Autonomous Learning in DFT

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The phenomenon of learning

Learning is the act of acquiring new, or modifying and reinforcing existing knowledge, behaviors, skills, values, or preferences… Learning produces changes in organism and the changes produces are relatively permanent…

Learning in different disciplines

- Machine learning: learning to classify entities, learning to approximate functions, learning to discover dependencies, learning to discover and use regularities

- Animal learning: classical and instrumental conditioning, habituation

- Infant (and adult) learning: memory, rule learning, perceptual learning, motor learning

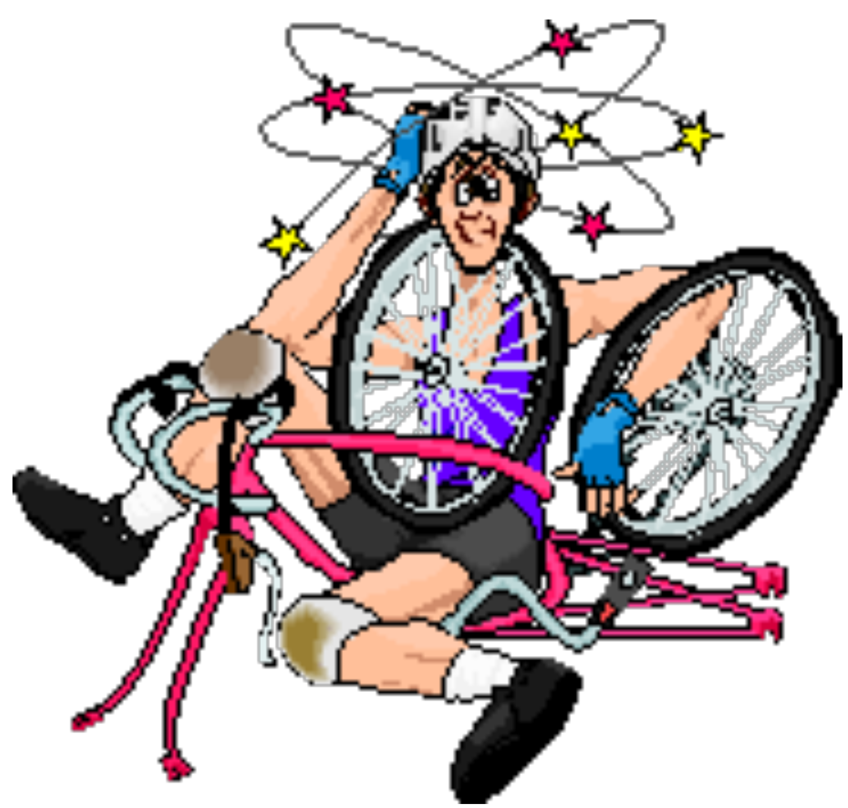
- Learning new skills and behaviours

Autonomous learning

- …learning, which co-occurs with behaviour

Behavior is a mess

- It unfolds in a dynamical, partially unknown environment, which is accessed through limited sensors and a noisy motor system with its own complexities and (a-priori unknown) dynamics



Autonomous learning and behaviour are intimately interwoven

- behavioural variables are a priory “meaningless” to the system

- to learn to behave, the agent has to behave

How may DFT help to clean-up the behavioural “mess”?

- detection and stabilisation of representations of relevant states of the environment

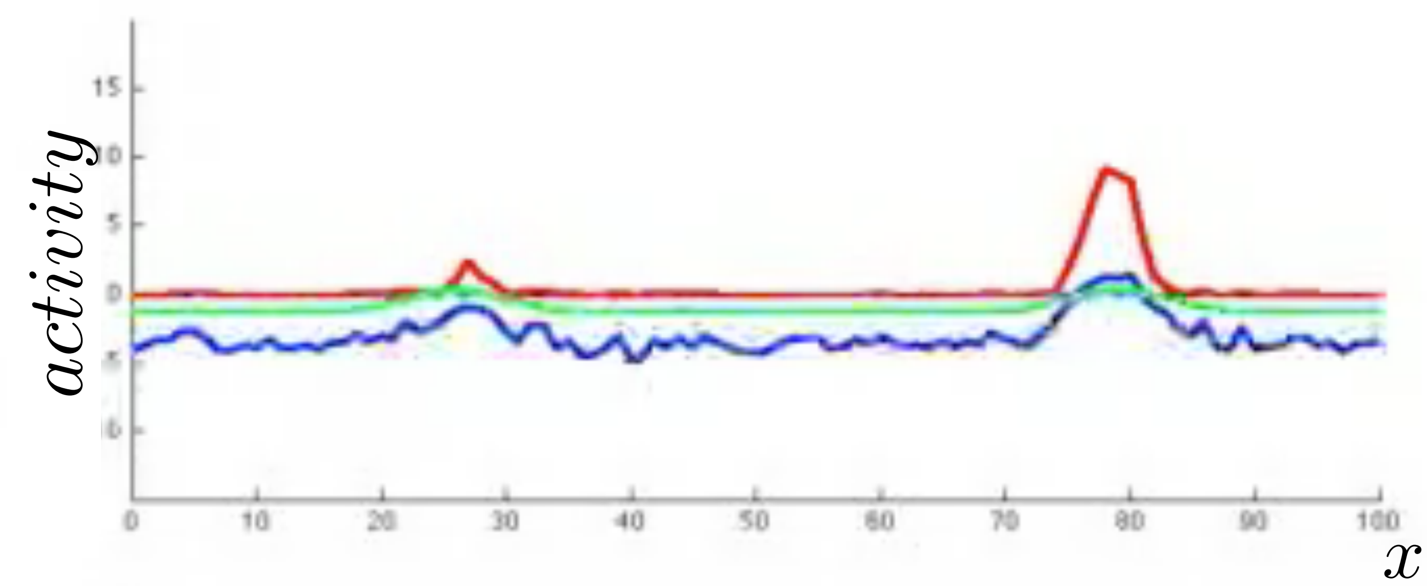
- representation and stabilisation in time of the agent’s intentions

- making decisions about when to initiate and terminate actions

- → decide when and what to learn

Learning mechanisms in DFT

Sustained activation and detection instability



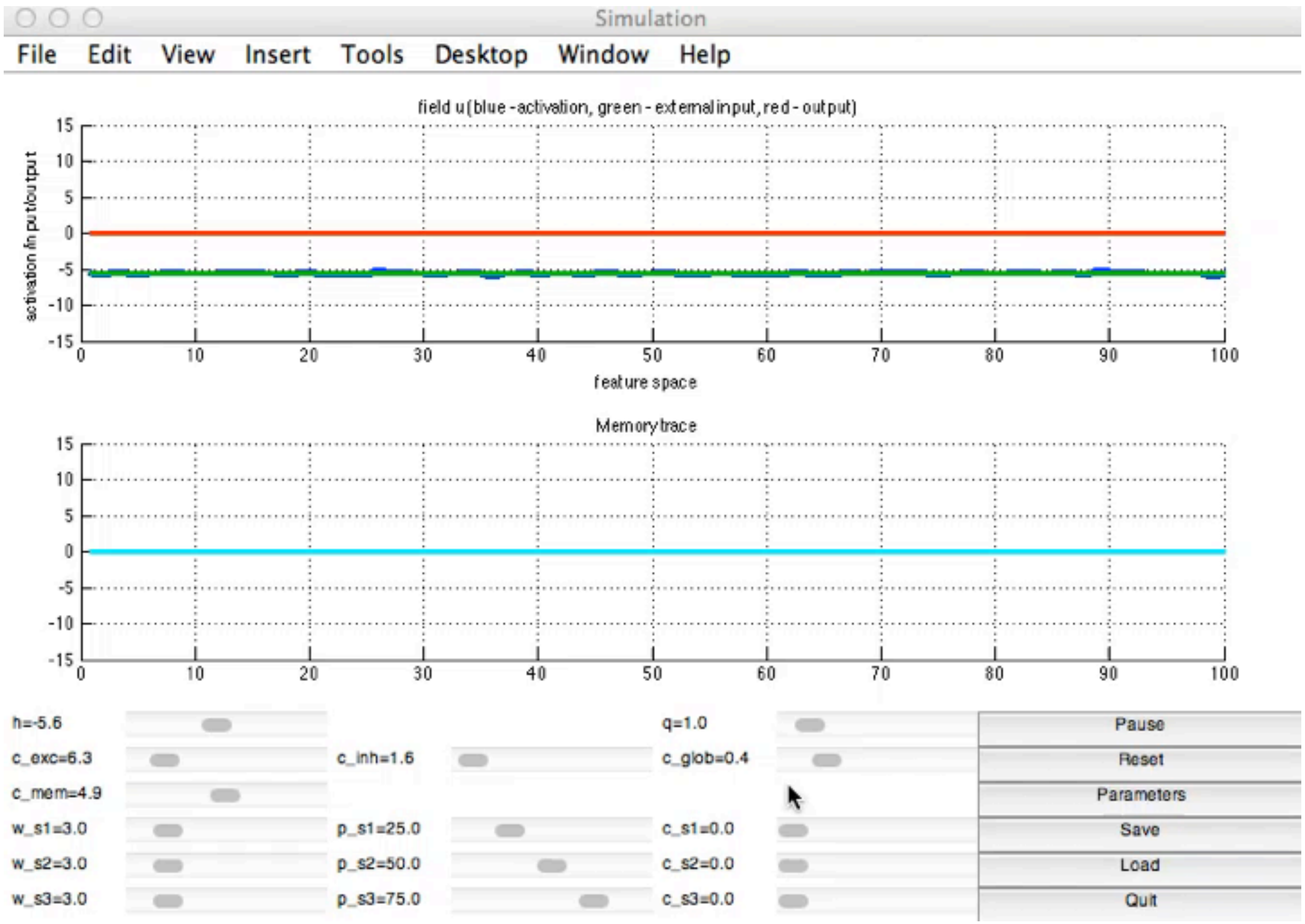
$$\tau \dot{u}(x,t) = -u(x,t) + h + \boxed{\int f\big(u(x',t)\big)\omega(x-x')dx'} + I(x,t)$$

