Event-based vision and processing for tiny drones

Guido de Croon

Full Professor

MAVLab, Faculty of Aerospace Engineering

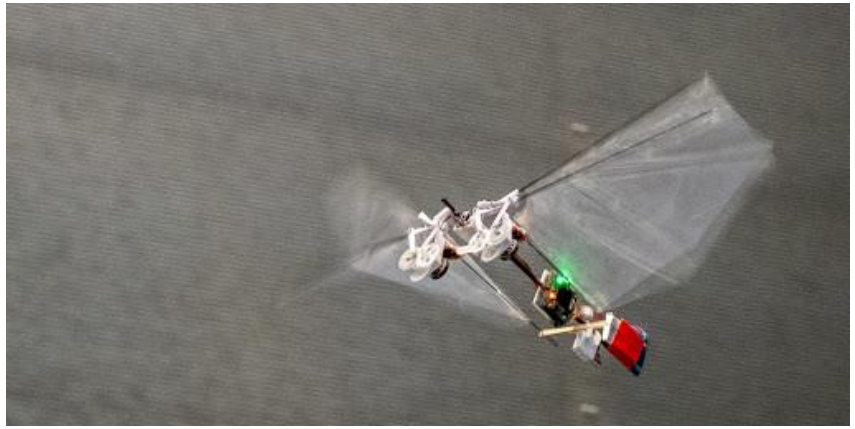
TU Delft

Tiny, light-weight, agile drones

M. Karásek, F.T. Muijres, C. De Wagter, B.D.W. Remes, G.C.H.E. de Croon, "A tailless aerial robotic flapper reveals that flies use torque coupling in rapid banked turns", *Science*, Vol 361, Iss 6407, 2018

Size, Weight, and Power (SWaP)

- **33 cm wingspan, 29 g (flight 6 W)**
- **STM32F4 (0.2 W, 4 g)**
  - 168 MHz processor
  - 192 kB of memory



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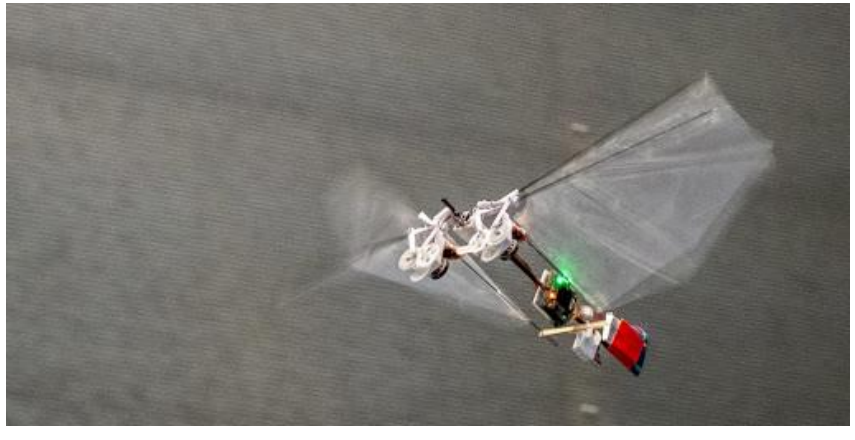
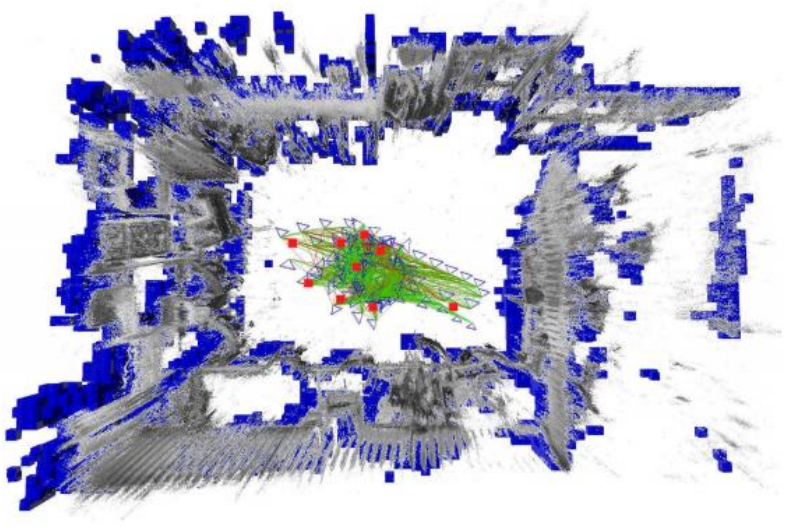


Map from [1]



SLAM: ~100s-1000s MBs memory [2]

[1] von Stumberg, L., et al. From monocular SLAM to autonomous drone exploration. In *2017 European Conference on Mobile Robots (ECMR 2017)* (pp. 1-8). IEEE.

[2] Bodin, B. et al. SLAMBench2: Multi-objective head-to-head benchmarking for visual SLAM. in 2018 IEEE International Conference on Robotics and Automation (ICRA) 1–8 (2018).

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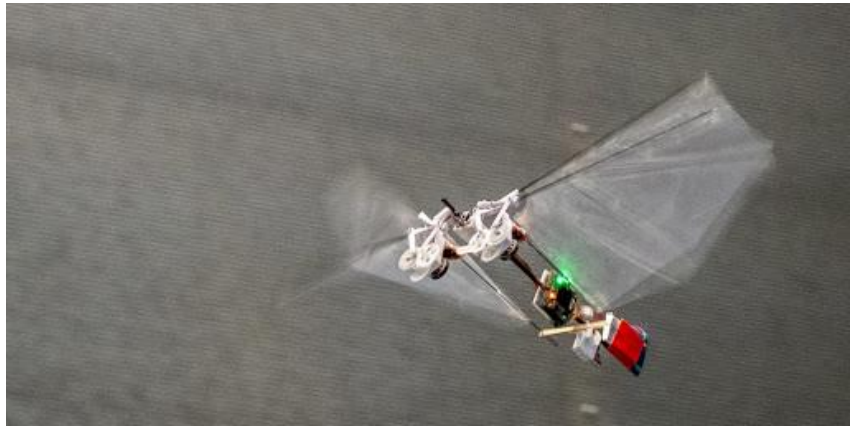
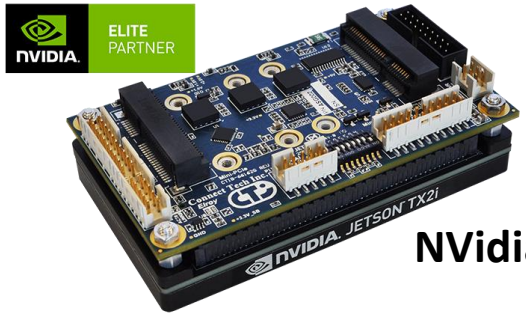




NVidia Jetson TX2

Processors:
- 6-core 2 GHz
- 256-core GPU

Memory:
- 8 GB

Mass:
- 85 g

Power:
- 7.5 W

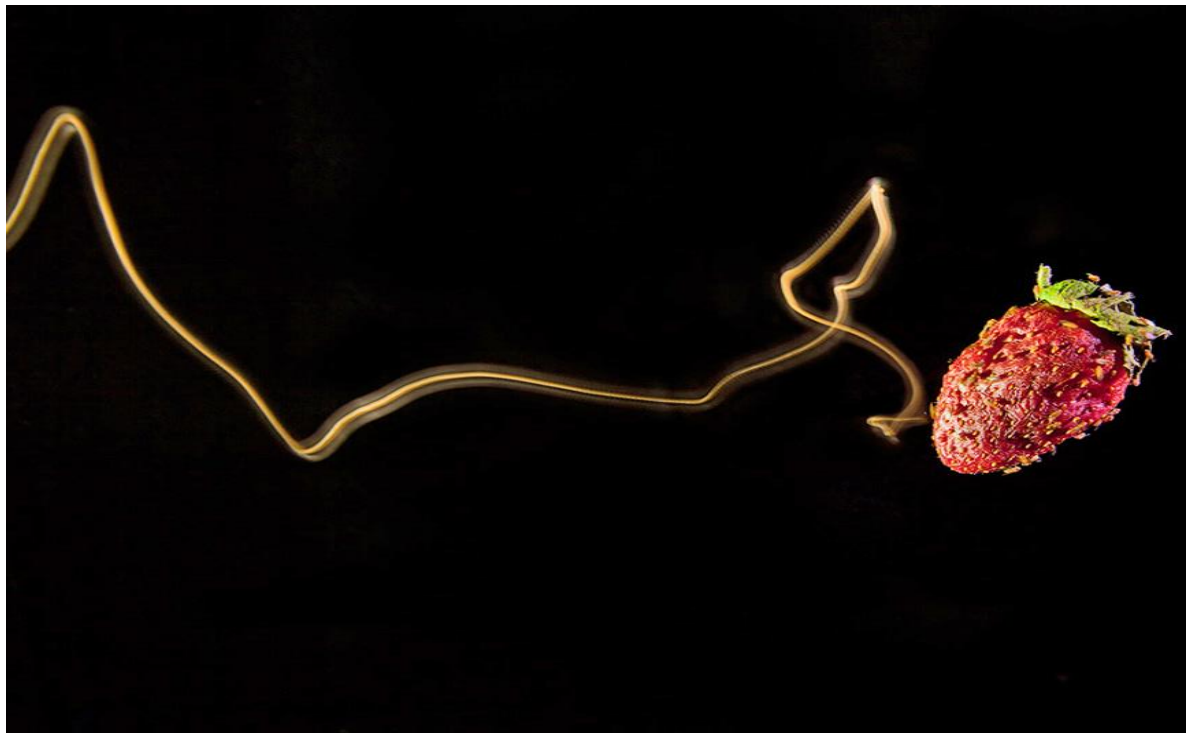
How to make tiny drones autonomous?

Draw inspiration from nature!

Fly, avoid obstacles, navigate, find food and shelter, interact socially with other fruit flies, learn, …

All for ~100,000 neurons!

Linking together simple behaviors



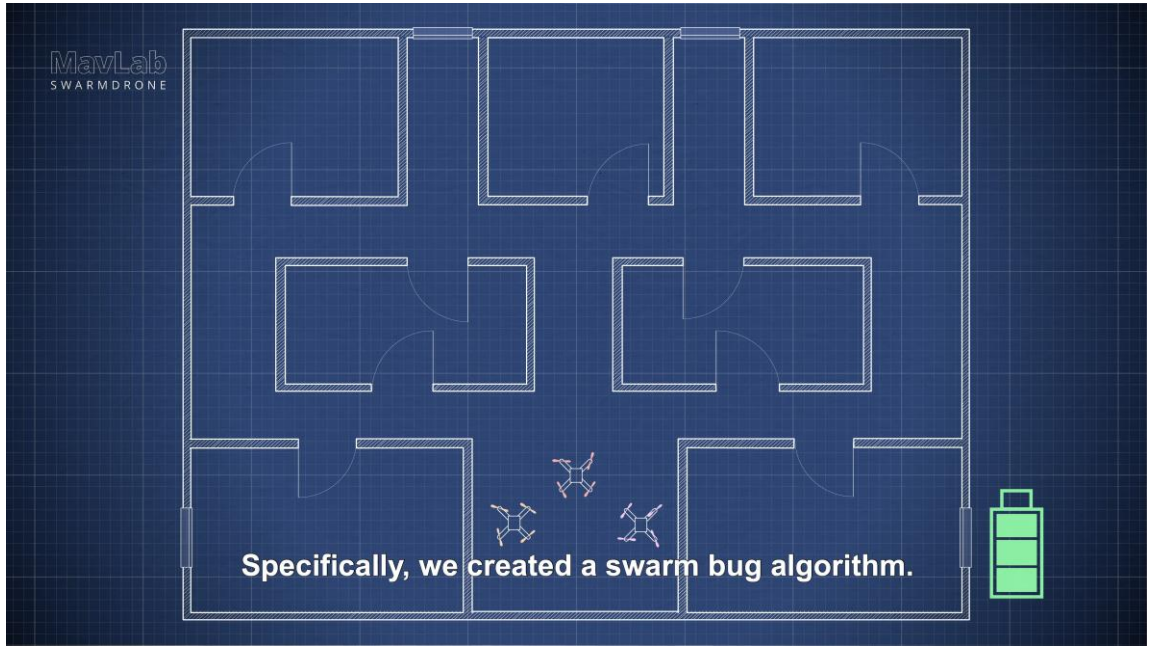
(Credit: © 2013 Floris van Breugel)

van Breugel, F., & Dickinson, M. H. (2014). Plume-tracking behavior of flying Drosophila emerges from a set of distinct sensory-motor reflexes. *Current Biology*, *24*(3), 274-286.

