A Cortically-inspired Architecture for Event-based Visual Motion Processing: From Design Principle to Real-world Applications

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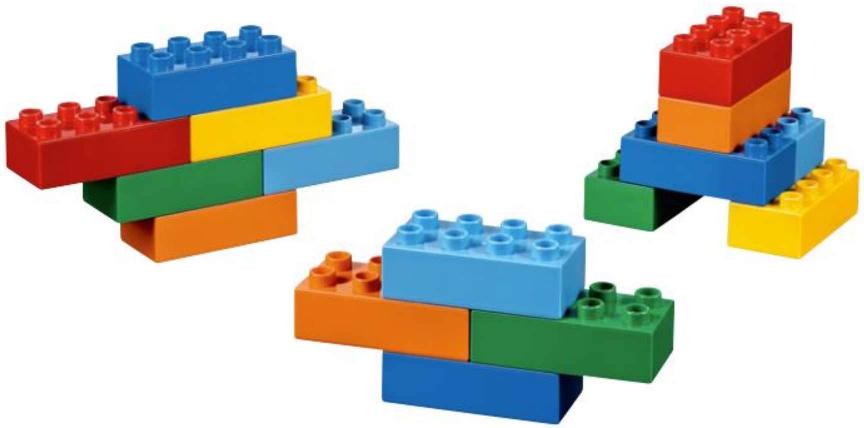
Motivation and objective



- A *"build-to-comprehend"* paradigm
- A *compositional approach* to built complex visual descriptors

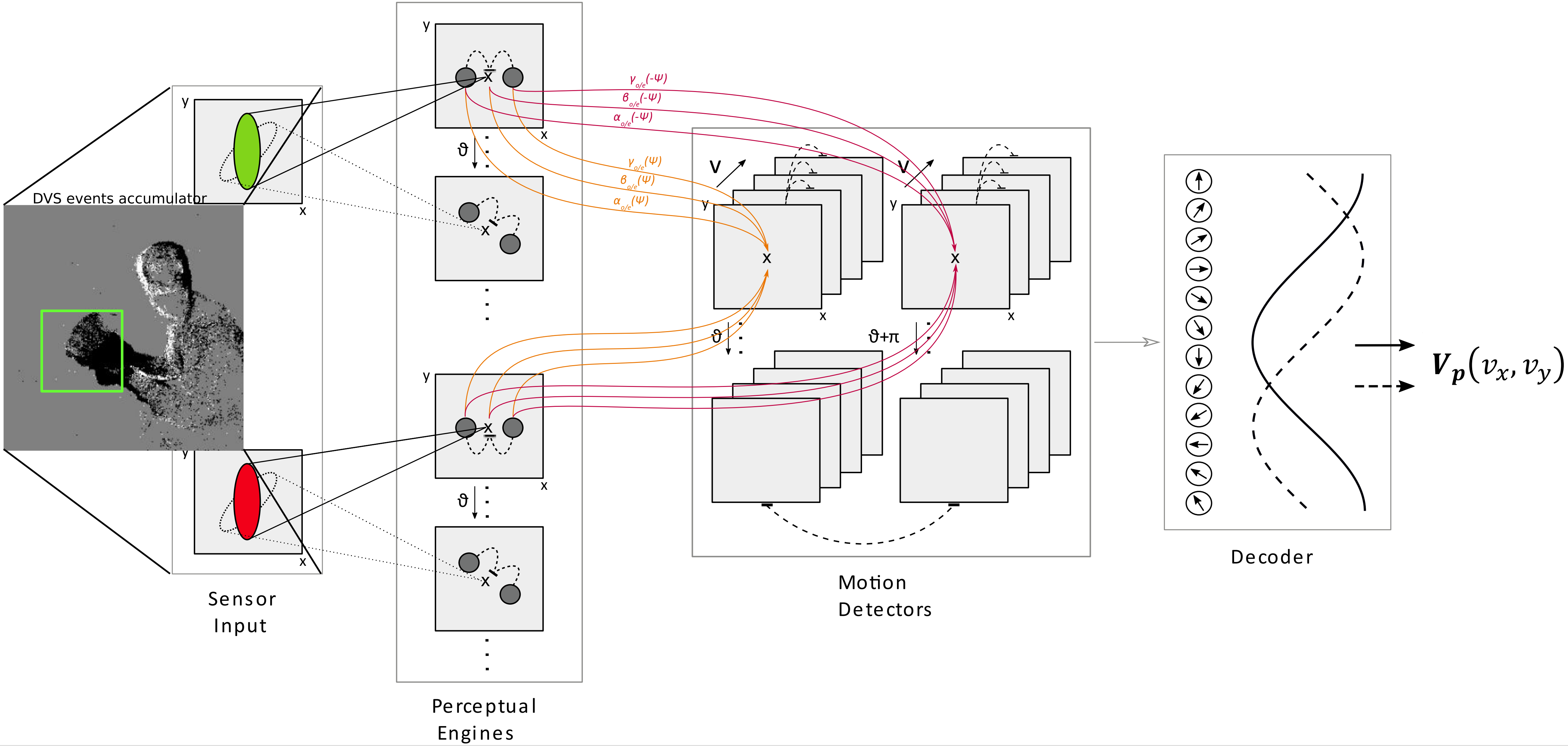
What?