Sustained activation and detection instability

- the state of the system changes in the detection instability
- new input is received in a different way than before the detection instability
- but this change is not of a permanent nature

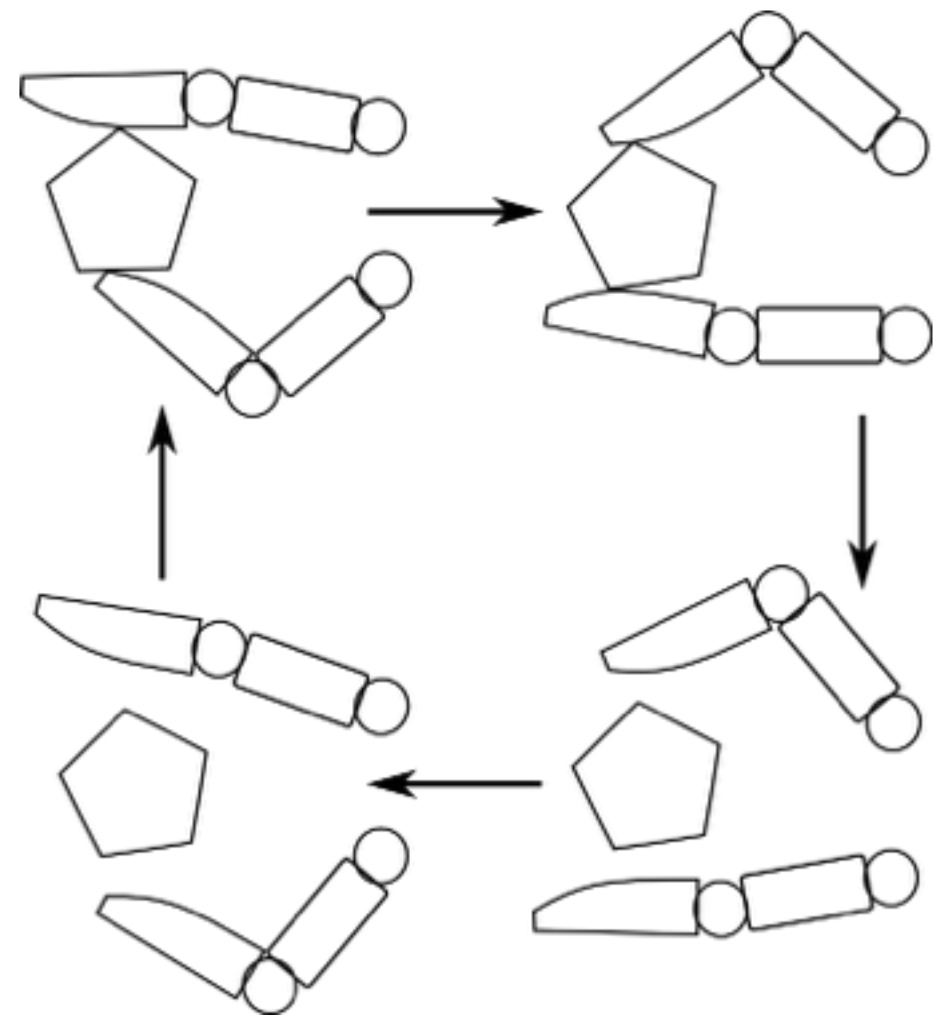
Preshape: memory trace

$$\tau_l \dot{P}(x,y) = \lambda_{build}\Big(-P(x,y) + f\big(u(x,y)\big)\Big) f\big(u(x,y)\big) - \lambda_{decay} P(x,y)\Big(1 - f\big(u(x,y)\big)\Big)$$