Linking together simple behaviors

[1]

[2]



[1] Tijmons, S., de Croon, G.C.H.E., Remes, B.D.W., De Wagter, C., & Mulder, M. (2017). Obstacle avoidance strategy using onboard stereo vision on a flapping wing mav. *IEEE Transactions on Robotics*, *33*(4), 858-874.

[2] McGuire, K. N., De Wagter, C., Tuyls, K., Kappen, H. J., & de Croon, G. C. H. E. (2019). Minimal navigation solution for a swarm of tiny flying robots to explore an unknown environment. *Science Robotics*, 4(35), eaaw9710.

Linking together simple behaviors

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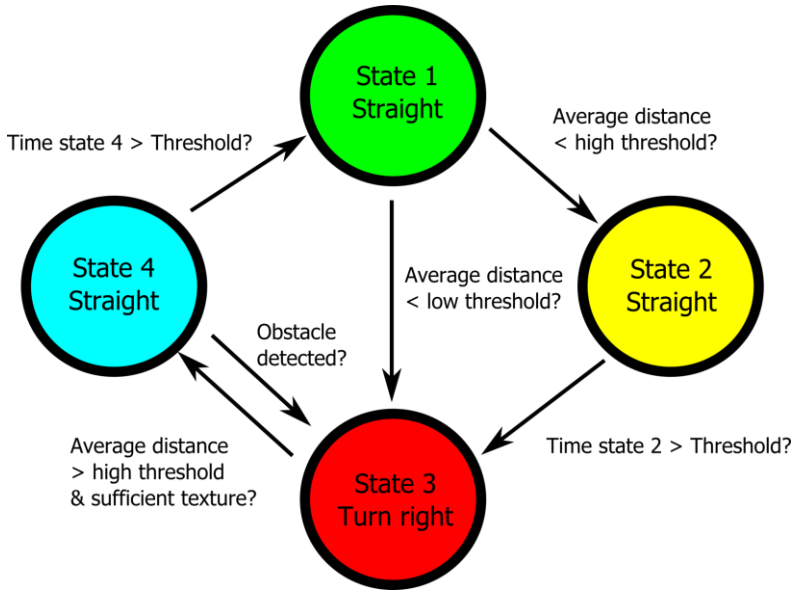
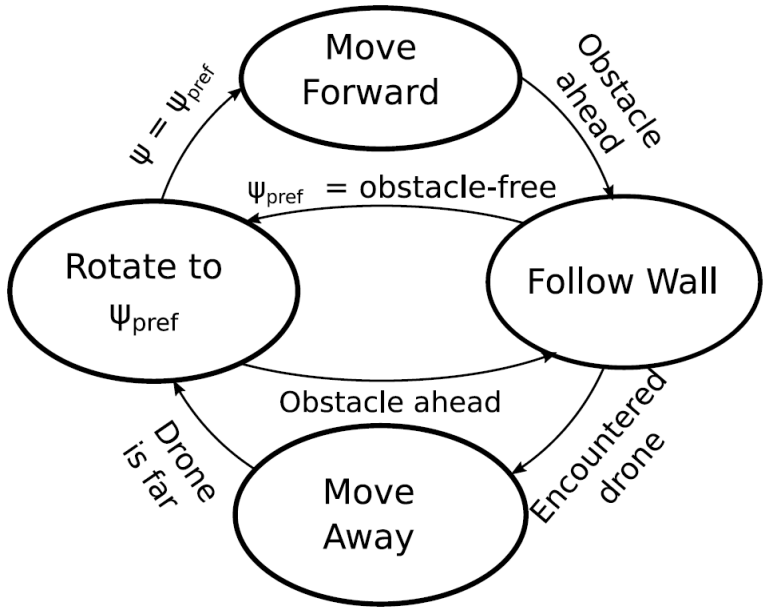


[2]



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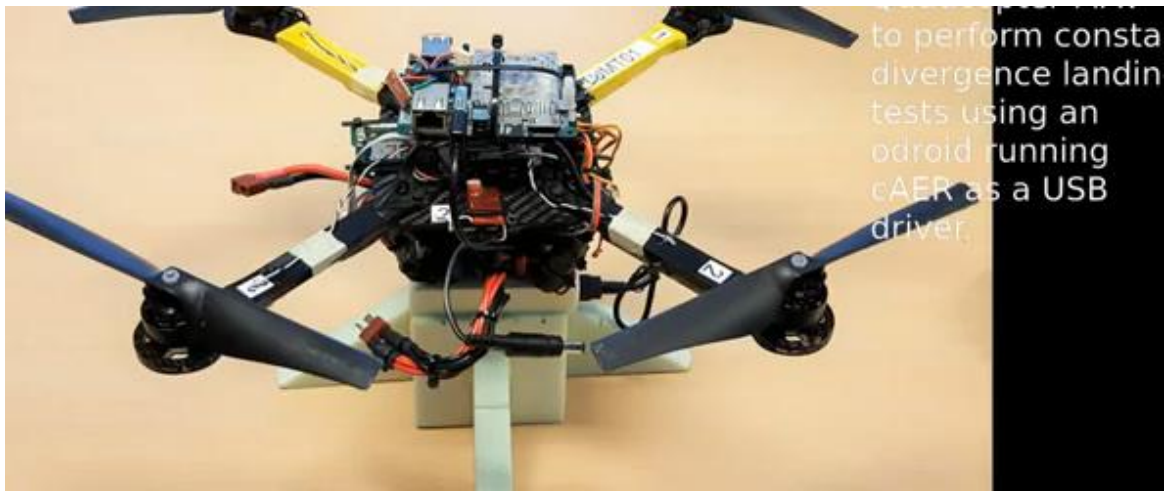
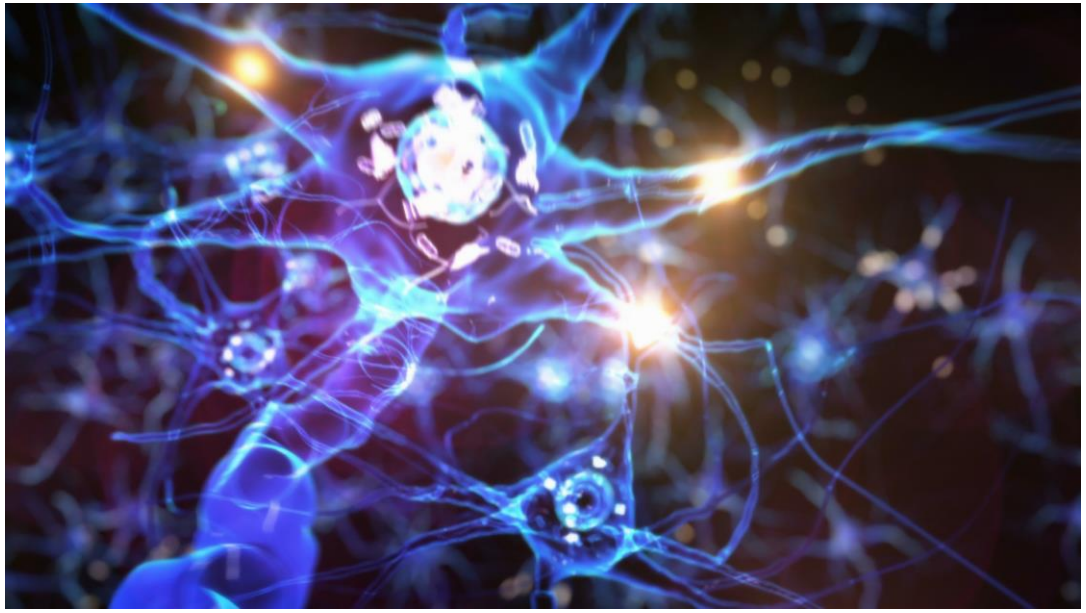
Neuromorphic sensing and computing

Event-based cameras



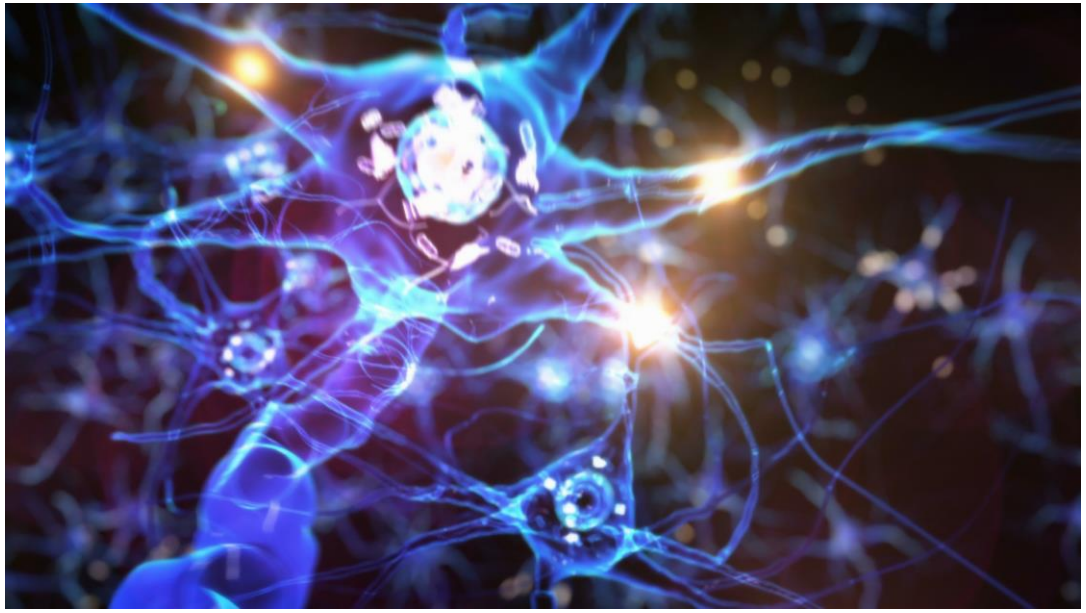
- Only perceive changes in brightness
- Sparse events
- Extremely fast and energy efficient

Spiking neural networks



- Temporal dynamics closer to those of real neurons
- Sparse parallel processing
- Fast and energy efficient

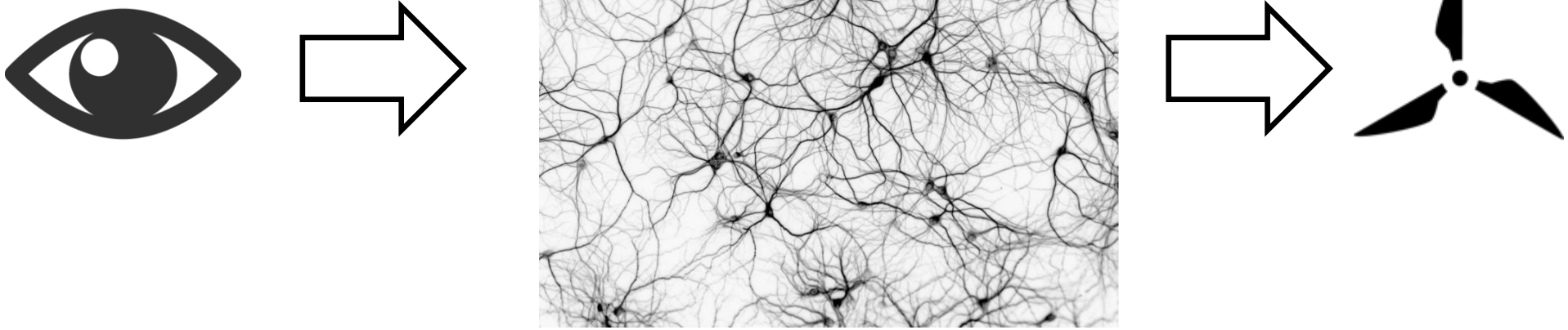
Spiking neural networks



- Temporal dynamics closer to those of real neurons
- Sparse parallel processing
- Fast and energy efficient

But: more challenging to design and train!