- Design and test a *multilayer SNN* for motion estimation that functionally mimics the cortical motion pathway

How?

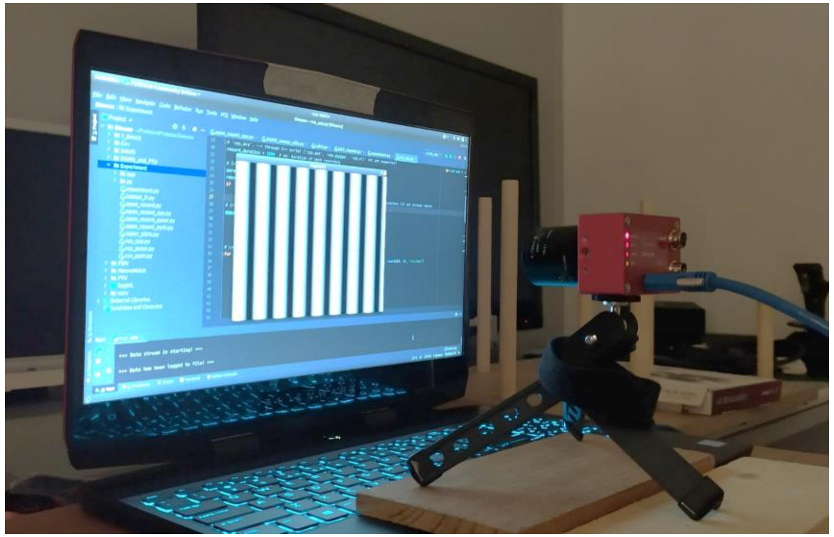
- Translating principled *firing-rate* computational models into *event-based SNNs*

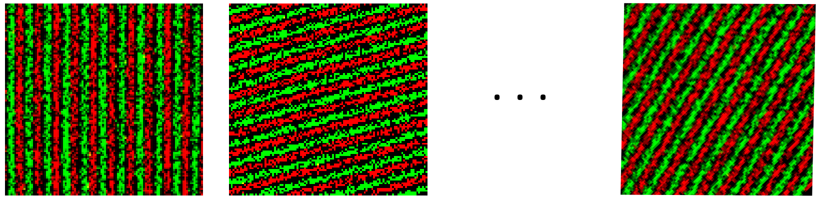
The Architecture



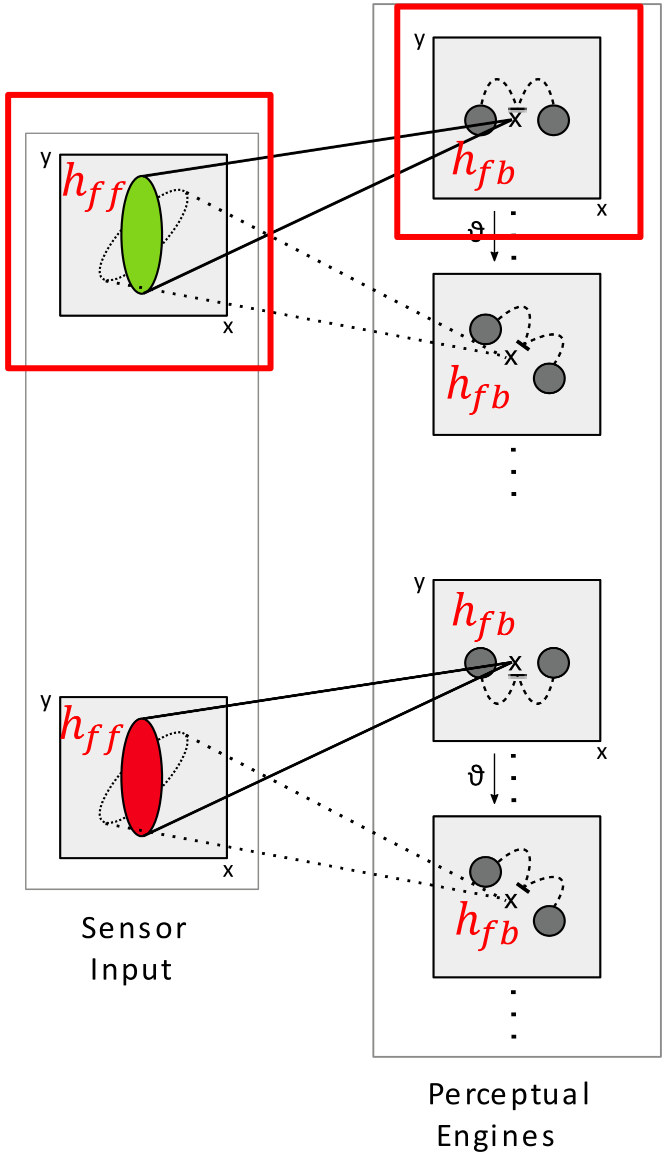
Event-based dataset

- <u>Synthetic stimuli</u>: sinusoidal drifting gratings with different orientation, spatial frequency and speed
- θ: $[0°, 180°)$ evenly spaced with step of 15 °
- *sf*: from 0.2 to 1.6 *cyc/deg* with step of 0.2 *cyc/deg*
- v_s: $\pm 1, 2, 3, 4$ *deg/sec*
- <u>Natural stimuli</u>: drummer's movement