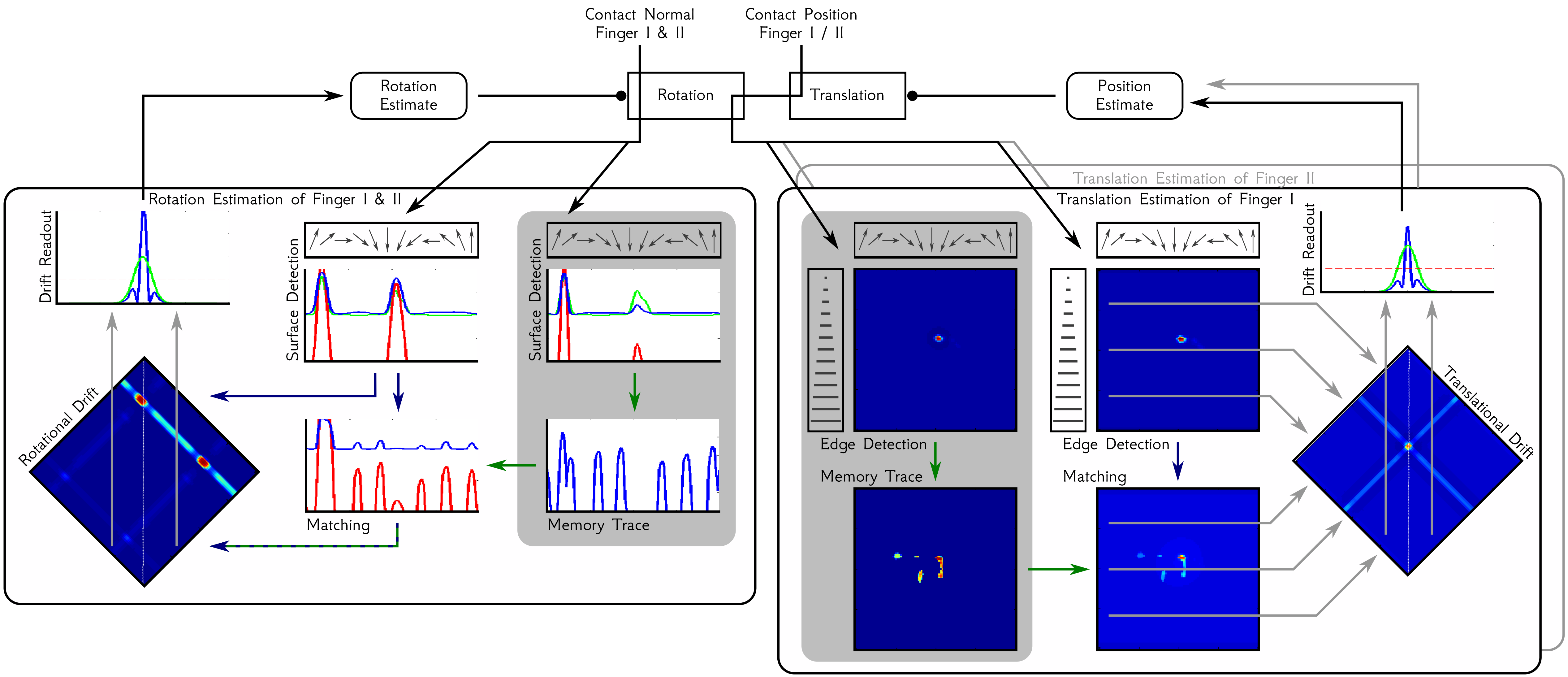


Example 1

- Learning object representation based on haptic input



Learning object representation based on haptic input



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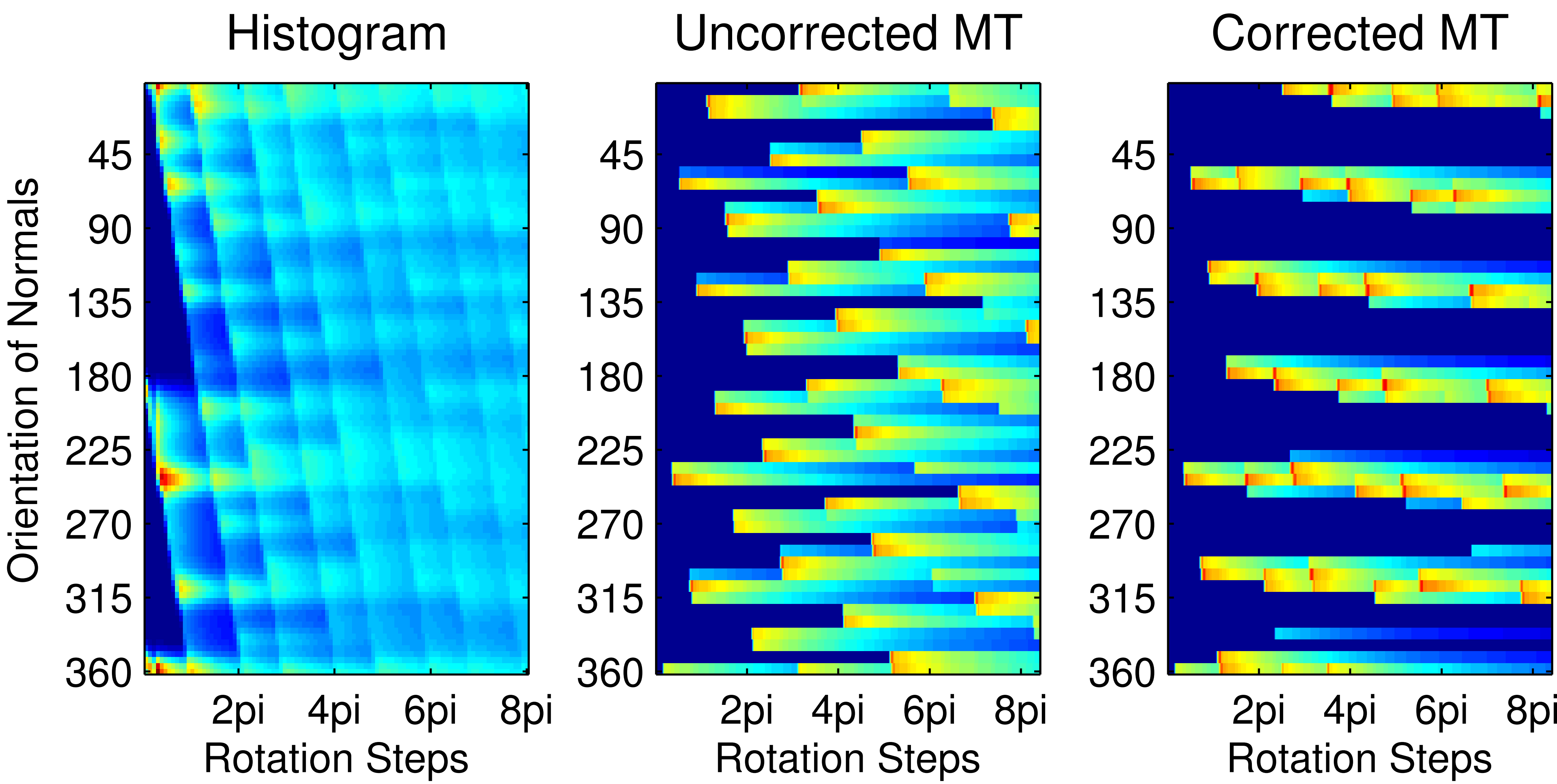
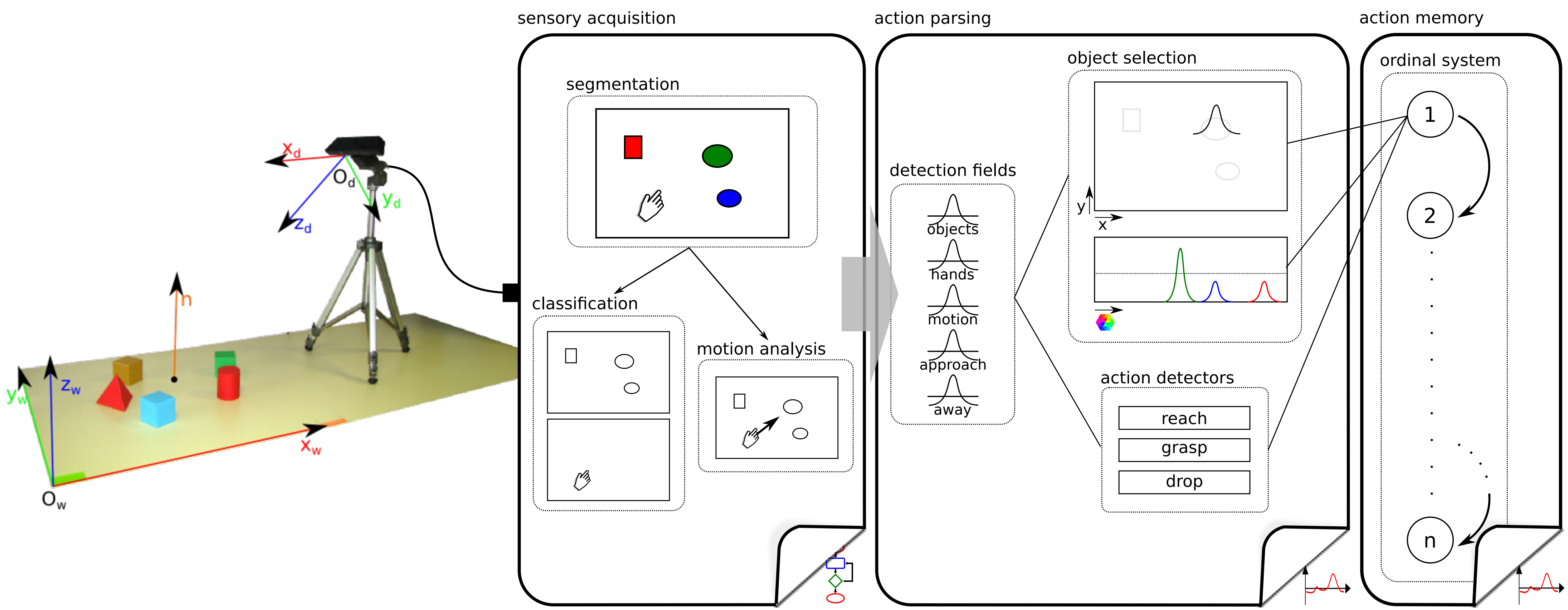


Example 2

- ‘Parsing’ (learning) a sequence of actions



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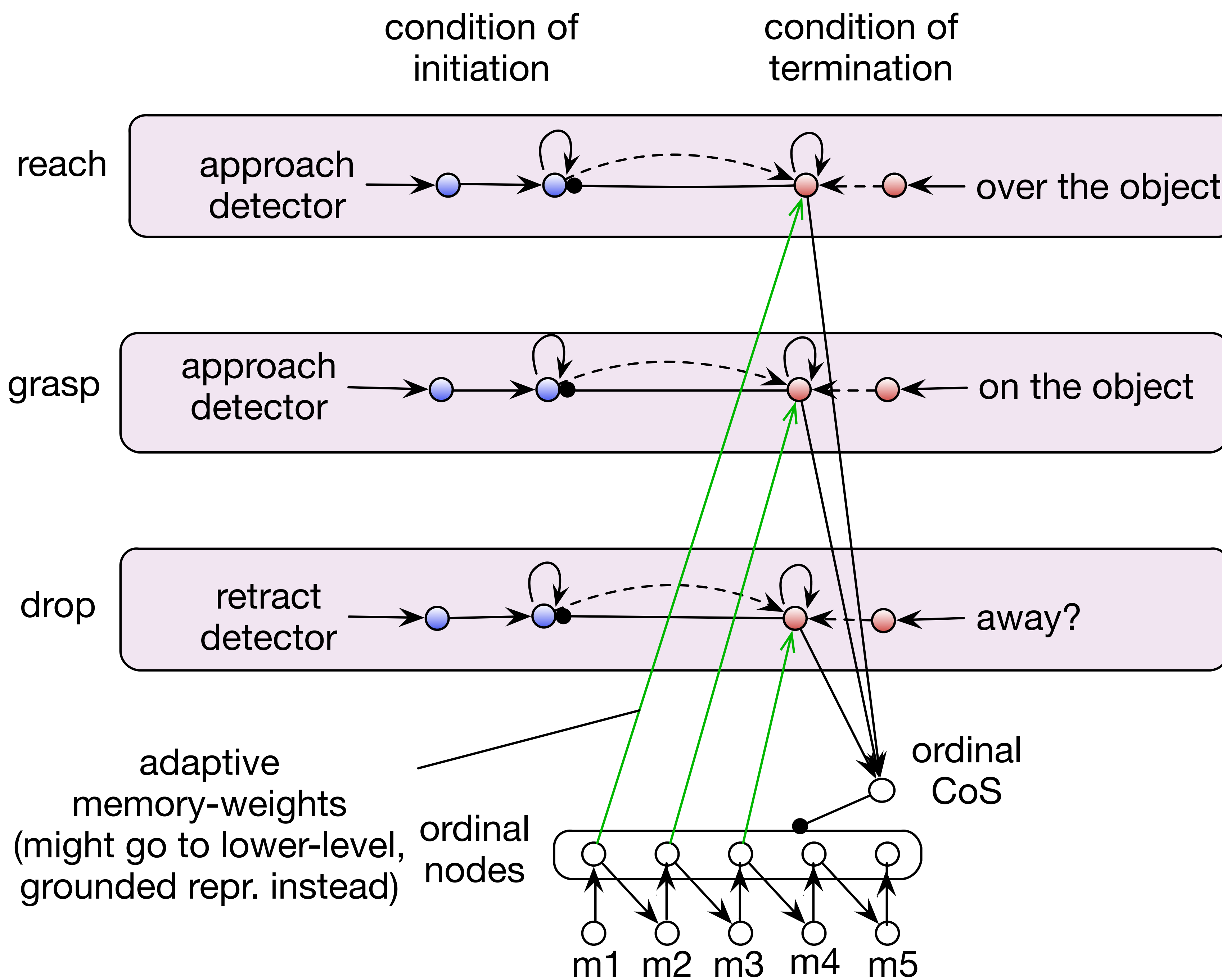