Goal: Fully neuromorphic, vision-based autonomous flight



Case study: optical flow landing

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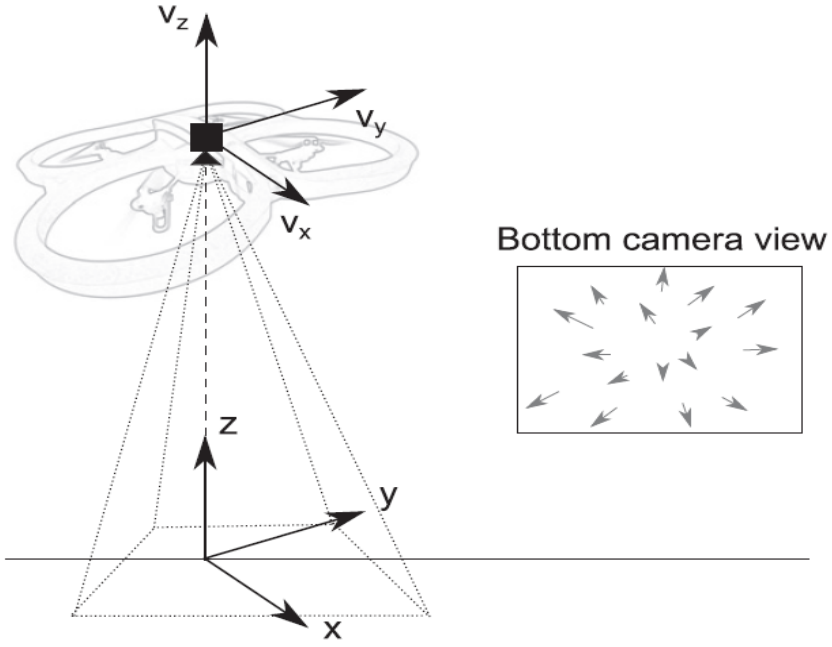
Honeybees land vertically by keeping optical flow divergence constant

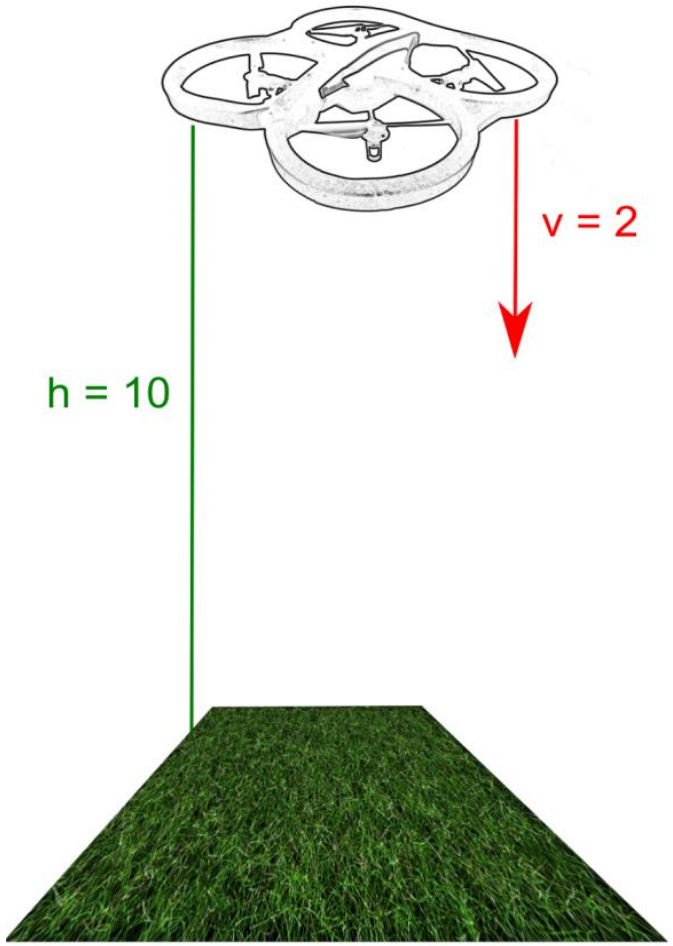
Baird, E., Boeddeker, N., Ibbotson, M. R., & Srinivasan, M. V. (2013). A universal strategy for visually guided landing. *Proceedings of the National Academy of Sciences*, *110*(46), 18686-18691.

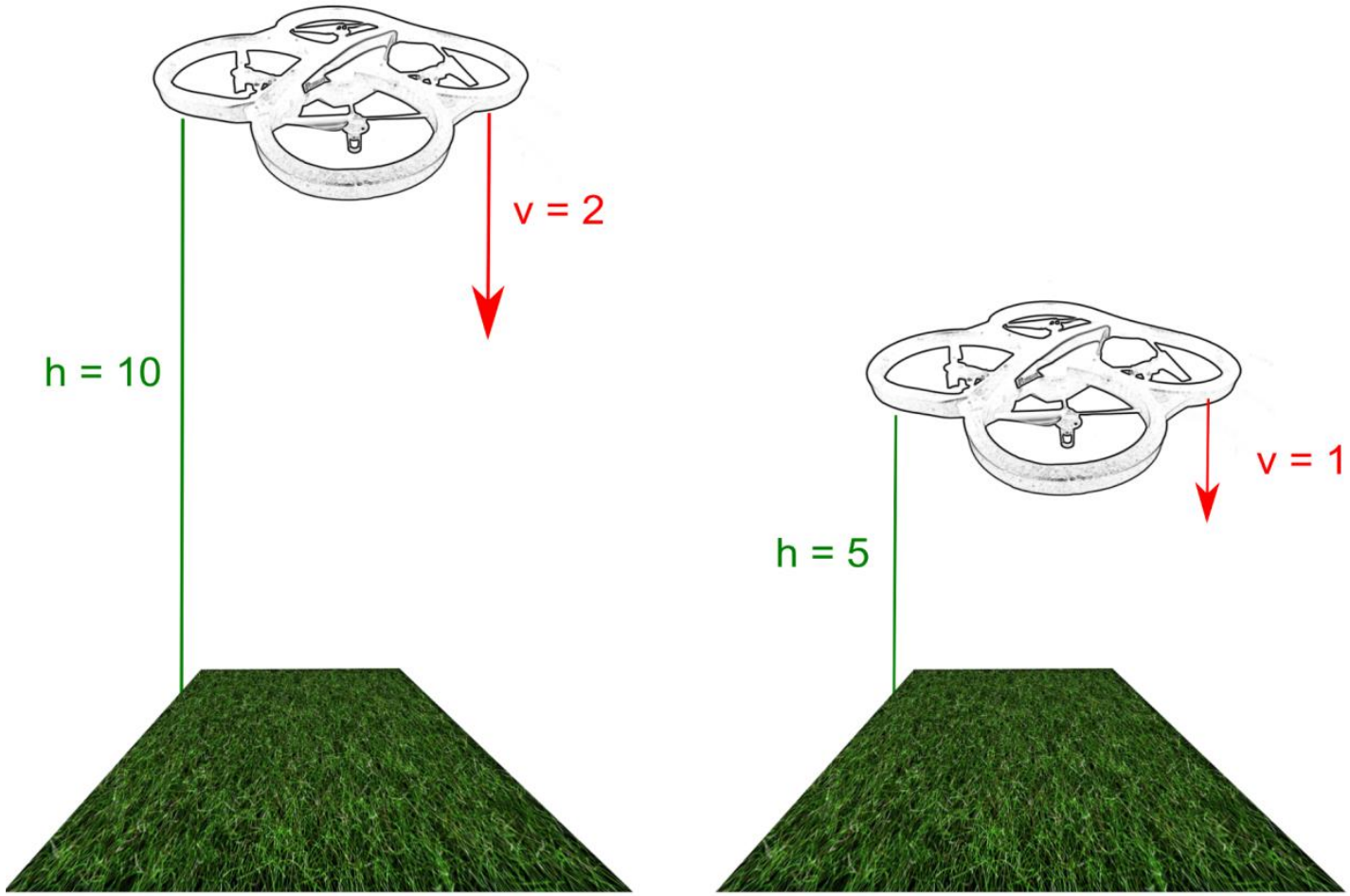
Case study: Optical flow landing

Honeybees land vertically by keeping optical flow divergence constant

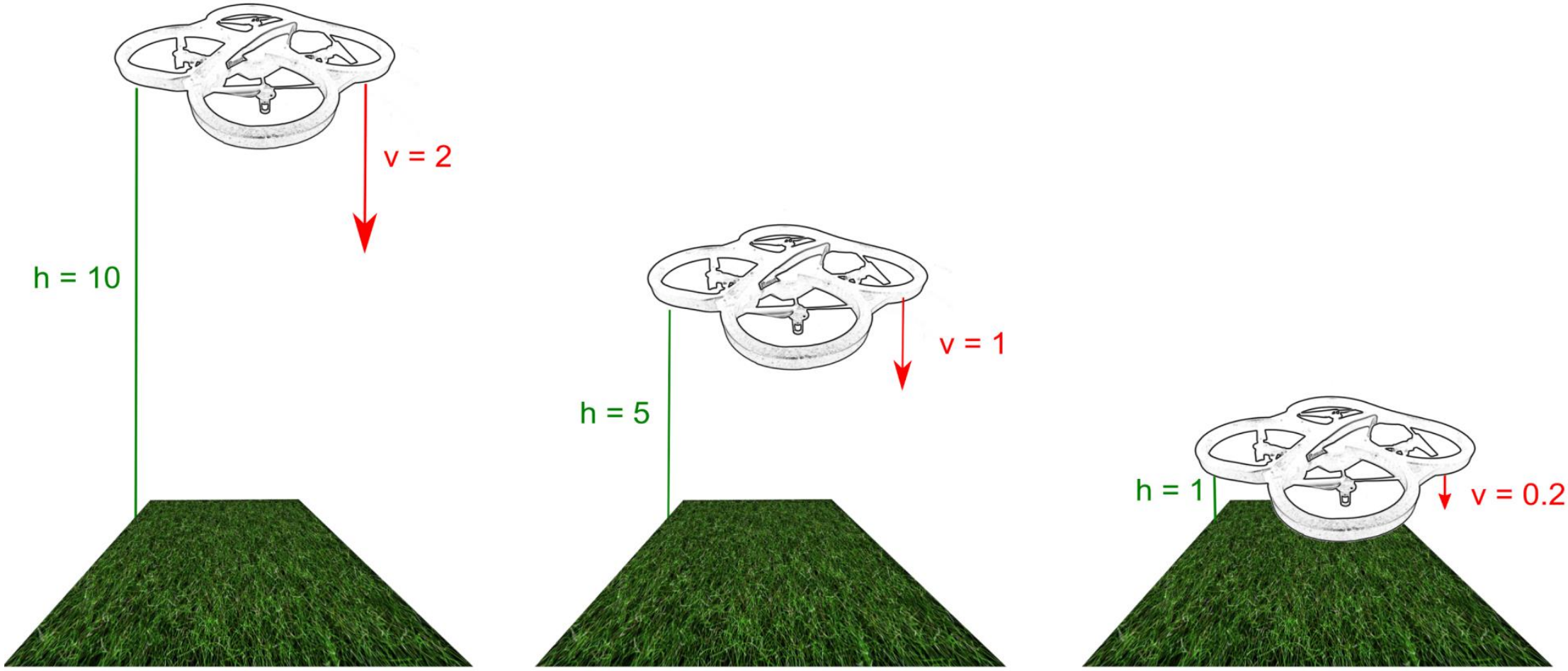


$$D = -vz / z = C$$


v = 2
h = 10



Delft


v = 2
h = 10
v = 1
h = 5
h = 1
v = 0.2

Difficult?

“Naïve” approach: **Thrust = gain x (D - D*)**

Difficult?

