Event-Driven Sensing and Processing for Humanoid Robots

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Smart Autonomous Systems

Digital vs Neural

- largely serial computation
- variables: “0”, “1”
- fast, precise computing elements

- largely parallel computation
- variables: analog
- slow, imprecise computing elements (neurons, synapses)
- adaptive (plasticity), context dependent computation

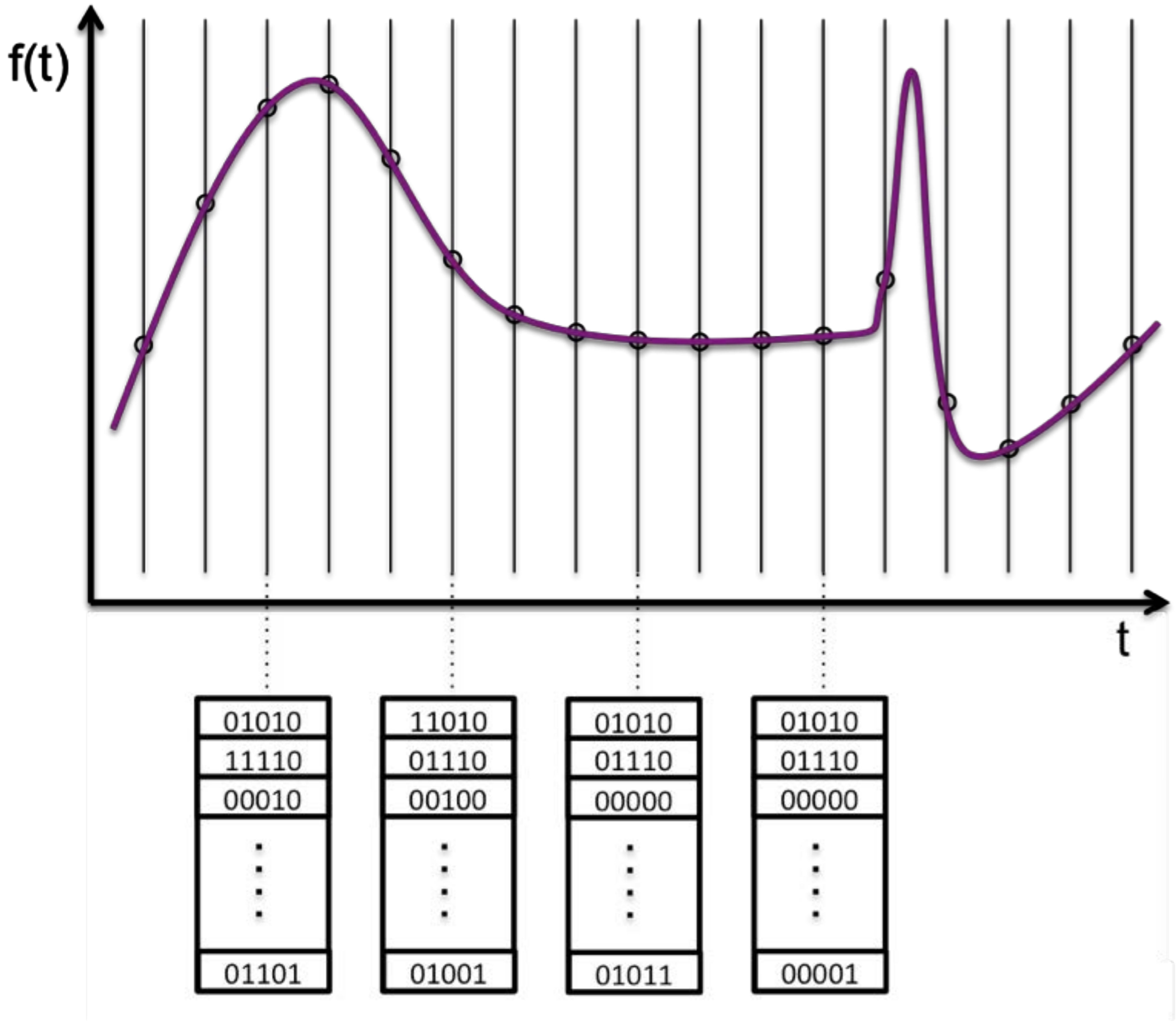
Sensory Acquisition and Processing

- Clock-Driven

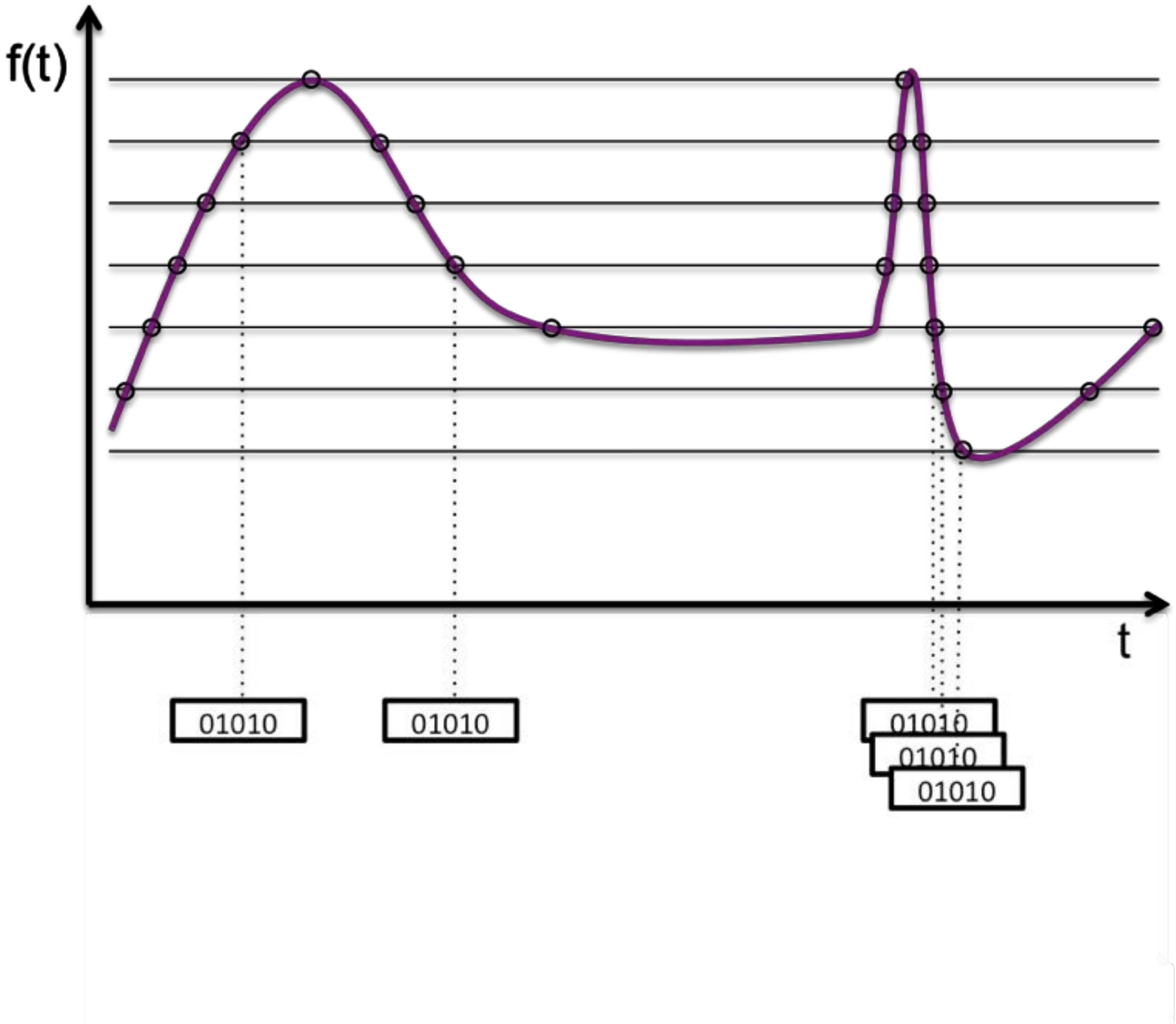
- Event-Driven

Event-Driven Sensing and Processing

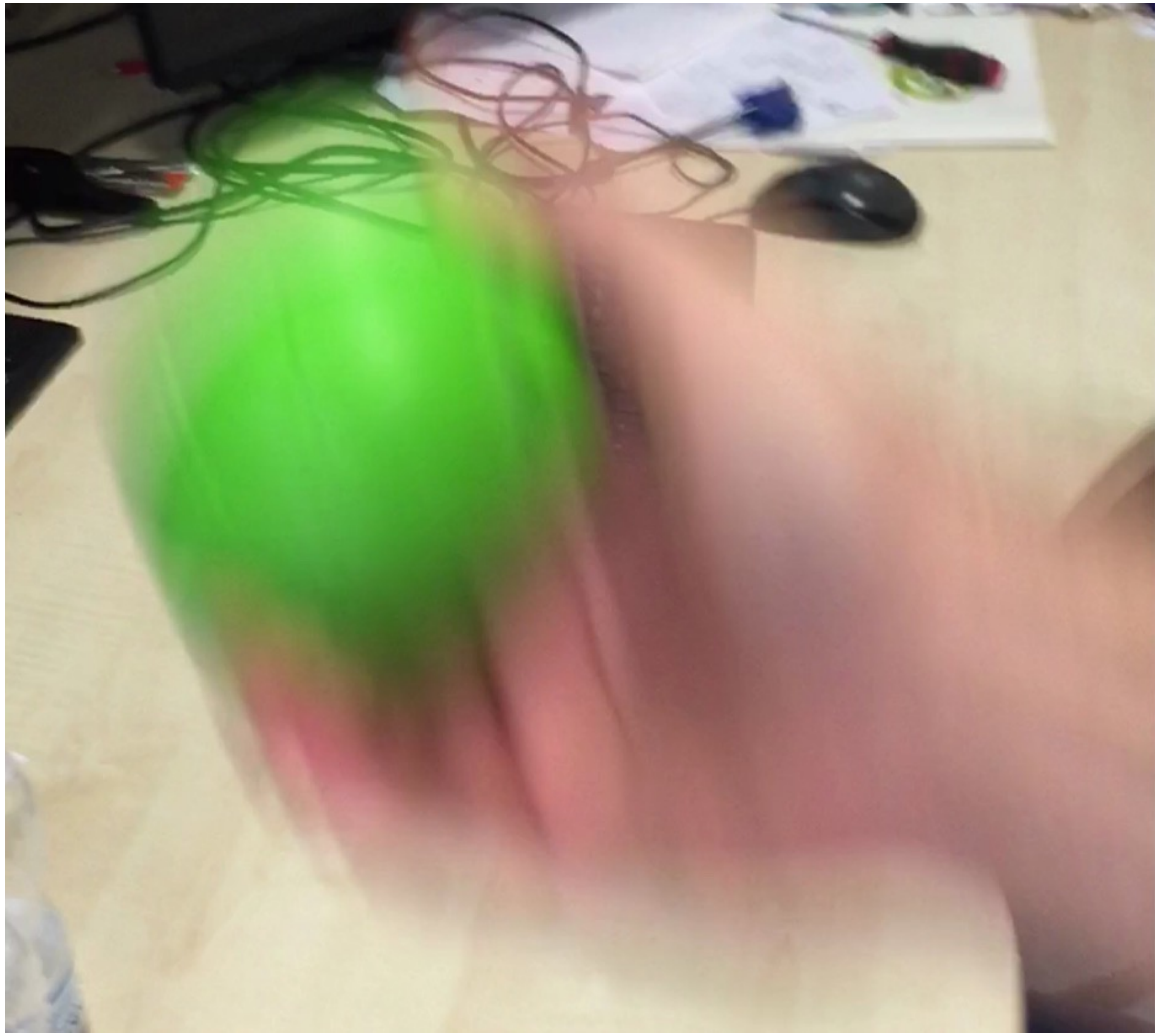
Clock-Based Sampling — fixed Δt



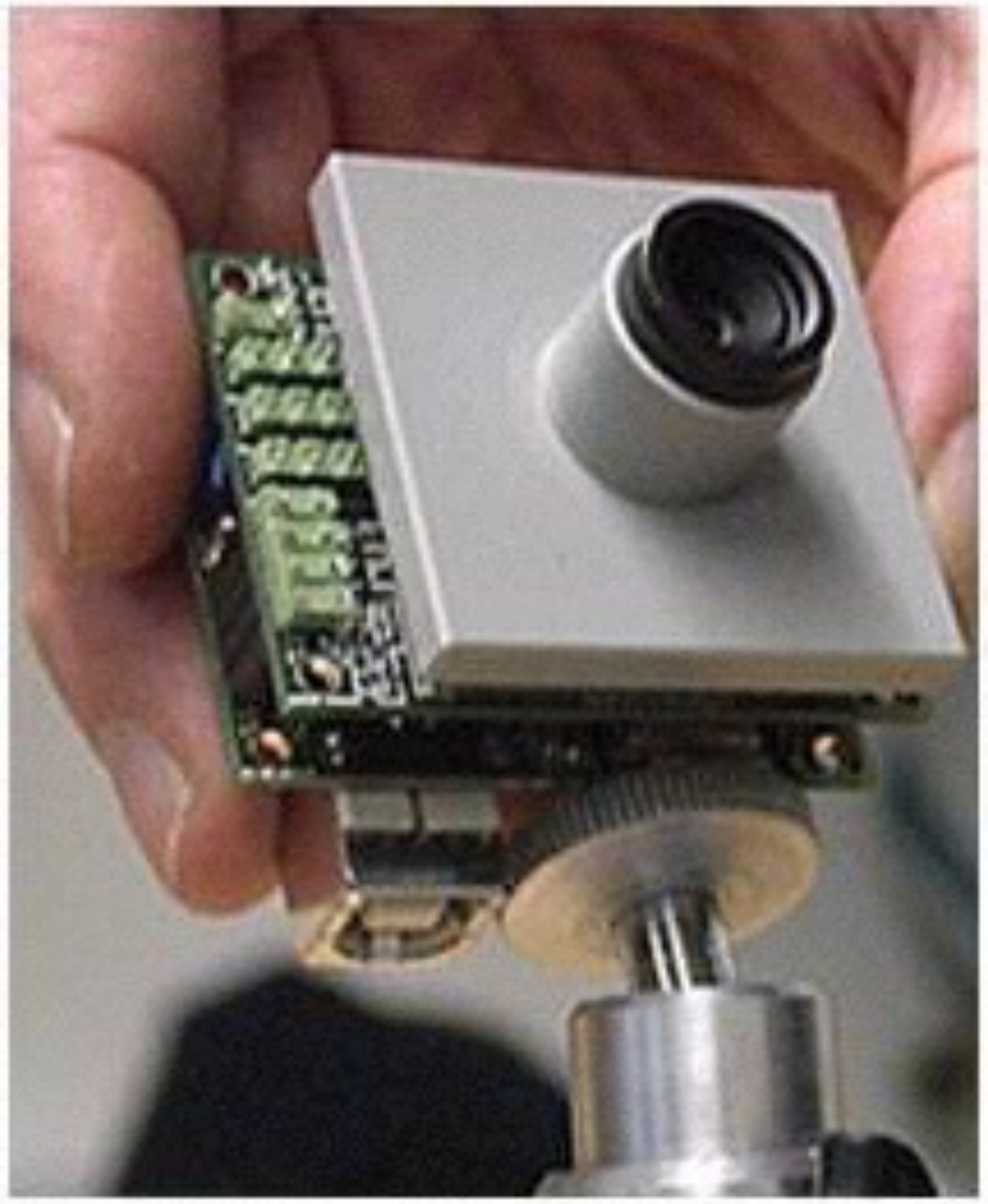
Data-Driven Sampling — fixed Δf

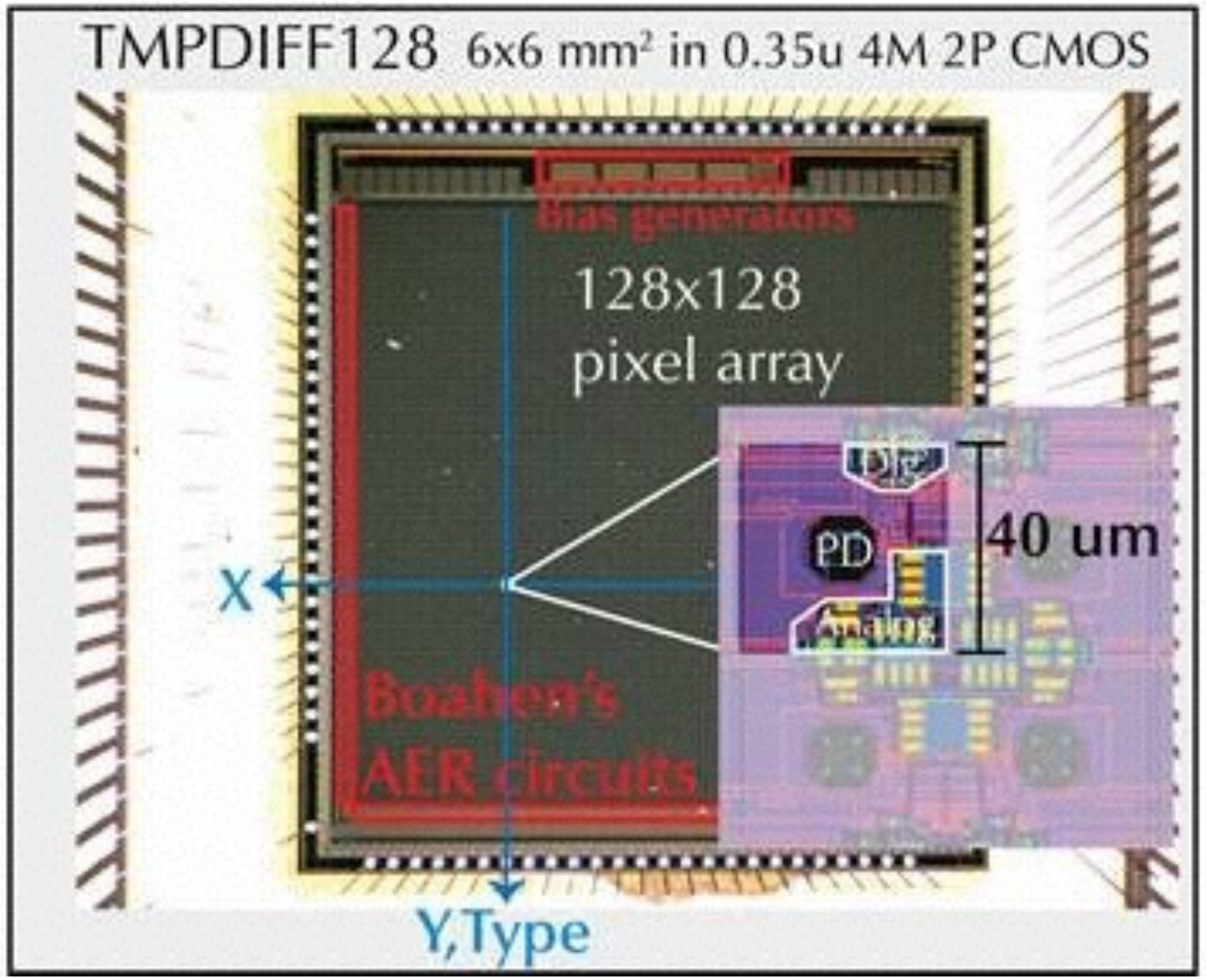


Event-Driven Sensing — Dynamic Vision Sensor



Event-Driven Sensing — Dynamic Vision Sensor





128x128 resolution

120dB dynamic range

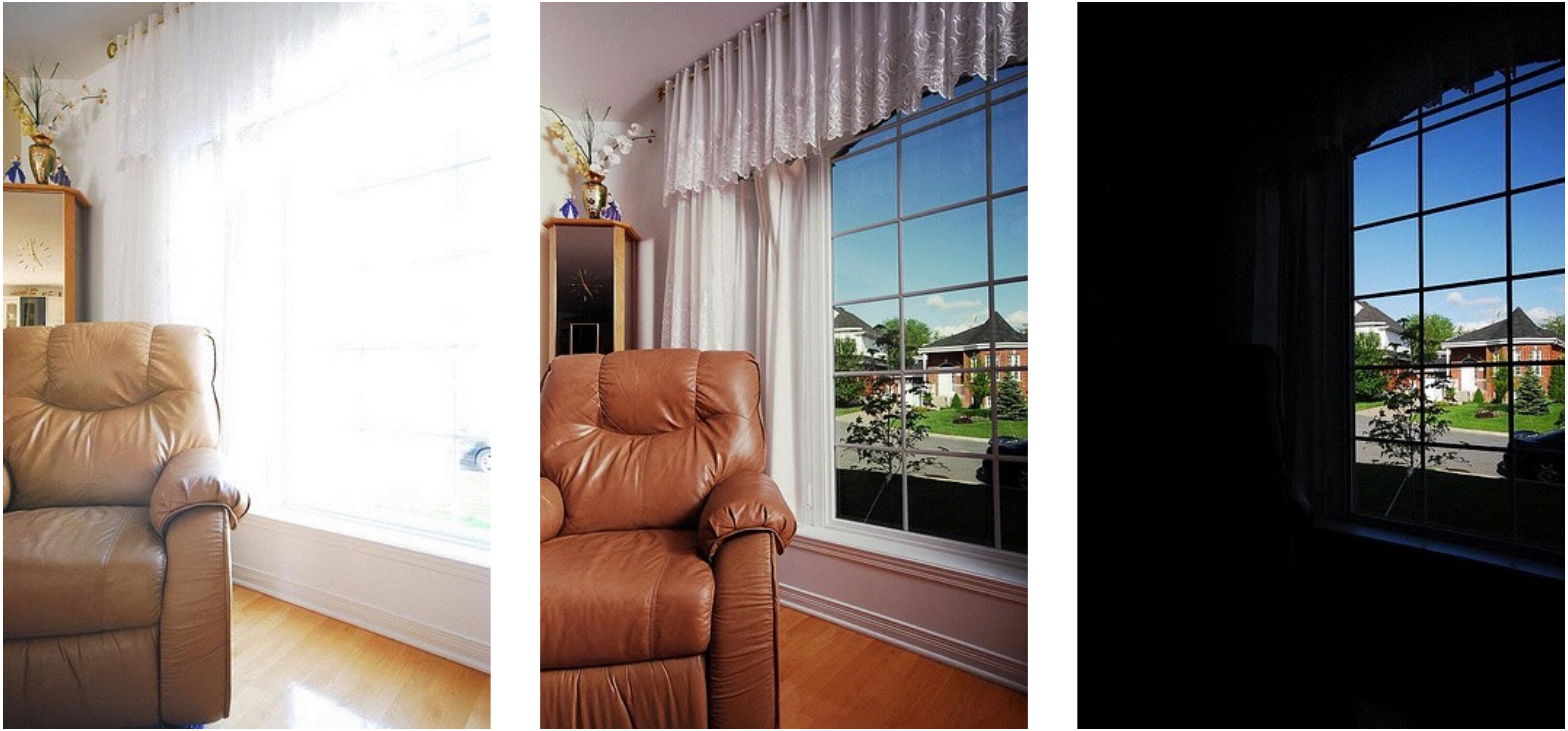
15 μs latency

25 ns temporal resolution

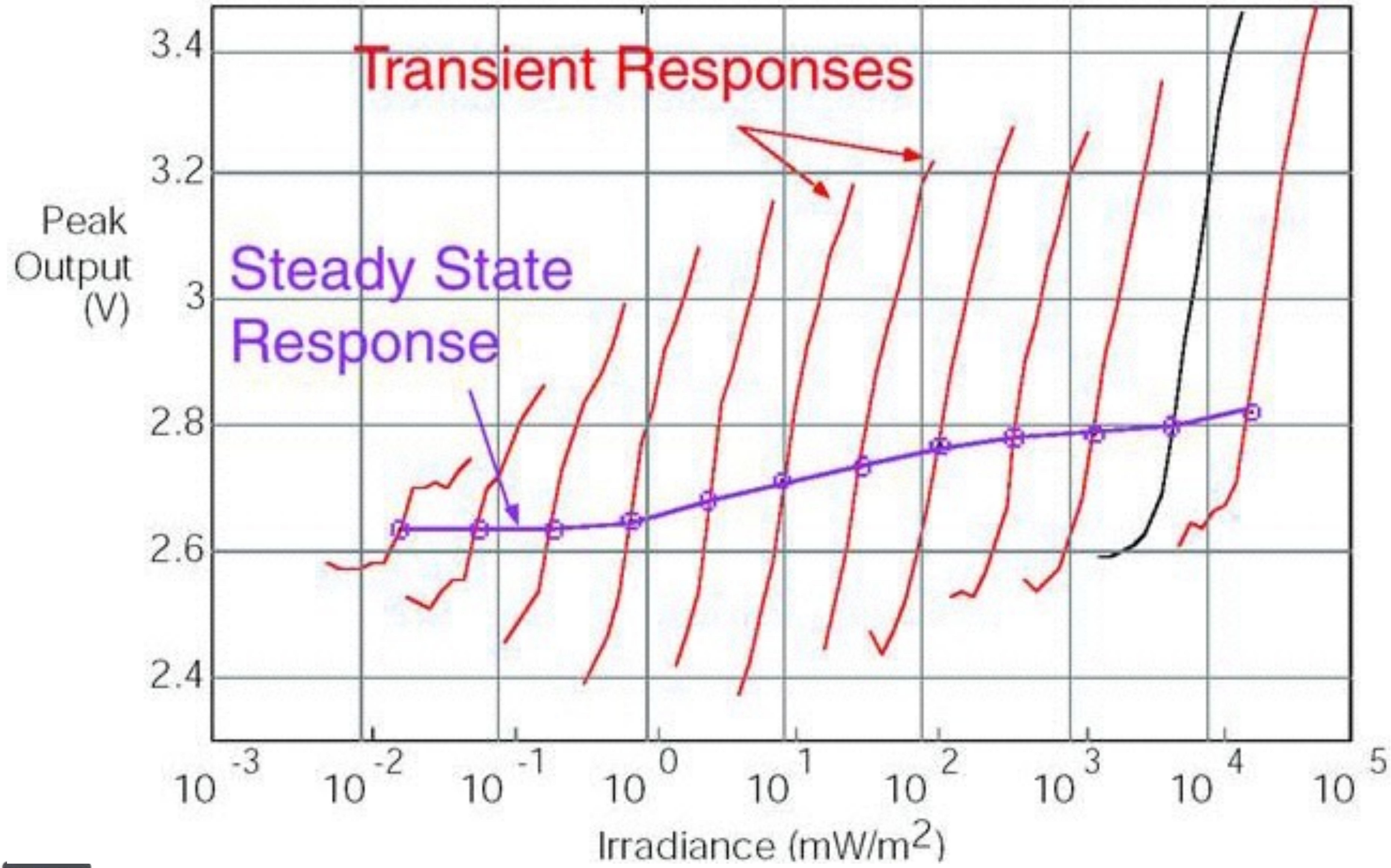
23mW power consumption

Event-Driven Sensing — Dynamic Vision Sensor

Dynamic Range

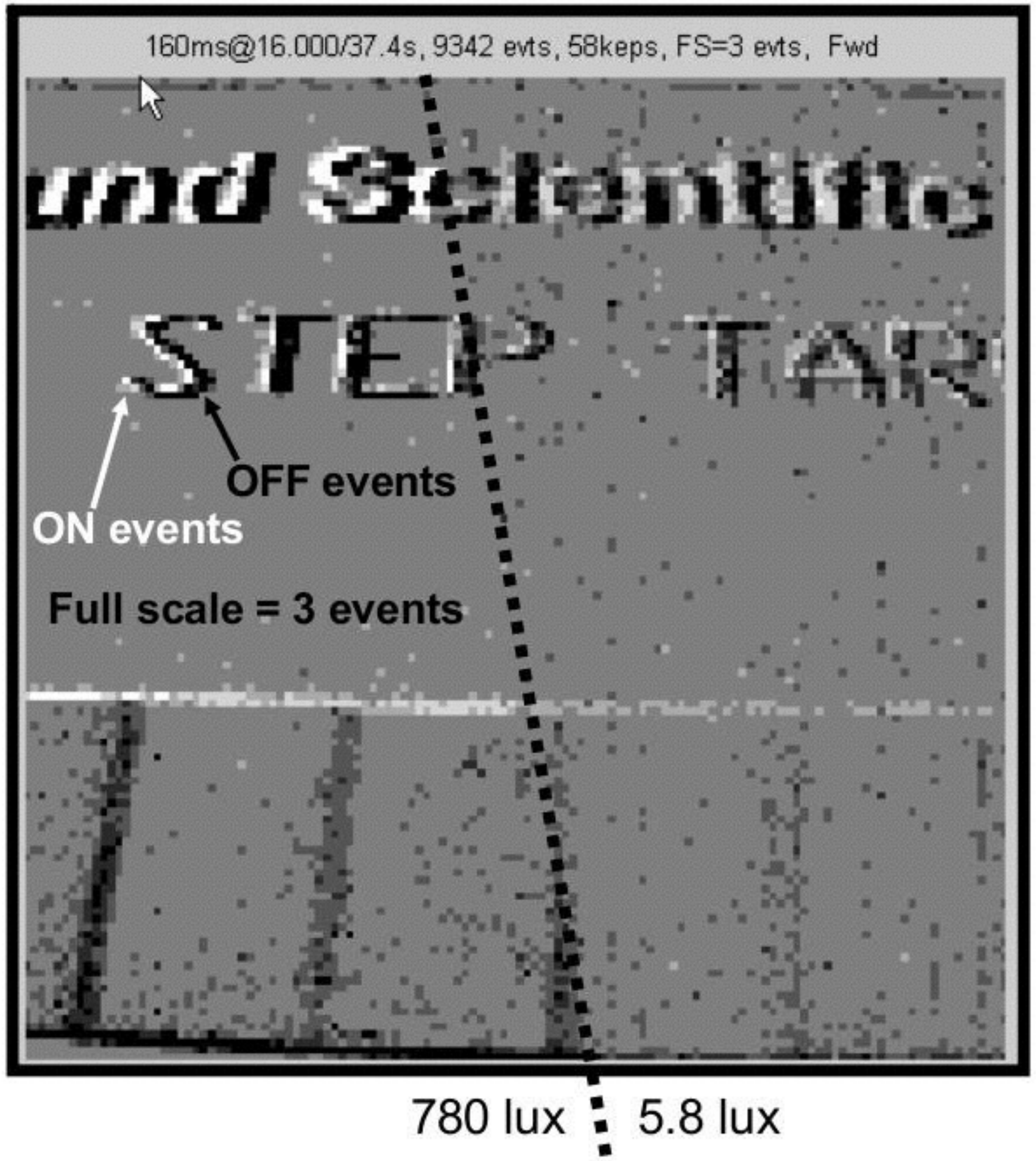


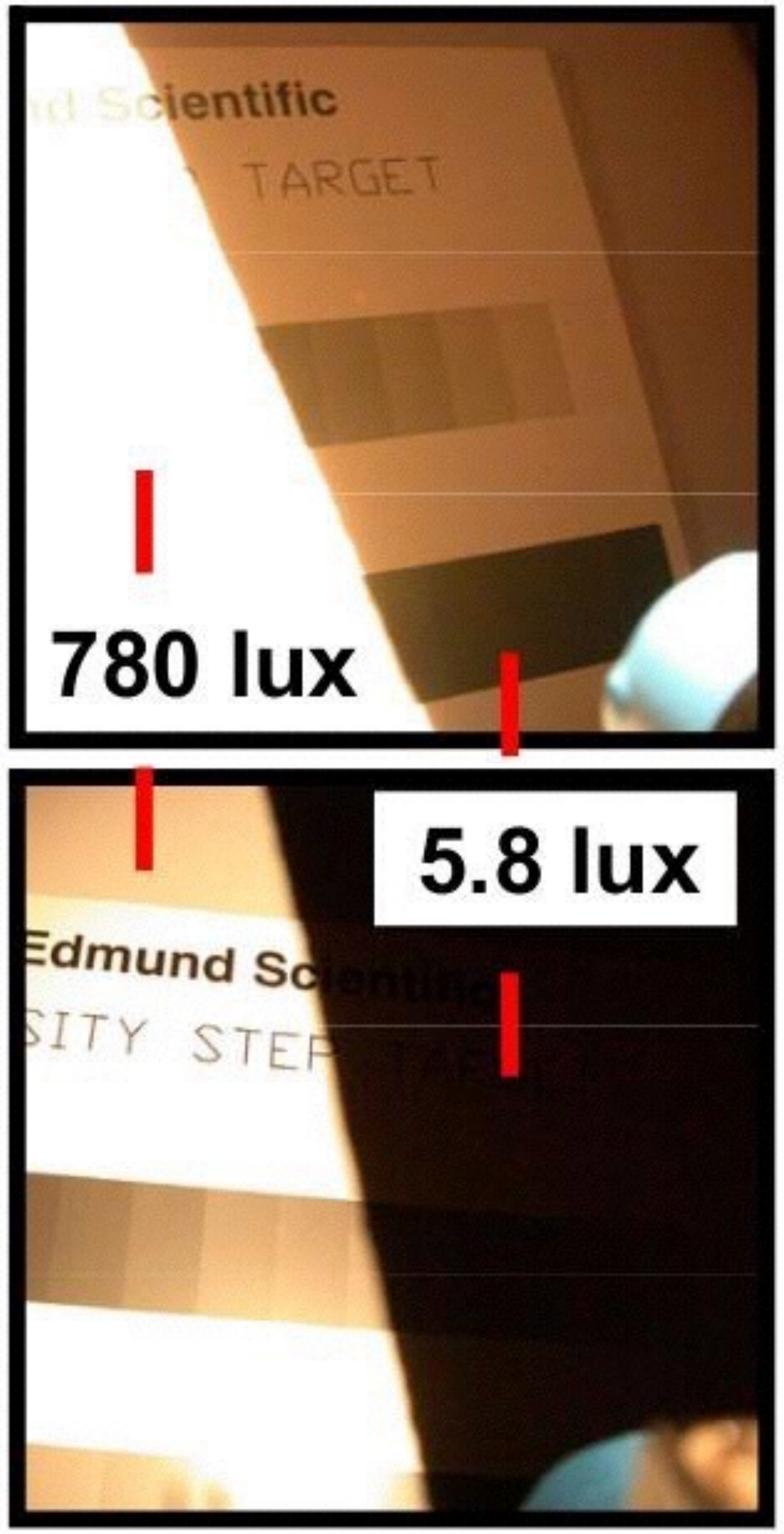
Event-Driven Sensing — Dynamic Vision Sensor



