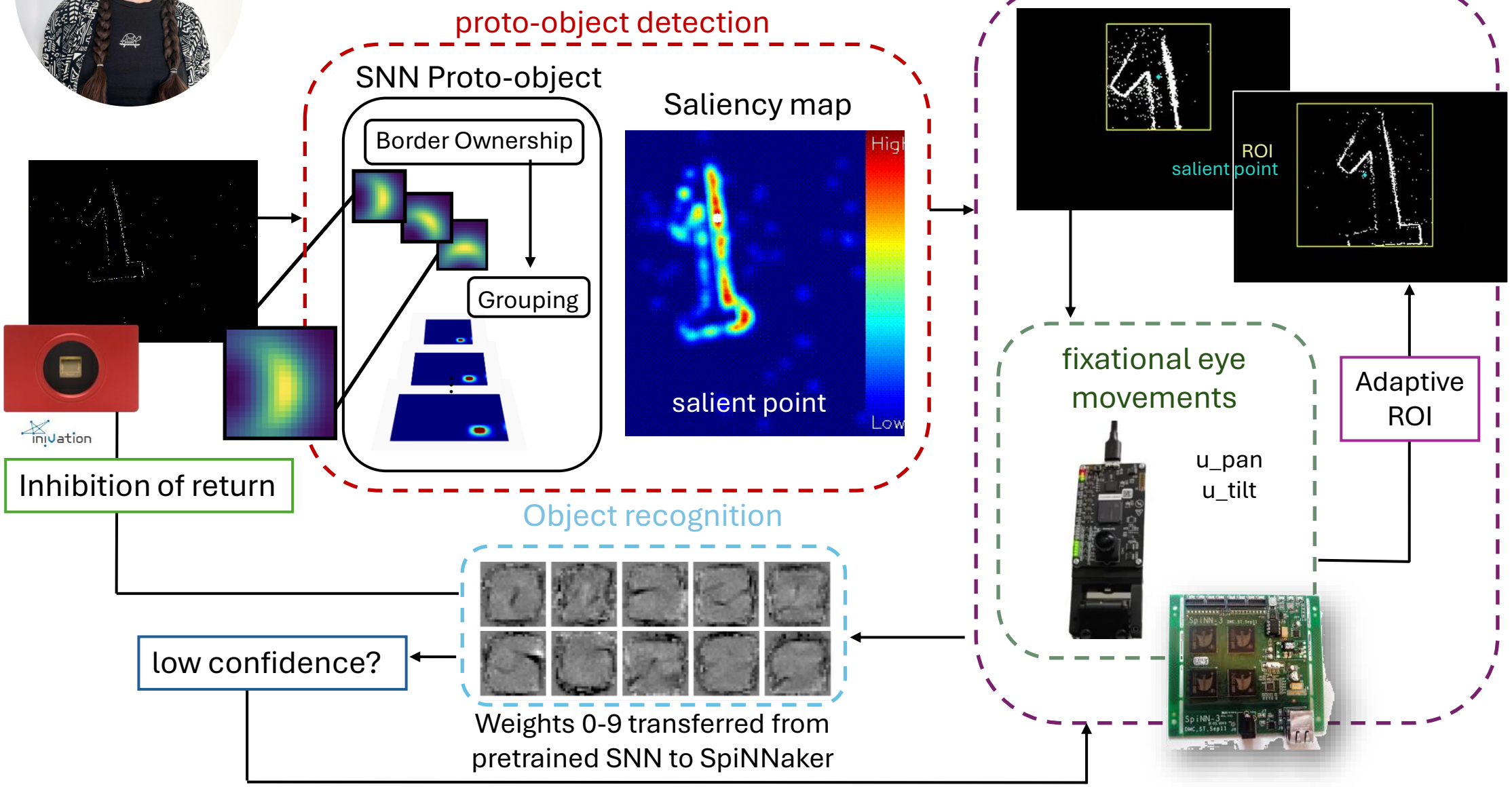


Olha Vedmedenko
Bachelor student
Faculty of Information Technology at CTU
SNNs on the SpiNNaker neuromorphic platform





Neuromorphic active object recognition



Neuromorphic active object recognition



Neuromorphic visual attention for Sign-language recognition on SpiNNaker

Šárka Lísková^{1*}, Olha Vedmedenko^{2*}, Mazdak Fatahi², Matej Hoffmann¹, P. Michael Furlong³, and Giulia D'Angelo¹

¹Dept. of Cybernetics, Faculty of Electrical Engineering, Czech Technical University in Prague, Czech Republic

²Faculty of Information Technology, Czech Technical University in Prague, Czech Republic

³Université de Lille, CNRS, Centrale Lille, UMR 9189 CRISTAL, F-59000 Lille, France

*National Research Council of Canada & Systems Design Engineering, University of Waterloo, Canada

Platform	Accuracy SL-MNIST		Accuracy ASL-DVS
	35 ms	100 ms	35 ms
Mac (simulation)	74.61%	83.82%	92.27%
SpiNNaker	-	71.7%	83.1%

Layer	SL-MNIST Avg Spikes	ASL-DVS Avg Spikes
Conv (L1)	719.31	720.95
Hidden (L2)	2235.82	1681.92
Output (L3)	156.35	73.09
Total	3111.48	2475.96
Energy consumption	≈ 24891.84 nJ	≈ 19807.68 nJ
Power consumption	≈ 0.711 mW	≈ 0.565 mW

Sign-language recognition has achieved substantial classification accuracy in recent years; however, the high power requirements of most existing methods limit their suitability for real-time deployment. Neuromorphic sensing and processing offer an alternative paradigm based on sparse computation that supports low-latency and energy-efficient processing.

In this work, we introduce an end-to-end neuromorphic architecture for American Sign Language (ASL) fingerspelling recognition. The proposed system integrates a spiking visual attention mechanism for region-of-interest extraction with a compact spiking neural network deployed on the SpiNNaker neuromorphic platform. We benchmark the proposed system against two datasets: a simulated event-based version of the Sign Language and a natively recorded ASL-DVS dataset, whilst providing a comprehensive overview of sign-language recognition on neuromorphic hardware.

This work yields competitive performance in simulation (92.27%) and comparable performance on neuromorphic hardware deployment (83.1%), while achieving the most energy-efficient architecture (0.565 mW) and low latency (3 ms) across all tested approaches. Despite its compact design, the system maintains the suitability of task-dependent visual attention for edge deployment.

Visual attention, active object recognition, Sign-language recognition, event-based sensing, and neuromorphic computing.

I. INTRODUCTION

Sign language and gestures, including Sign-language, play an important role in human communication, particularly for deaf and hard-of-hearing users. Recent literature focuses primarily on accuracy of Sign-language recognition [1]; however, for interaction to be effective and reactive, gesture-recognition systems must achieve low latency, low power consumption, and high robustness to environmental variability. For smooth

deployment on robotic platforms or wearable devices.

In humans, visual attention mechanisms enable selective processing of task-relevant regions of interest (ROIs), focusing perceptual resources toward salient scene elements while filtering irrelevant information [4]. This offers a bio-inspired strategy for achieving both efficiency and responsiveness. By contrast, modern, data-driven systems [5] that process the entire visual field uniformly allocate computational resources to non-informative regions of the scene, compromising both efficiency and robustness.