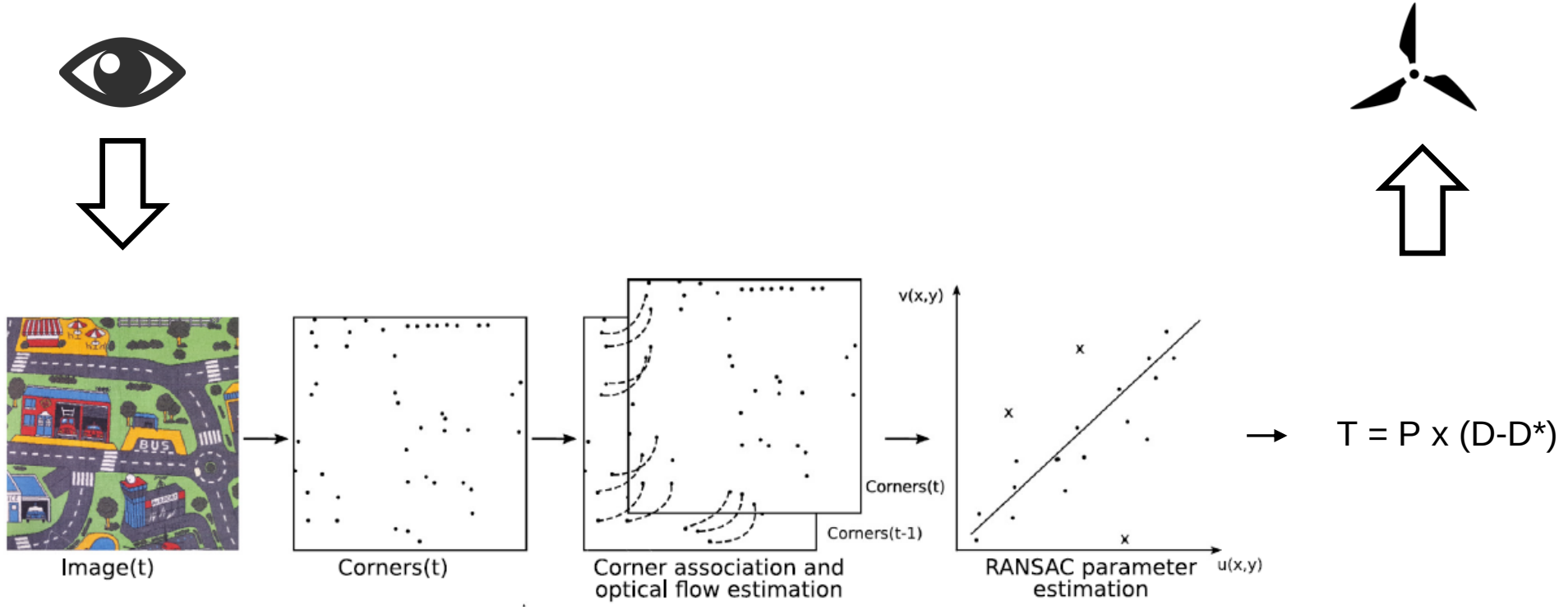
“Naïve” approach:

Thrust = gain x (D - D*)

de Croon, G.C.H.E. (2016). Monocular distance estimation with optical flow maneuvers and efference copies: a stability-based strategy. Bioinspiration & biomimetics, 11(1), 016004.

Our approach

Traditional pipeline



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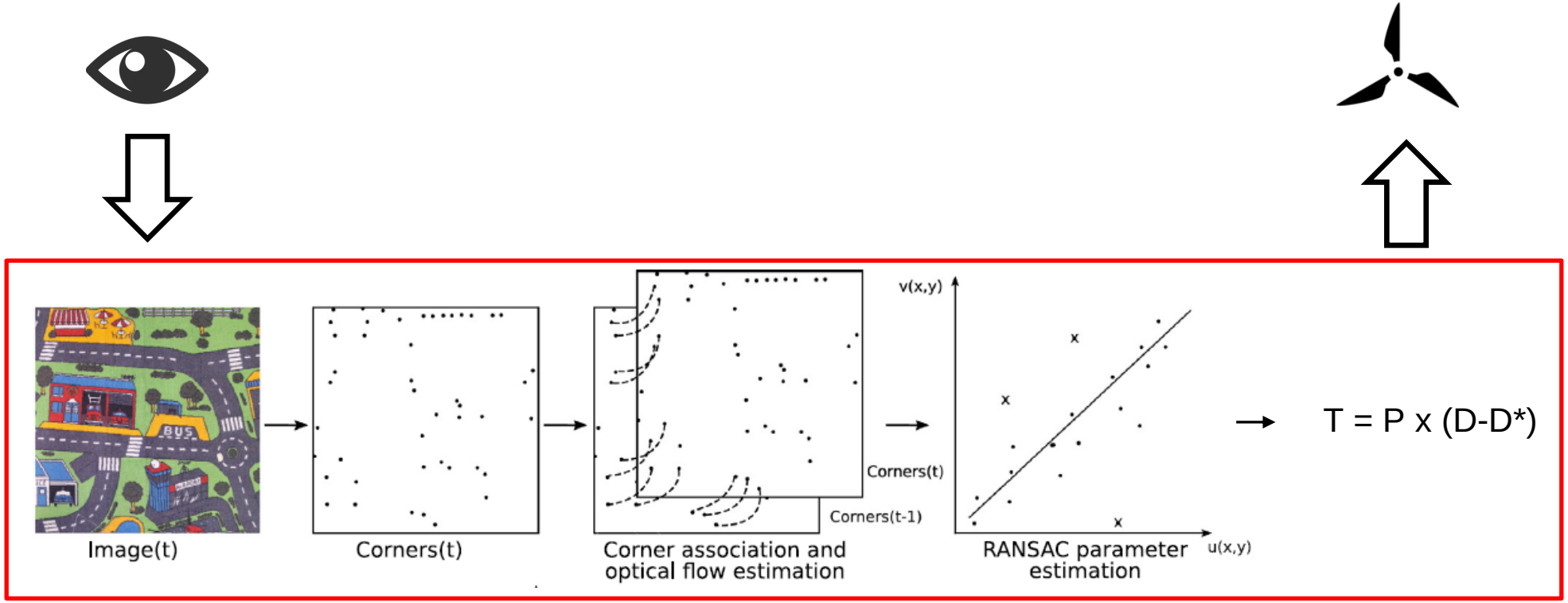


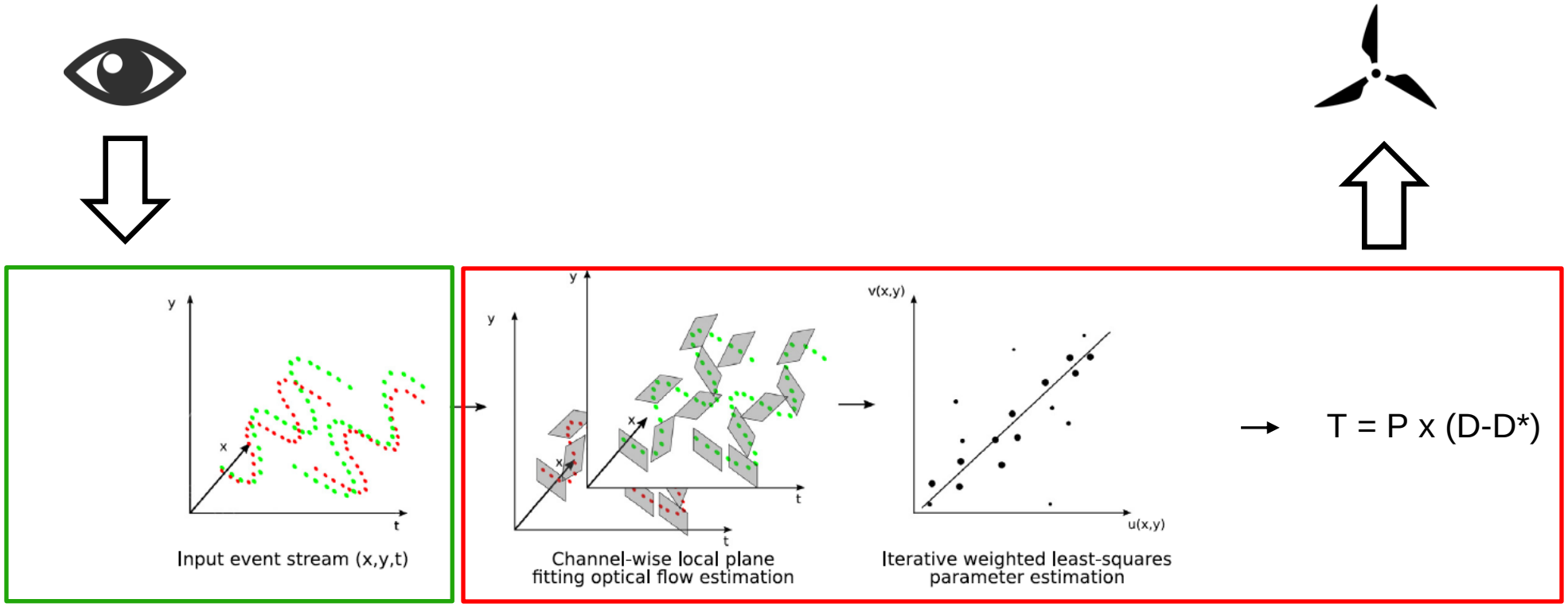
Color coding

Traditional element (images, processing)

Neuromorphic:

- **Offboard / not in the loop**
- **Onboard & in the loop, but on conventional hardware**
- **Onboard & in the loop, on neuromorphic hardware**

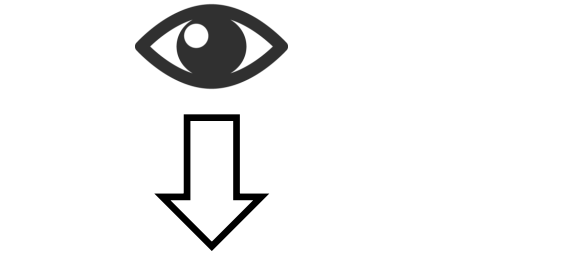
Event-based vision

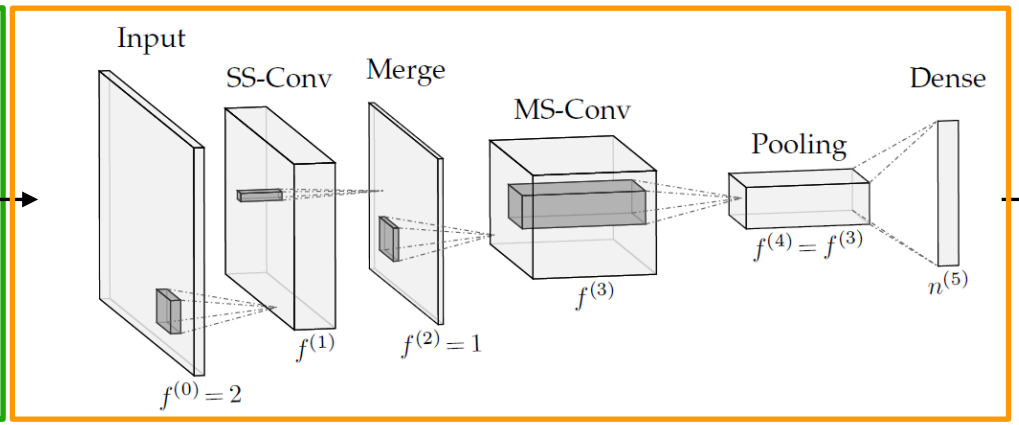


Pijnacker Hordijk, B. J., Scheper, K. Y., & De Croon, G.C.H.E. (2018). Vertical landing for micro air vehicles using event-based optical flow. Journal of Field Robotics, 35(1), 69-90.