V1 receptive fields (RFs)



$$\begin{cases} x_\vartheta = x\cos + y\sin\left(\vartheta - \frac{\pi}{2}\right) \\ y_\vartheta = -x\sin + y\cos\left(\vartheta - \frac{\pi}{2}\right) \end{cases}$$

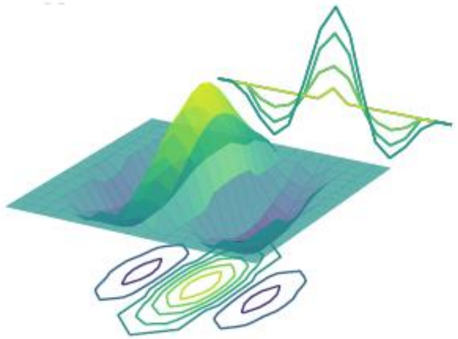
Feed-forward kernels:

$$h_{ff} = \frac{1}{2\pi p \sigma_{ff}} e^{-\frac{x_\vartheta^2/p^2 + y_\vartheta^2}{2\sigma_{ff}^2}}$$

Recurrent kernels:

$$h_{fb} = \frac{1}{2\pi p \sigma_{fb}} \left(e^{-\frac{(x_\vartheta^2 + d) + y_\vartheta^2}{2\sigma_{fb}^2}} + e^{-\frac{(x_\vartheta^2 - d) + y_\vartheta^2}{2\sigma_{fb}^2}} \right)$$