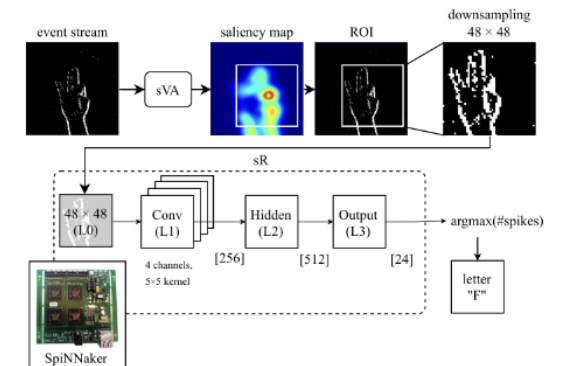
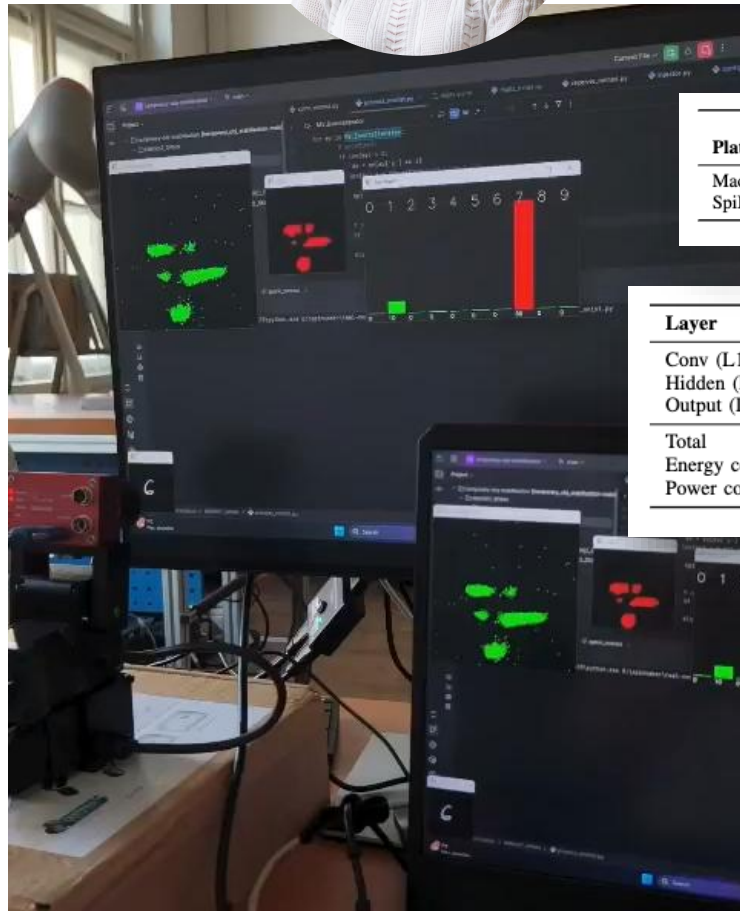
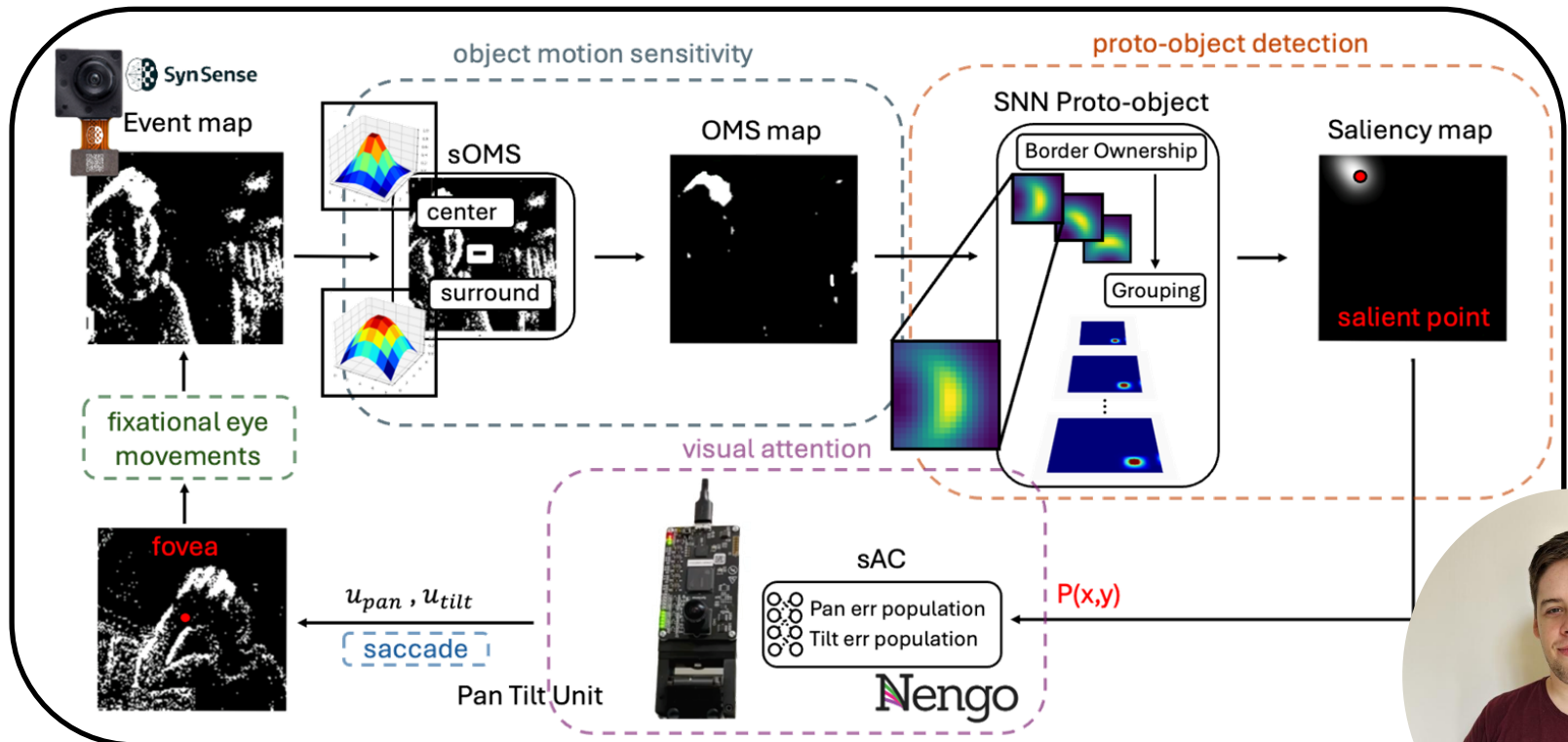