$$\frac{d\log(I)}{dt} = \frac{1}{I}\frac{dI}{dt}$$

Event-Driven Sensing — Dynamic Vision Sensor





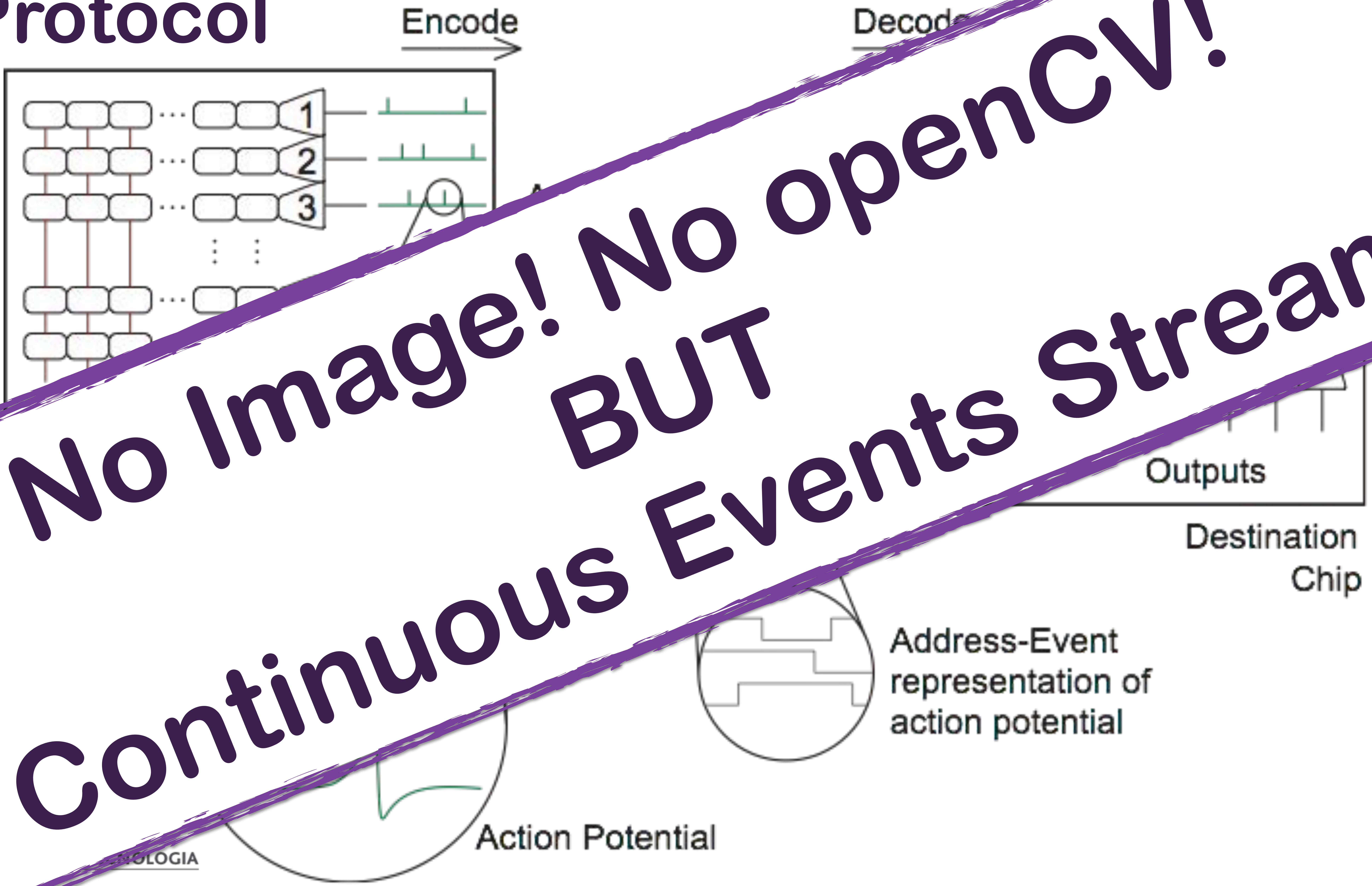
Edmund 0.1 density chart
Illumination ratio=135:1

120dB dynamic range

Clocked vs Event-Driven Vision

Conventional high-speed vision systems	Event-driven vision	Benefits
Requires fast PC/GPU/…	Works with any laptop, better with spike-based hardware	Lower costs, Lower power consumption
Highly redundant data, Extremely large data storage (often several TB)	No redundant data, Low storage requirements	Lower costs, More portable, Easier and faster data management
Batch-mode acquisition Off-line post-processing	Real-time acquisition Extremely low latency	Continuous processing No downtime, lower costs
Low dynamic range ordinary sensitivity	High sensitivity	Lower costs
Needs special bright lighting (lasers, strobes, etc.) for short exposure times	No special lighting needed	Simpler data acquisition
Limited dynamic range, typically 50 dB	Very high dynamic range 120 dB	Usable in more real-world situations
Latency - need to wait for one frame to be acquired	Very short latency — 15µs	Enables extremely short reaction times

Event-Driven Sensing and Processing
AER Protocol



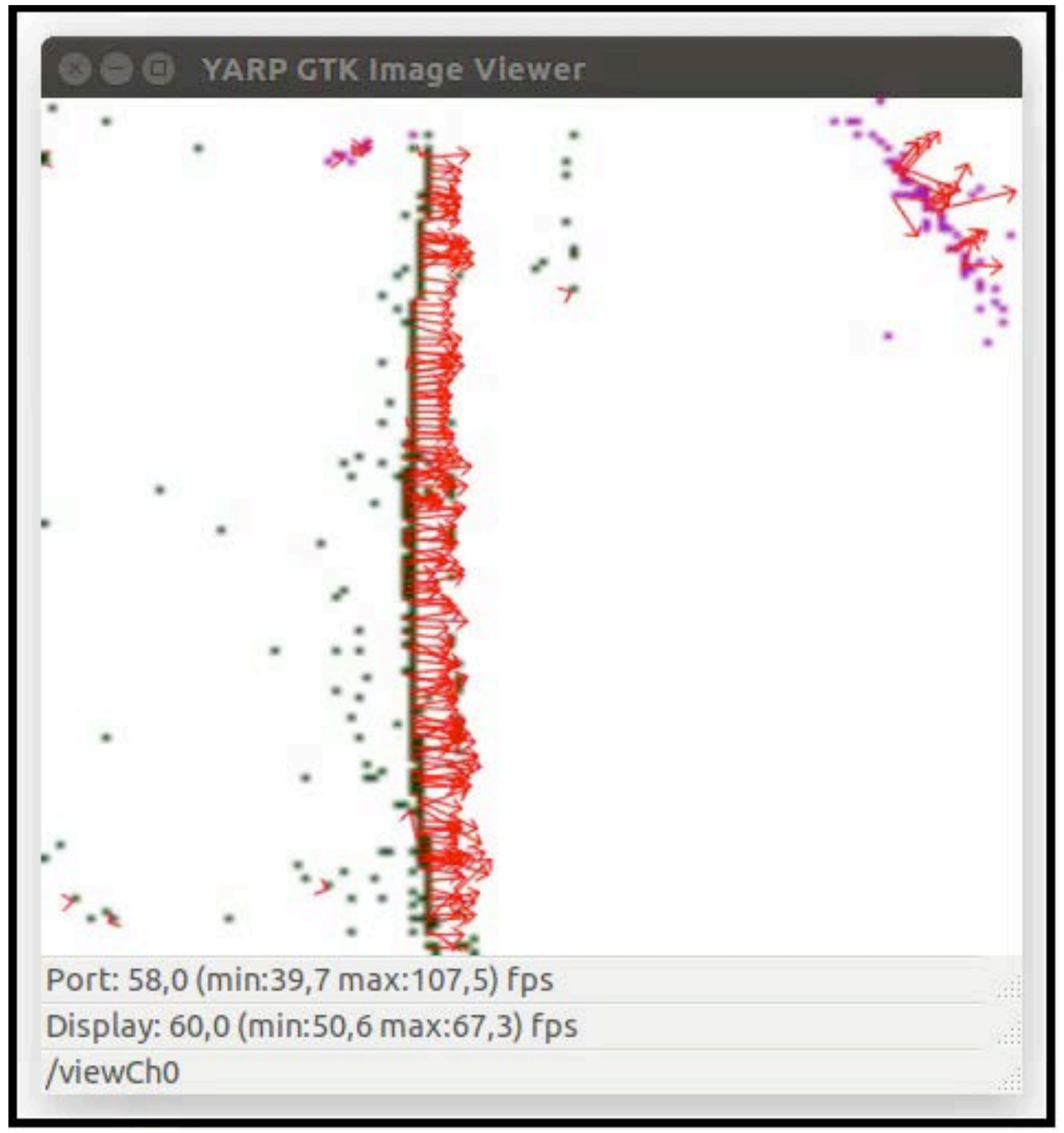
No Image! No openCV!
BUT
Continuous Events Stream