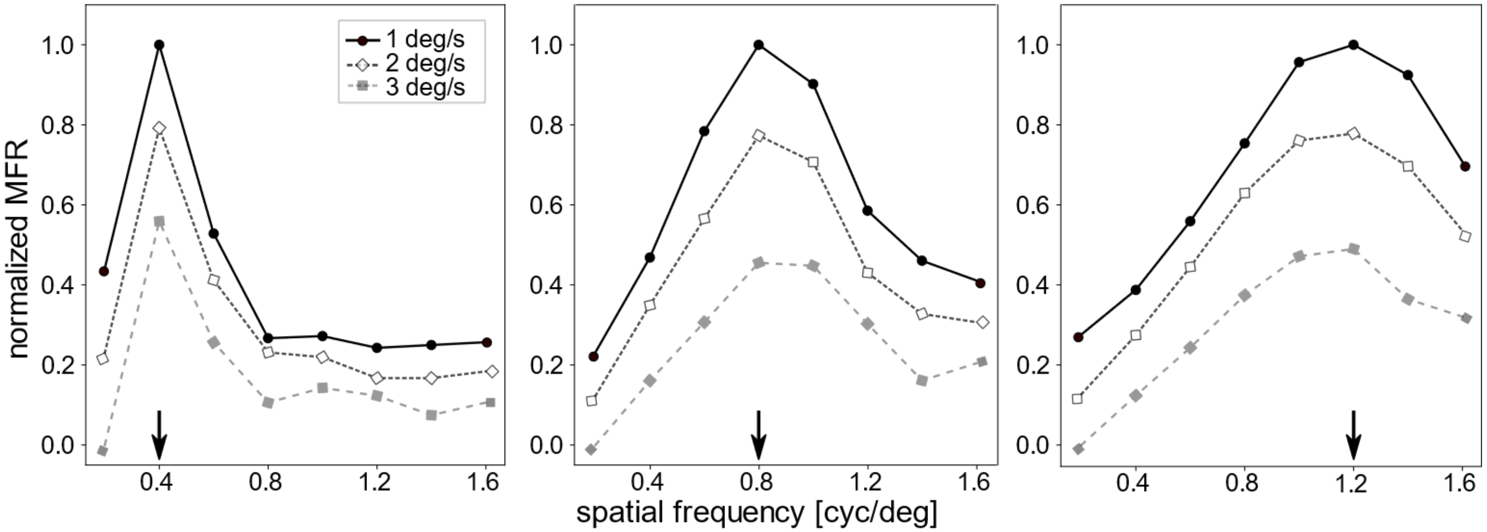
Receptive fields even symmetry

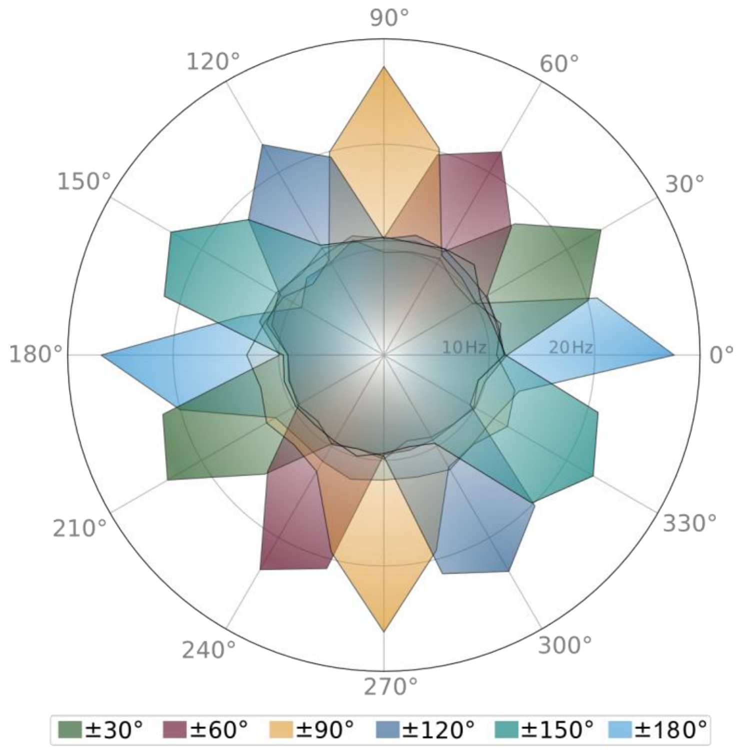


Static Gabor-like RF:

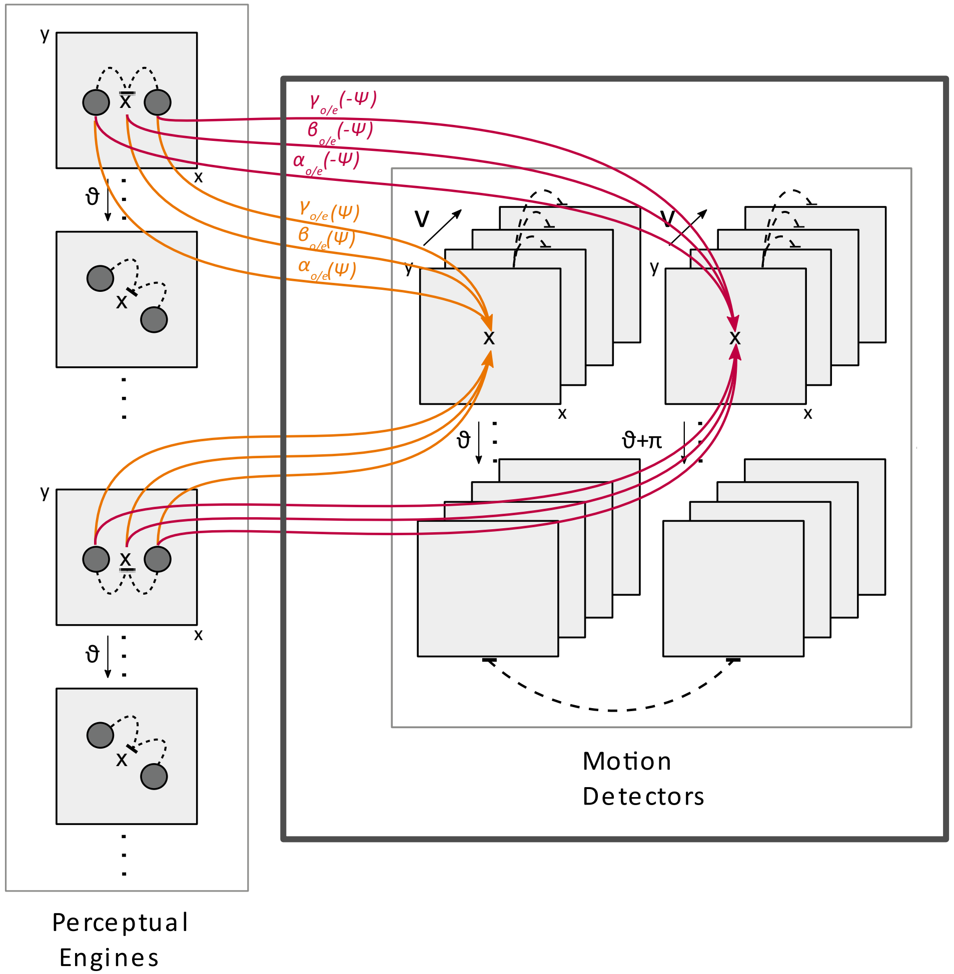
$$g(\boldsymbol{n}) \simeq C\, e^{-t/\tau} e^{-\boldsymbol{n} * \boldsymbol{n}/\sigma^2} \cos(\boldsymbol{k_0} * \boldsymbol{n} \pm \Psi)$$