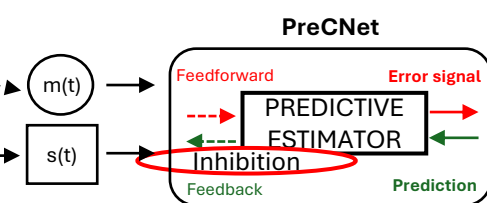
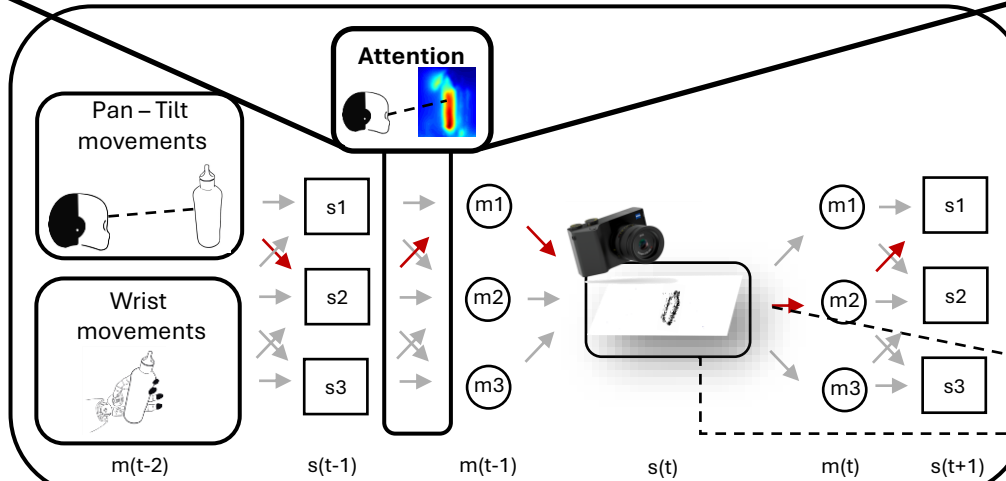
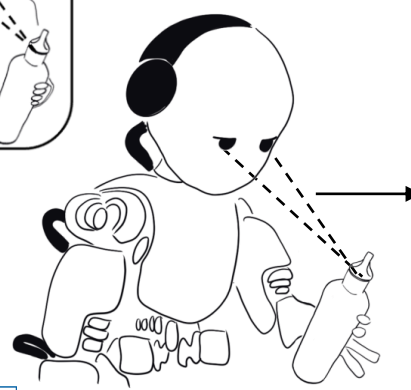
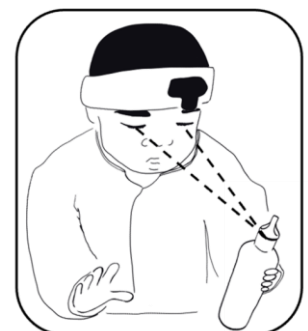
Fig. 1. **Neuromorphic Sign language recognition architecture:** Event streams are processed through the spiking visual attention (sVA) model to extract salient regions (ROIs), which are then downsampled and fed into the recognition network (sR) deployed on SpiNNaker. The network architecture comprises convolutional (L1, 256 neurons, 4 channels, 5 × 5 kernel), hidden (L2, 512 neurons), and output (L3, 24 output neurons) layers.



Attention



Sensorimotor Contingencies (SMCT) for object perception





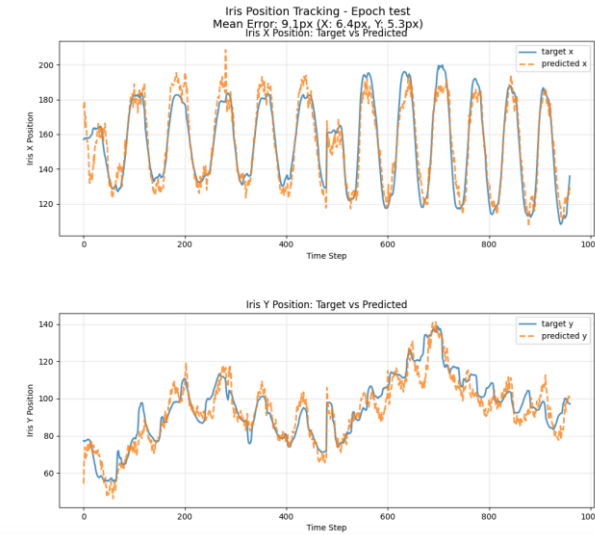
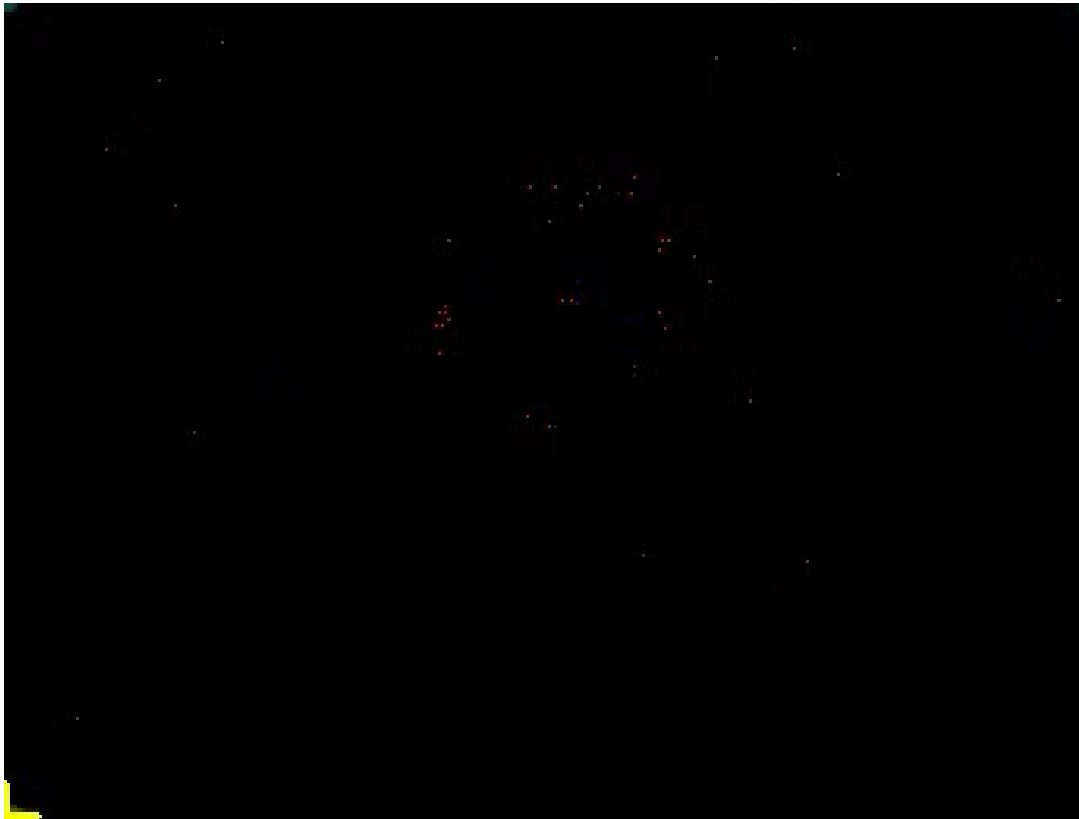
**NEURO-INSPIRED
PERCEPTION &
COGNITION**



Lukáš Bartůněk
Master student
Czech Technical University in Prague
SNN solutions for eye blinking detection and classification