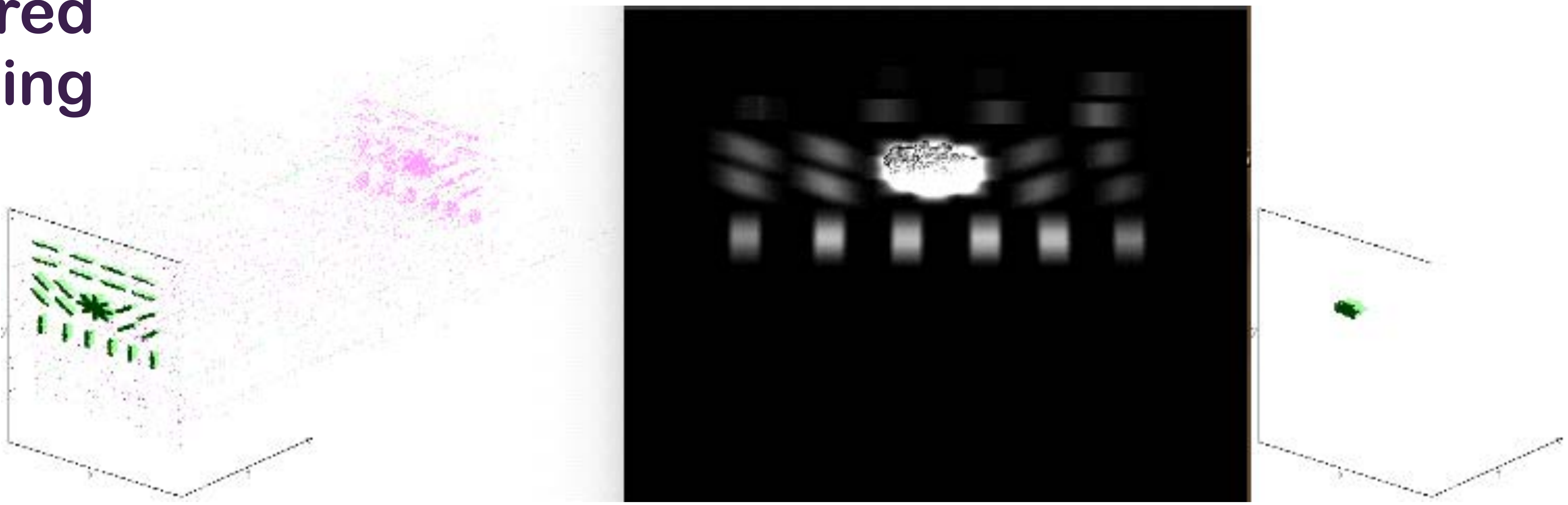
Tutorial #1
event-handling

Learn how to use
event-driven library

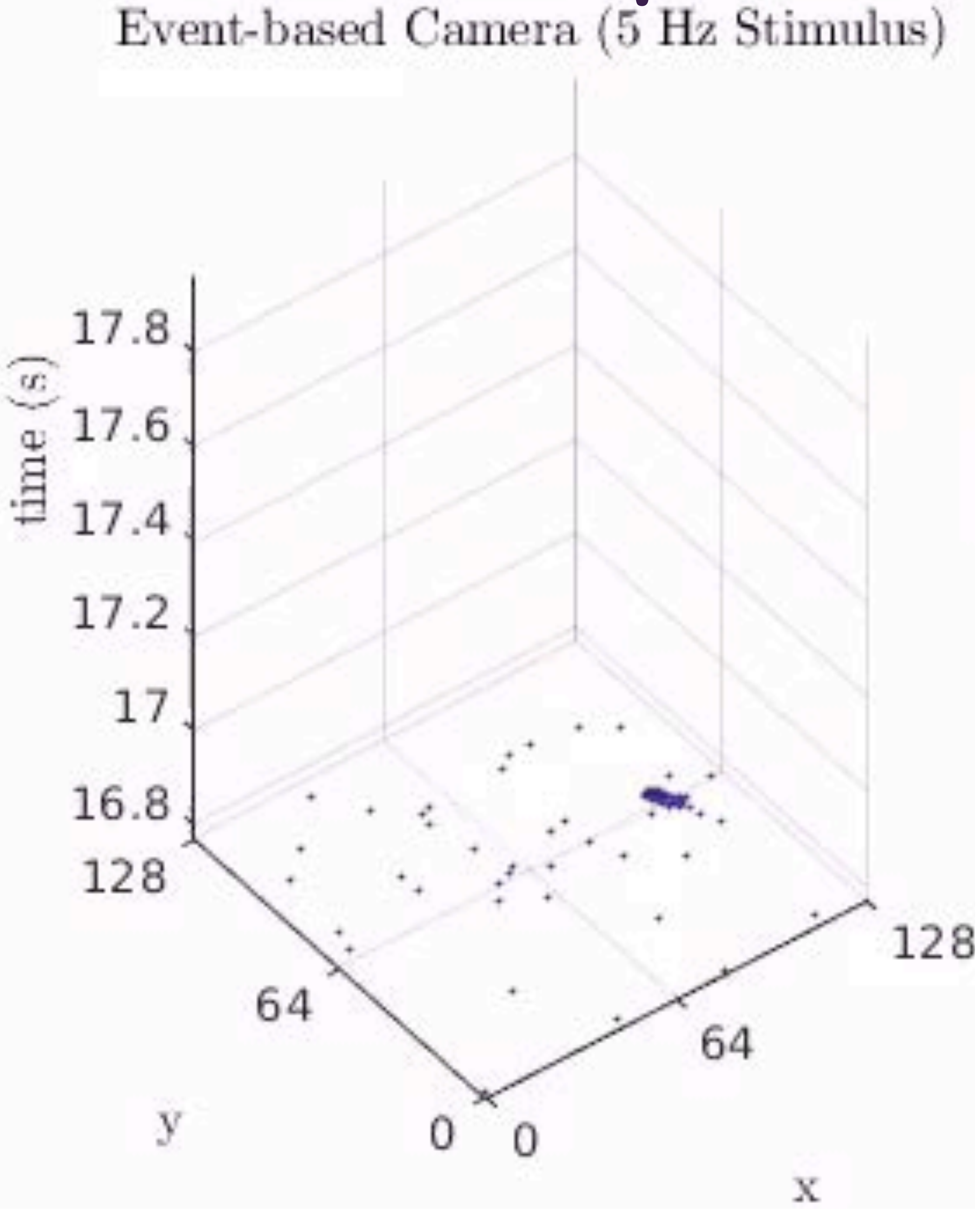
ED Vision

- Integrate events and reconstruct a frame -> use openCV
- Adapt Computer Vision algorithms to events -> ED Vision
- Implement neurally-inspired models of visual processing





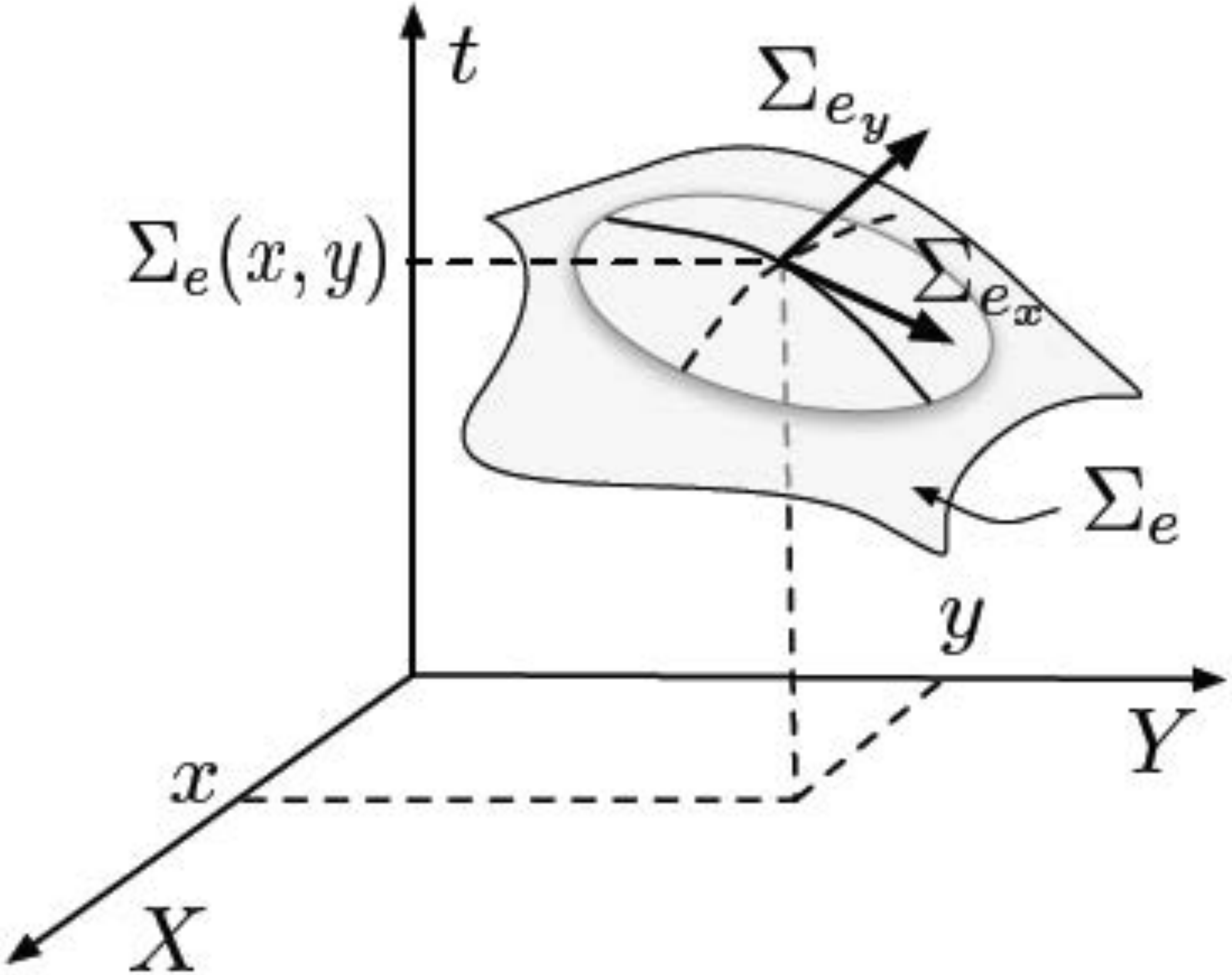
ED Vision — Optical Flow



$$e(\mathbf{p}, \mathbf{t}):$$

$$\Sigma_e : \mathbb{N} \to \mathbb{R}$$

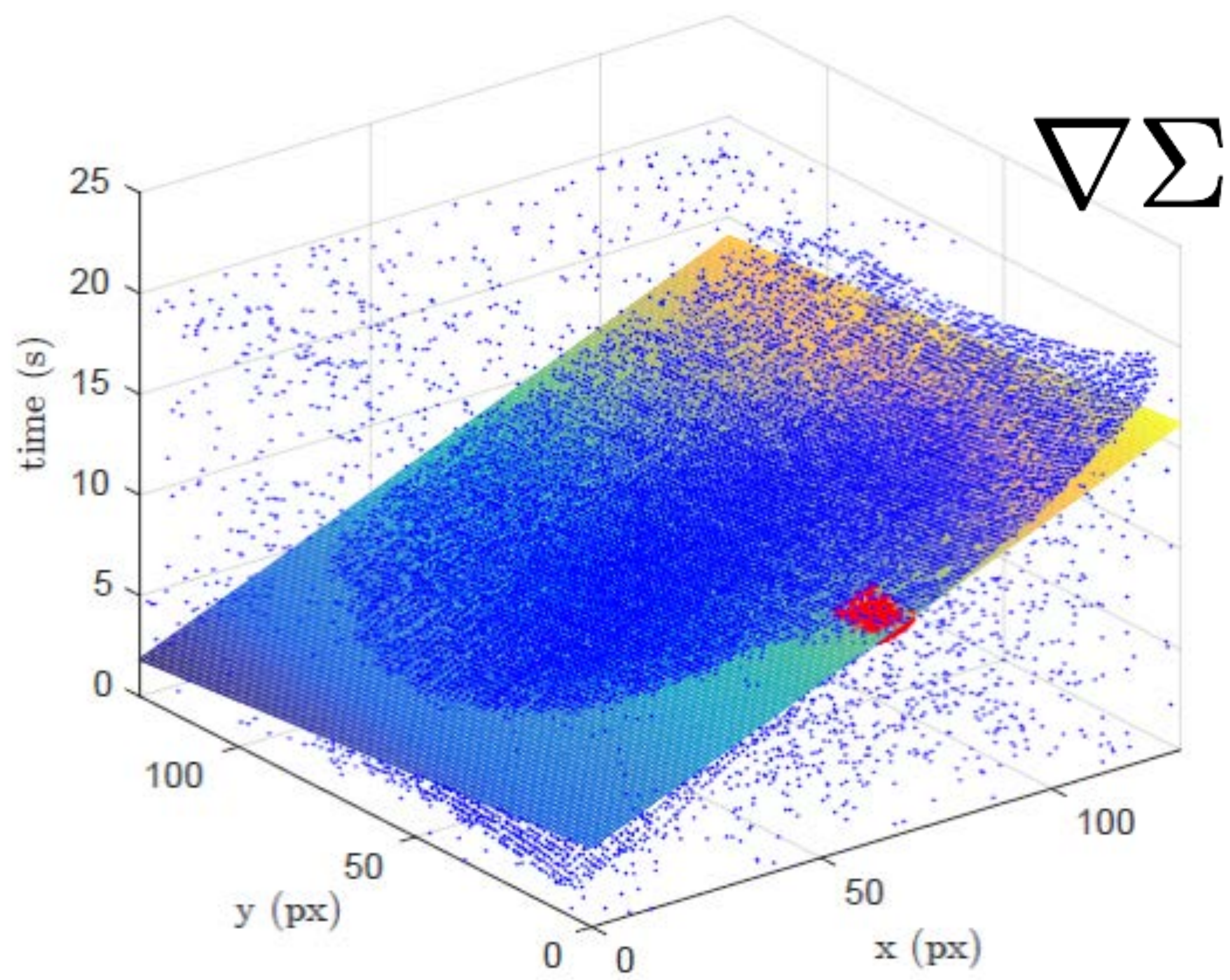
$$p \longmapsto \Sigma_e(\mathbf{p} = \mathbf{t})$$



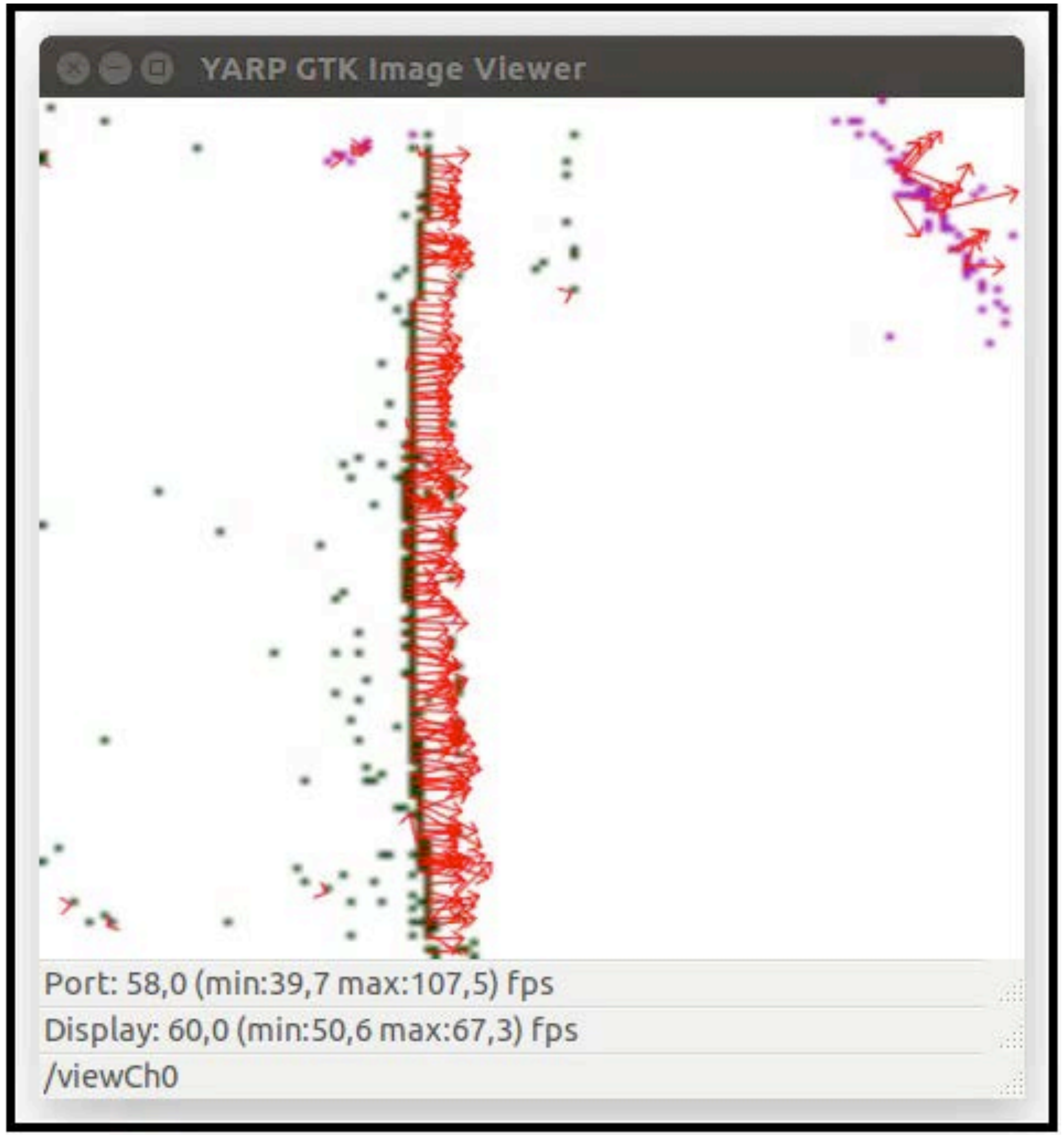
ED Vision — Optical Flow

$$\frac{\partial \Sigma_e}{\partial x}(x, y_0) = \frac{d\Sigma_e|_{y=y_0}}{dx} = \frac{1}{v_x(x, y_0)}$$

$$\frac{\partial \Sigma_e}{\partial y}(x_0, y) = \frac{d\Sigma_e|_{x=x_0}}{dx} = \frac{1}{v_y(x_0, y)}$$