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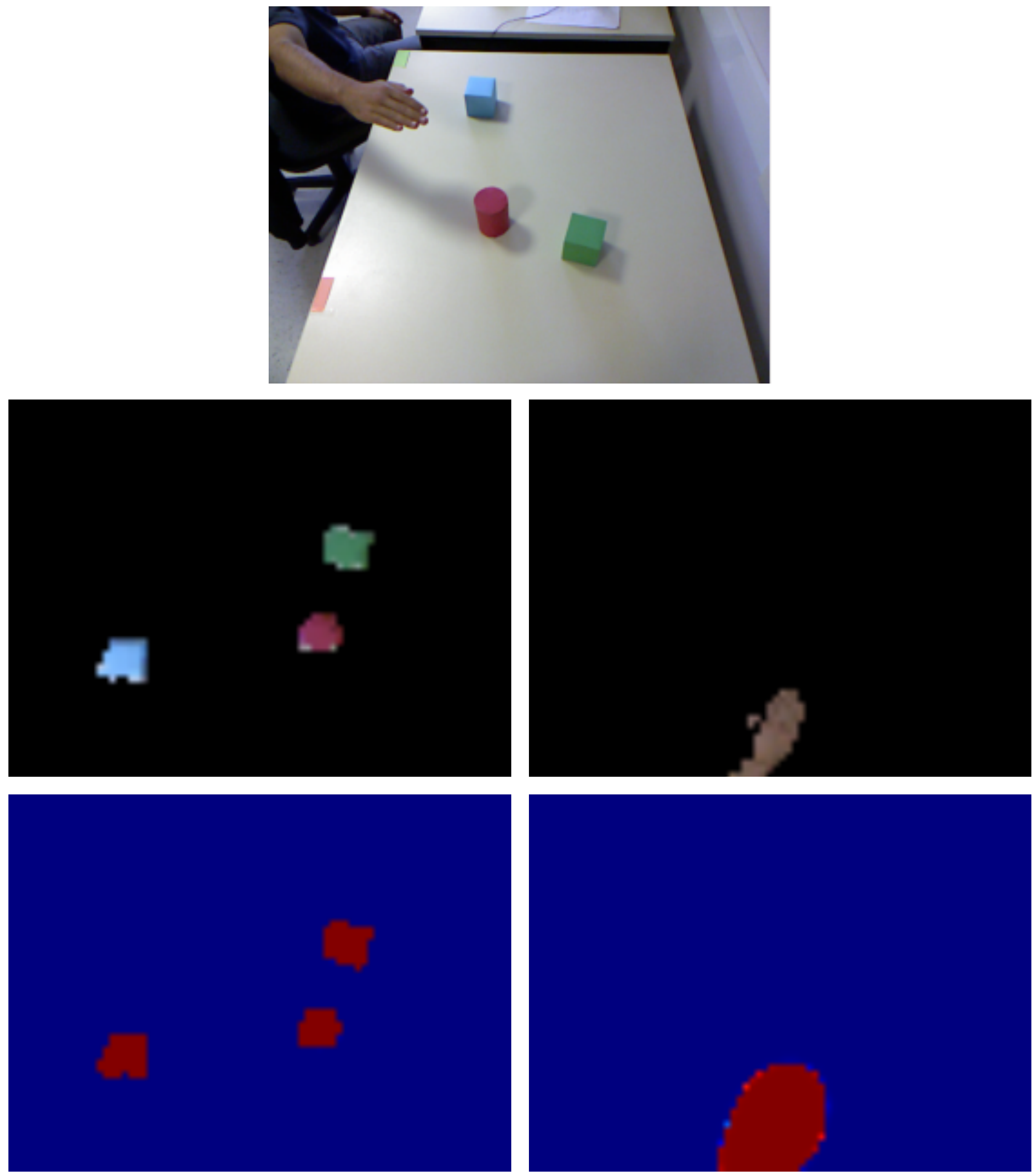

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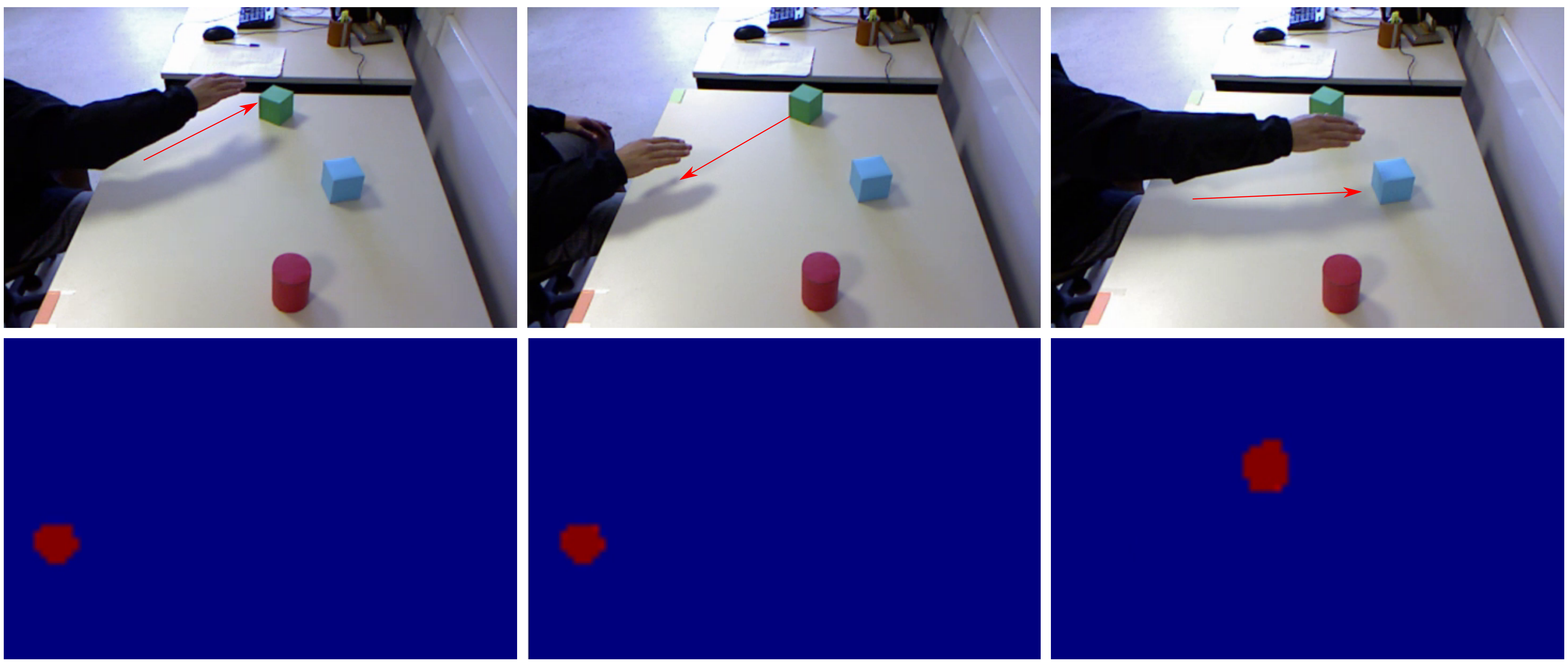