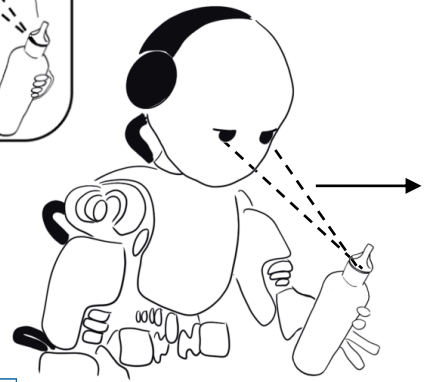
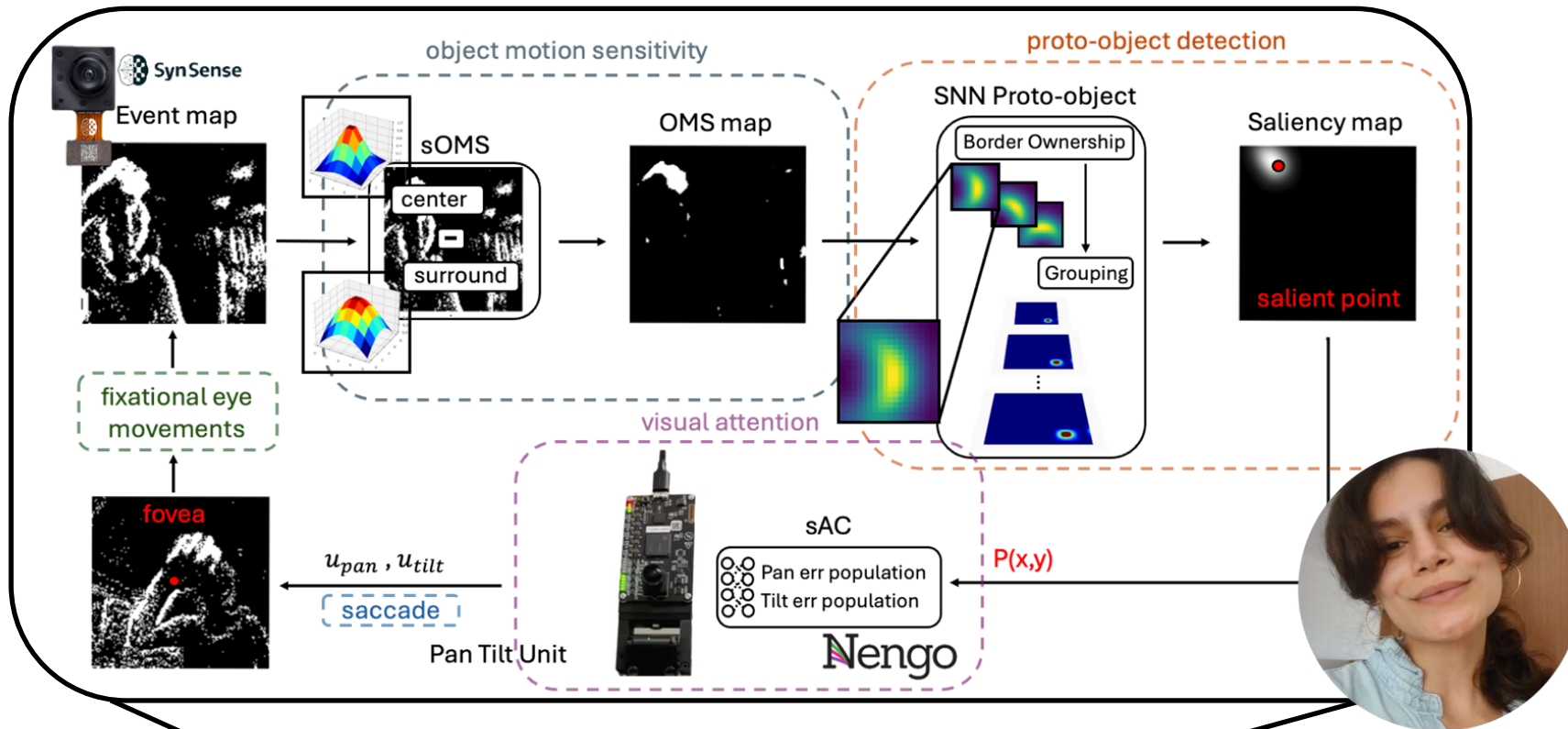
Event-based eye blinking and eye tracking



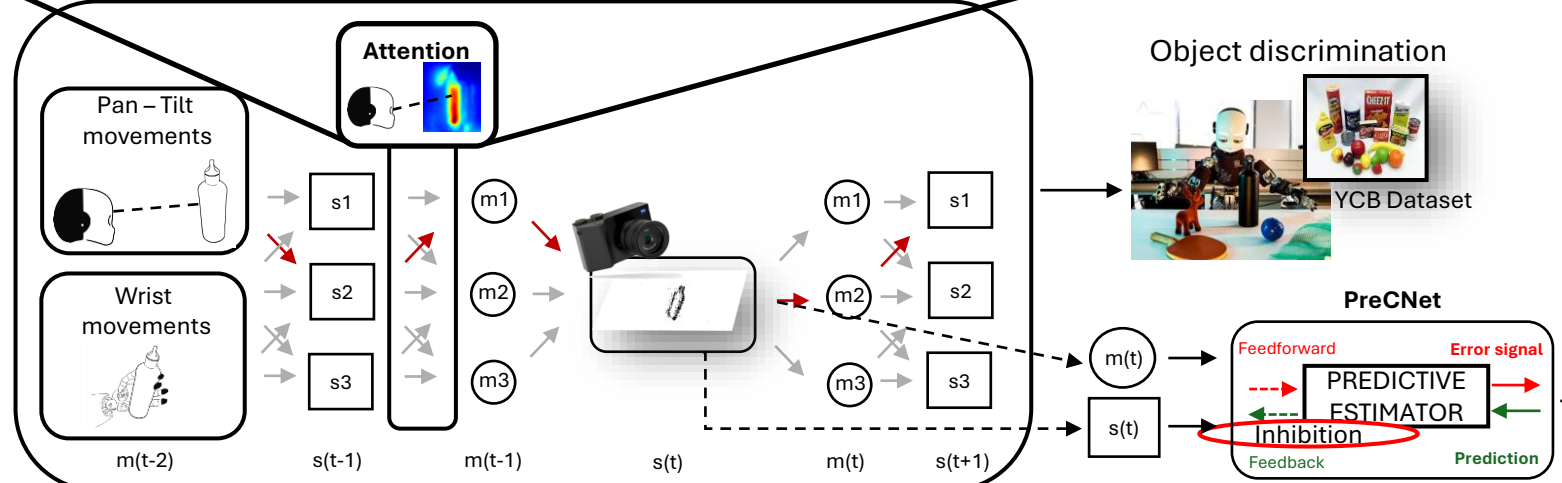
Model	Paradigm	Params	Window	Error (640×480)	NME (%)
<i>Non-Causal / Offline</i>					
MambaPupil [9]	Dense ANN	8.59M	10 ms	~1.60 px	0.20
E-SpikePT [13]	Hybrid SNN+ANN	N/A	10 ms	1.56 px	0.19
<i>Causal / Real-Time</i>					
3ET ConvLSTM [10]	Dense ANN	417K	10 ms	~17.60 px	2.20
JaneEye [11]	Light ANN	17.6K	10 ms	19.60 px	2.45
<i>Neuromorphic SNNs (Causal)</i>					
Ours (Valid / No Blinks)	HTC SNN	49.3K	3 ms	24.06 px	3.01
Ours (All Frames)	HTC SNN	49.3K	3 ms	25.34 px	3.16
Retina [12]	LIF SNN	63K	10 ms	28.64 px	3.58
AIS SNN Conversions [14]	LIF SNN	107K	10 ms	32.64 px	4.08

Table 6.1: Quantitative comparison of eye-tracking architectures. Temporal Resolution indicates the event integration window. Errors are reported as Mean Euclidean Distance scaled to the 640×480 sensor and Normalized Mean Error (NME).