Divergence* = 1 landing

Unsupervised learning of optical flow with an SNN



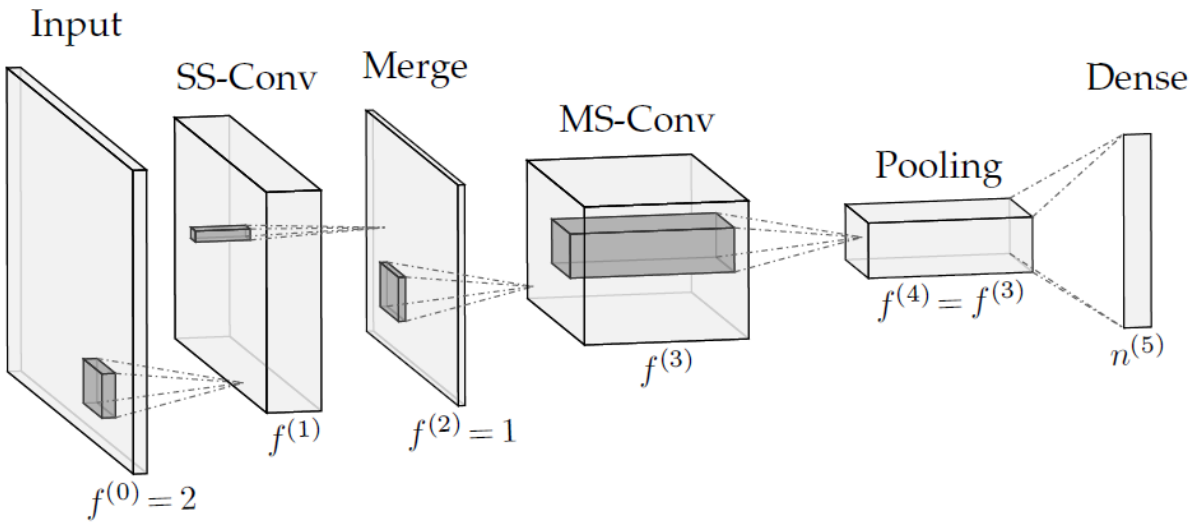


Not considered

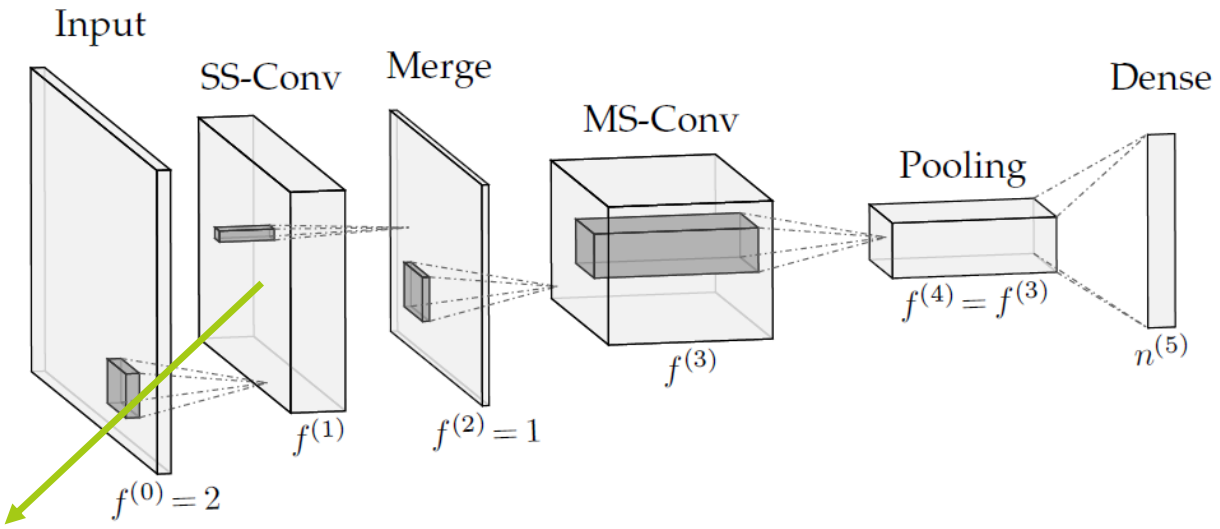
T = P x (D-D*)

Paredes-Vallés, F., Scheper, K. Y. W., & De Croon, G. C. H. E. (2019). Unsupervised learning of a hierarchical spiking neural network for optical flow estimation: From events to global motion perception. IEEE transactions on pattern analysis and machine intelligence.

Unsupervised learning with modified STDP

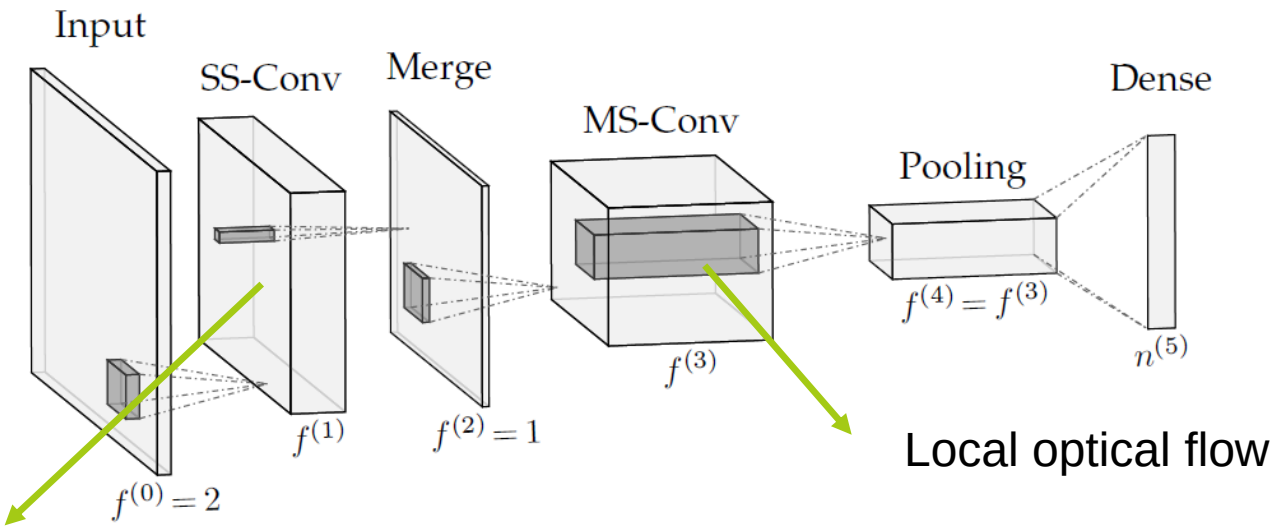


Unsupervised learning with modified STDP



Textural features

Unsupervised learning with modified STDP



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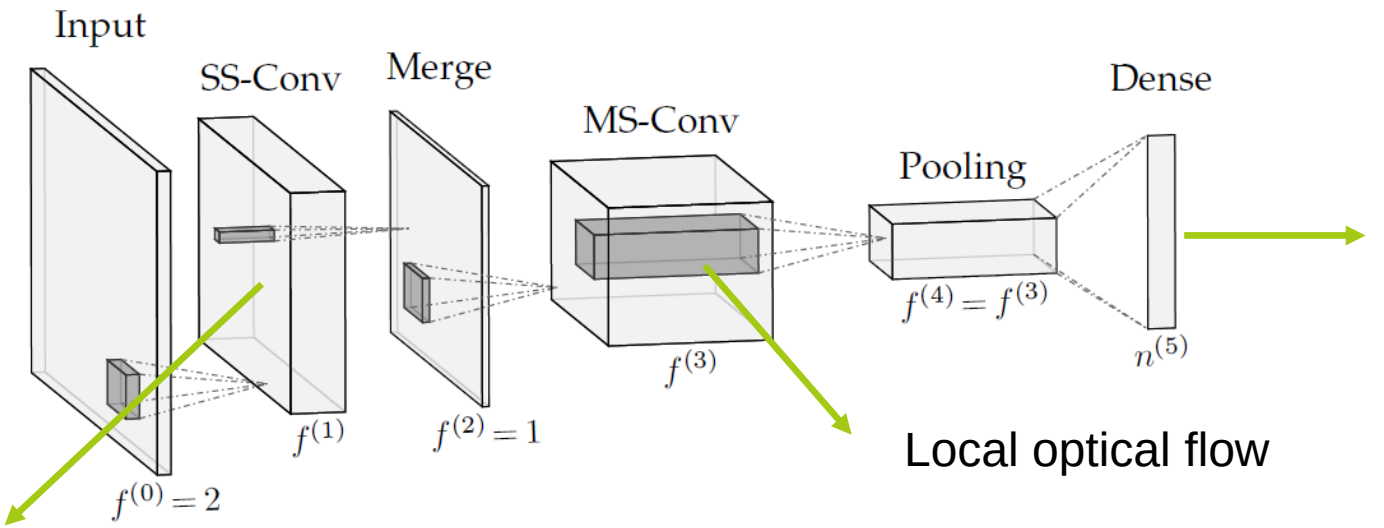

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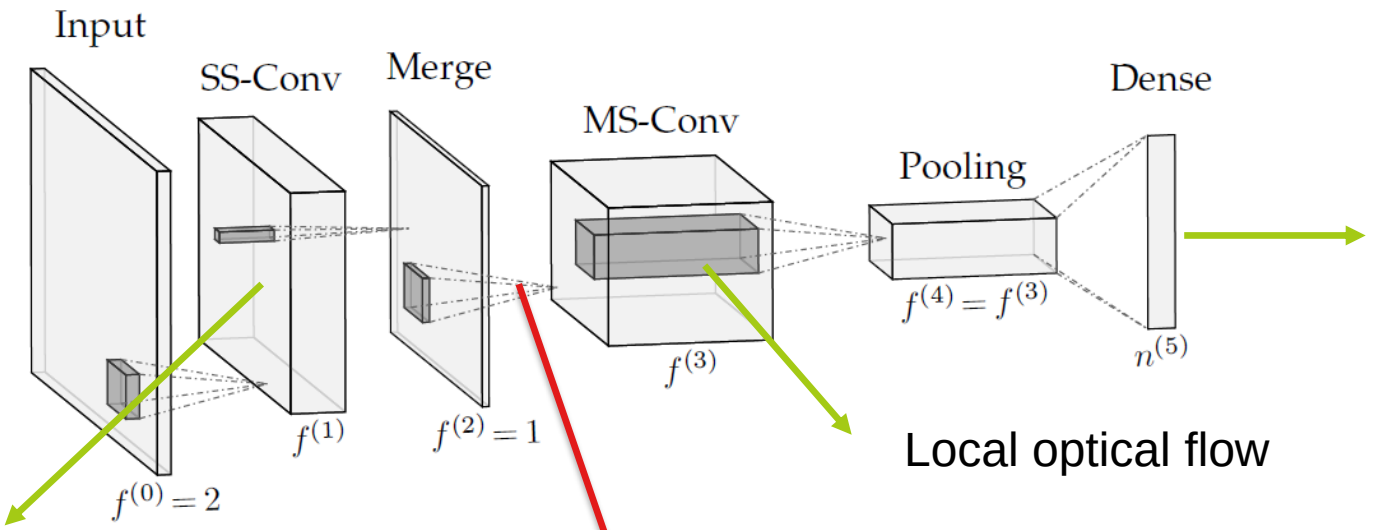
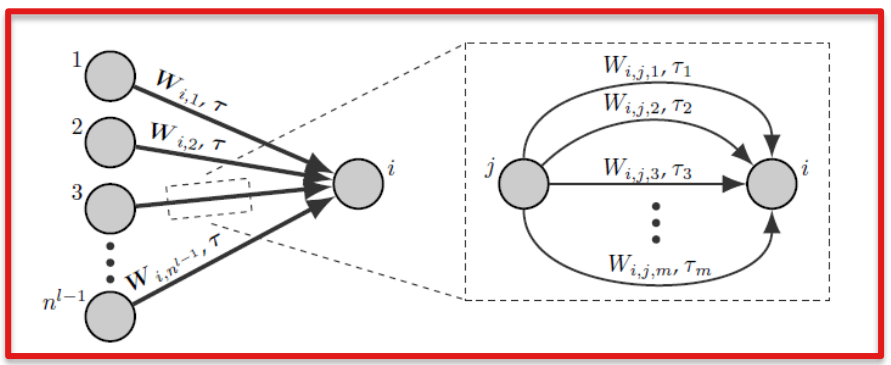