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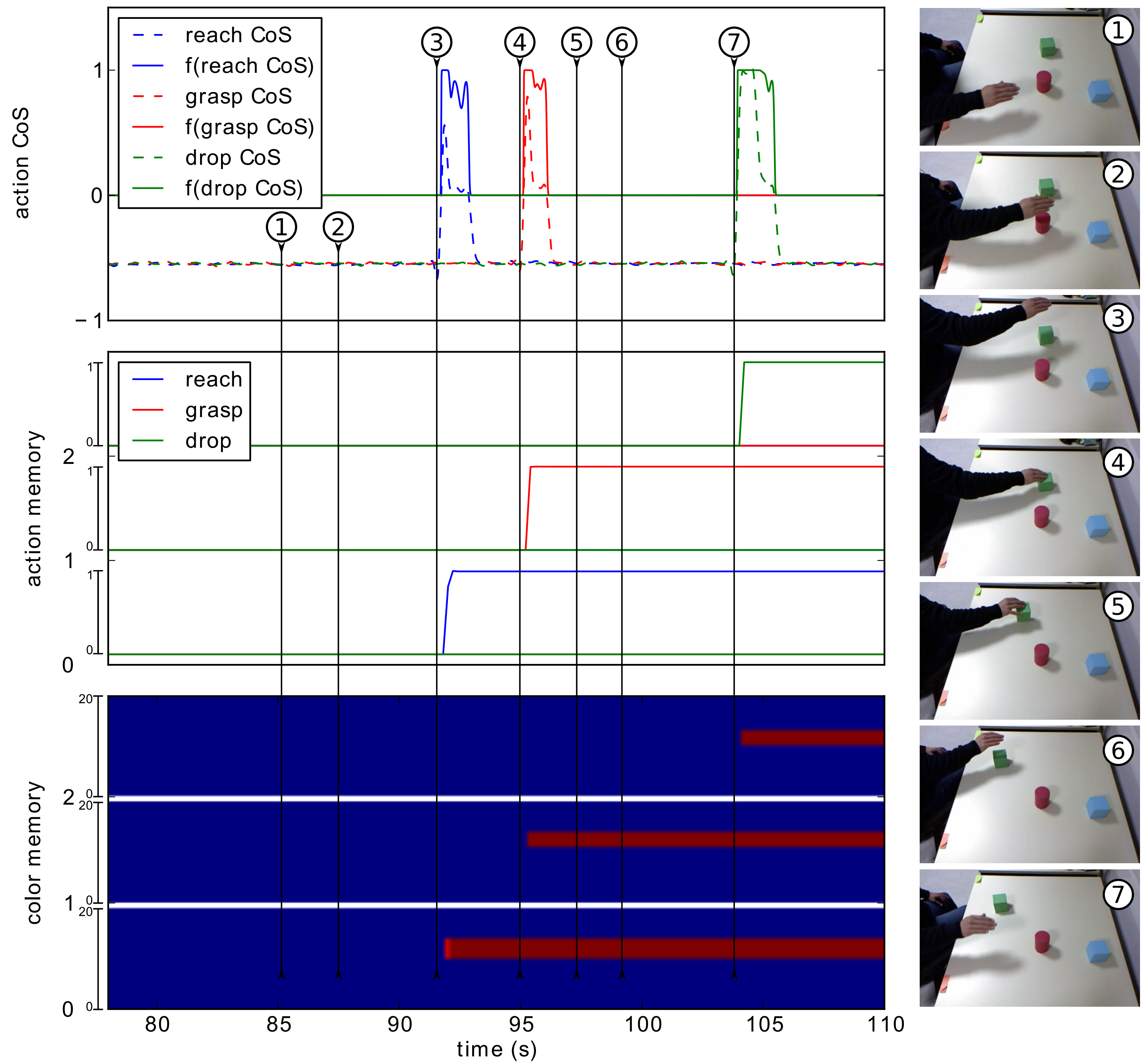

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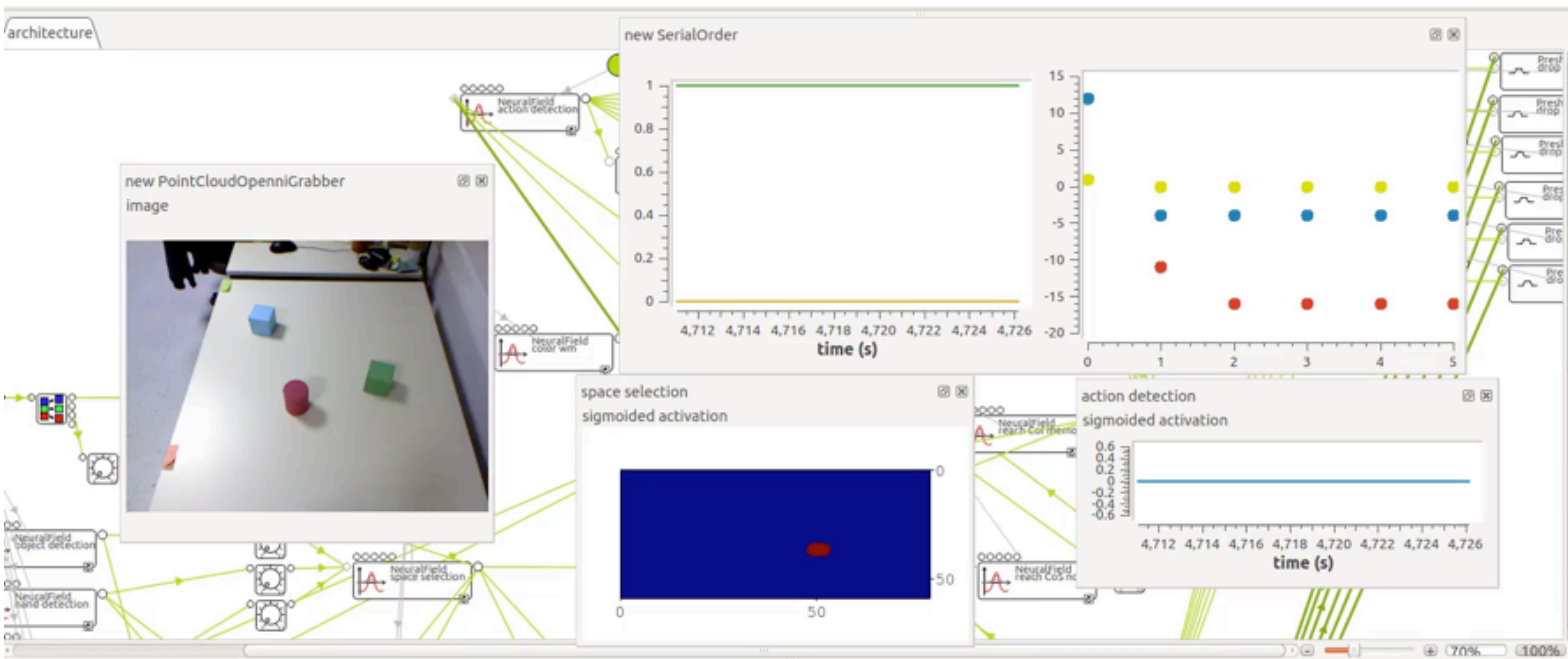
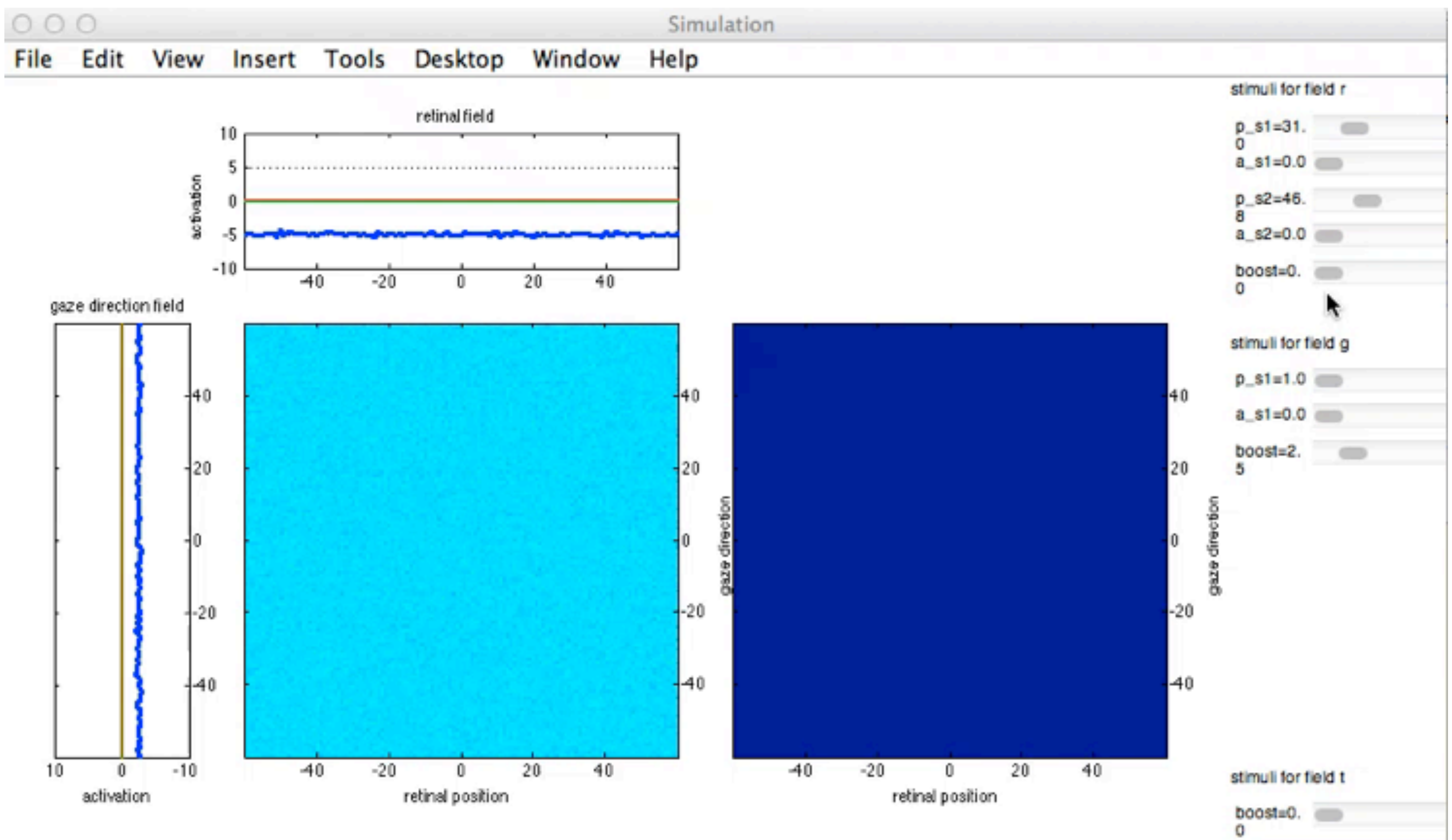