Attention



Sensorimotor Contingencies (SMCT) for object perception





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PERCEPTION &
COGNITION



Rayane Rocha
Bachelor student - visiting 2026
Universidade Federal da Paraíba (UFPB)
SNNs language-based visual attention



ROBOPROX WOMEN FORUM
To bring more women to robotics.

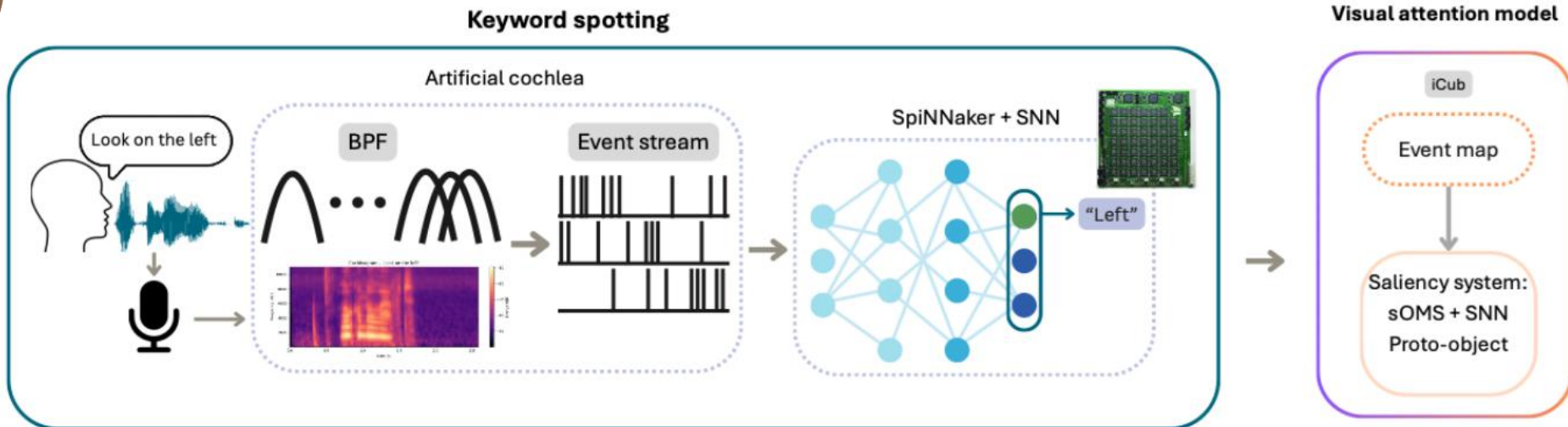
"This innovative bio-inspired approach to robotics lies in its ability to bridge neuromorphic software and hardware, enabling low latency, and multimodal visual attention with minimal power consumption on a neuromorphic platform."