$$\nabla \Sigma_e = \left(\frac{1}{v_x}, \frac{1}{v_y}\right)$$



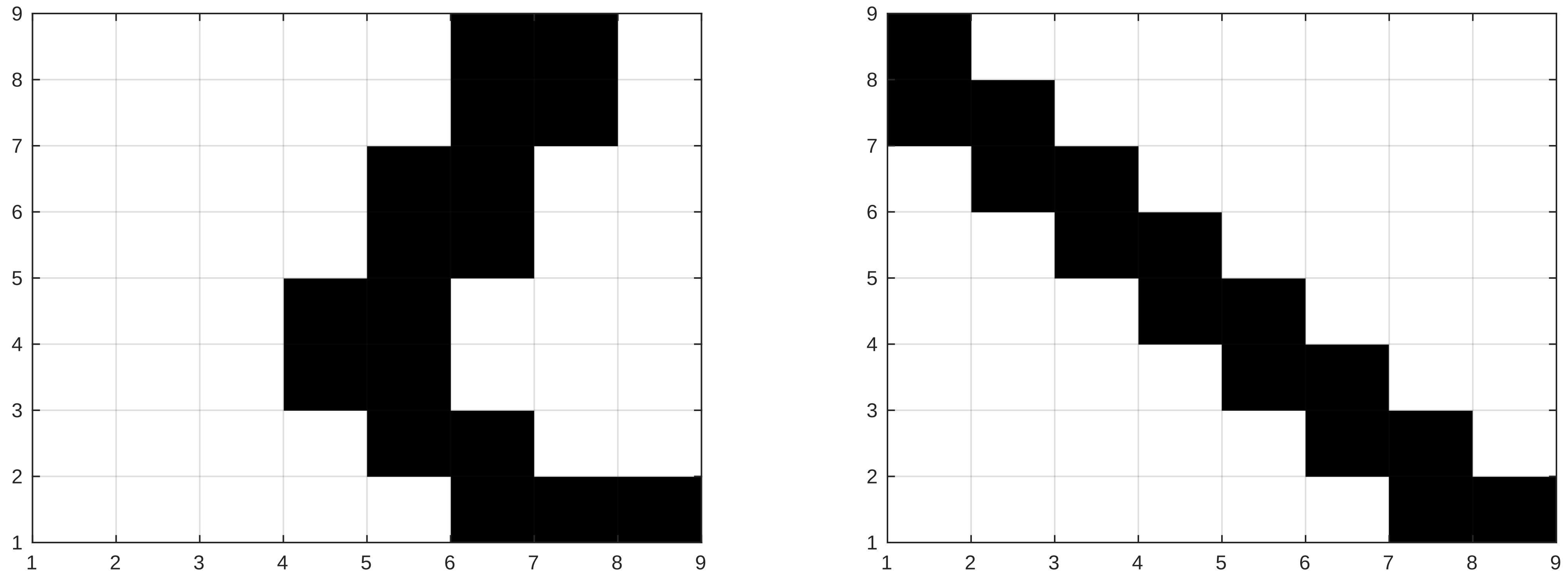
ED Vision — Corner Detection

Binary Image Patch

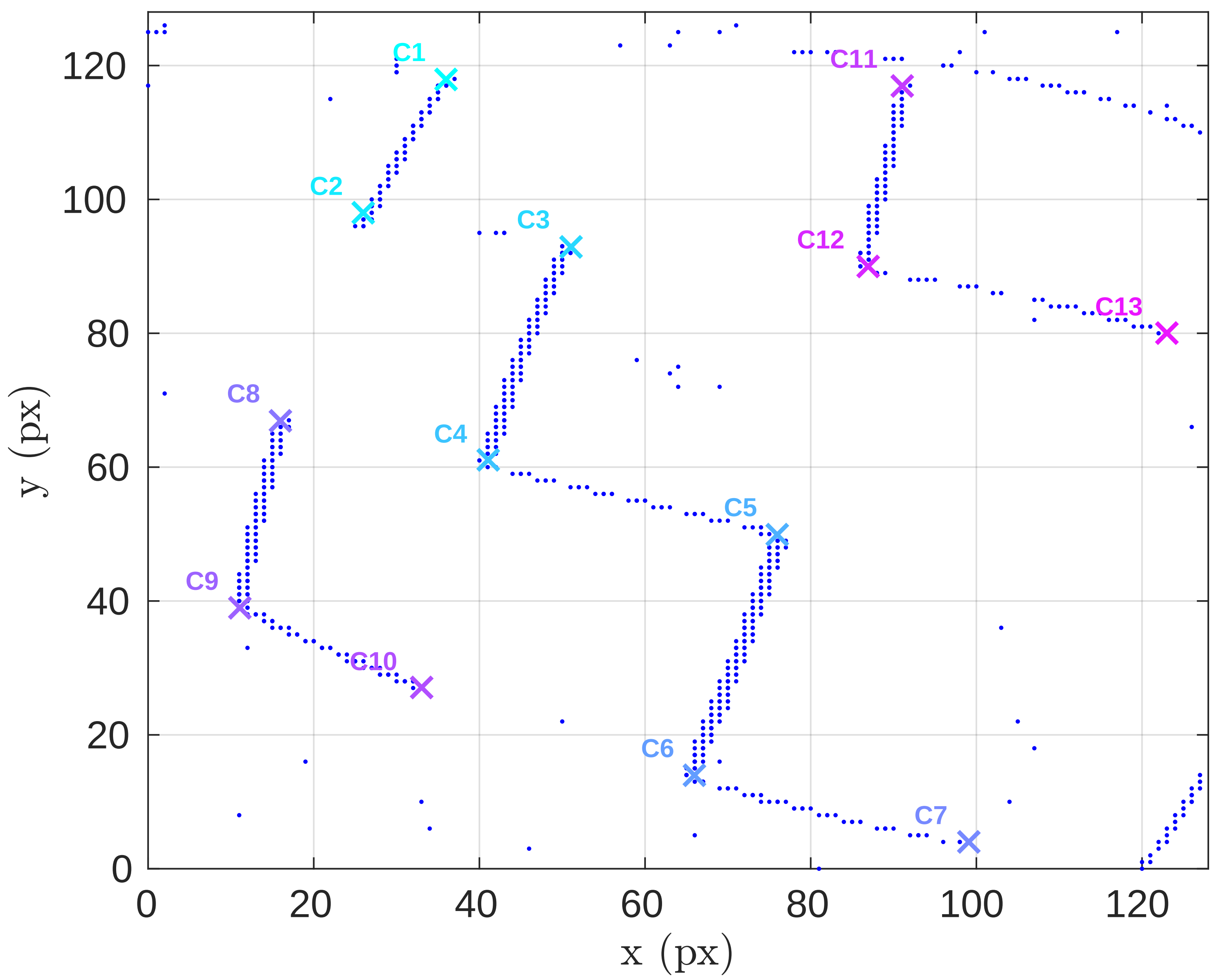
- spatial derivatives

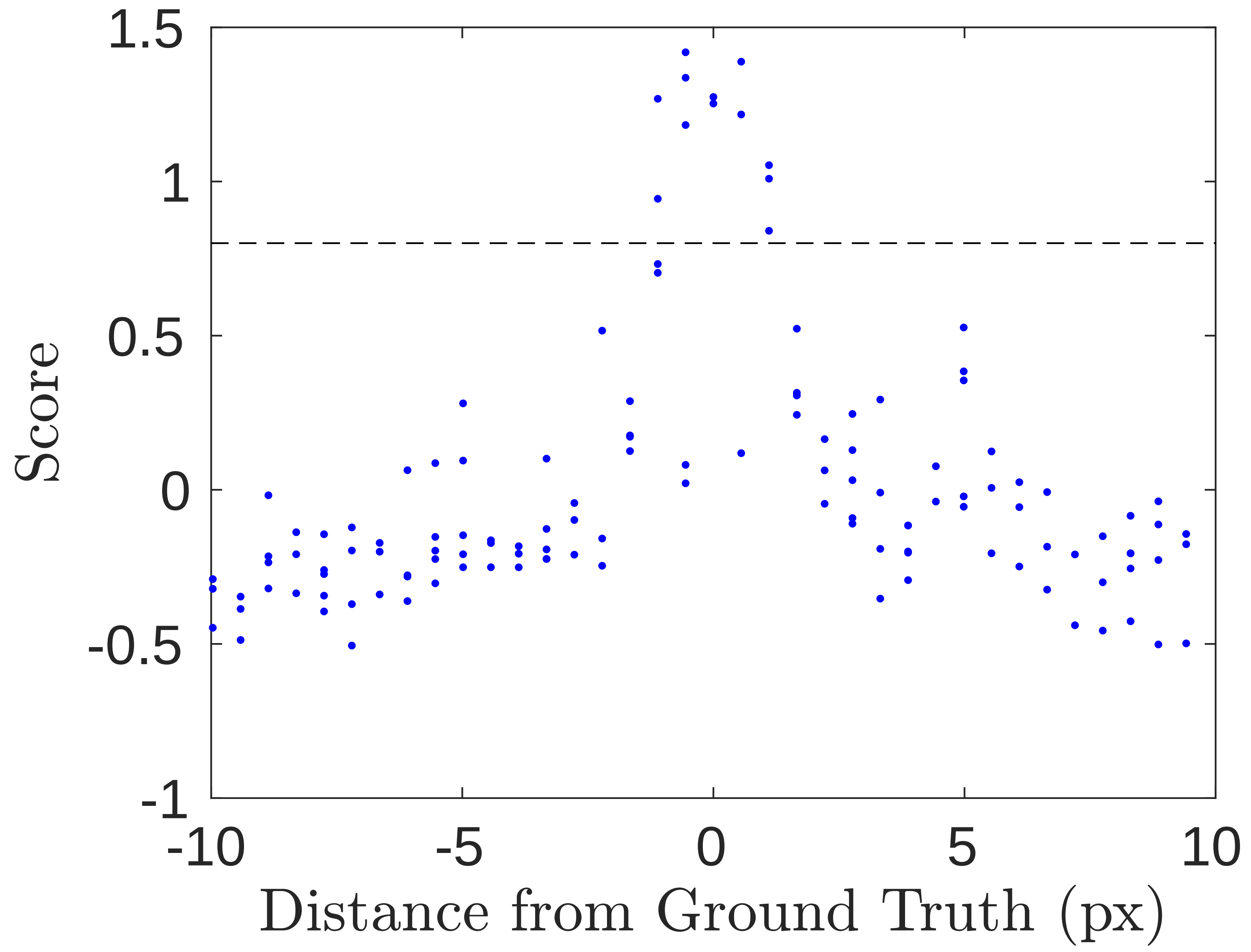
ED Harris Score — R

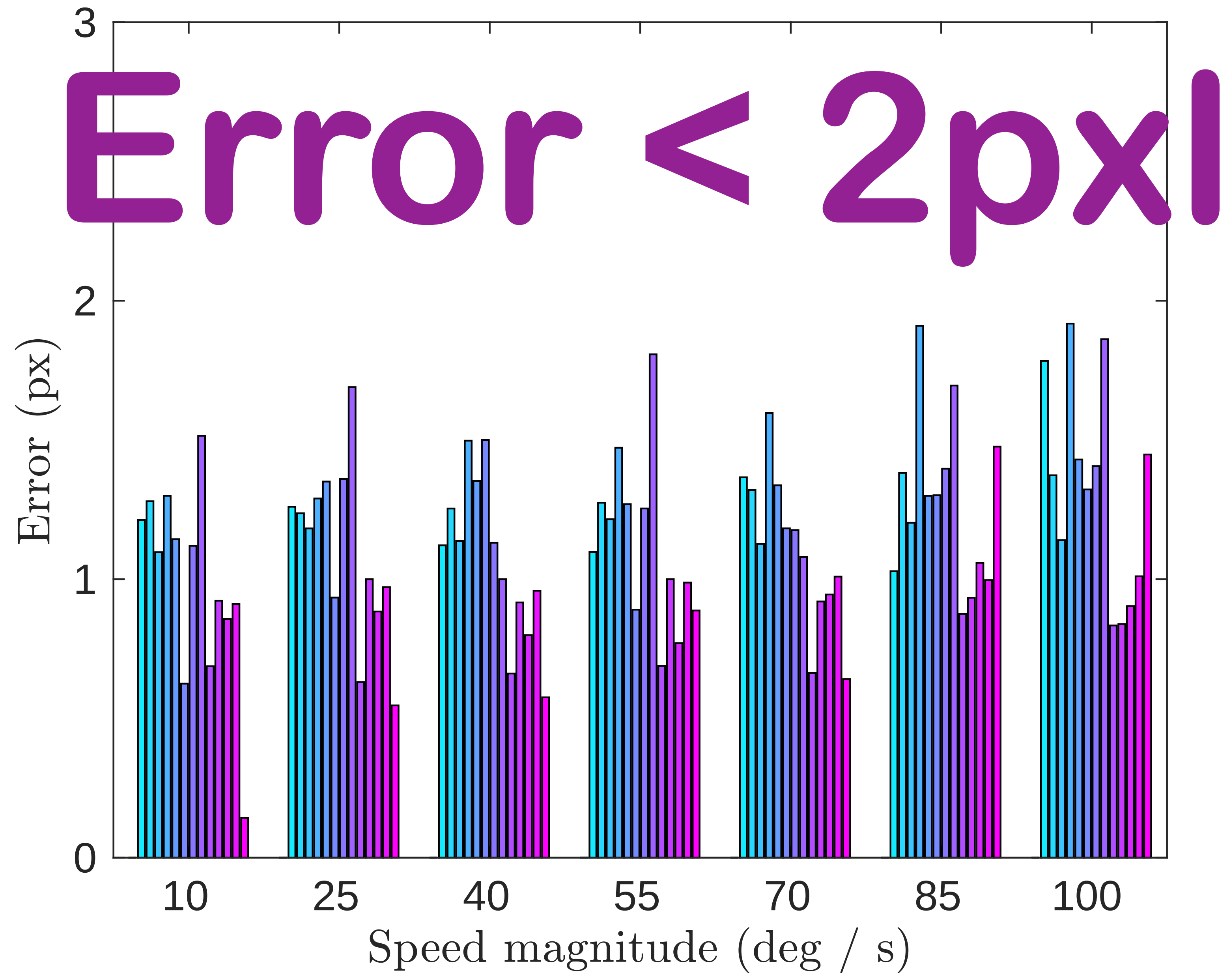
- flat: two small eigenvalues
  R small
- edge: one small and one big
  R negative
- corner: two large eigenvalues
  R big