Preshape in higher-dimensional DNFs

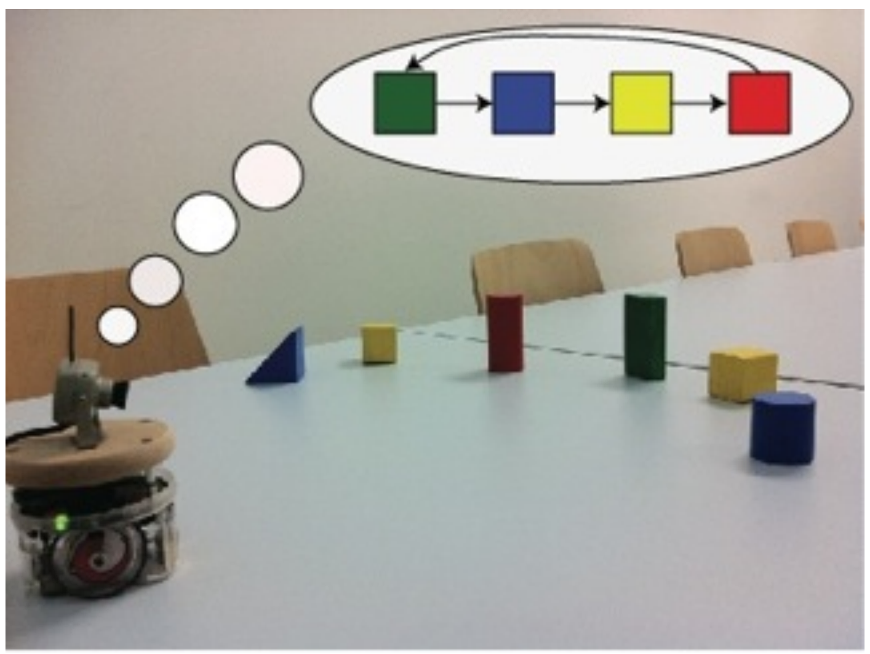
$$\tau_T \dot{T}(x,y) = -T(x,y) + h + F_{lat} + f(u_{vis}(x)) + f(u_{mot}(y))$$

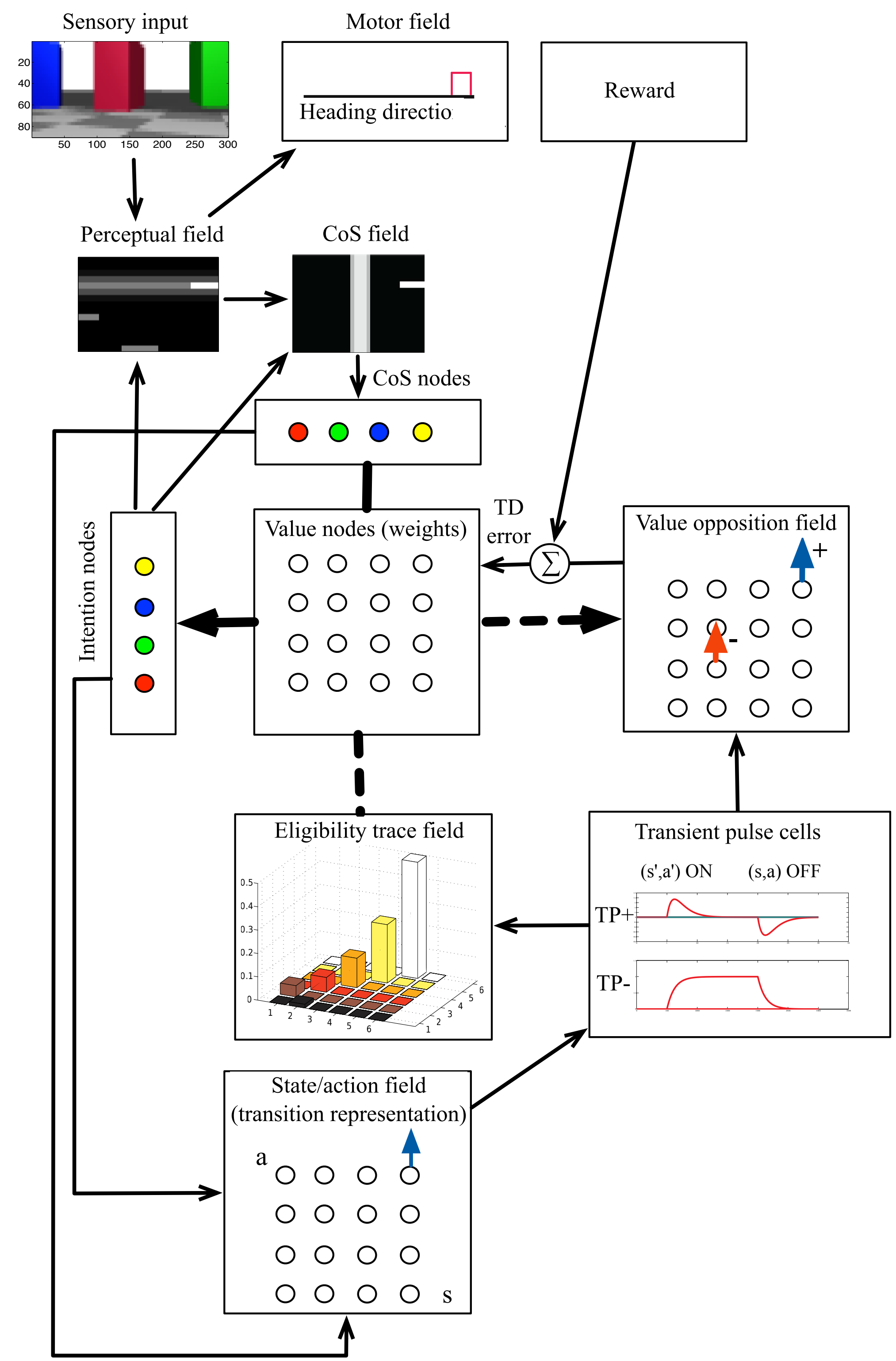
$$\tau_l \dot{P}(x,y) = \lambda_{build}\Big(-P(x,y) + f\big(T(x,y)\big)\Big) f\big(T(x,y)\big) - \lambda_{decay} P(x,y) \Big(1 - f\big(T(x,y)\big)\Big)$$