Rayane Rocha
UFPB Brazil

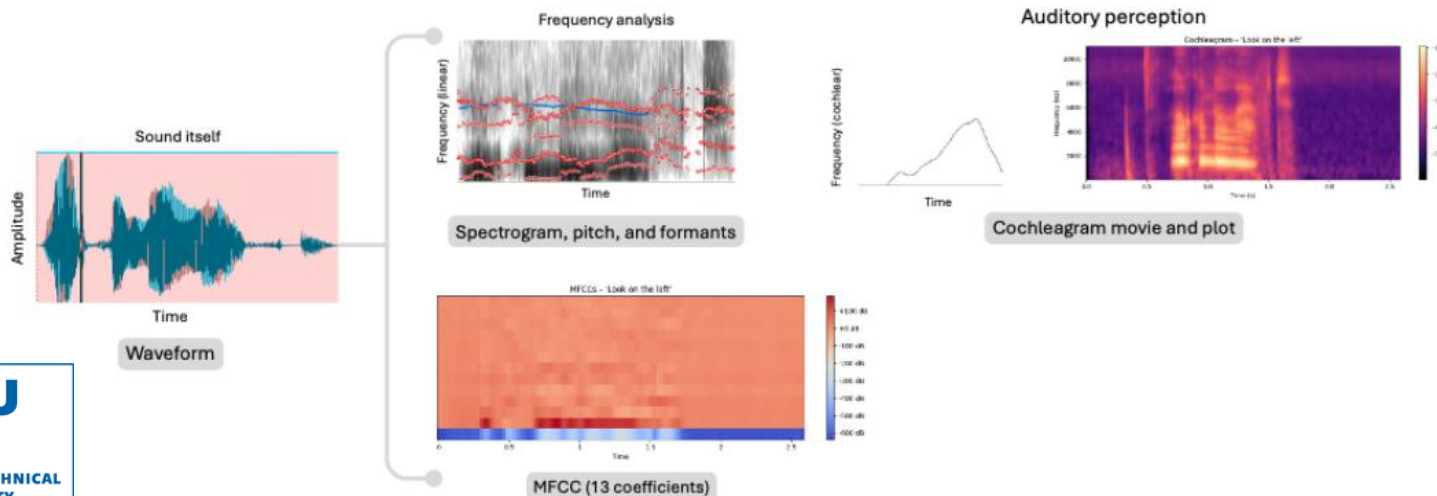
Co-funded by the European Union



Talk to look: visual attention influenced by spoken commands



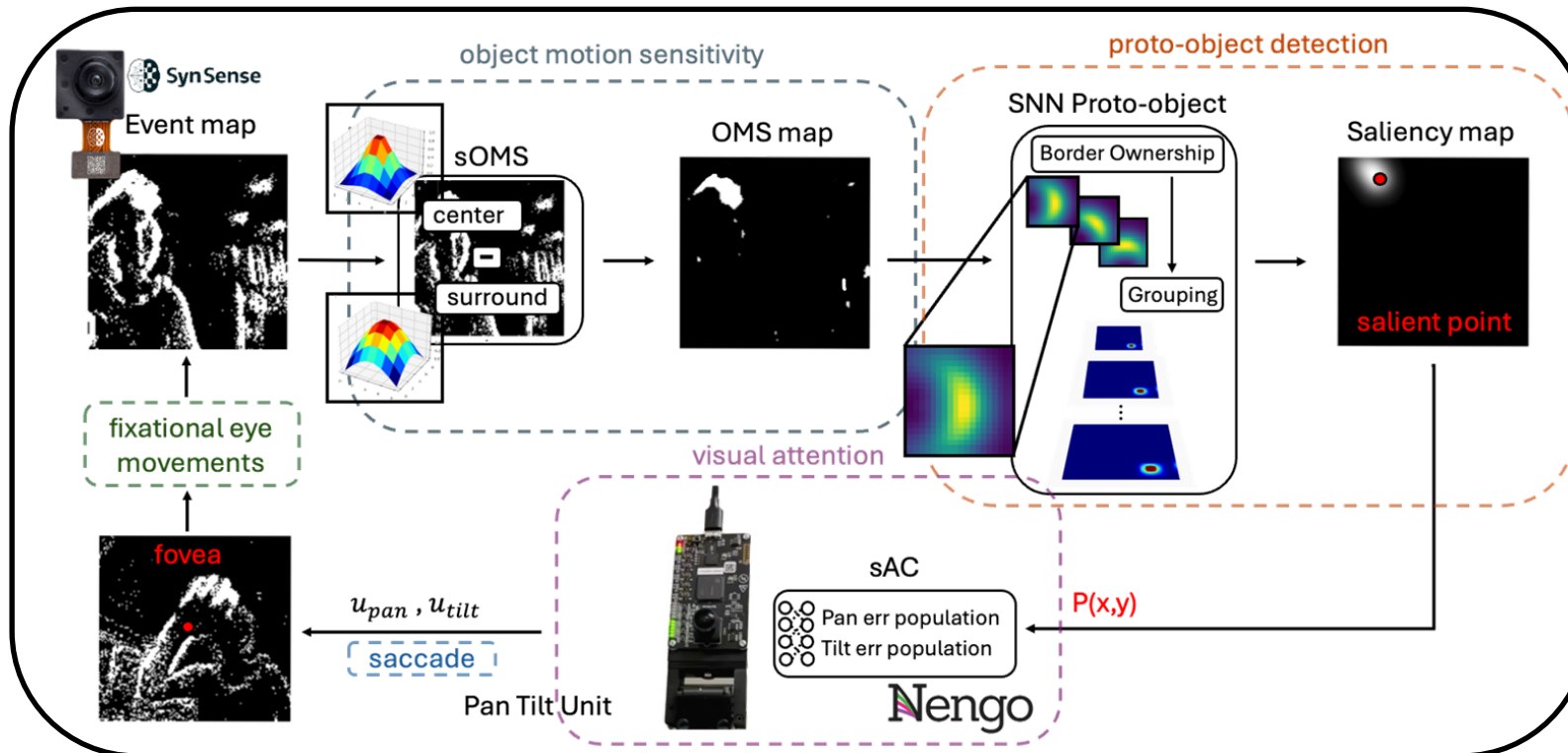
Why a cochlear model?
Raw data and different FEx for the sentence "Look on the left"



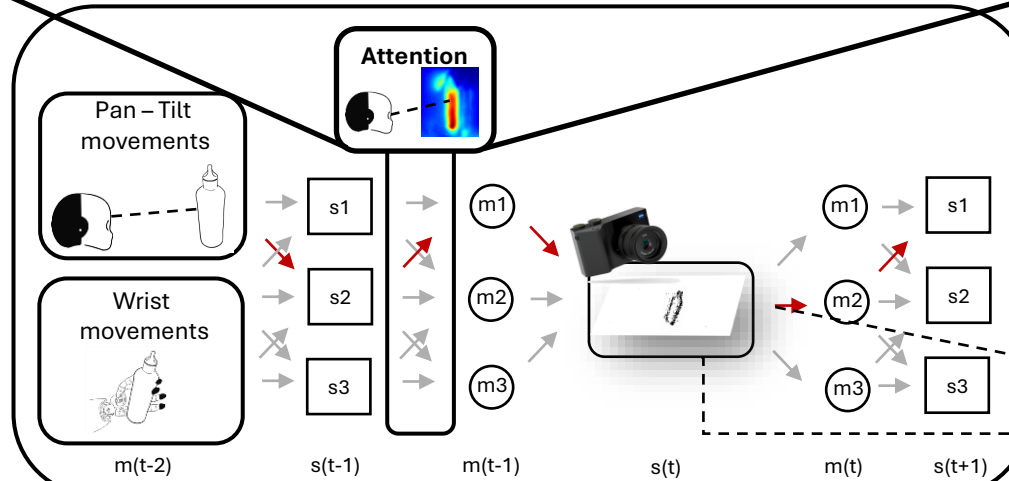
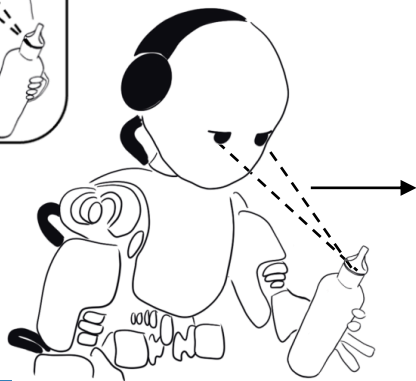
Less power consuming than LLMs and effective for short commands