Global flow field properties

Local optical flow

Textural features



Results

Results

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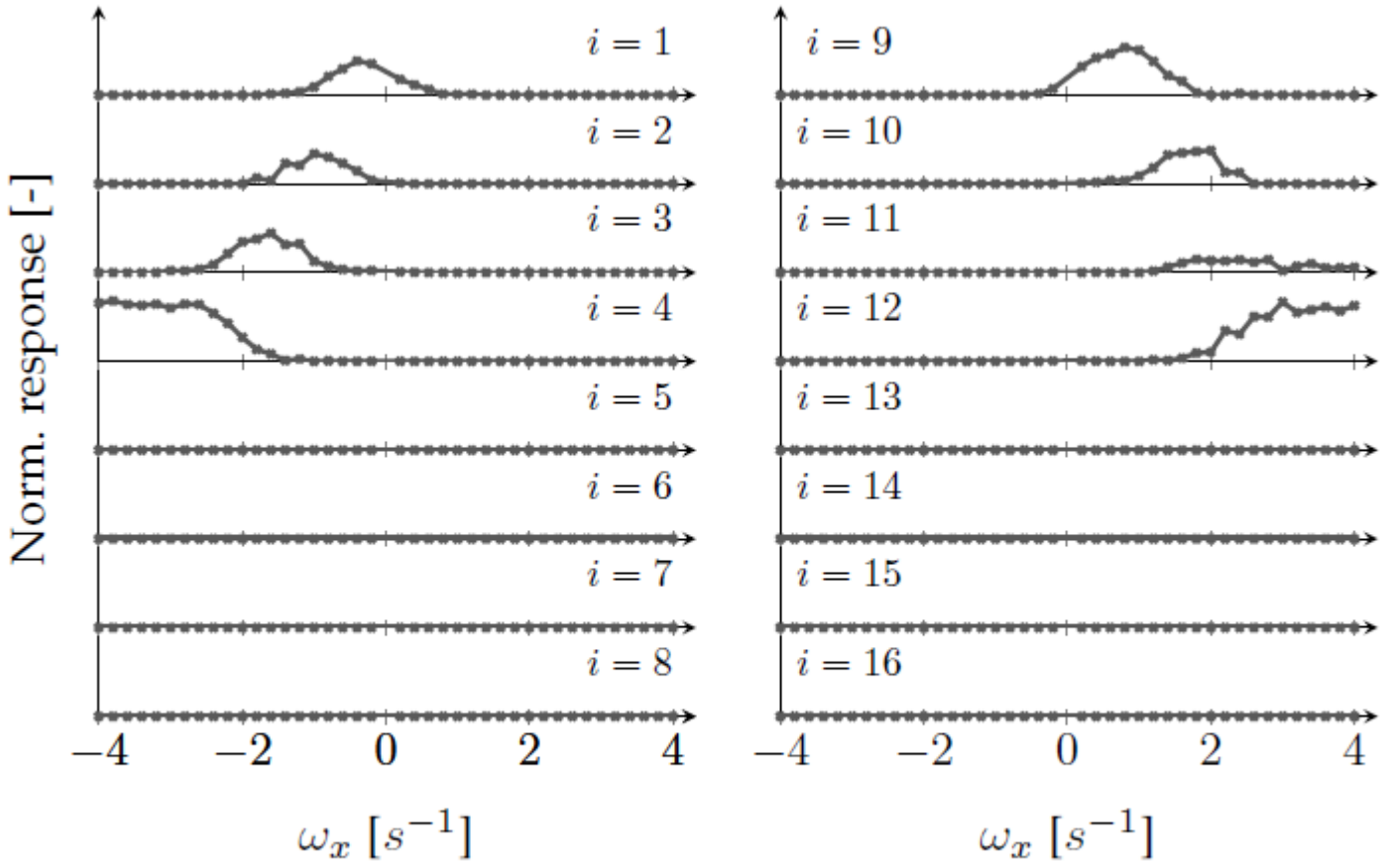
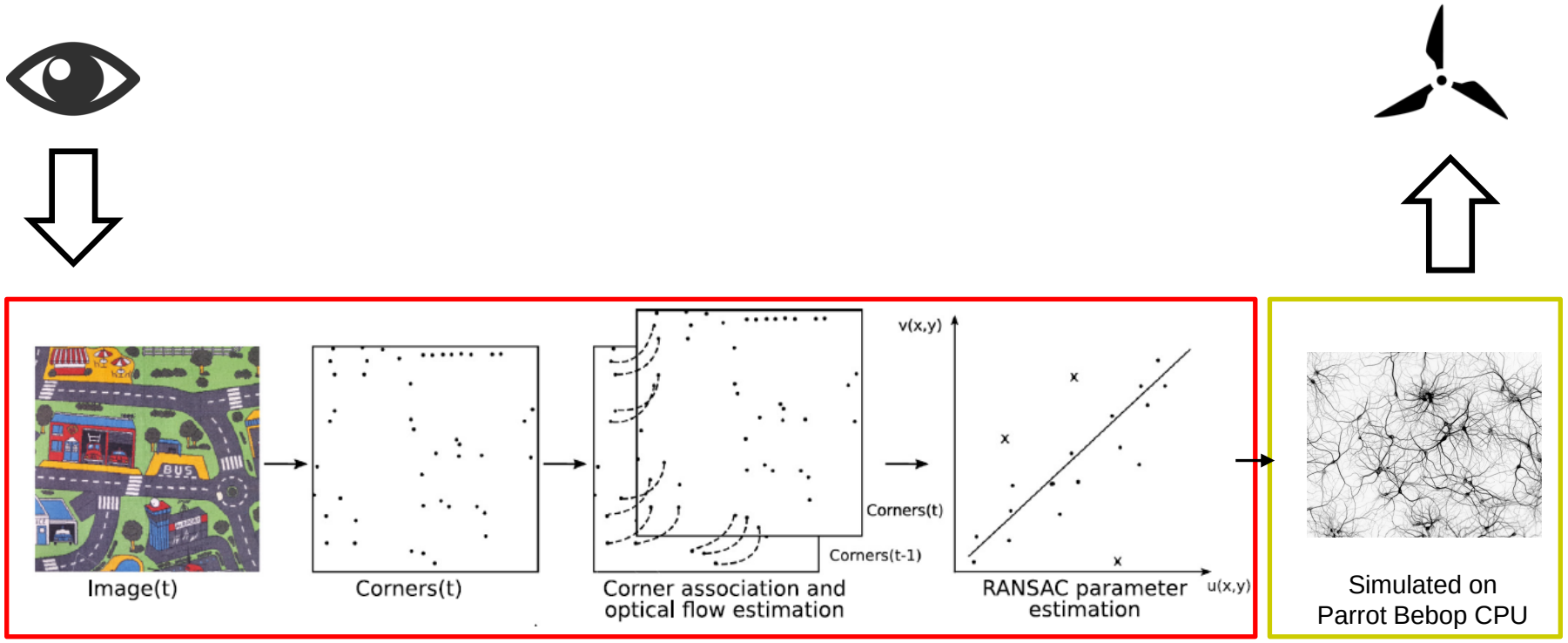
Output – global flow observables



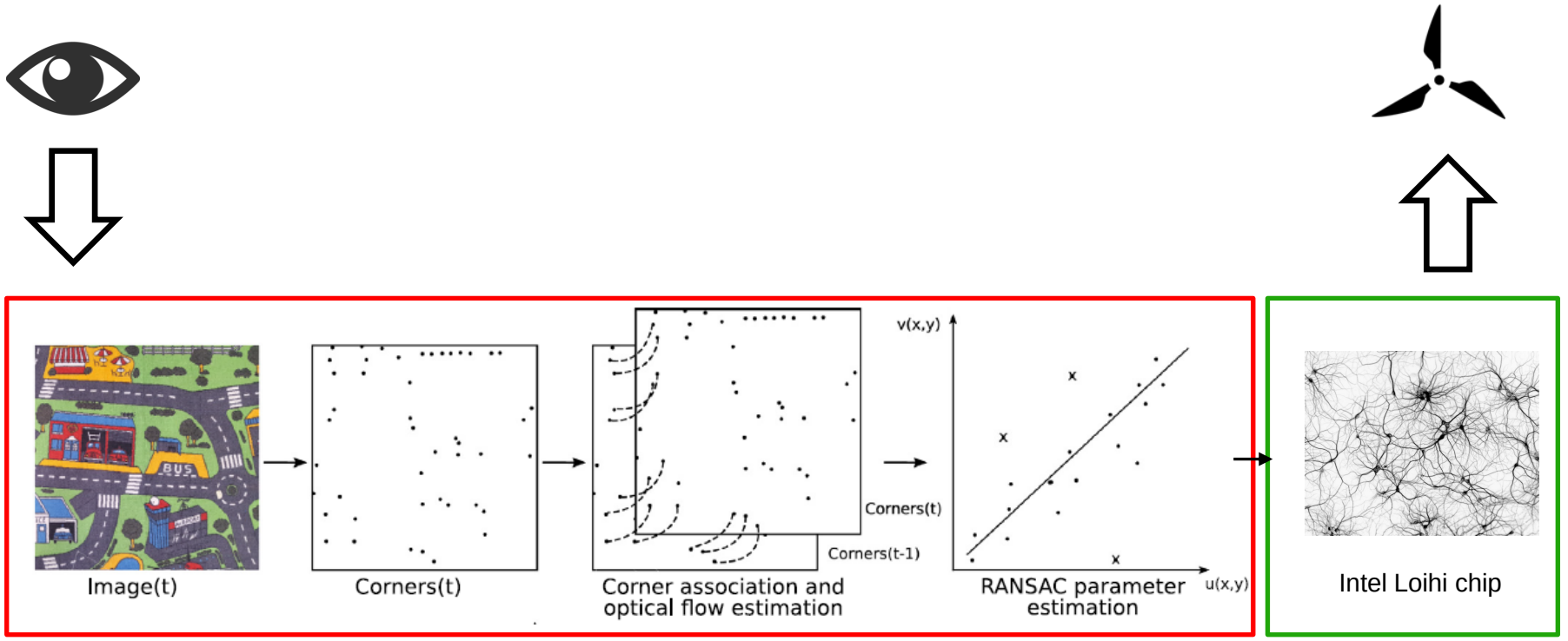
(a) Pure horizontal global motion

CMOS camera + onboard, CPU-based SNN



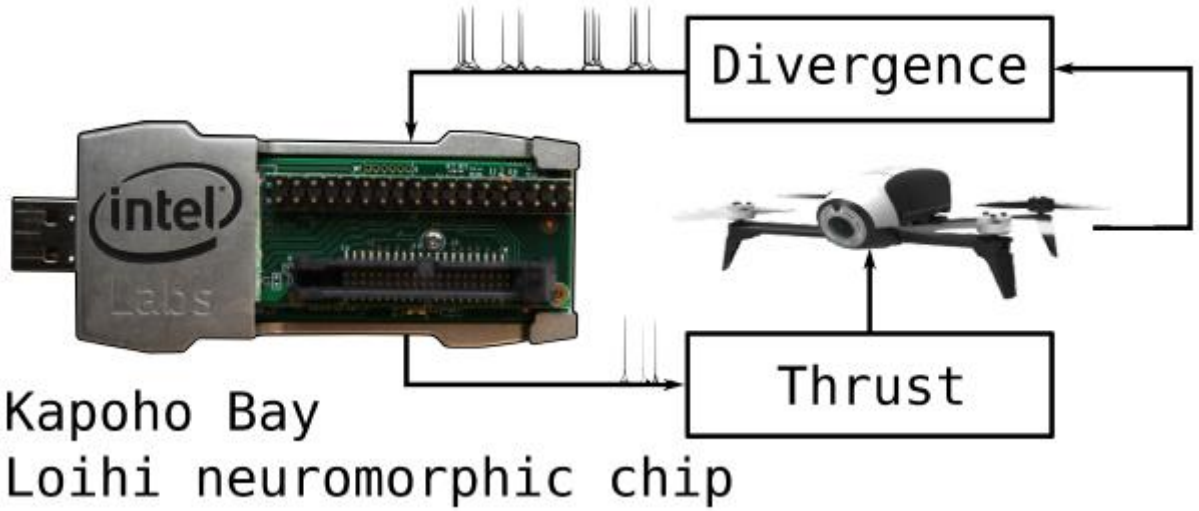
Hagenaars, J. J., Paredes-Vallés, F., Bohté, S. M., & de Croon, G.C.H.E. (2020). Evolved Neuromorphic Control for High Speed Divergence-based Landings of MAVs. RA-L, IROS 2020