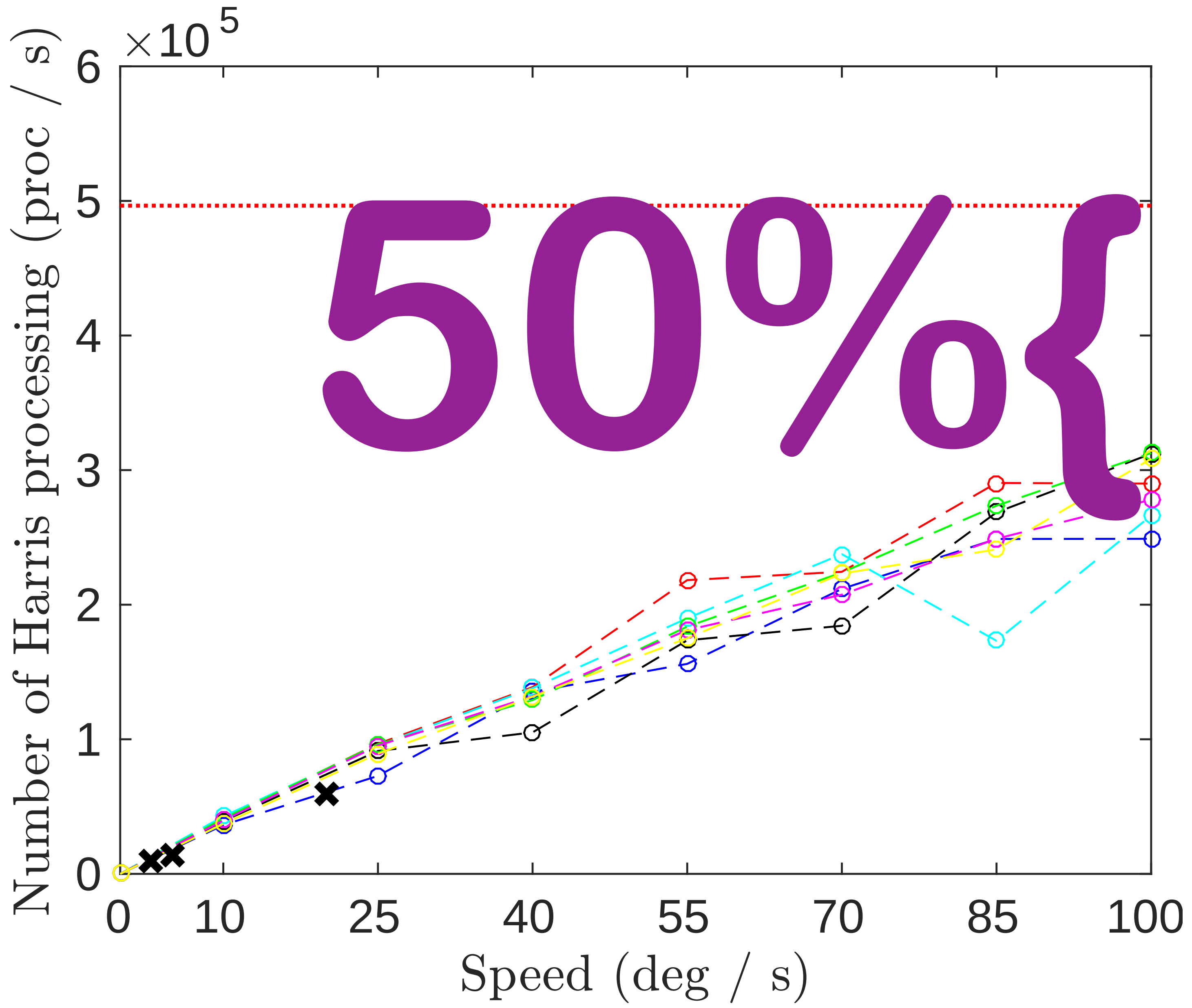


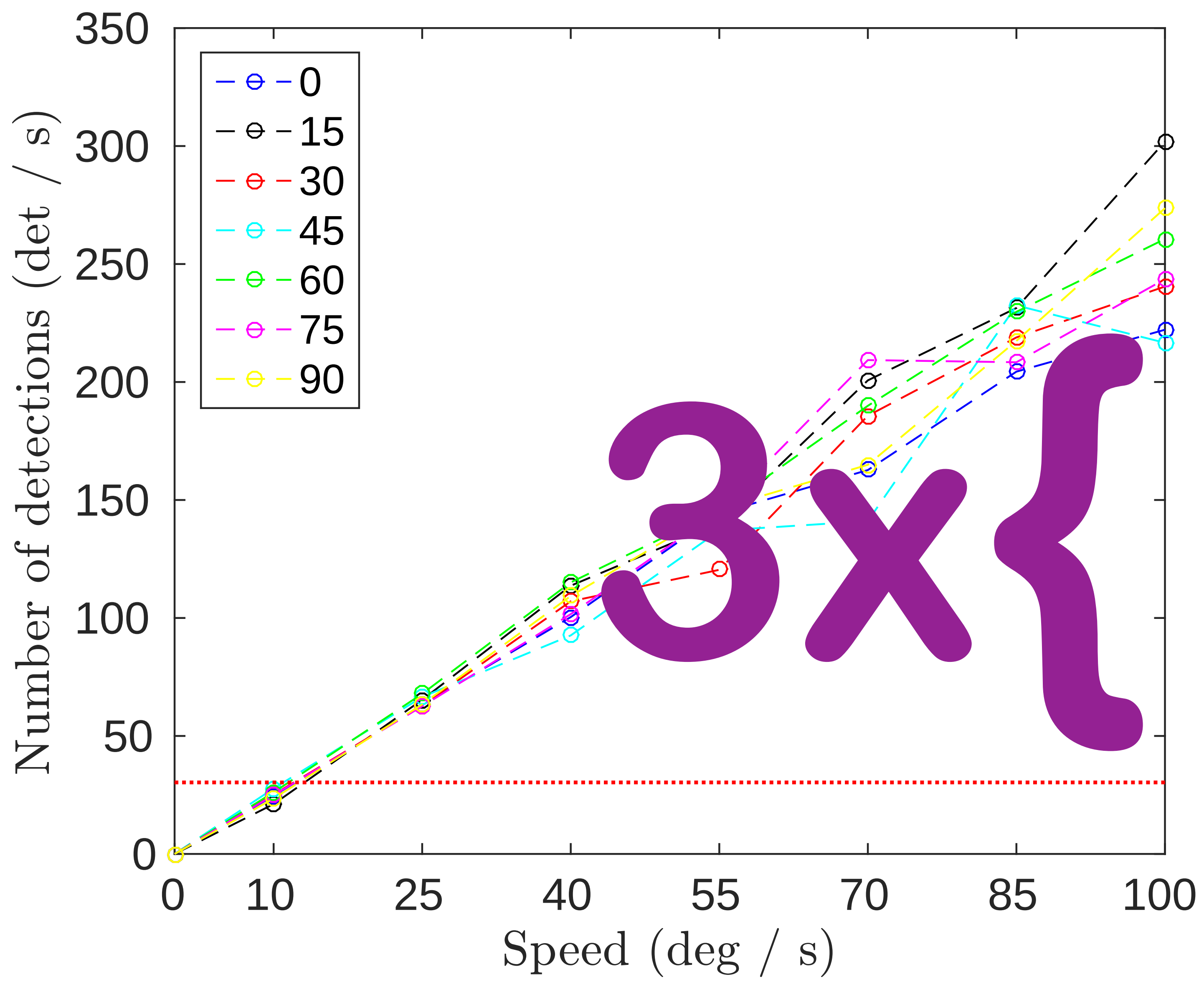
ED Vision — Corner Detection



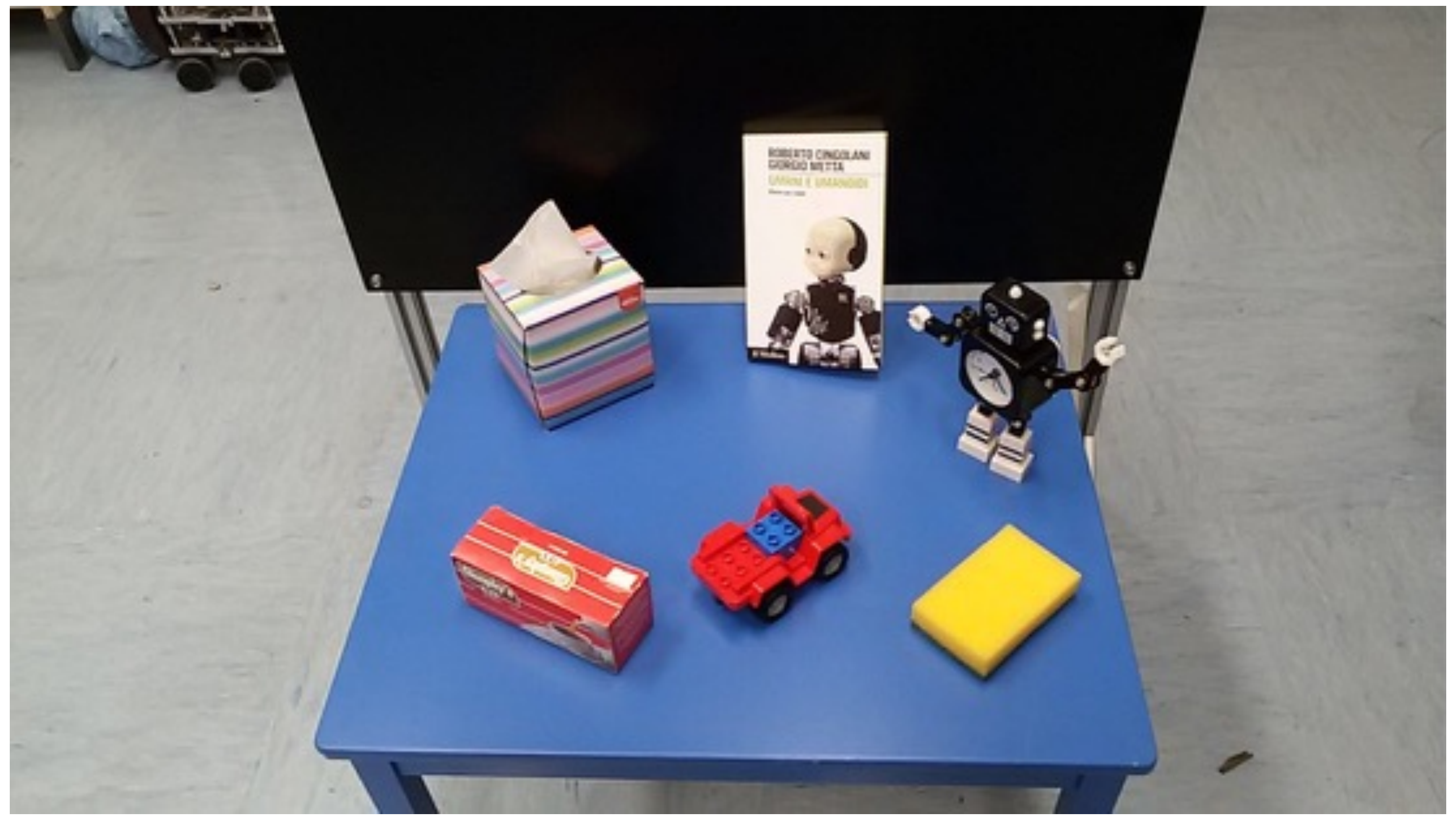


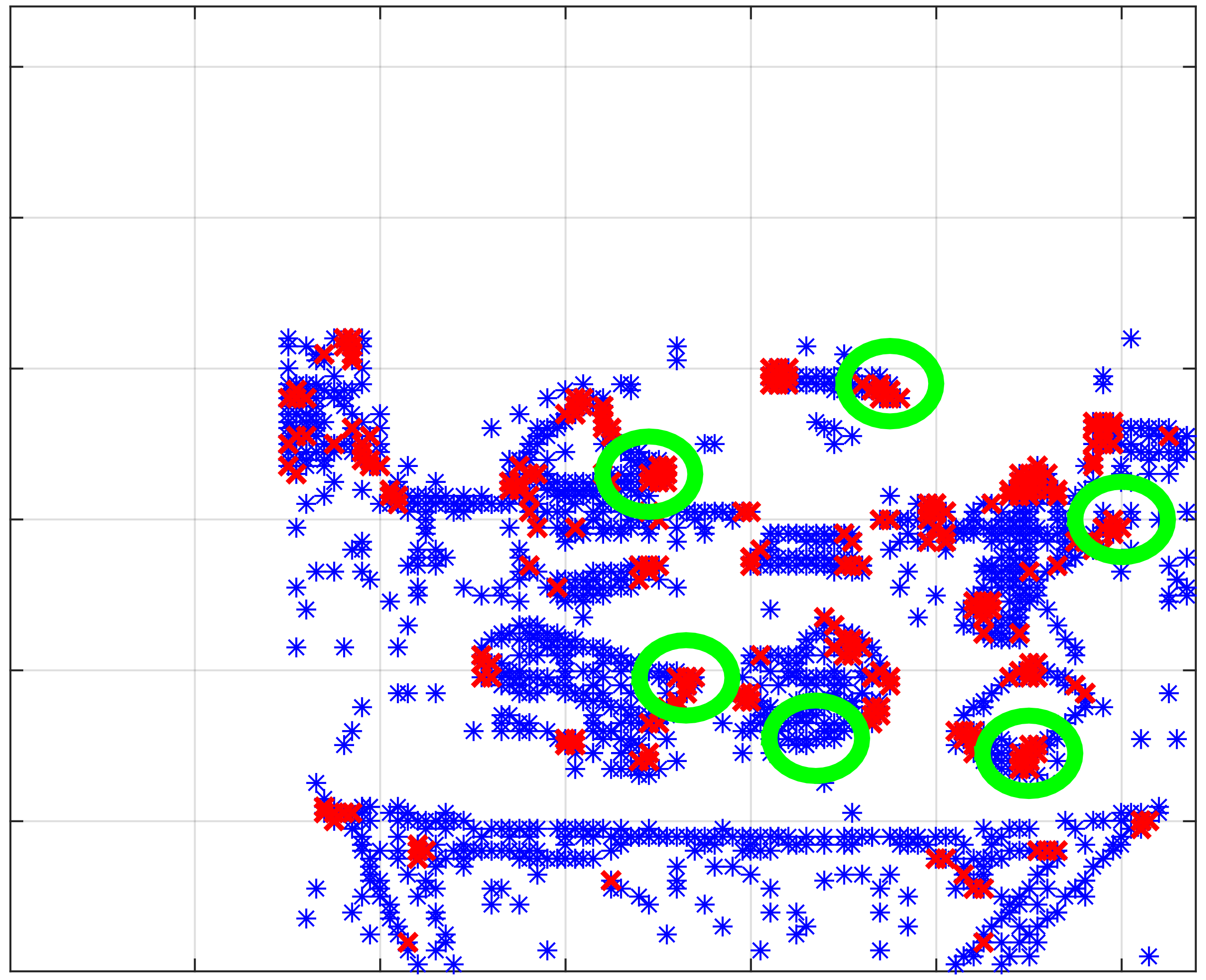


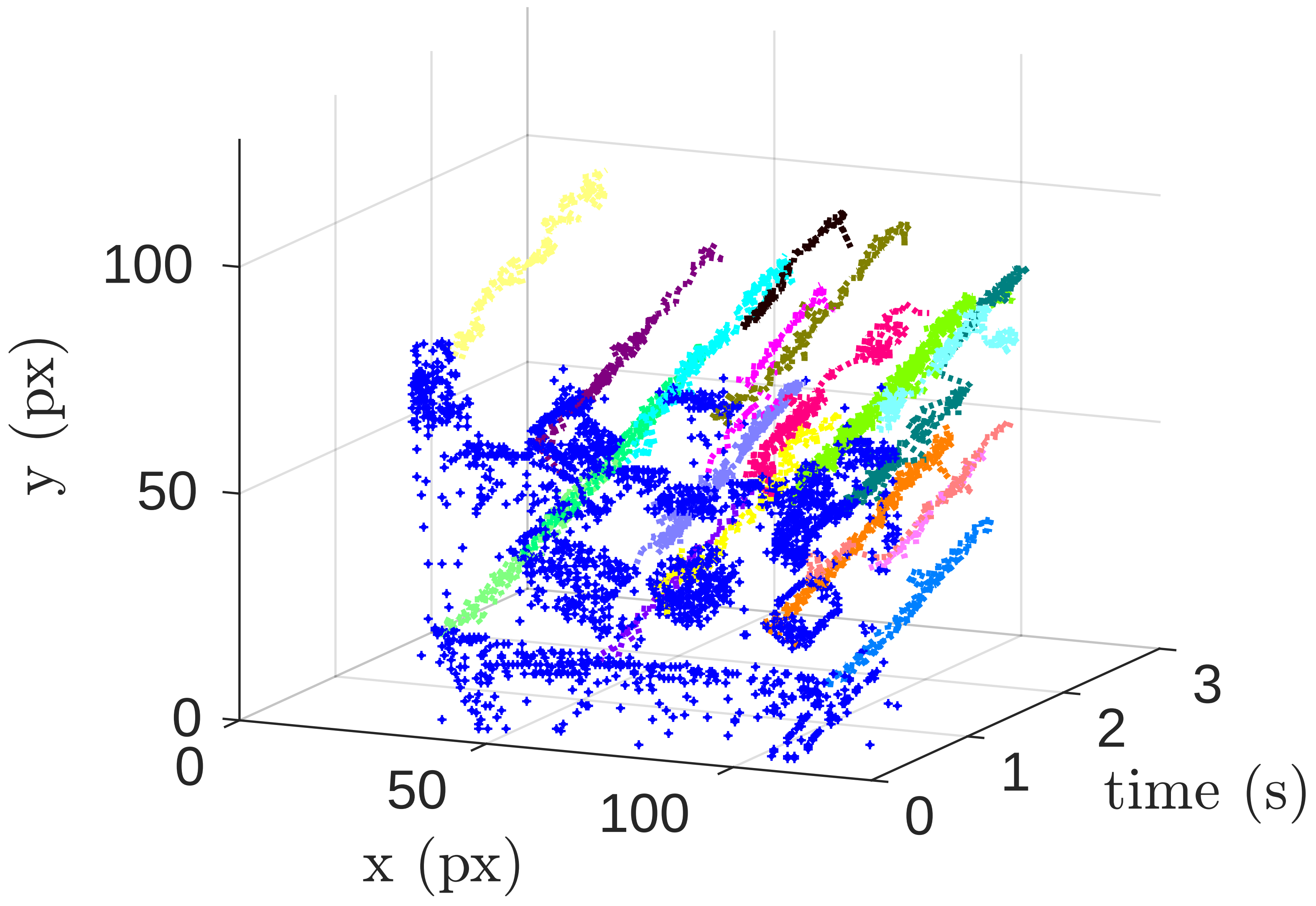


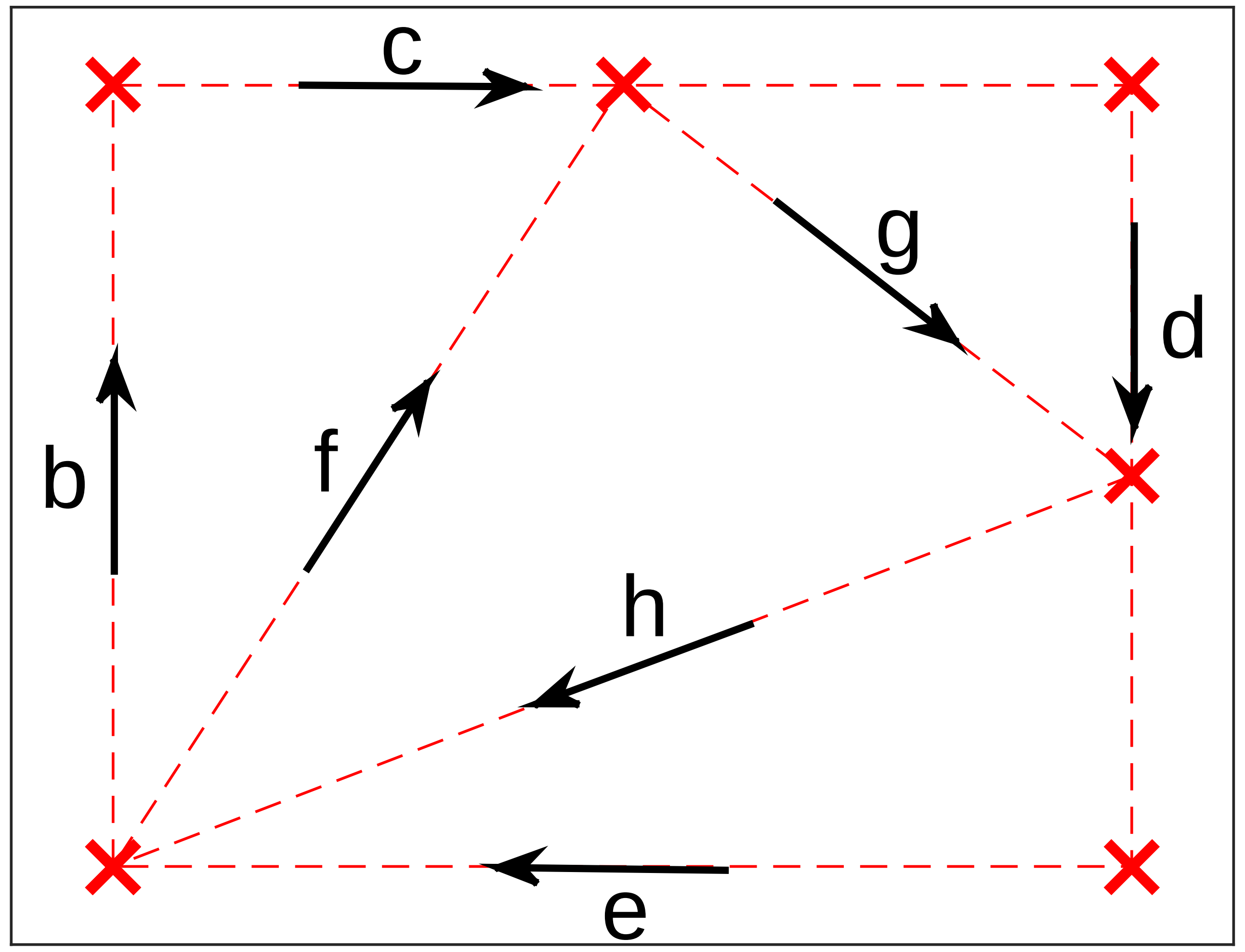


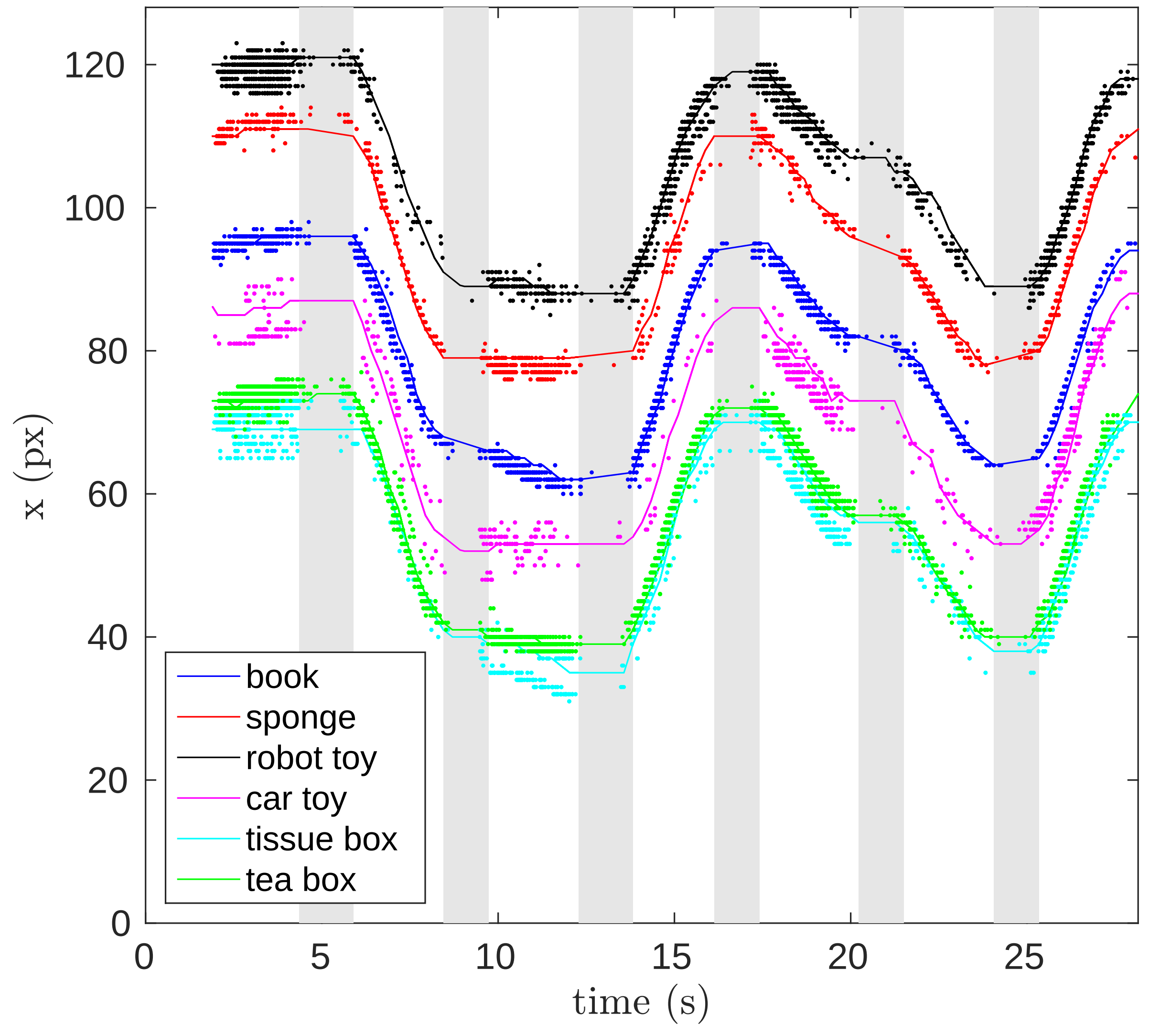
ED Vision — Corner Detection

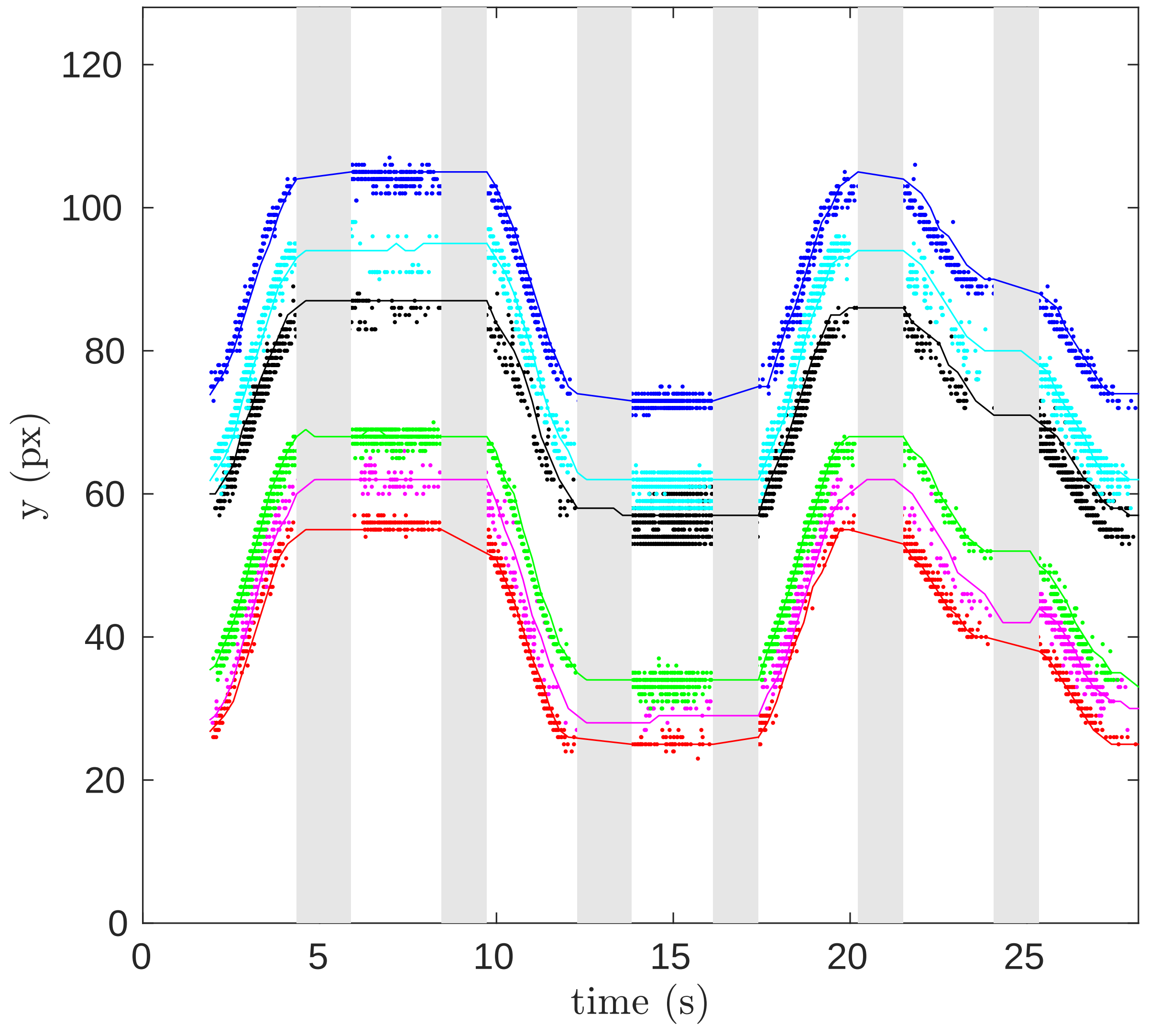


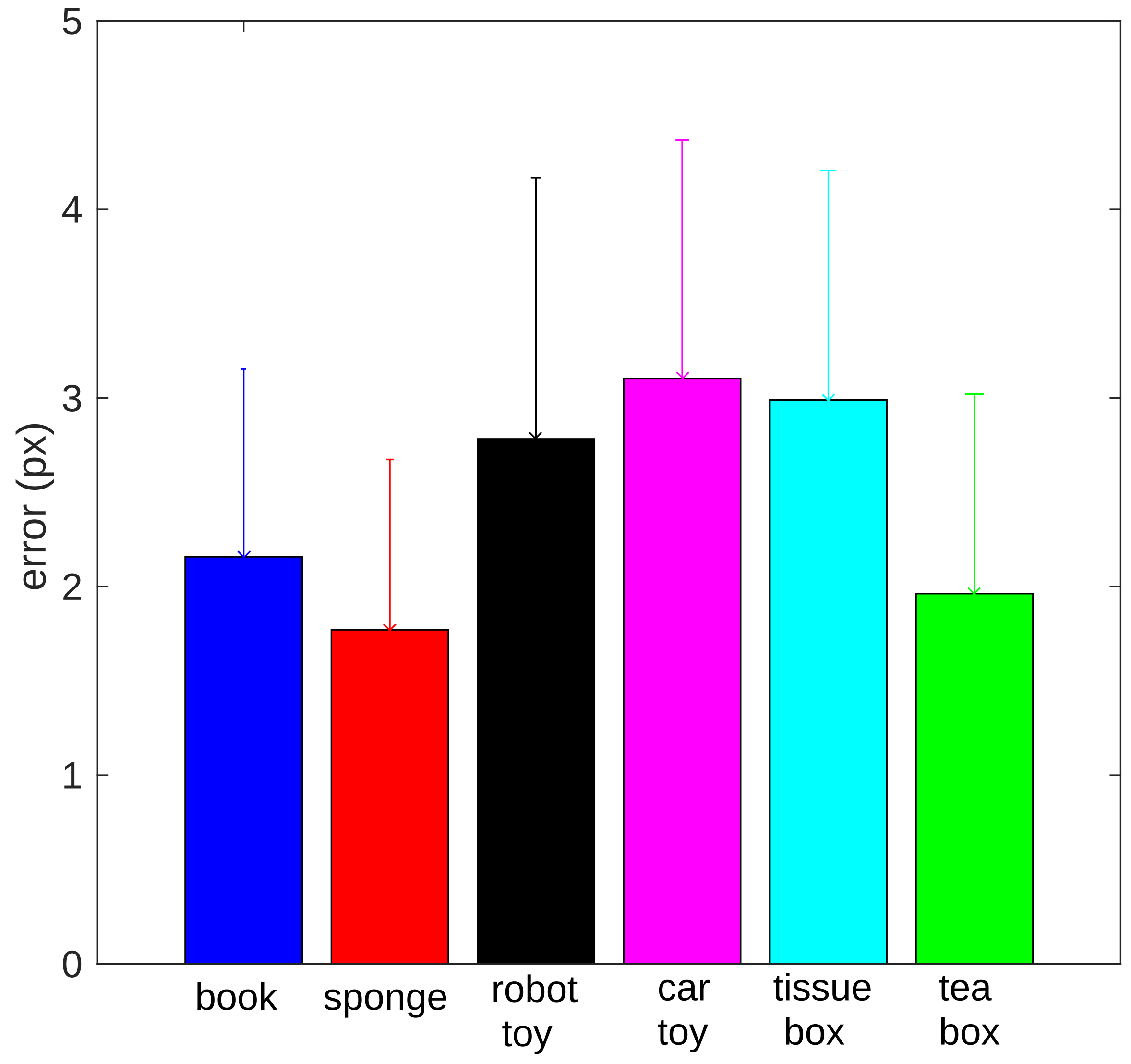




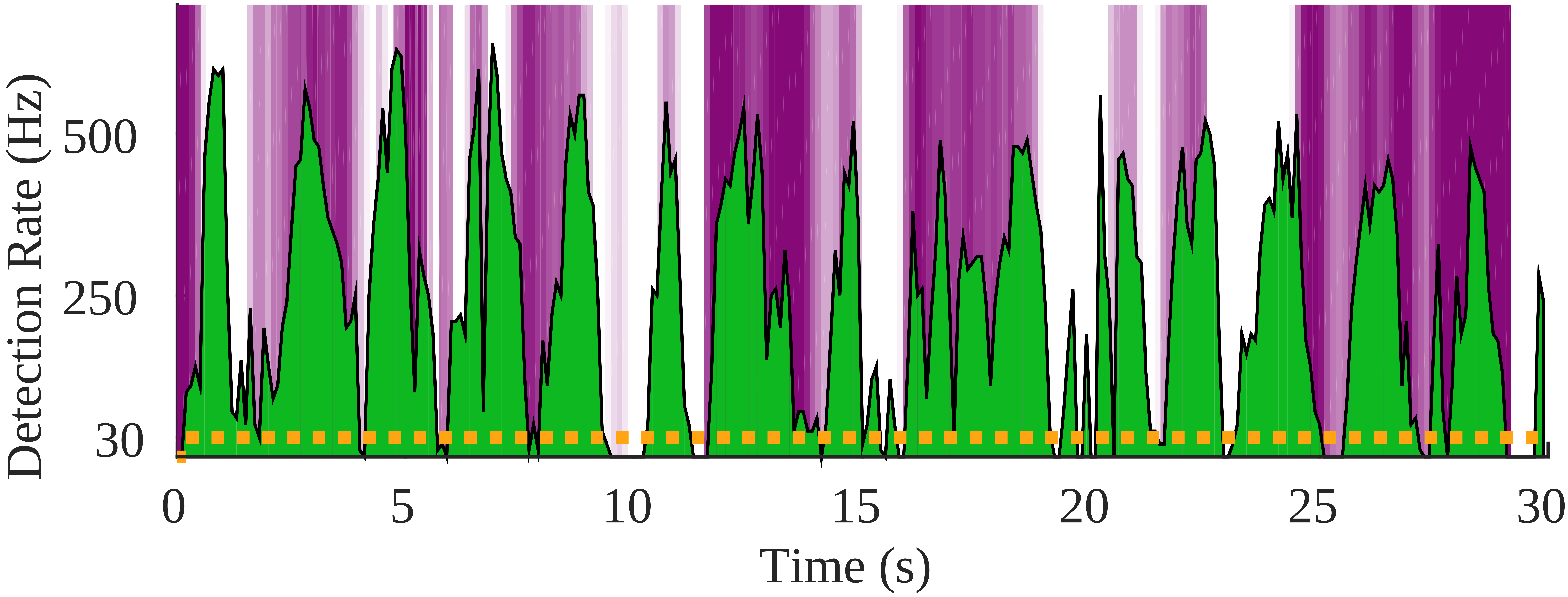








Ball Detection



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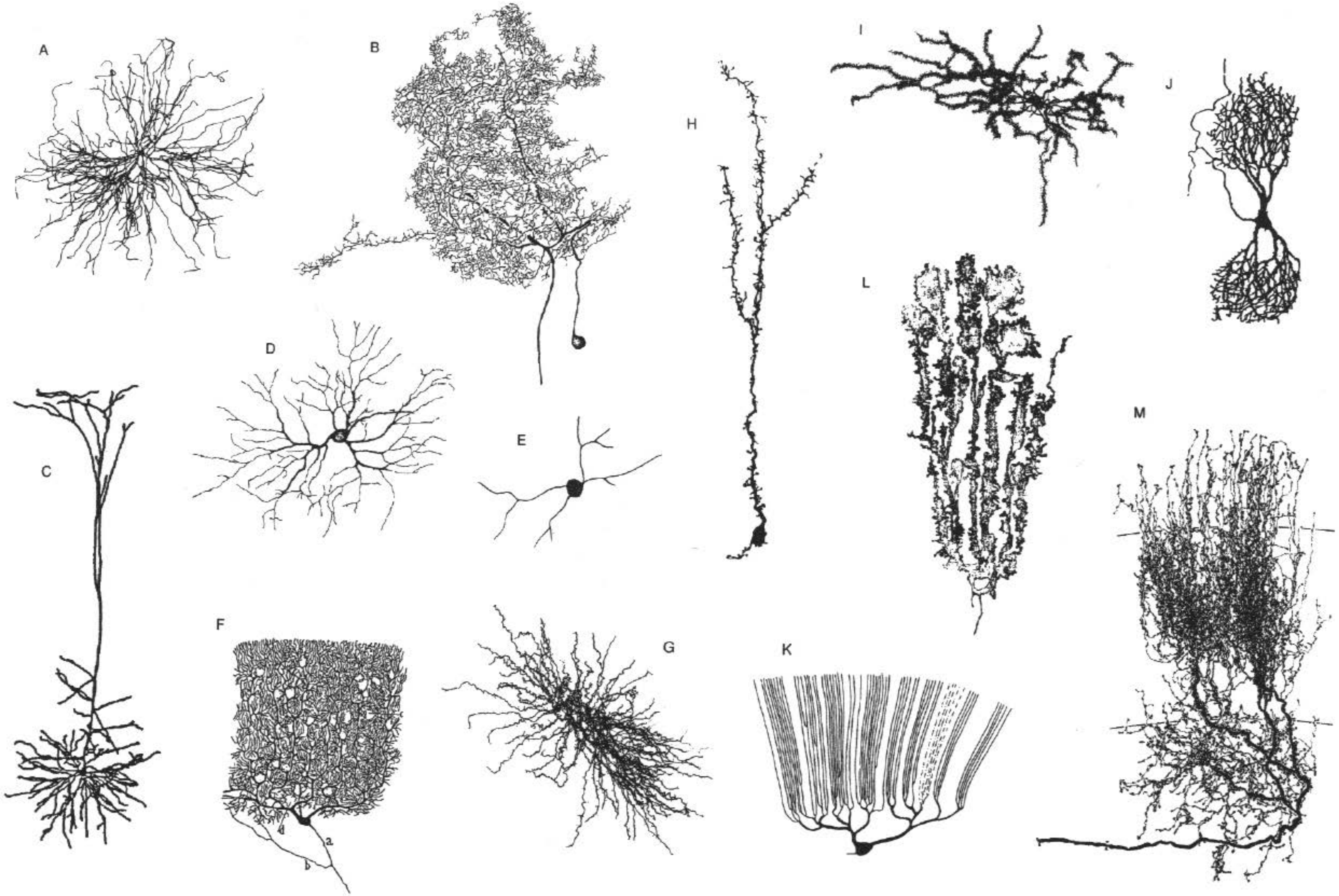
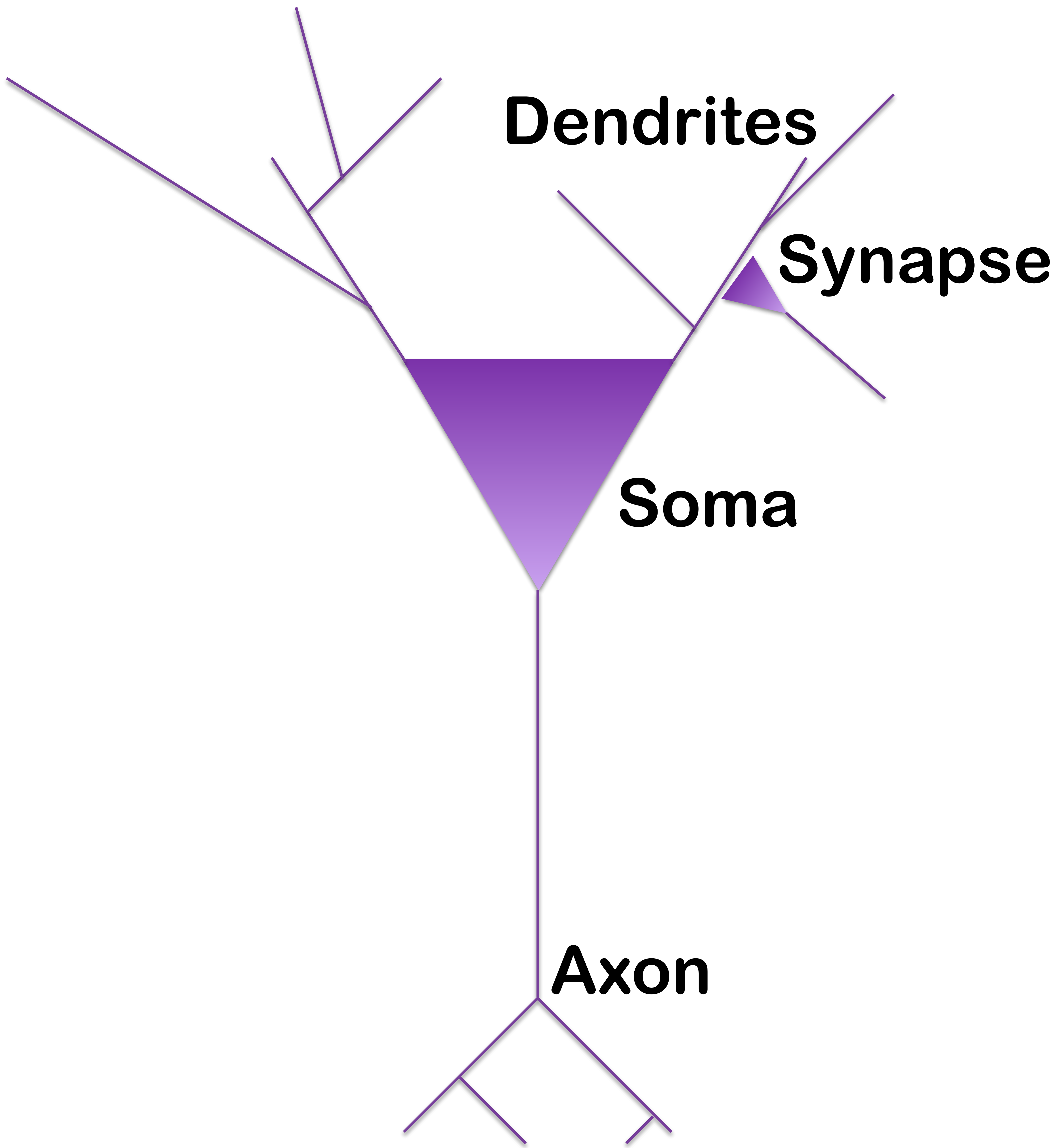
Tutorial #2
Optical Flow

Advanced event-driven library use

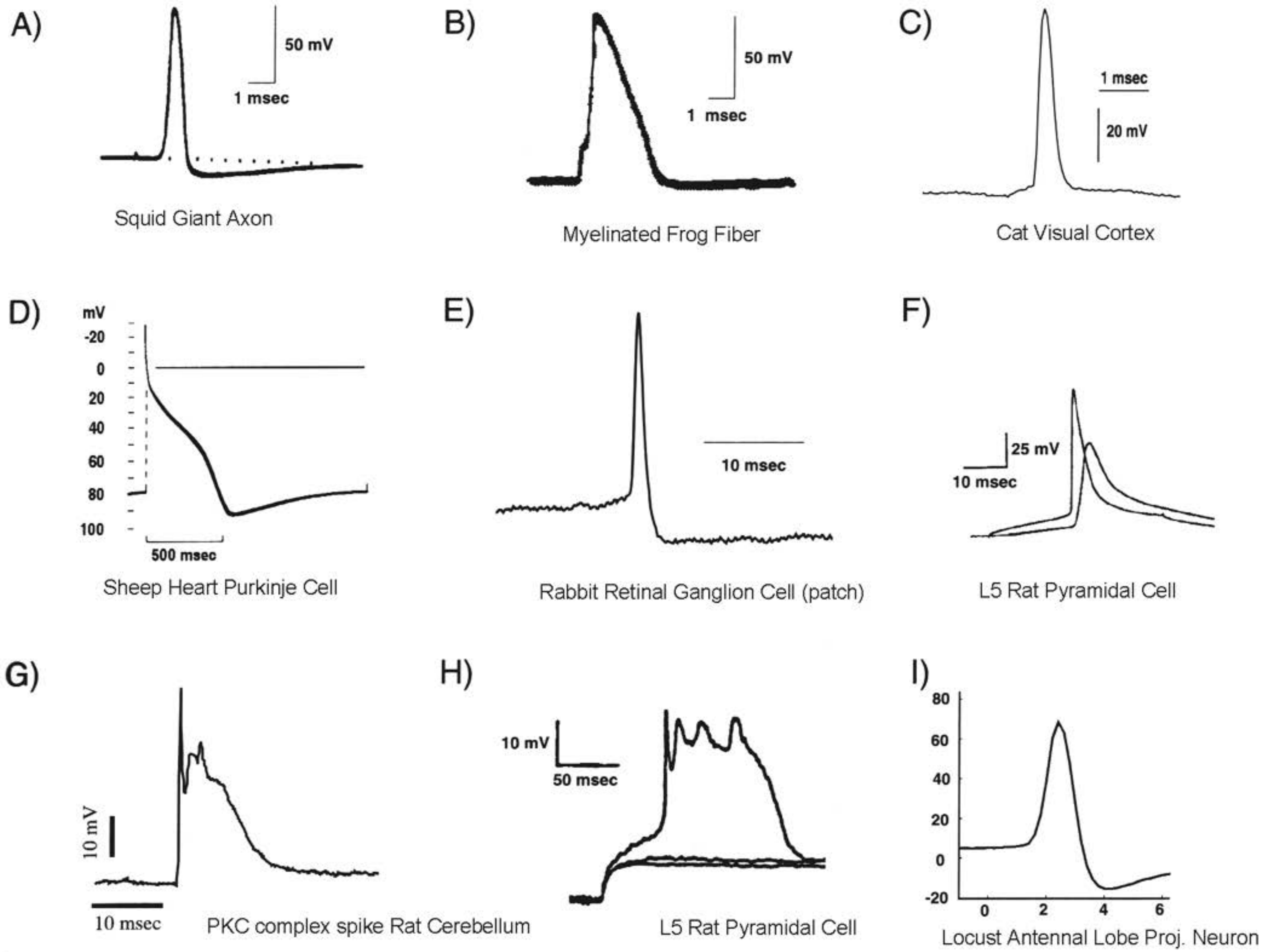
Neurons



Neurons