Only the signal of one word is sufficient to drive attention

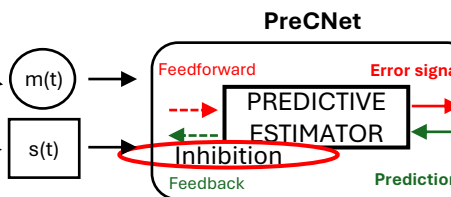
Attention



Sensorimotor Contingencies (SMCT) for object perception



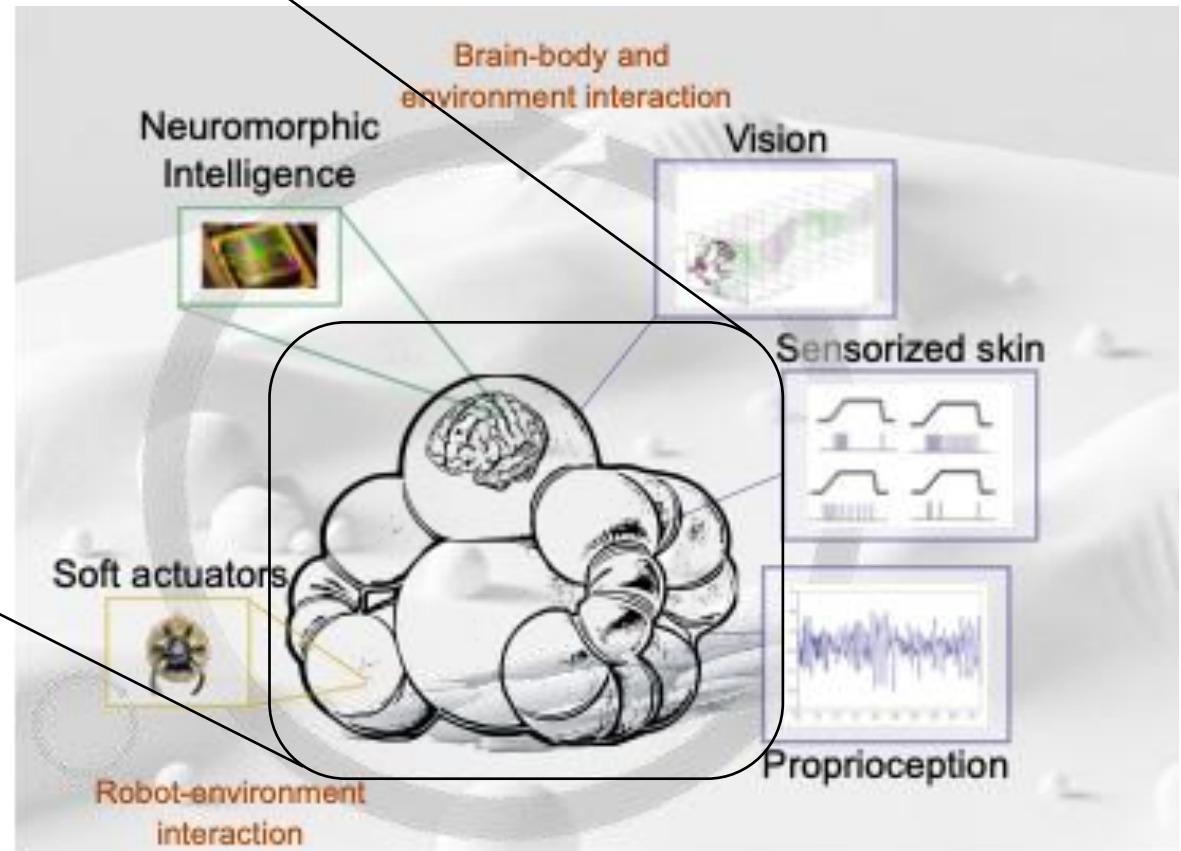
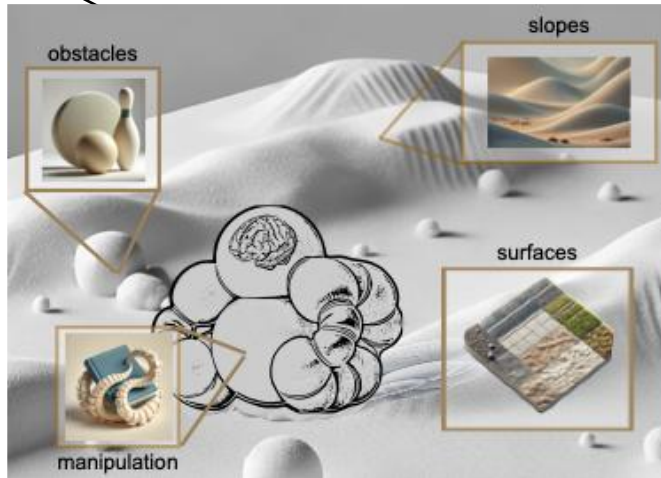
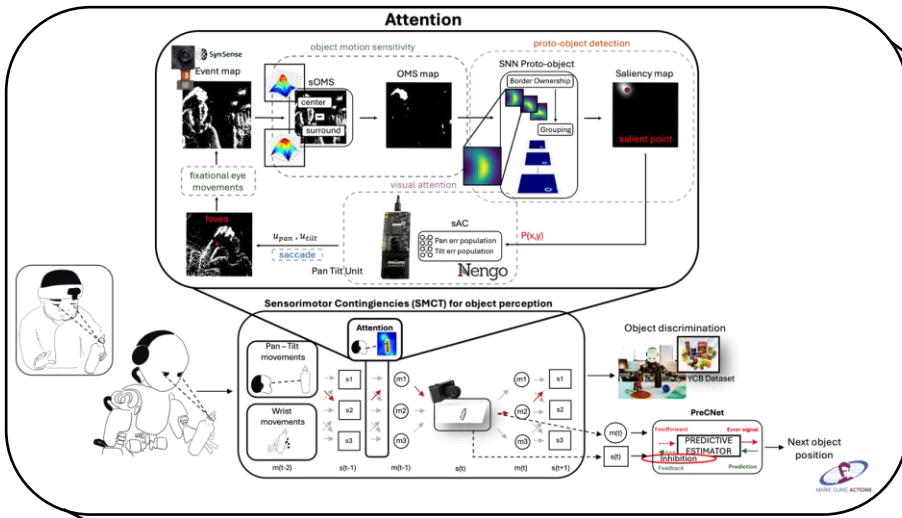
Object discrimination



Next object position

A Benchmarking Framework for Embodied Neuromorphic Agents

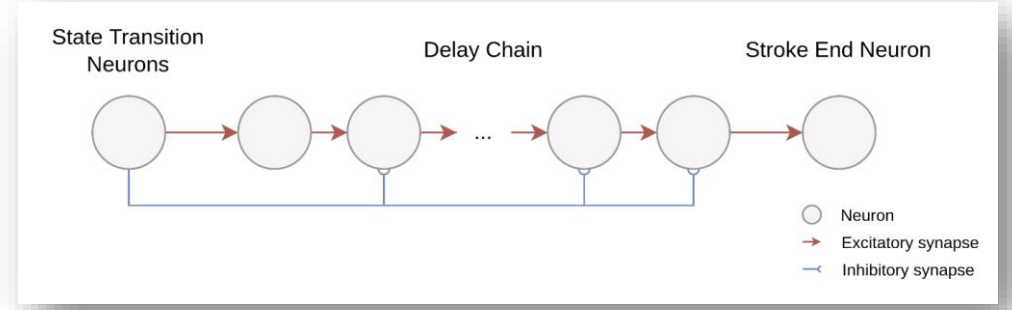
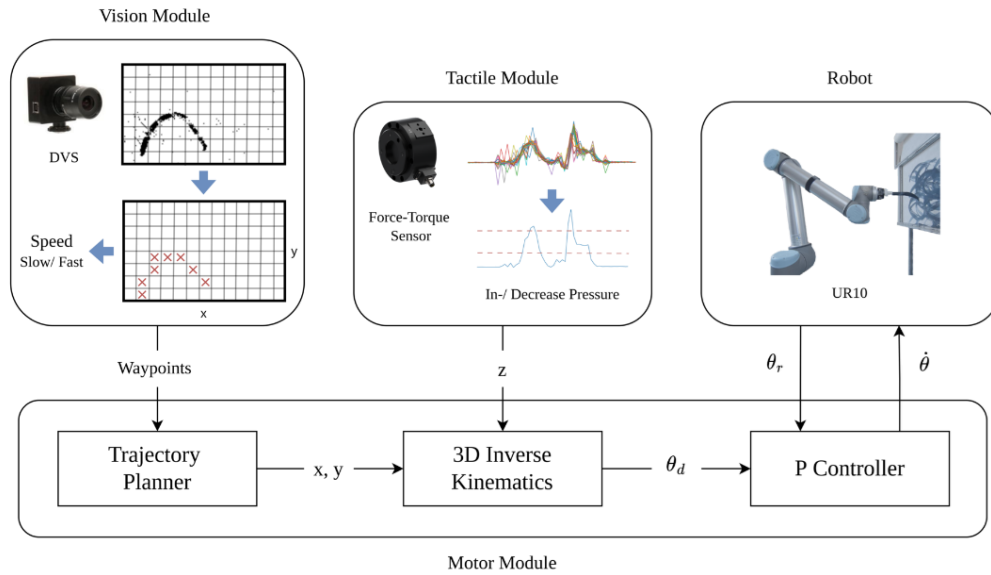
Co-designing “**brain**” and “**body**” unlocks new levels of *efficiency, resilience, and adaptability*