Using Intel's neuromorphic Loihi chip



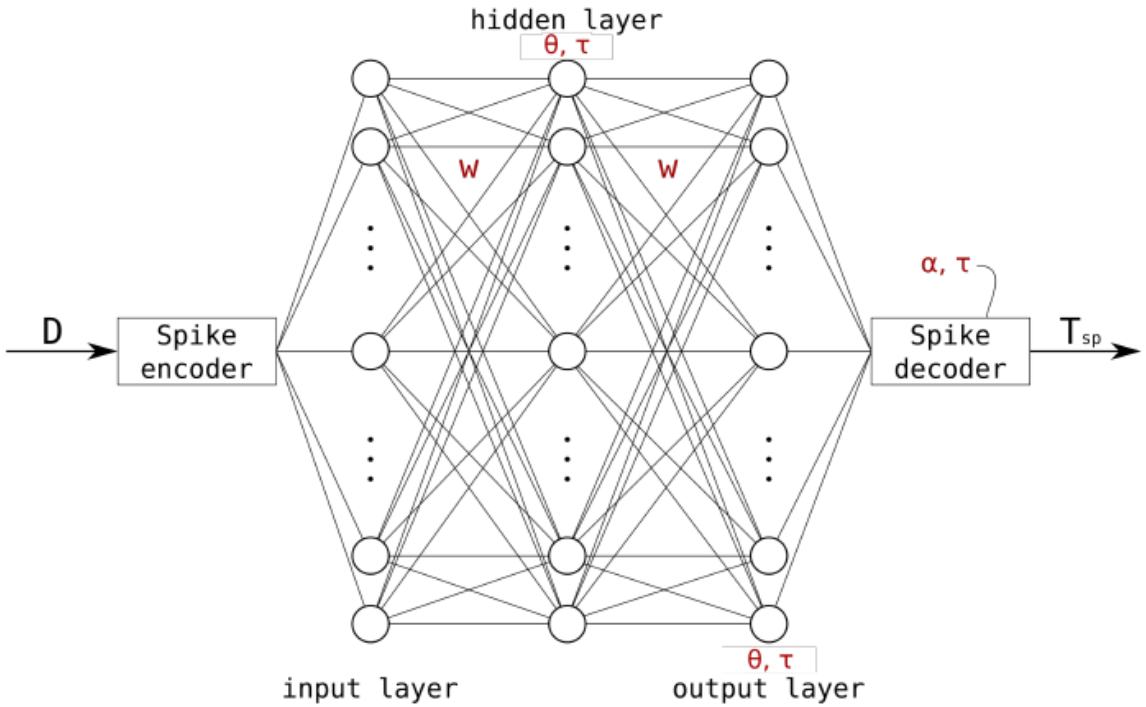
Neuromorphic control for optic-flow-based landings of MAVs using the Loihi processor.
Julien Dupeyroux, Jesse J. Hagenaars, Federico Paredes-Valles and Guido C.H.E. de Croon – ICRA 2021.

Our approach



Our approach

Evolve the SNN in simulation and transfer to reality



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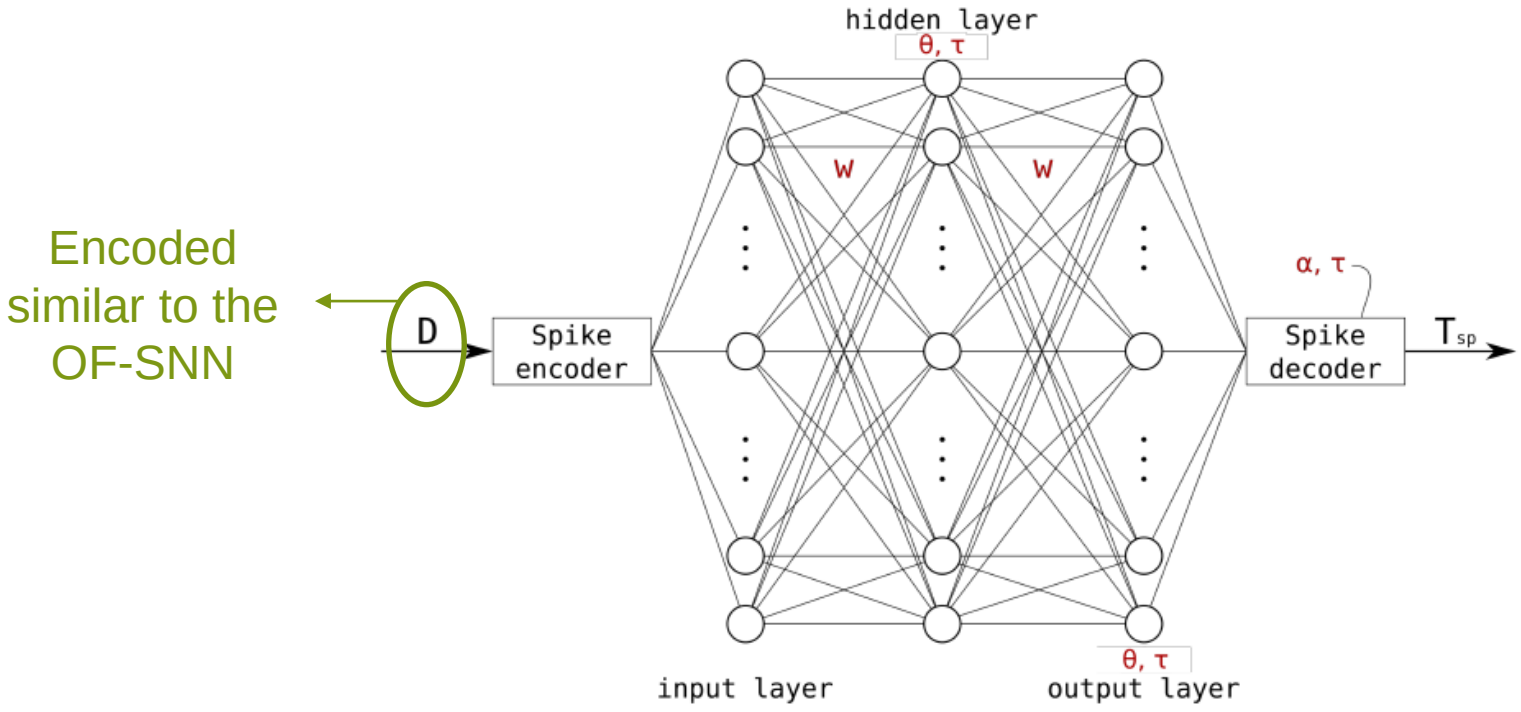

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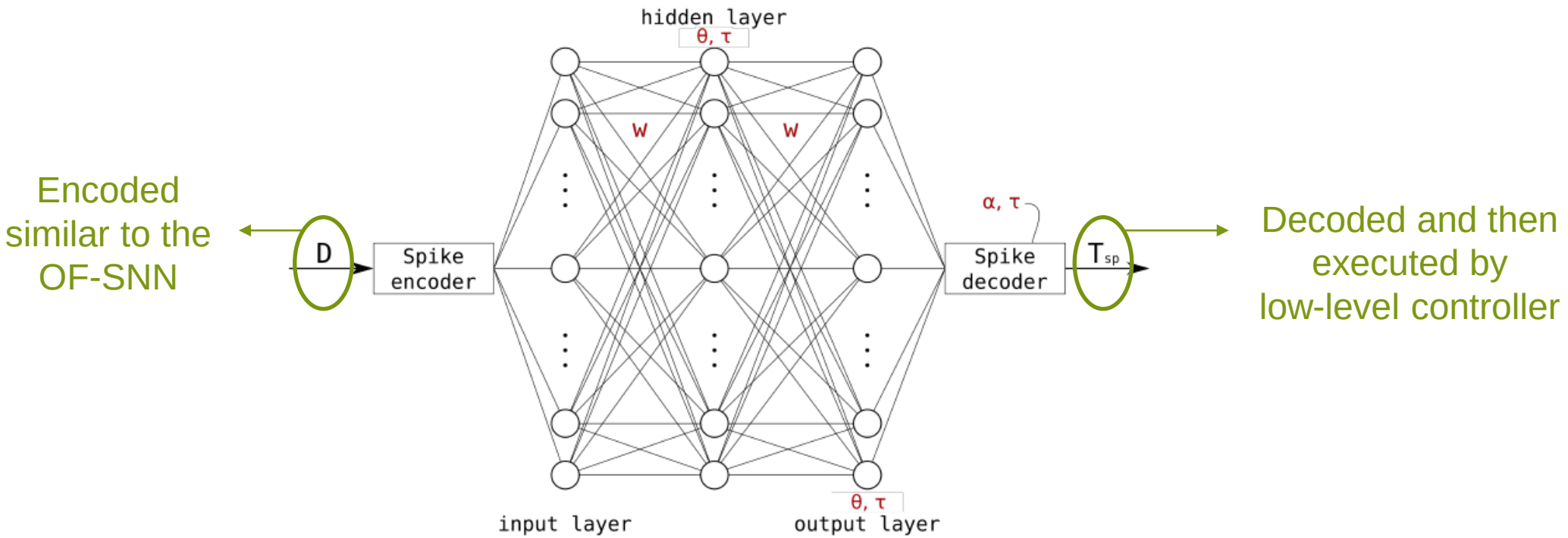

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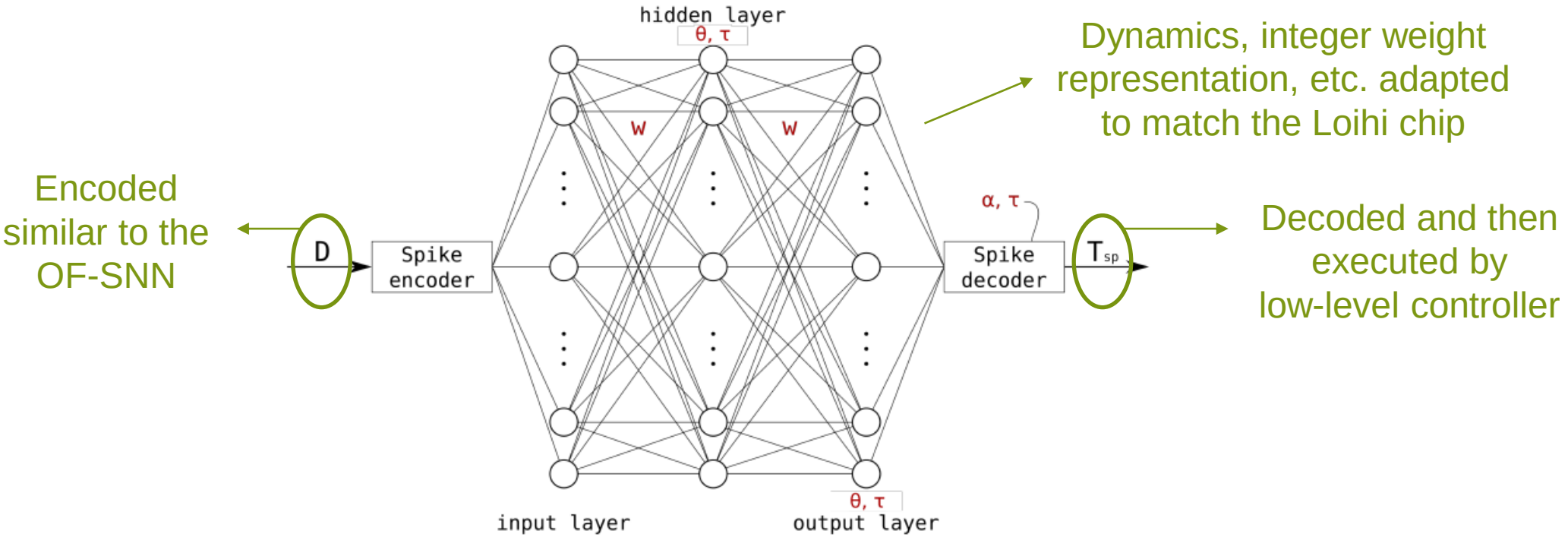