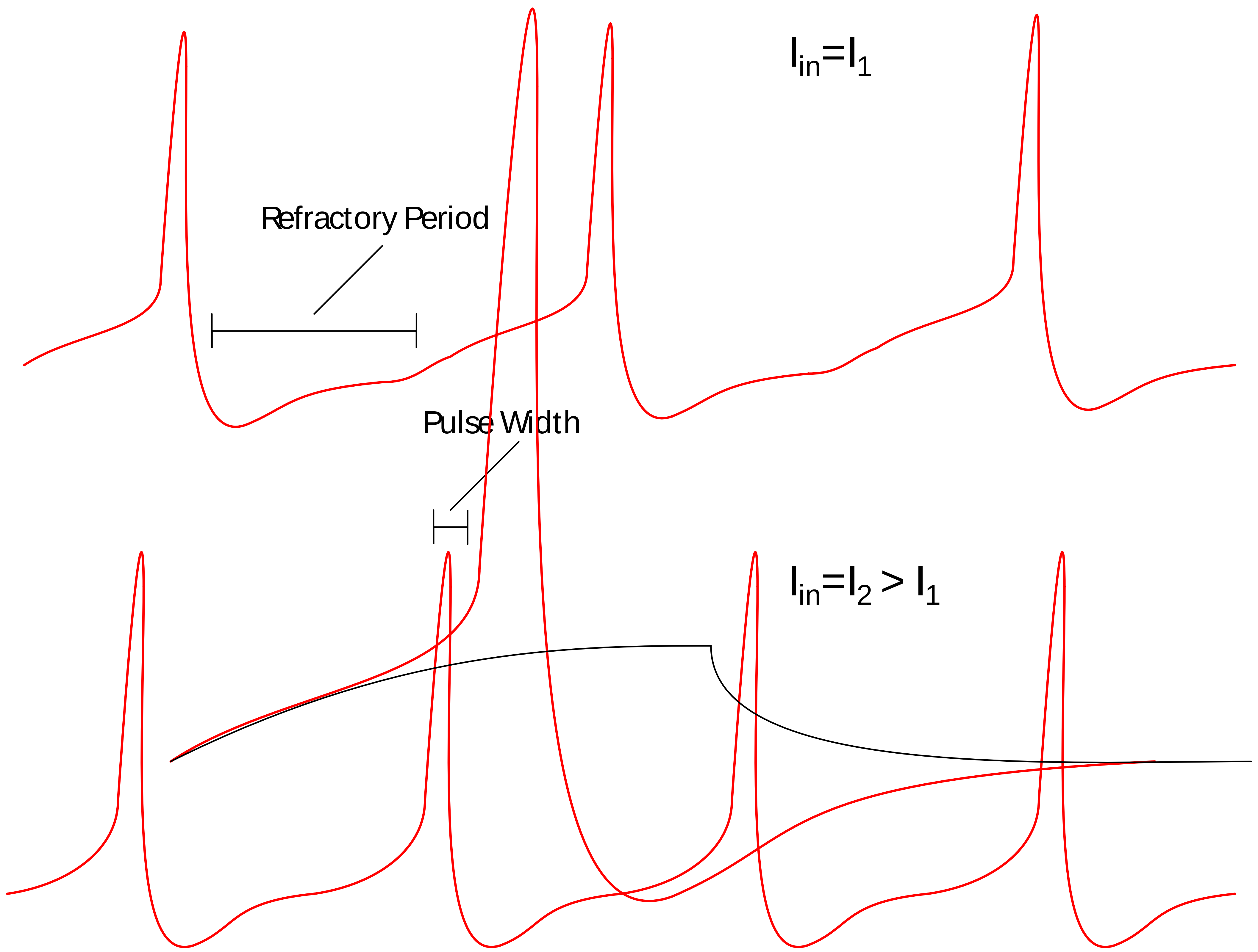


Dendrites
Synapse
Soma
Axon



A)
50 mV
1 msec
Squid Giant Axon
B)
50 mV
1 msec
Myelinated Frog Fiber
C)
1 msec
20 mV
Cat Visual Cortex
D)
mV
-20
0
20
40
60
80
100
500 msec
Sheep Heart Purkinje Cell
E)
10 msec
Rabbit Retinal Ganglion Cell (patch)
F)
25 mV
10 msec
L5 Rat Pyramidal Cell
G)
10 mV
10 msec
PKC complex spike Rat Cerebellum
H)
10 mV
50 msec
L5 Rat Pyramidal Cell
I)
80
60
40
20
0
-20
0
2
4
6
Locust Antennal Lobe Proj. Neuron

Neurons — Action Potential

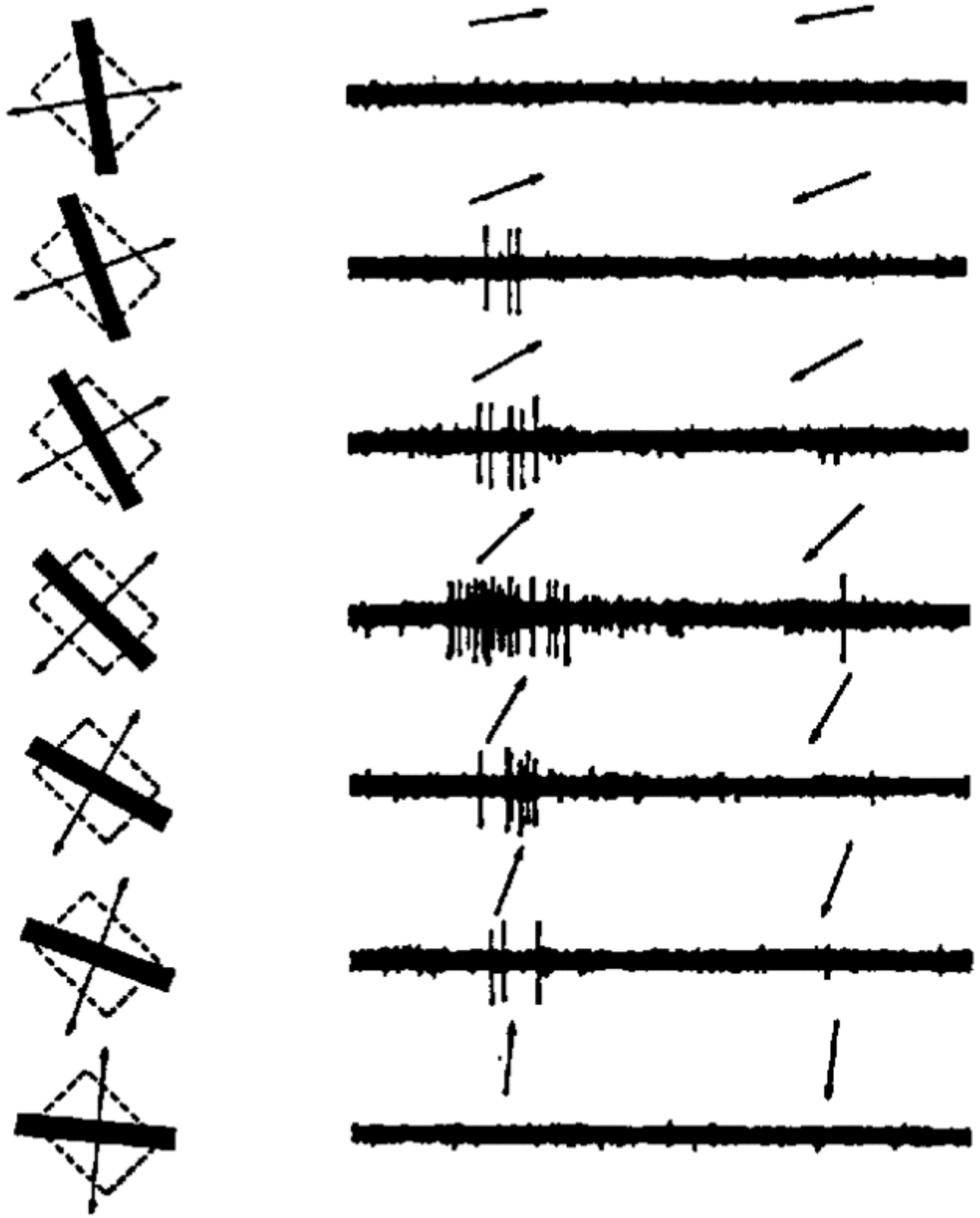


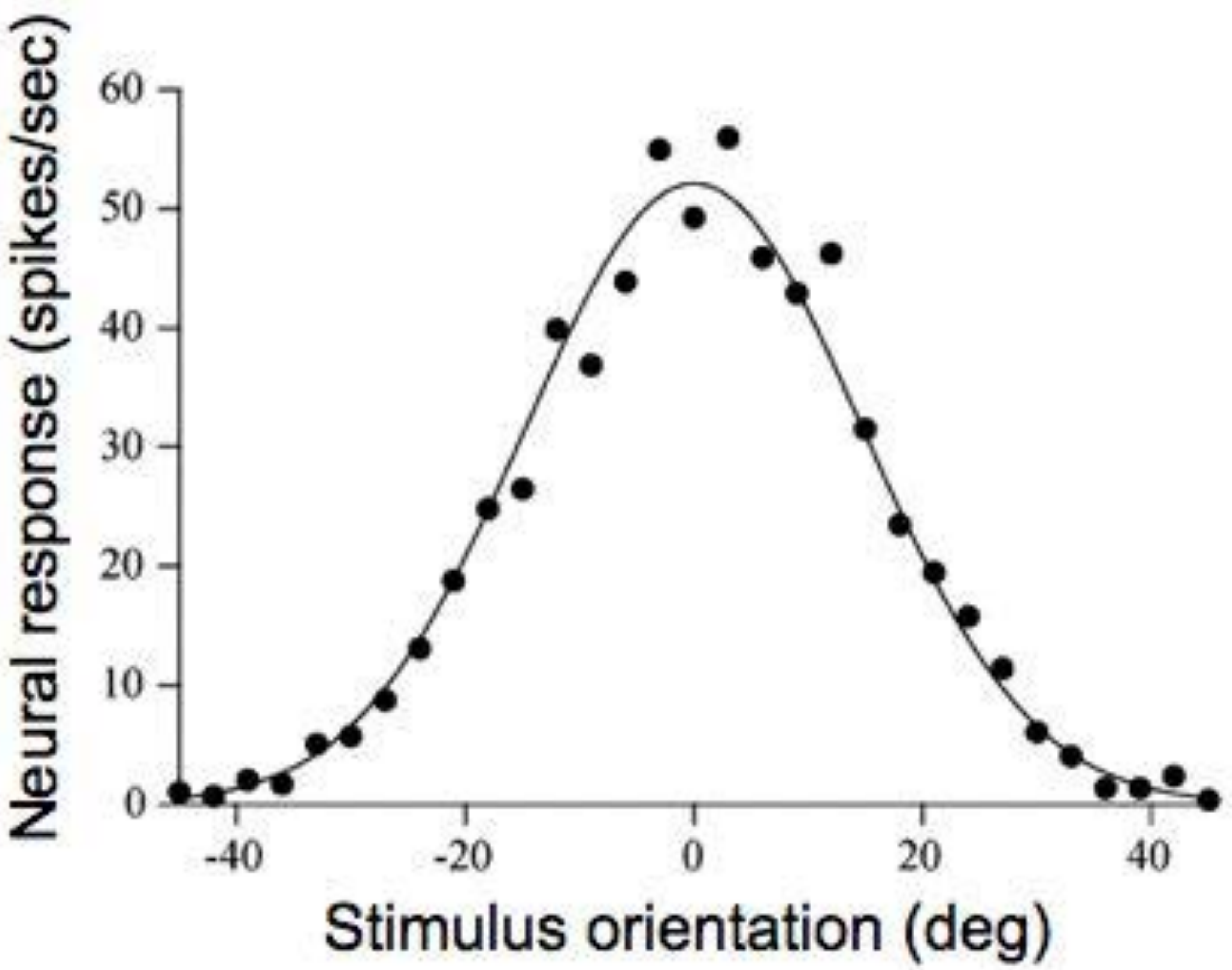
A simplified model is the Leaky Integrate and Fire neuron:

$$\tau_m \frac{dv}{dt} = -v(t) + Ri(t)$$

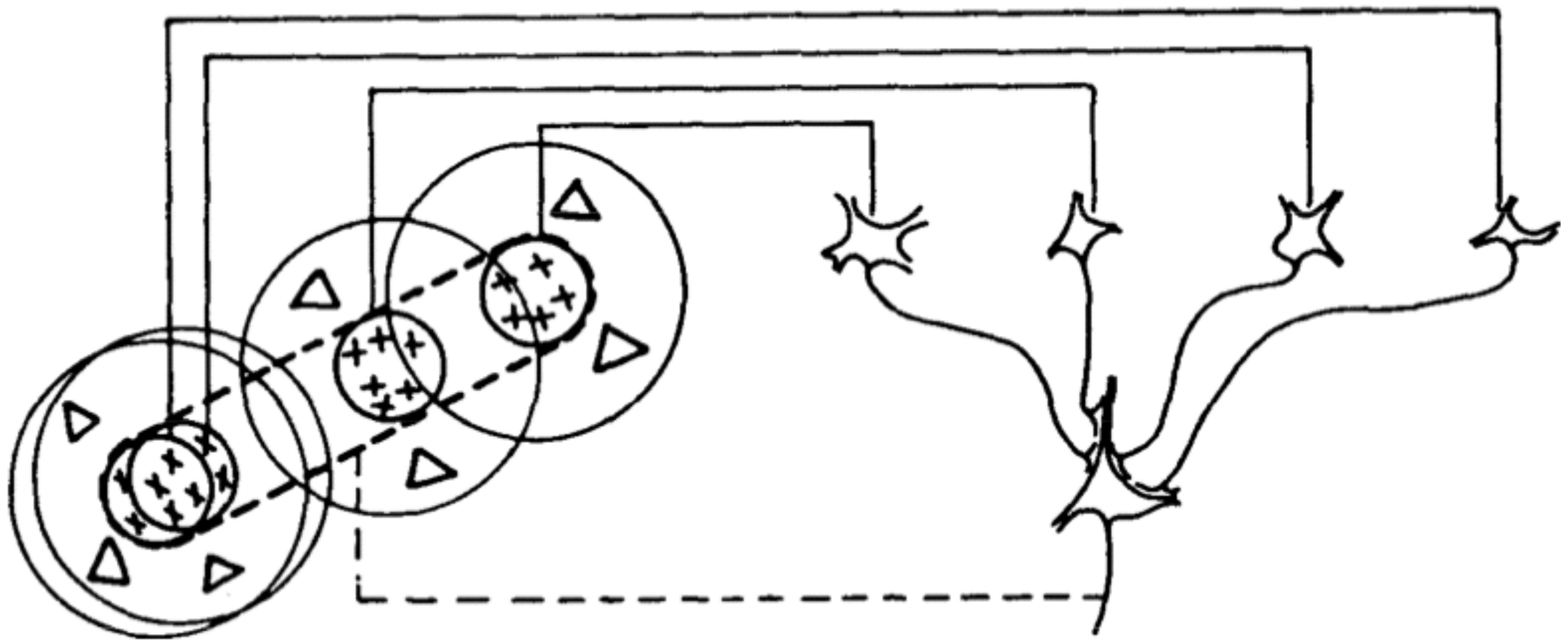
$$\text{if } v > v_{thr} \text{ fire and reset!}$$