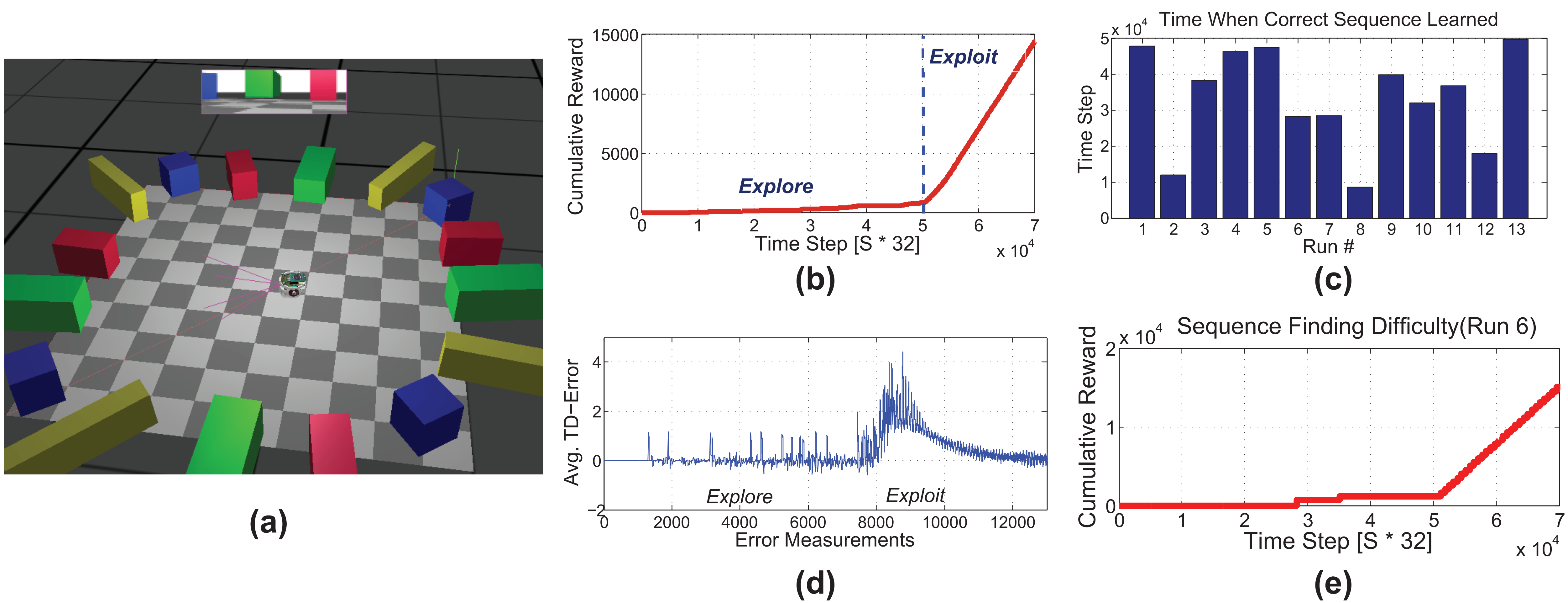
Example 1

Value representation in a neural-dynamic RL agent



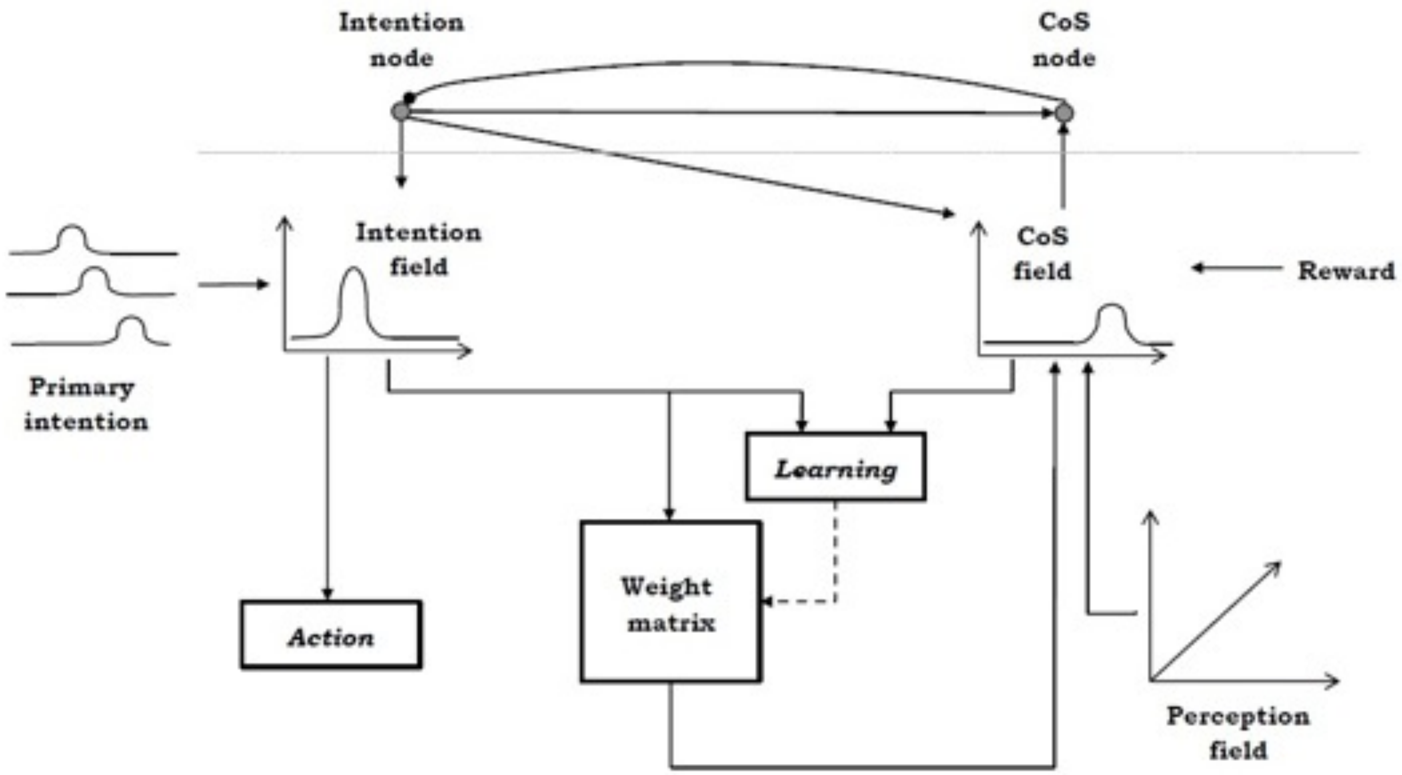


Value representation in a neural-dynamic RL agent



Example 2

- Learning CoS by accumulating memory trace



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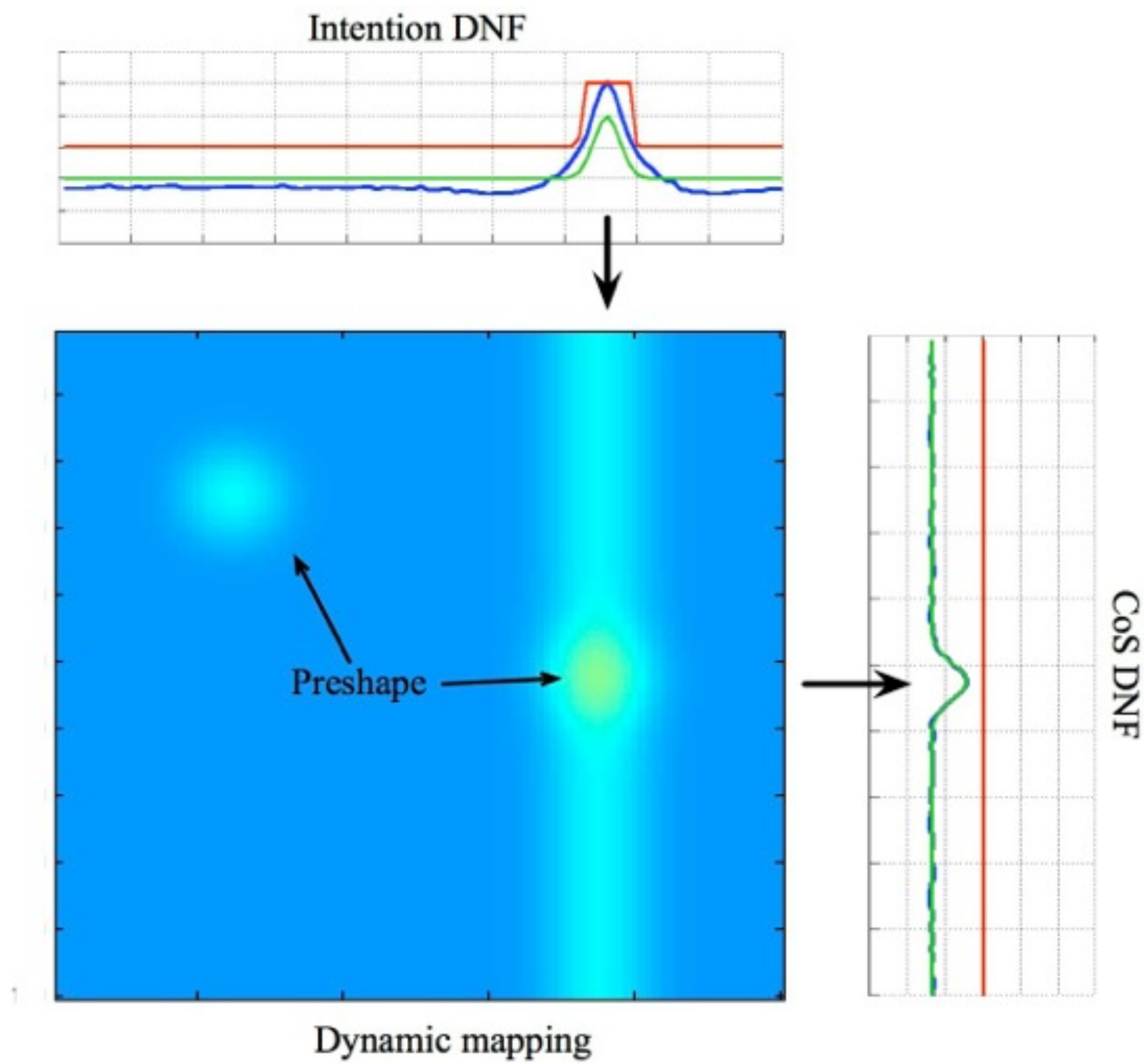