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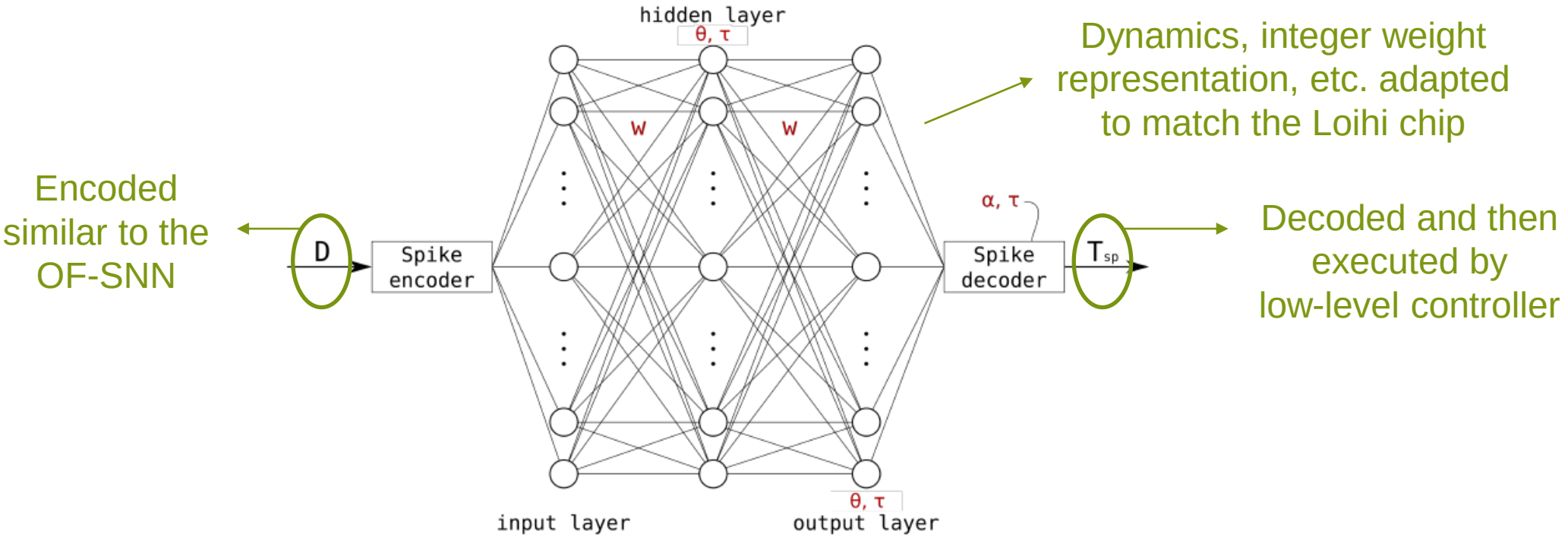
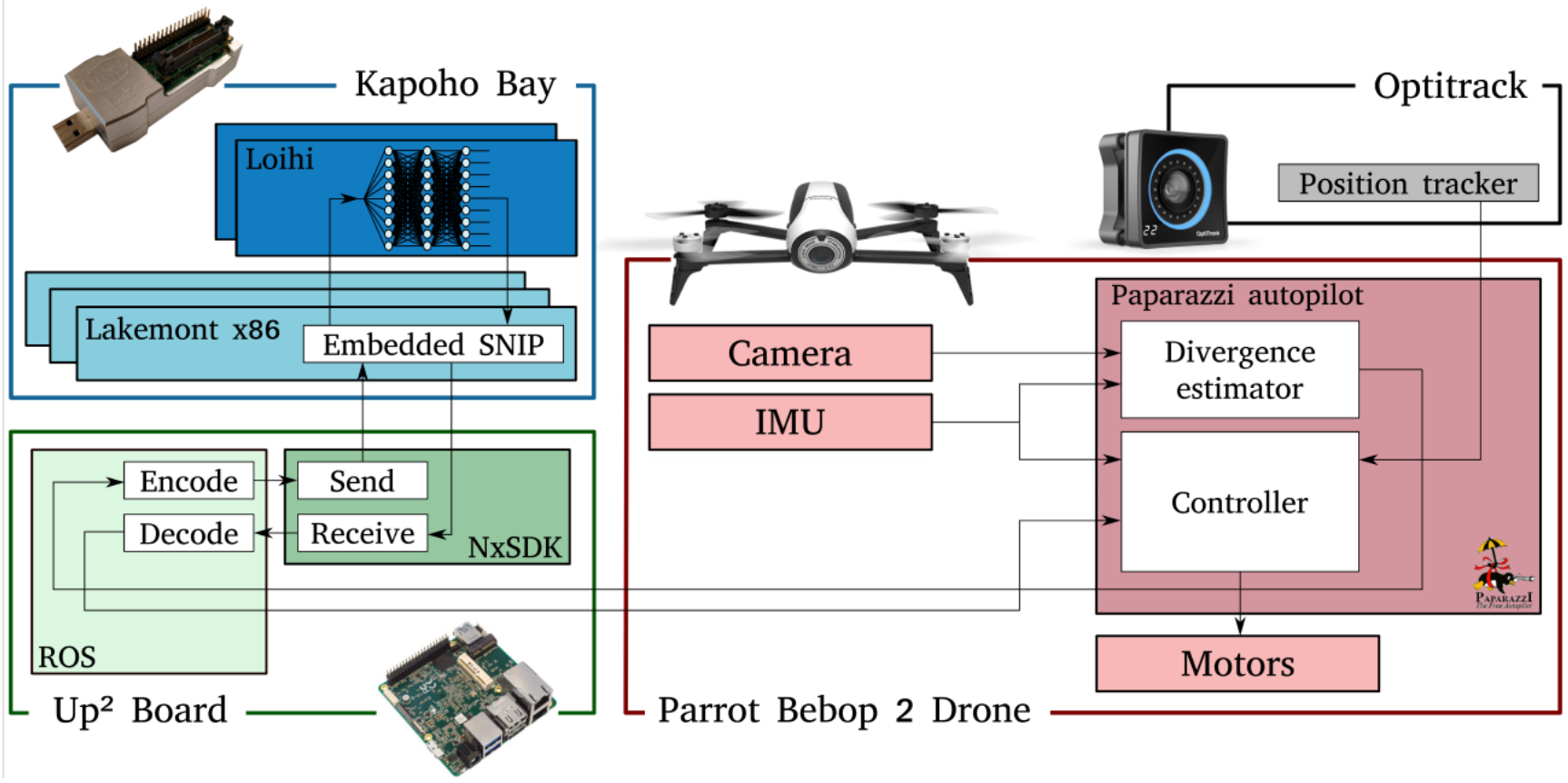
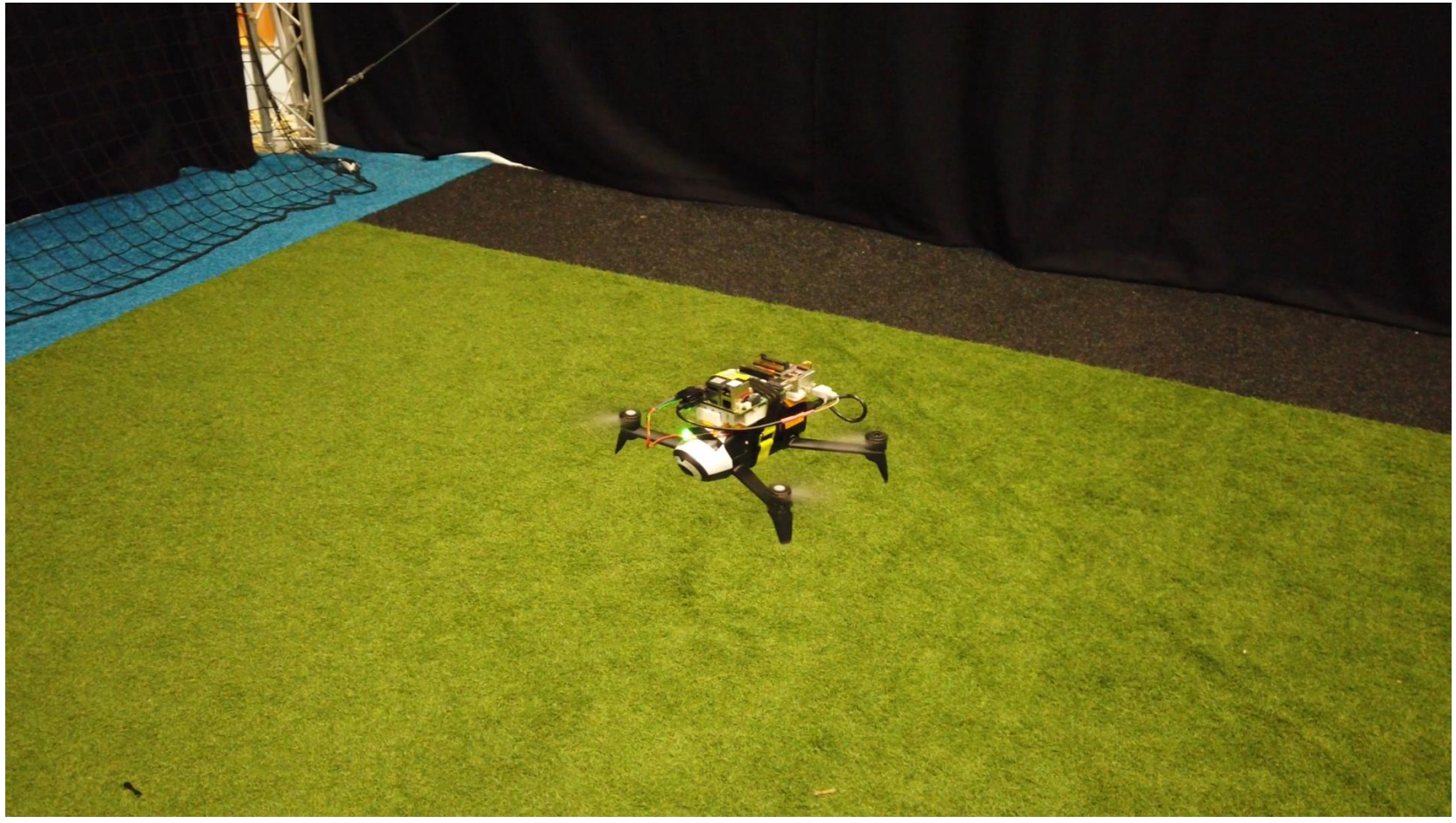


Unpredictable elements (initial height, delay, jitter, etc.) randomized during evolution

Our approach



Results



Conclusion

Neuromorphic sensing and processing form a huge promise for insect-inspired autonomous flight of tiny drones

Future:

- Fully neuromorphic pipeline
- Improve learning mechanisms for SNNs
- Tackle increasingly complex tasks

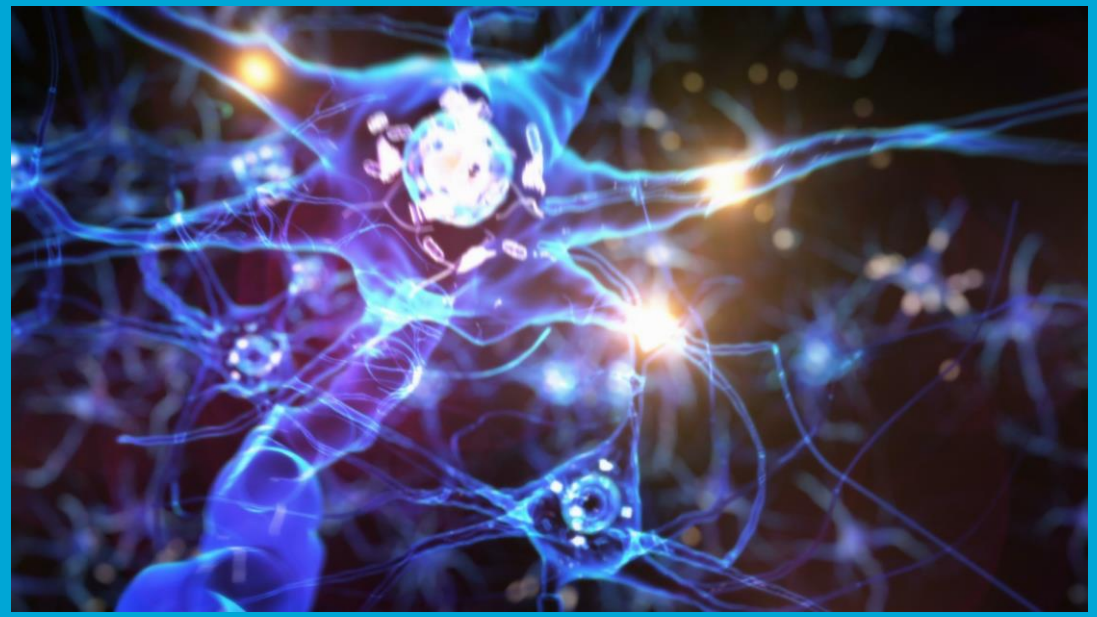
Researchers involved in the neuromorphic work

Federico Paredes-Vallès, Kirk Scheper, Julien Dupeyroux, Jesse Hagenaars, Bas Pijnacker Hordijk (all TU Delft), Sander Bohté (UvA)

More information

mavlab.tudelft.nl

Questions?



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