Neurons — Receptive Field



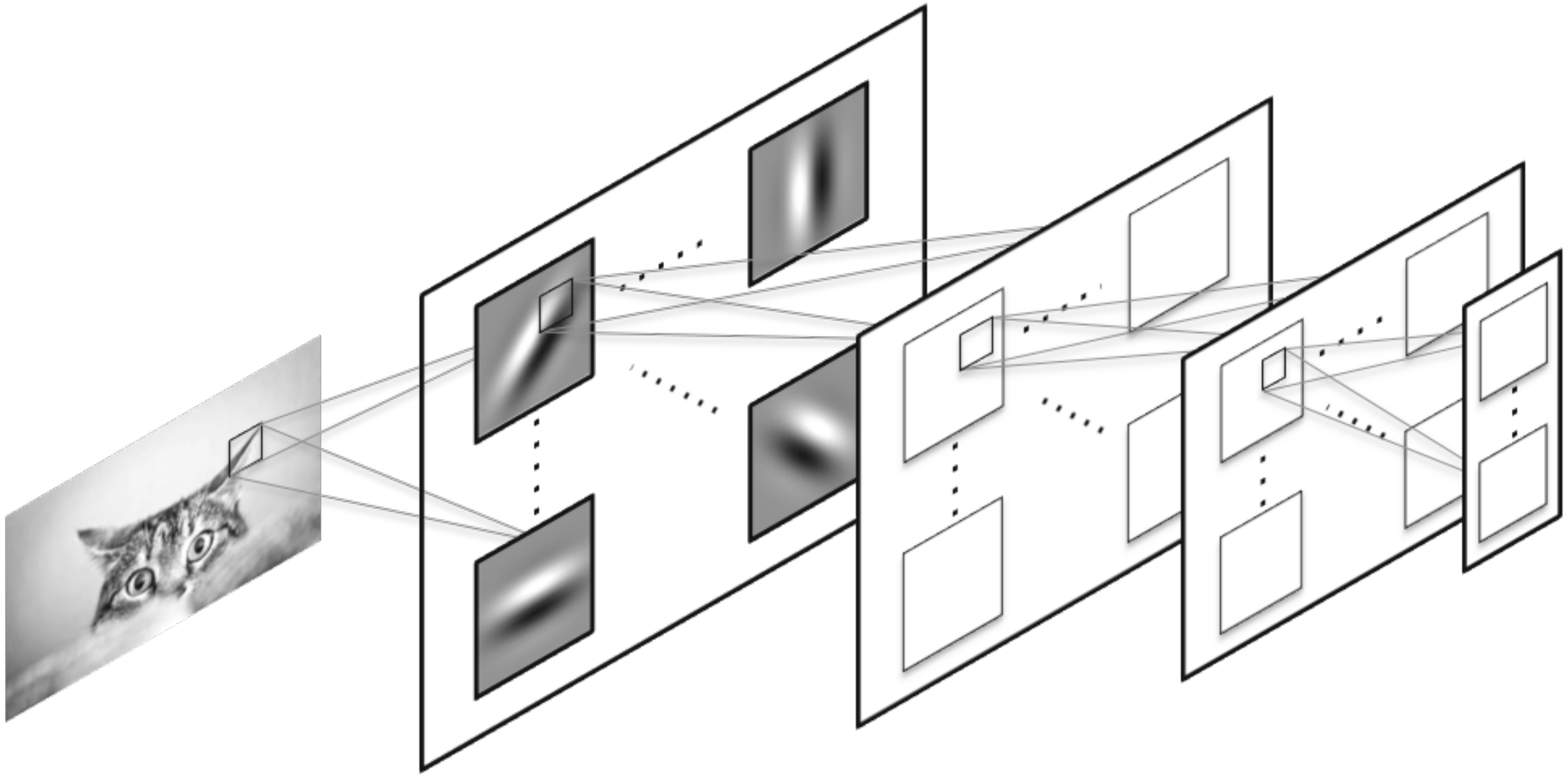


Hubel&Wiesel 1968

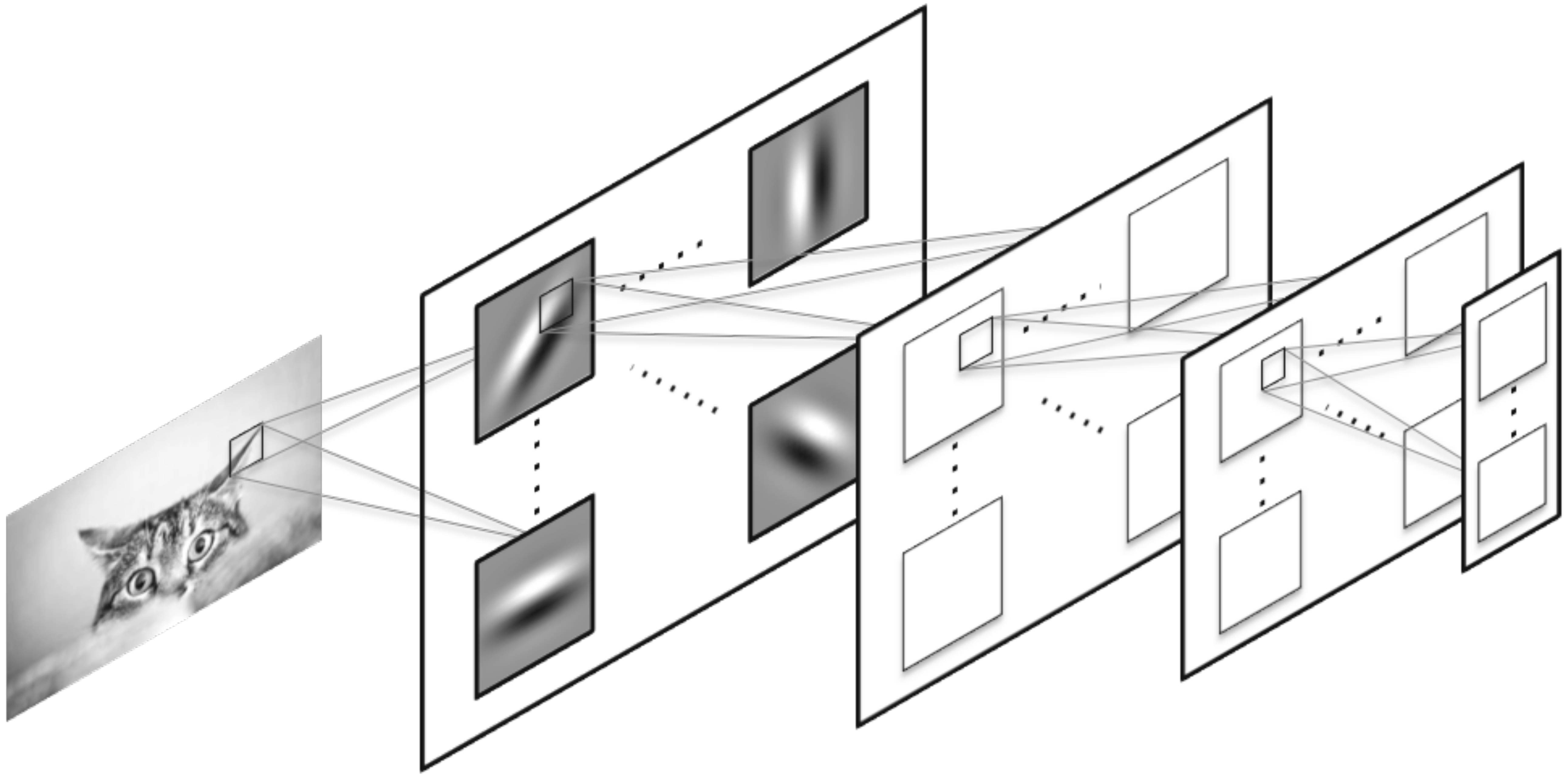


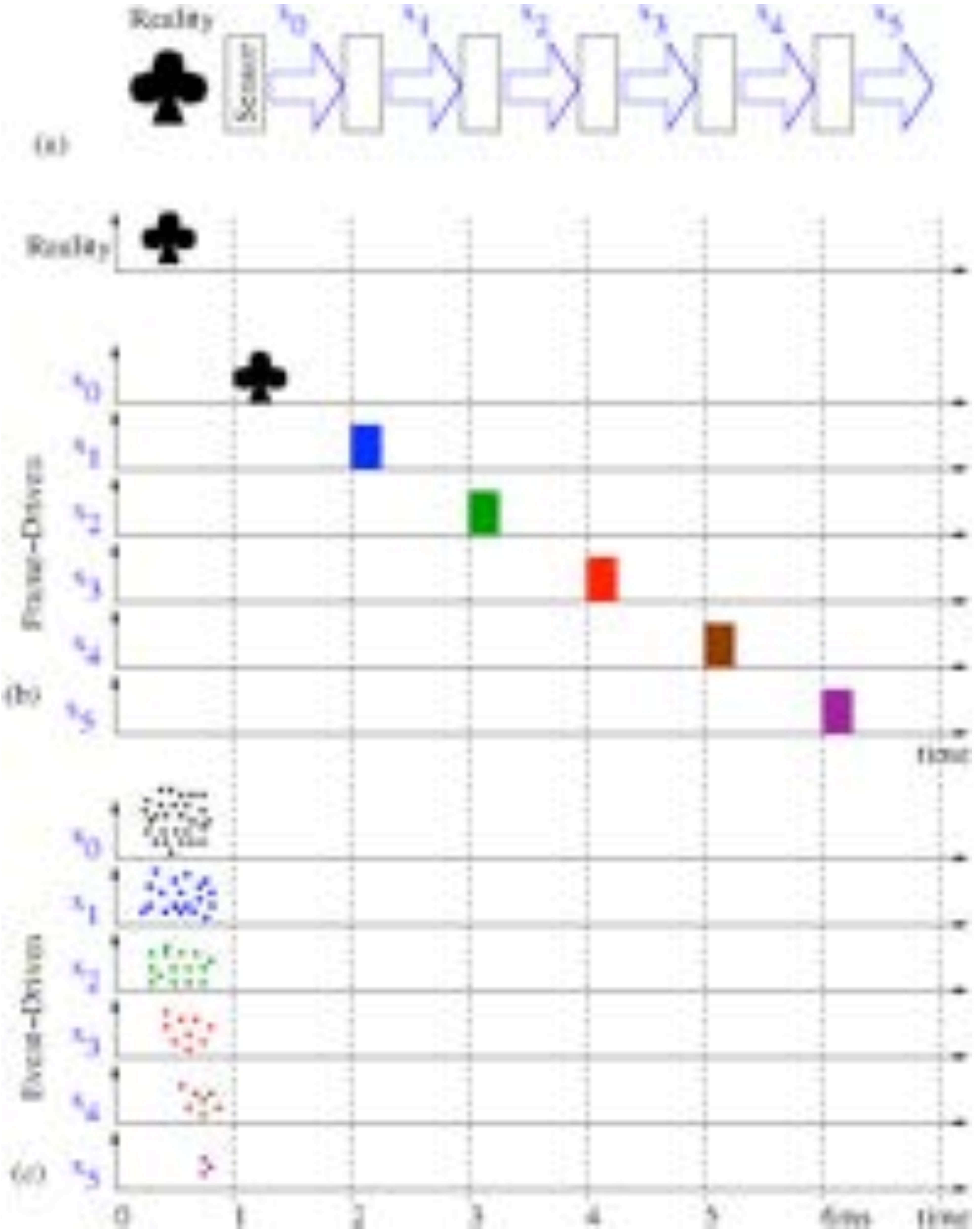
Neurons — Receptive Field

2D Gabor Filter



ED Vision – PseudoSimultaneous





Courtesy of
B. Linares-Barranco

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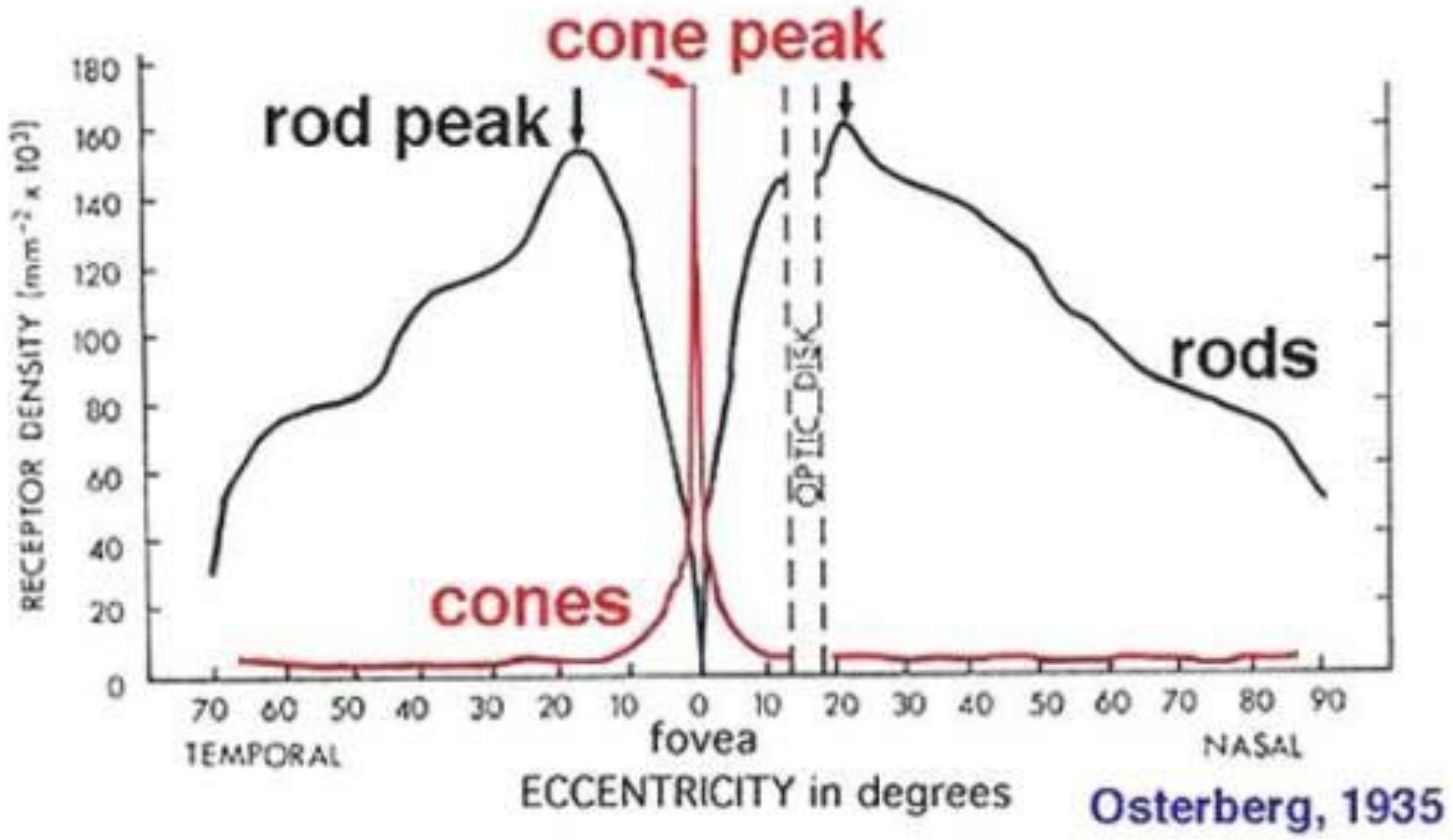
Attention

Fovea and Periphery

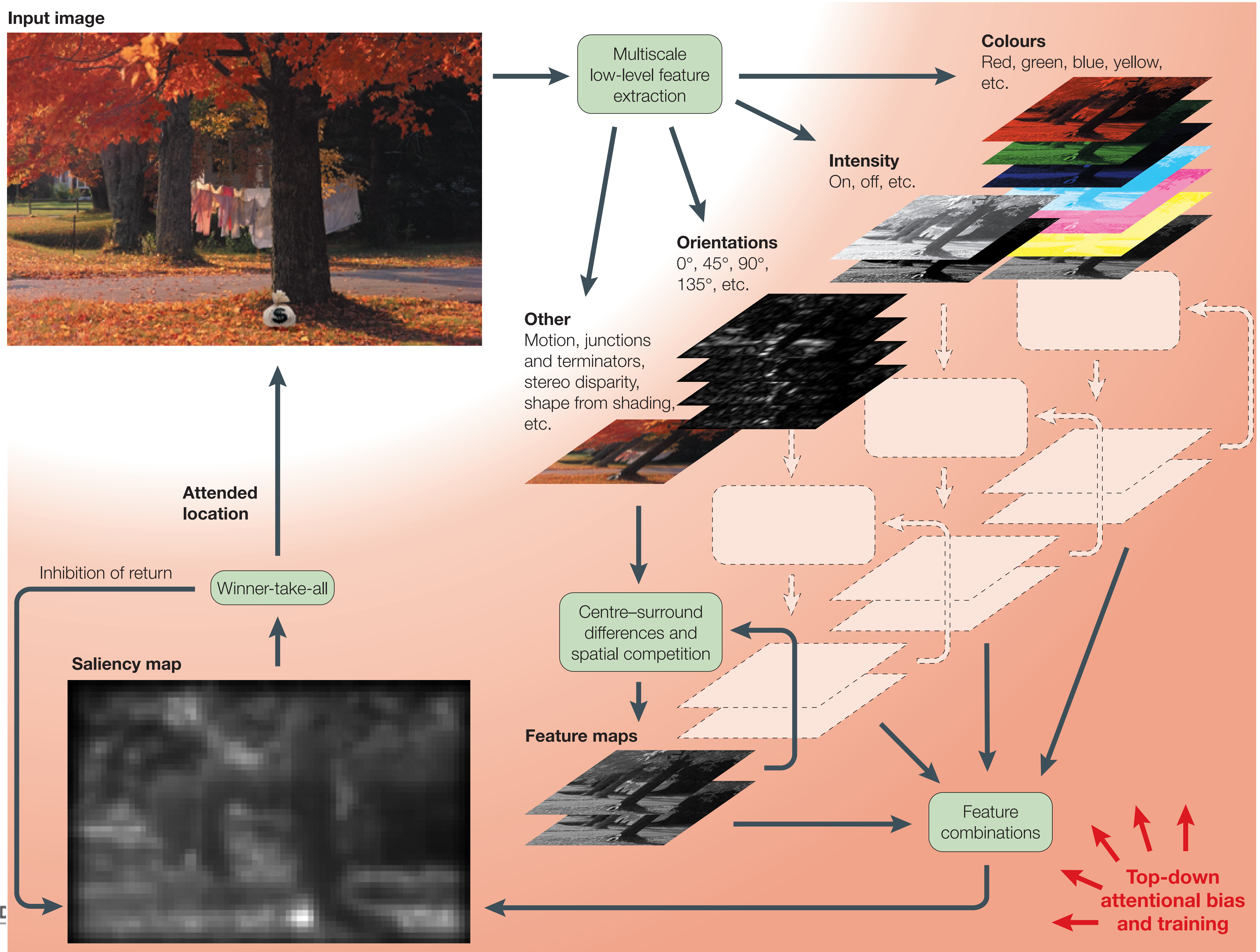


- **High Resolution in the Fovea**
- **Large field of view**
- **Limit the amount of data**

5000 pixels
plus 27000
“traditional”
pixels

5000 pixels
plus 27000 retina-like pixels

Attention



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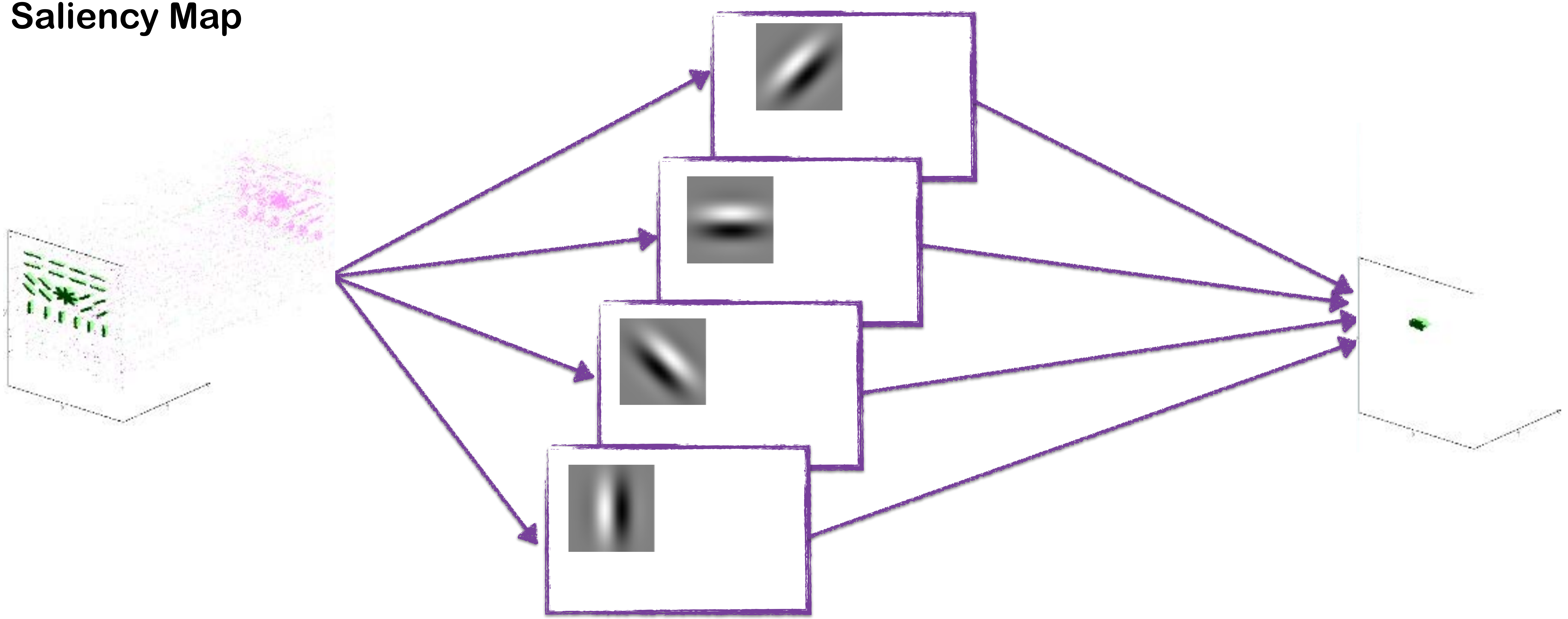
Attention — ASSIGNMENTS!!!!