Spatial frequency
and orientation tuning





Motion Energy Unit



Spatio-temporal RFs:

$$g(\boldsymbol{n}) \simeq C\, e^{-\boldsymbol{n}*\boldsymbol{n}/\sigma^2} \cos(\boldsymbol{k_0} * \boldsymbol{n} \pm \Psi)$$

time

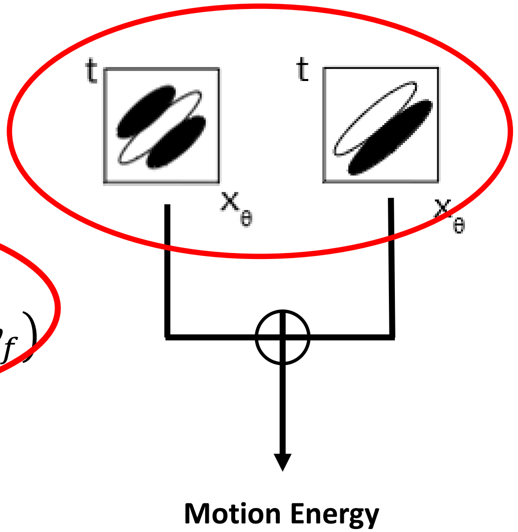
$$g(\boldsymbol{n}, t) \simeq C'\, e^{-t/\tau} e^{-\boldsymbol{n}*\boldsymbol{n}/\sigma^2} \cos(\boldsymbol{k_0} * \boldsymbol{n} \pm \omega_0 t)$$

where:

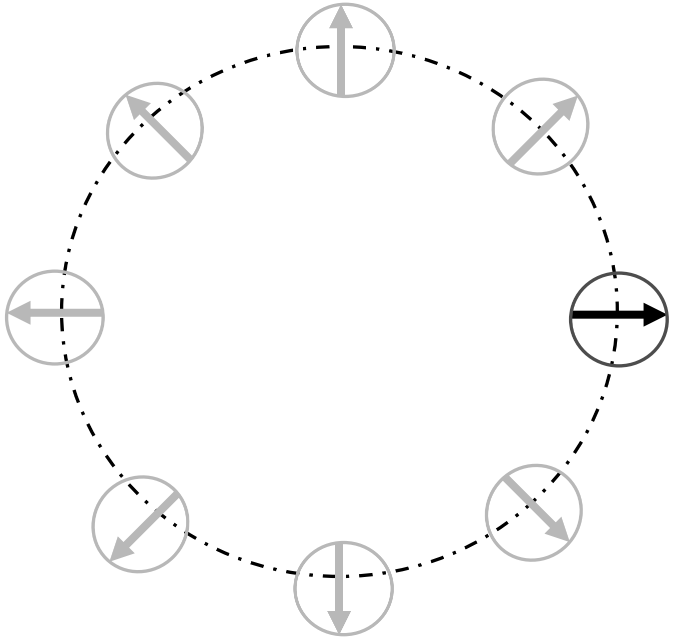
$$\omega_0 = \boldsymbol{v_f} * \boldsymbol{k_0}$$

Approx. "Energy Unit" response:

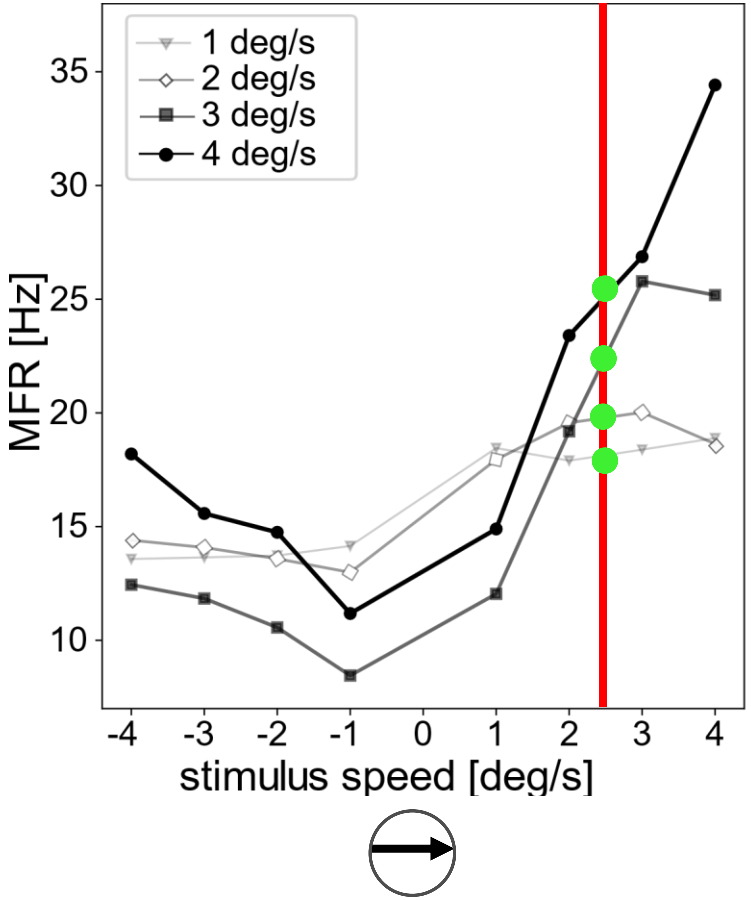
$$E(\boldsymbol{n}, t; \theta, v_f) = r_c^{ON}(\boldsymbol{n}, t; \theta, v_f) + r_s^{ON}(\boldsymbol{n}, t; \theta, v_f) + r_c^{OFF}(\boldsymbol{n}, t; \theta, v_f) + r_s^{OFF}(\boldsymbol{n}, t; \theta, v_f)$$