Set of **Tasks** and **Metrics** for evaluation and benchmark

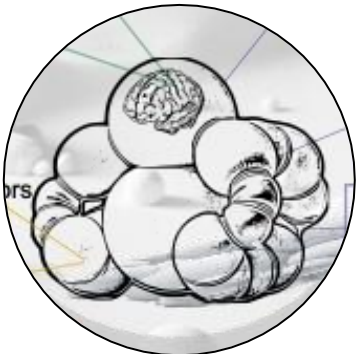


A neuromorphic electronic artist for robotic painting



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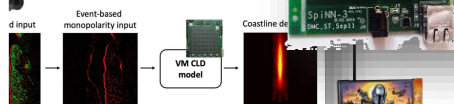


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Ev

ction on SpiNNaker

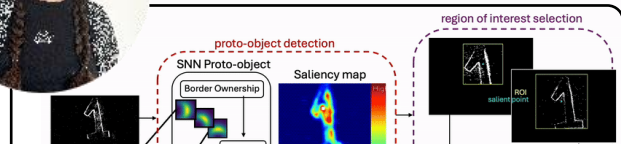
Université de Lille



20 ms is 0.3756 mW



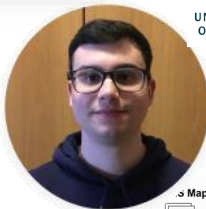
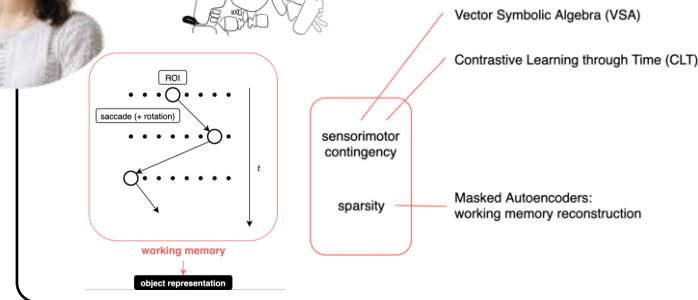
Visual stabilization for object recognition



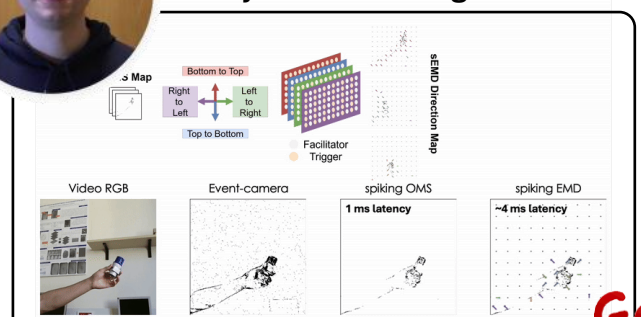
Visual prosthesis



Bioinspired active vision: learning through exploration

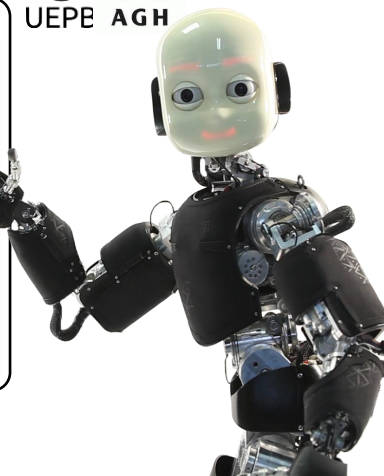
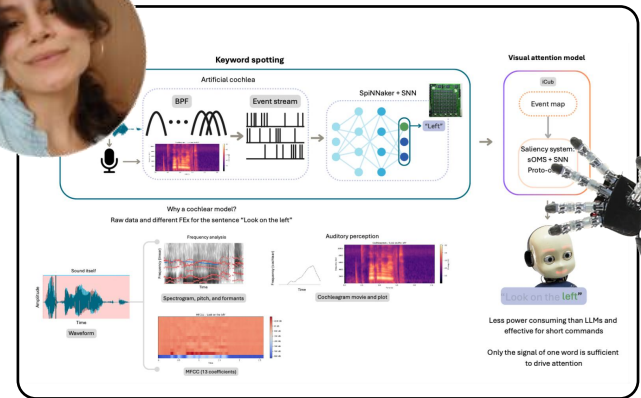


Motion direction detection through object motion segmentation



GeNN

Talk to look: visual attention influenced by spoken commands





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SynSense



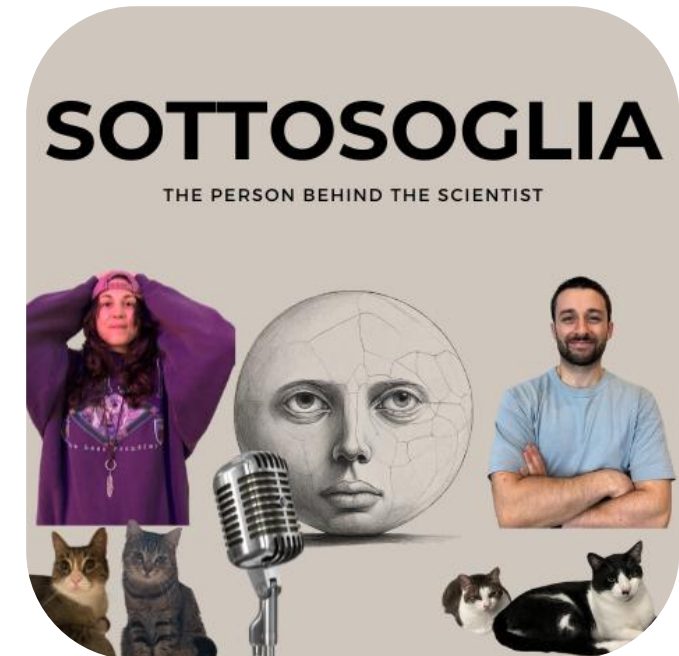
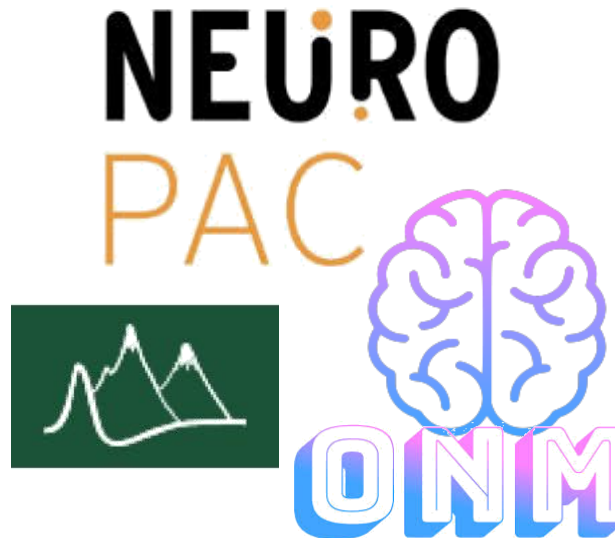
Giulia D'Angelo (She/Her)

Marie Skłodowska-Curie Postdoctoral Fellow | Co-Founder & Co-Creator Brains&Machines Podcast | Editor NeuroPAC | Young Ambassador for Women & Technologies.

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