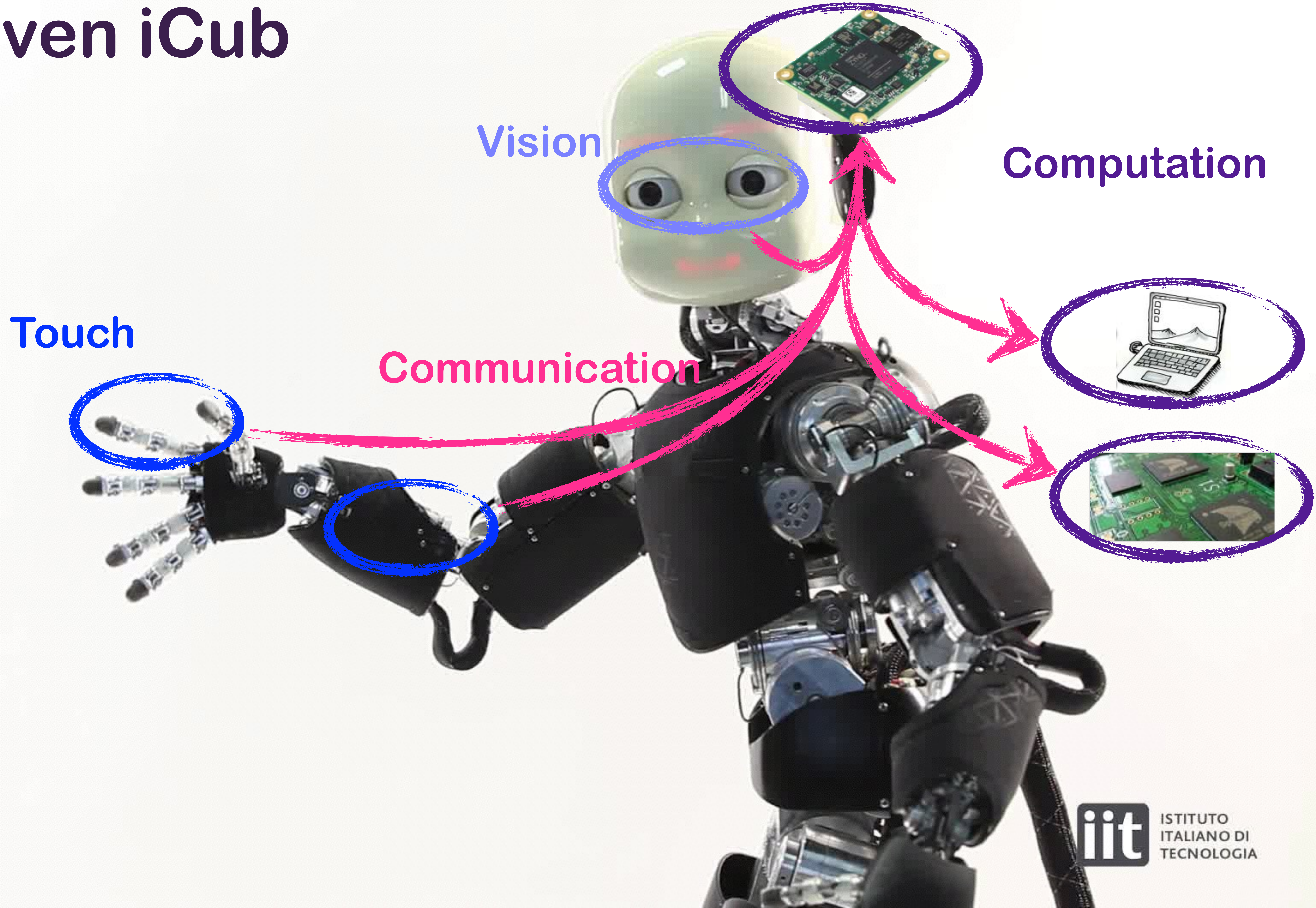
Assignment #1: build a spiking map based on Leaky Integrate and Fire Model

Assignment #2: build a spiking feature maps selective to different orientations (if you're courageous try Gabor filters ;-))

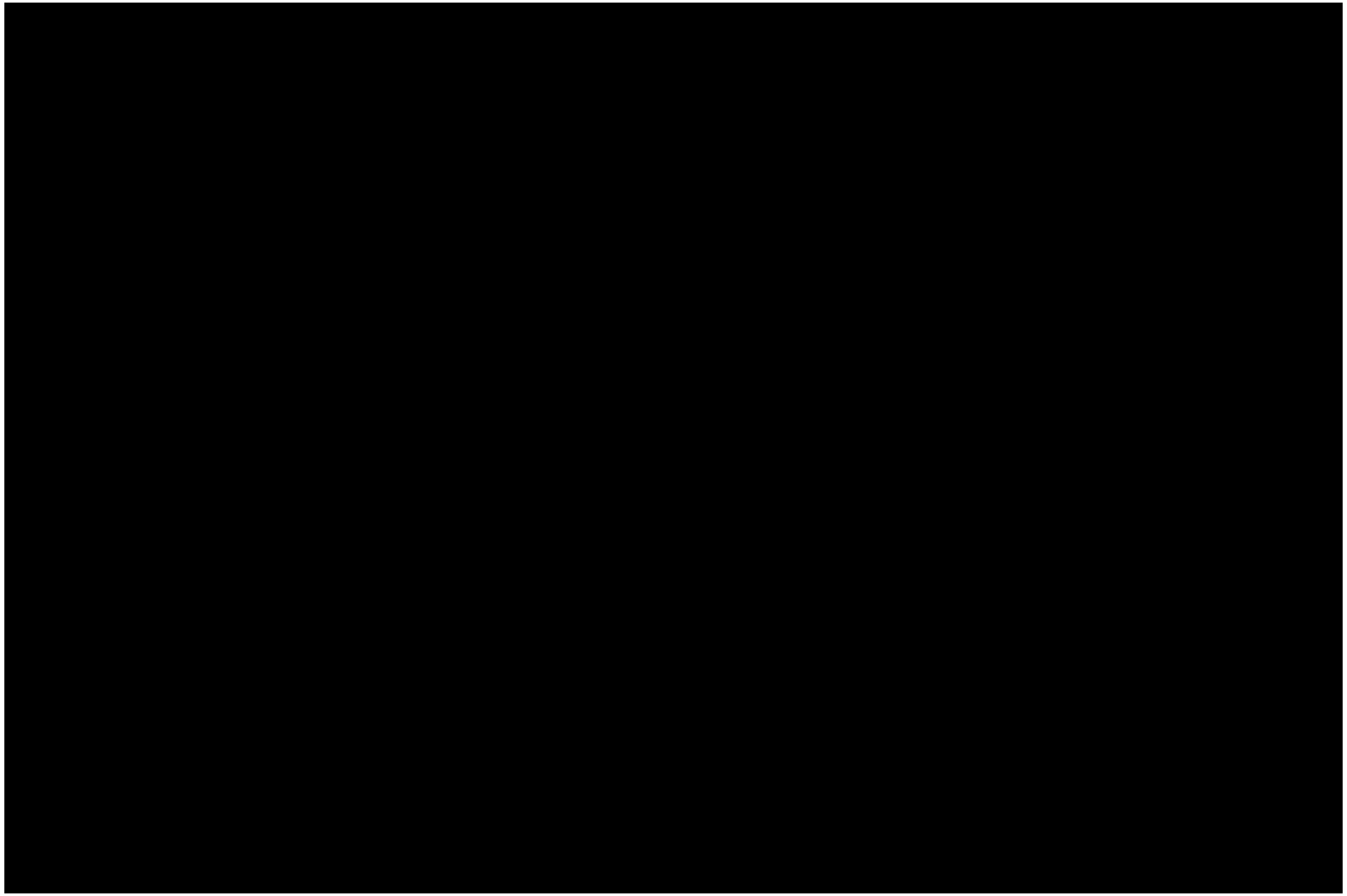
Assignment #3: connect the feature maps modules to create the hierarchy and the final Saliency Map



Event-Driven iCub

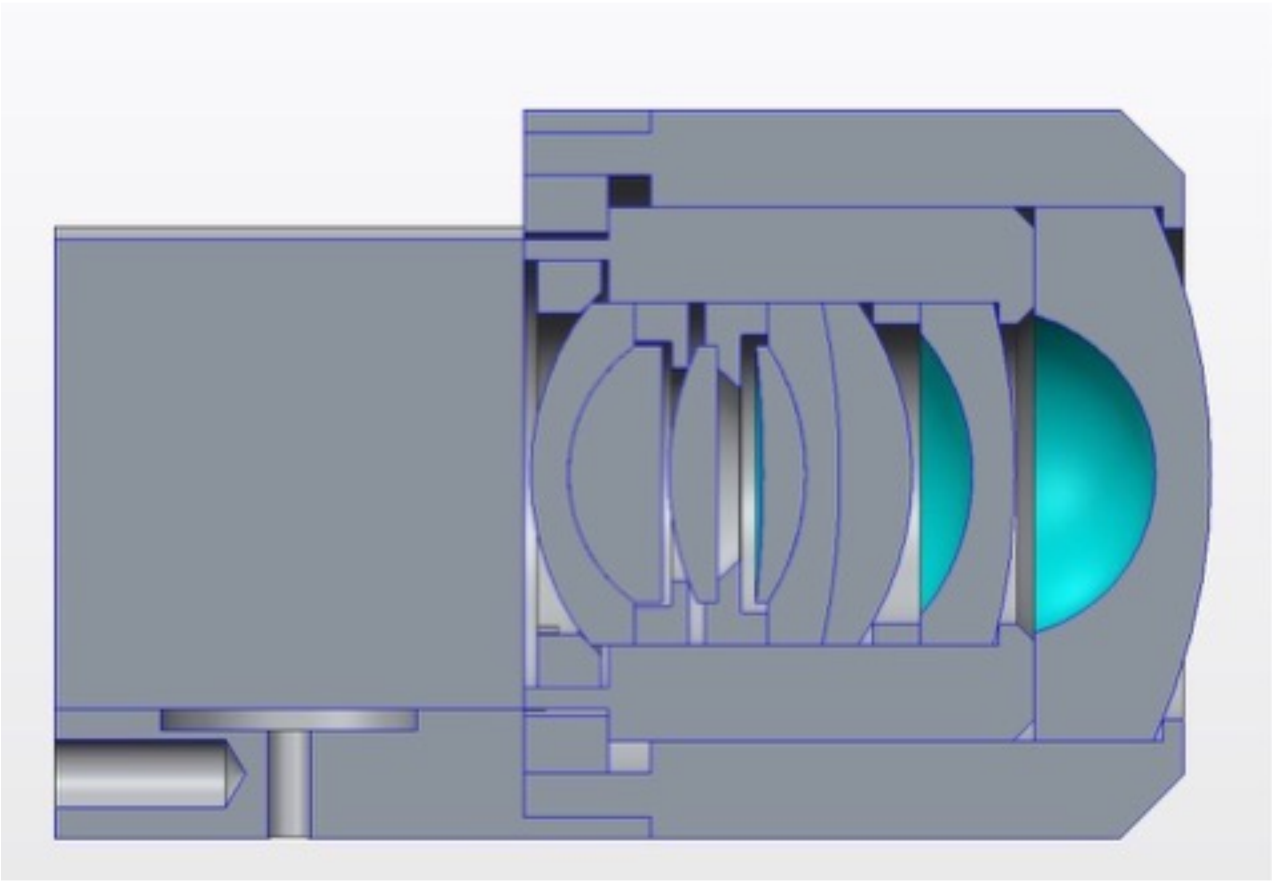


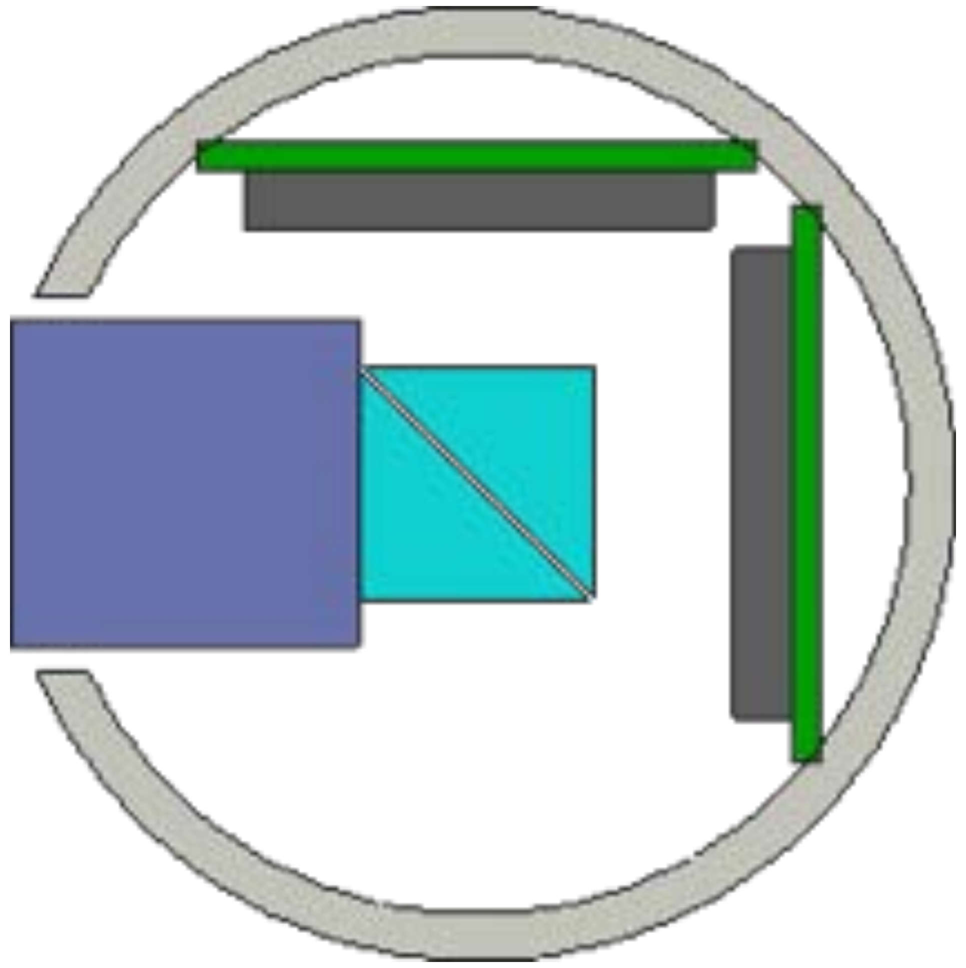
ED Sensors — Vision

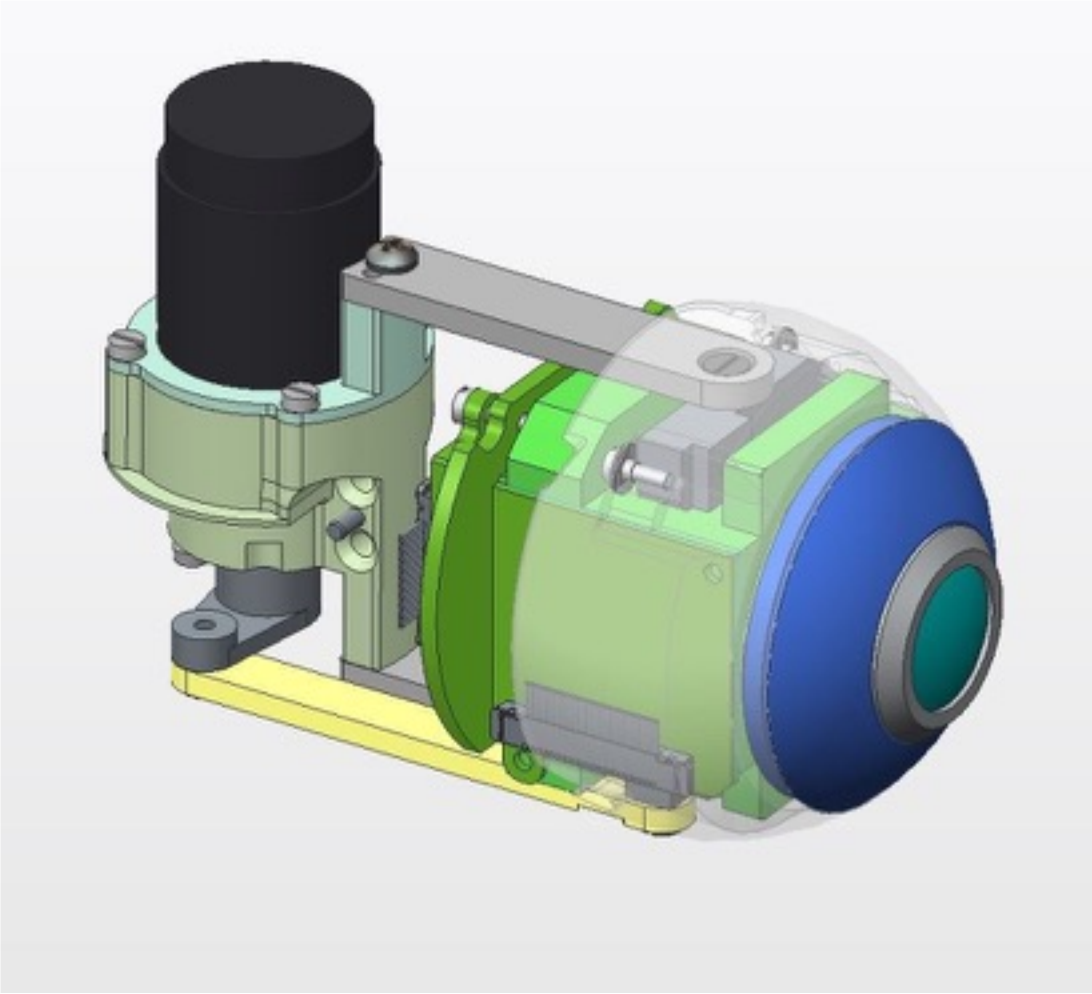


ATIS	CMOS
Spatial Res	240x304 2/3”
Temporal Res	1µs
AFOV	61°

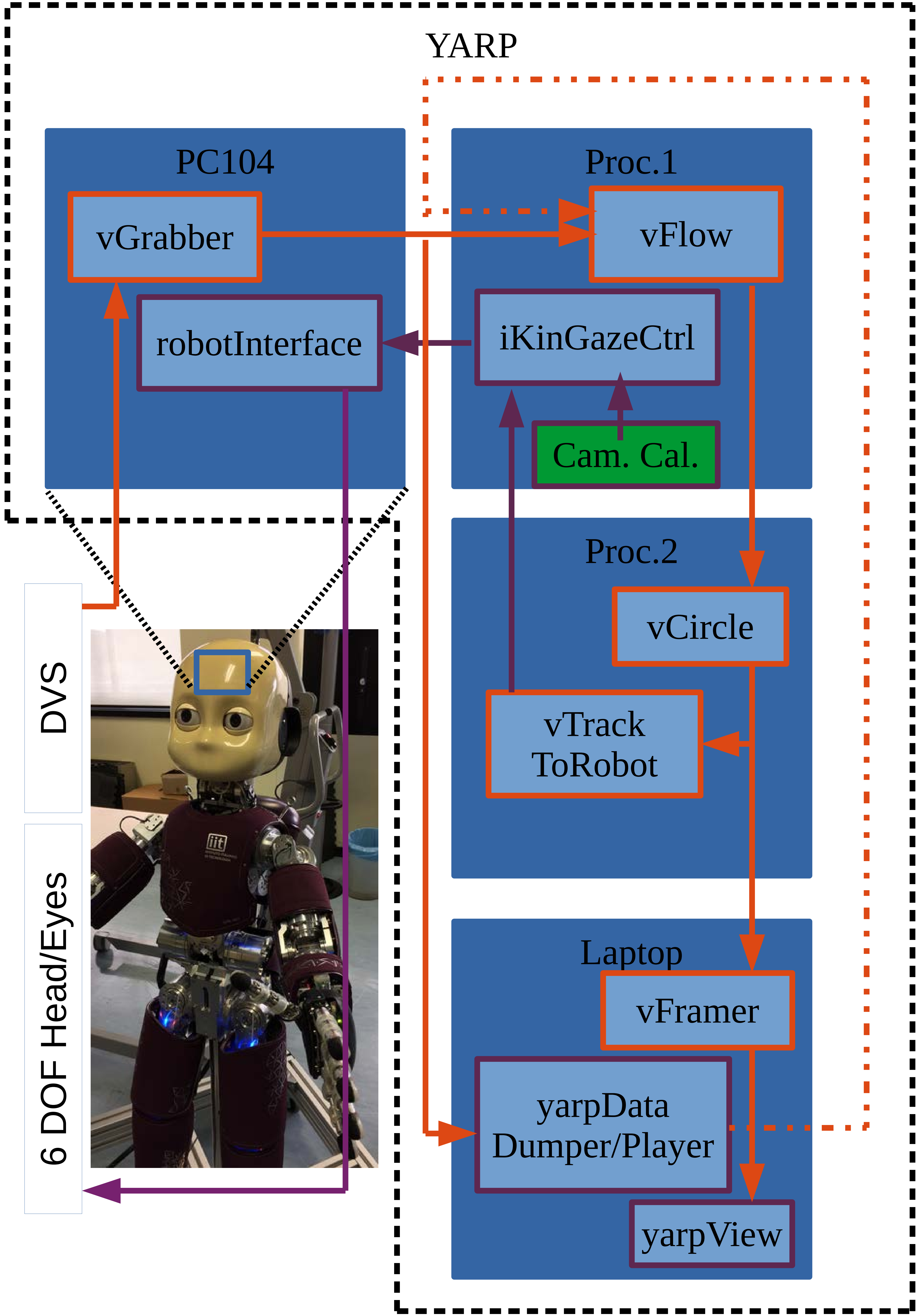
ED Sensors — Vision







Python	CMOS
Spatial Res	1,3Mpxl 1/2”
Temporal Res	42 fps (24ms)
AFOV	42°



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