Decoding stage



Sf tuning	0.6 *cyc/deg*
v_f *tuning*	$\pm$1, 2, 3, 4 *deg/s*
ω_0	0.6, 1.2, 1.8, 2.4 *cyc/s*

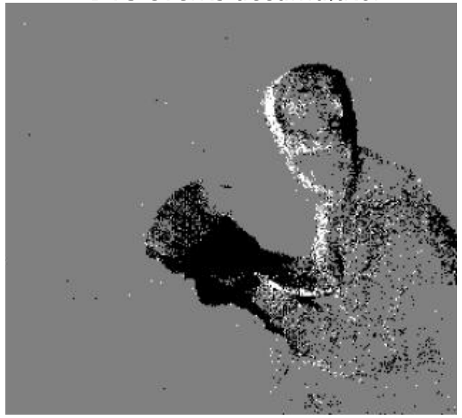


$$v_\theta(\boldsymbol{n},t) = \frac{\sum_i^N G(\boldsymbol{n}) * \boxed{E(\boldsymbol{n},t;\ \theta, v_{f_i})}}{\epsilon + \sum_i^N G(\boldsymbol{n}) * E(\boldsymbol{n},t;\ \theta, v_{f_i})}$$

Decoding stage

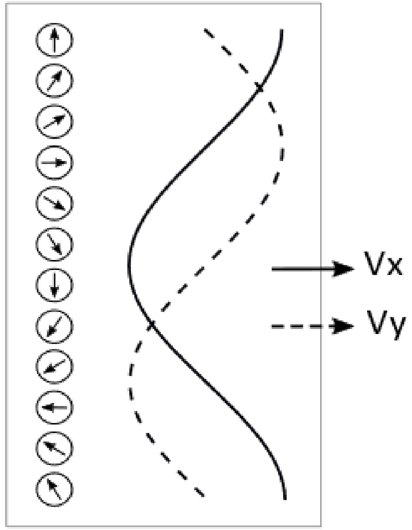
$$\boldsymbol{V_p}(v_x, v_y) \xrightarrow{IOC^*} \begin{cases} v_x(\boldsymbol{n}, t) = \dfrac{2}{N} \displaystyle\sum_{\theta_i = \theta_1}^{\theta_N} v_{\theta_i}(\boldsymbol{n}, t) \cos(\theta_i) \\ v_y(\boldsymbol{n}, t) = \dfrac{2}{N} \displaystyle\sum_{\theta_i = \theta_1}^{\theta_N} v_{\theta_i}(\boldsymbol{n}, t) \sin(\theta_i) \end{cases}$$

DVS events accumulator

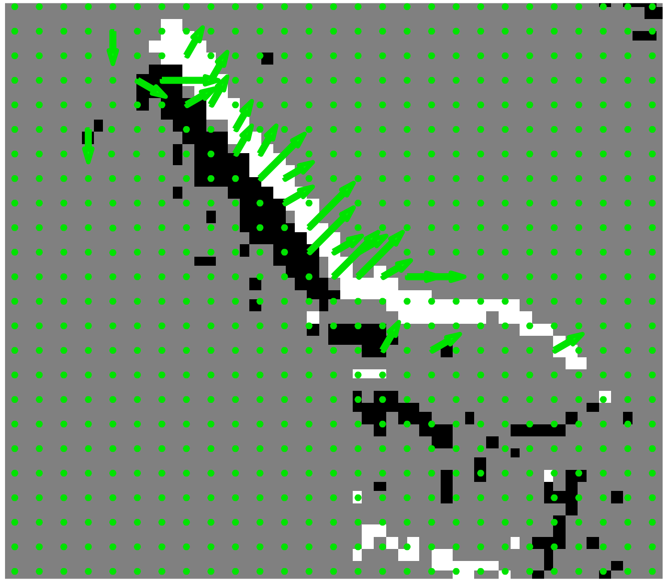


Stimulus

SNN



Decoder



Estimated Optical Flow

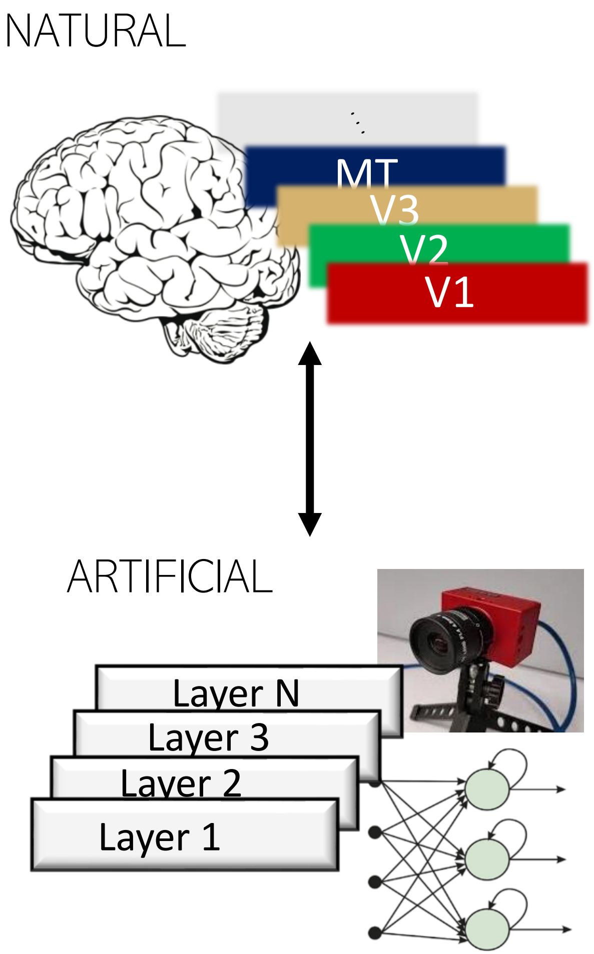
$$v_\theta(\boldsymbol{n}, t) = \frac{\sum_i^N G(\boldsymbol{n}) * \ E(\boldsymbol{n}, t;\ \theta, v_{f_i})}{\epsilon + \sum_i^N G(\boldsymbol{n}) * E(\boldsymbol{n}, t;\ \theta, v_{f_i})}$$

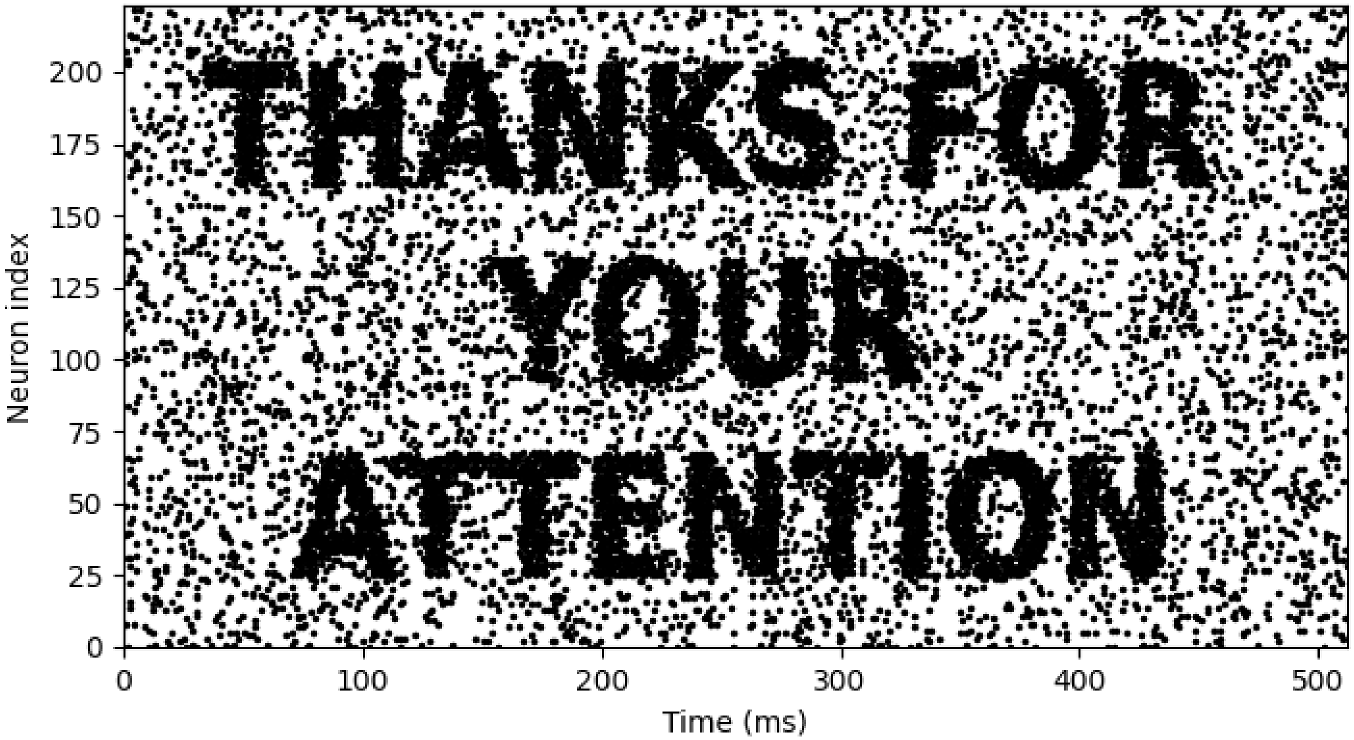
* Intersection-of-constraints mechanism

Conclusions

What is the "take-home-message" ?

- Reverse engineering the brain
- We presented a *bio-inspired* spiking neural network architecture
- *"perceptual engines"* provide computational primitives that can be composed to obtain more powerful image descriptors
- High usage flexibility both in firing-rate and spiking contexts





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- Extra -

Origin of the "time-variable synapses"

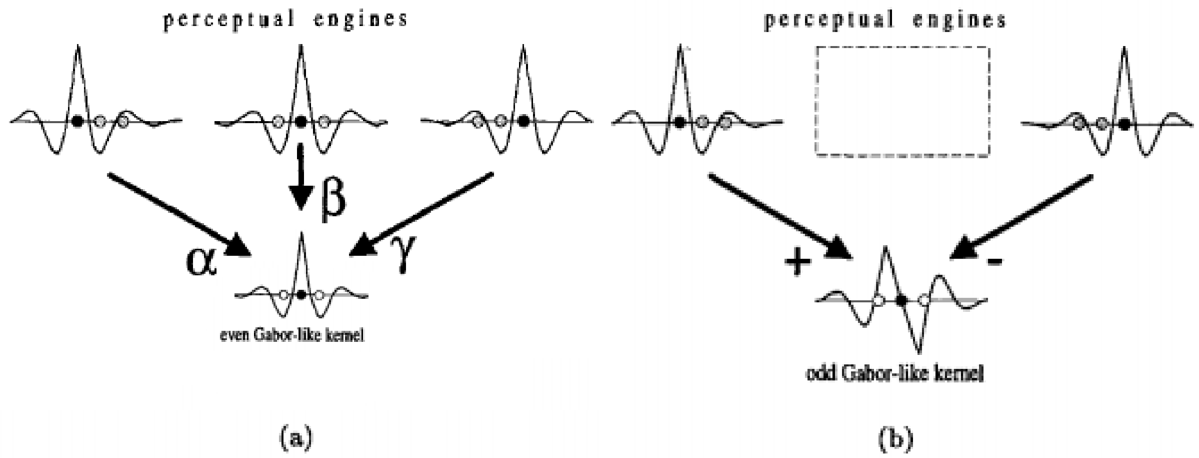

Fig. 5. Generation of even (a) and odd (b) Gabor-like filters through a combination of perceptual engines.

Gabor-like functions of any phase $\boldsymbol{\Psi}$:

$$\mathrm{g}(\boldsymbol{n}) = \alpha h(\boldsymbol{n} - \boldsymbol{d}) + \beta h(\boldsymbol{n}) + \gamma\, h(\boldsymbol{n} + \boldsymbol{d})$$
$$\simeq \mathrm{C}\, e^{-t/\tau} e^{-\boldsymbol{n}*\boldsymbol{n}/\sigma^2} \cos(\boldsymbol{k_0} * \boldsymbol{n} \pm \Psi)$$

where:

$$\begin{cases} \alpha = -Bsin(\Psi) - Acos(\Psi) \\ \beta = \cos(\Psi) \\ \gamma = Bsin(\Psi) - Acos(\Psi) \end{cases}$$

- L. Raffo, S. P. Sabatini, G. M. Bo, and G. M. Bisio. Analog VLSI circuits as physical structures for perception in early visual tasks. IEEE Transactions on Neural Networks, 9(6):1483–1494, 1998.

- Extra -

Neurons and synapses model

- **Adaptive Exponential Integrate-and-Fire neuron model (AdEx)**

$$C_m \frac{dV_m}{dt} = -g_L(V_m - E_L) + g_L\Delta_T e^{\frac{(V_m - V_T)}{\Delta_T}} - \omega + I$$

$$\tau_\omega \frac{d\omega}{dt} = \eta(V_m - E_L) - \omega$$

If the membrane voltage crosses a certain threshold voltage V_T , spike is emitted, and the neuron is reset:

$$V \rightarrow V_{rest}$$
$$\omega \rightarrow \omega + \kappa$$

C_m*: membrane capacitance*
V_m*: membrane potential*
V_T: threshold
E_L: leak reversal potential
g_L*: leak conductance*
Δ_T: slope factor
ω: adaptation current
I*: input (post-synaptic) current*
η: adaptation coupling parameter
τ_ω: adaptation time constant
τ: single time constant
κ: spike - triggered adaption

- **Synapse: exponential function**

$$g_{syn}(t) = \overline{g}_{syn} e^{\left(-\frac{t - t_0}{\tau}\right)}$$