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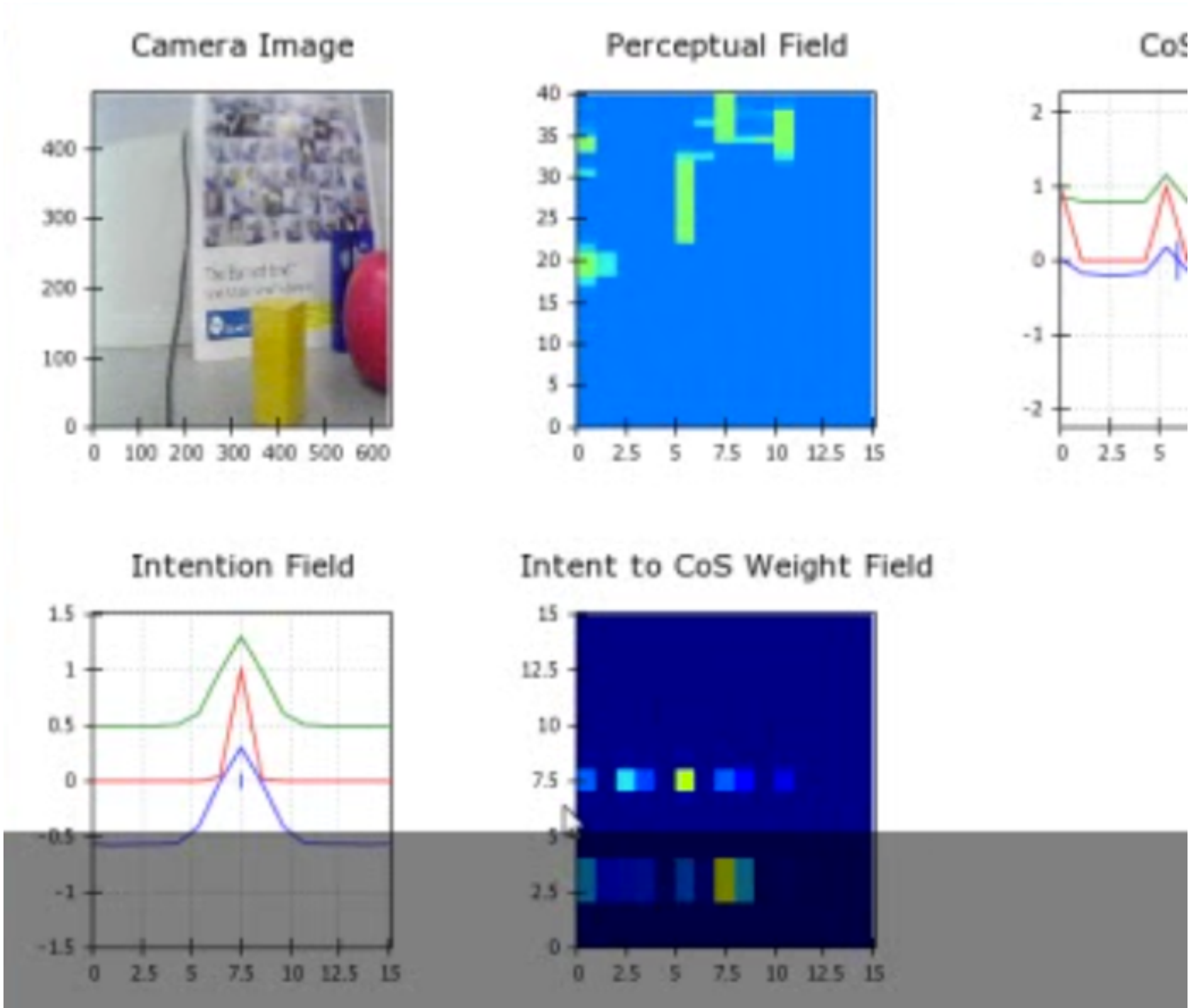

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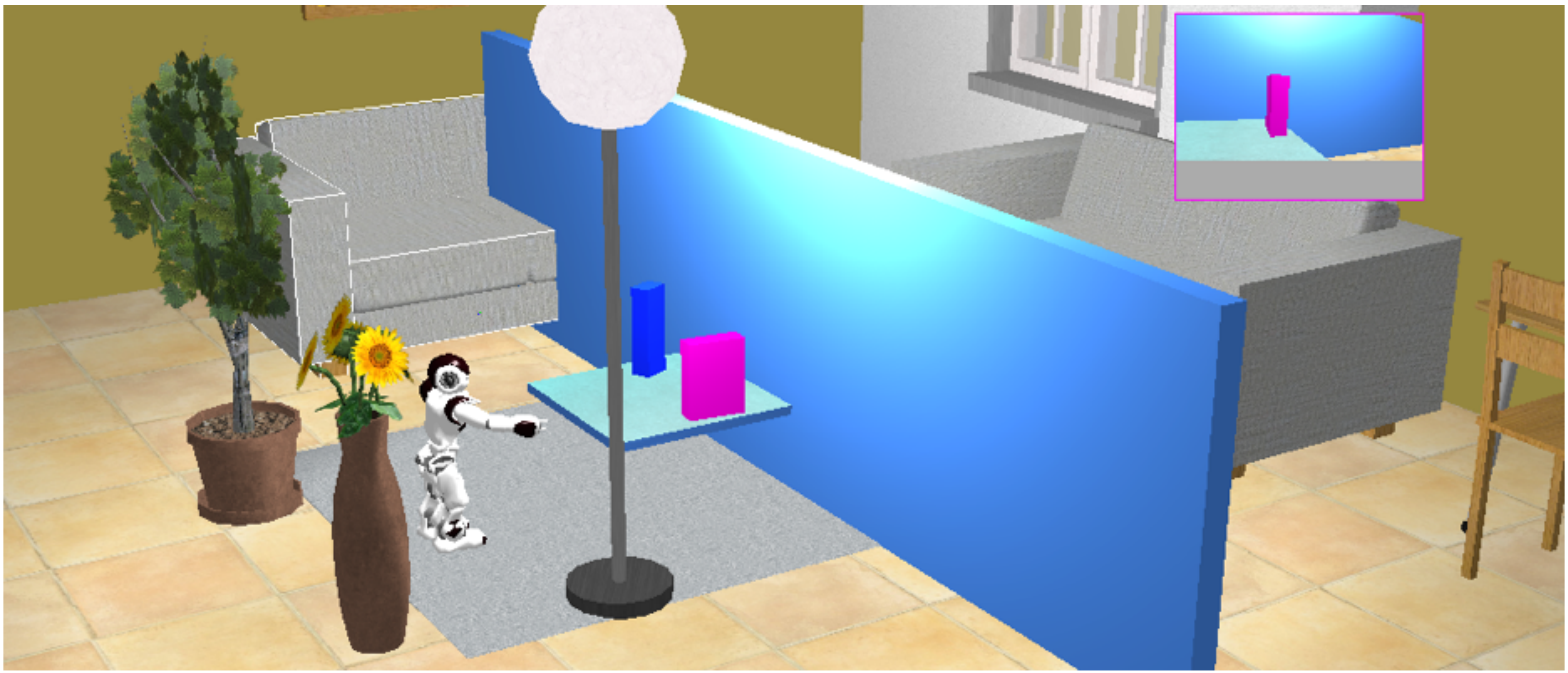

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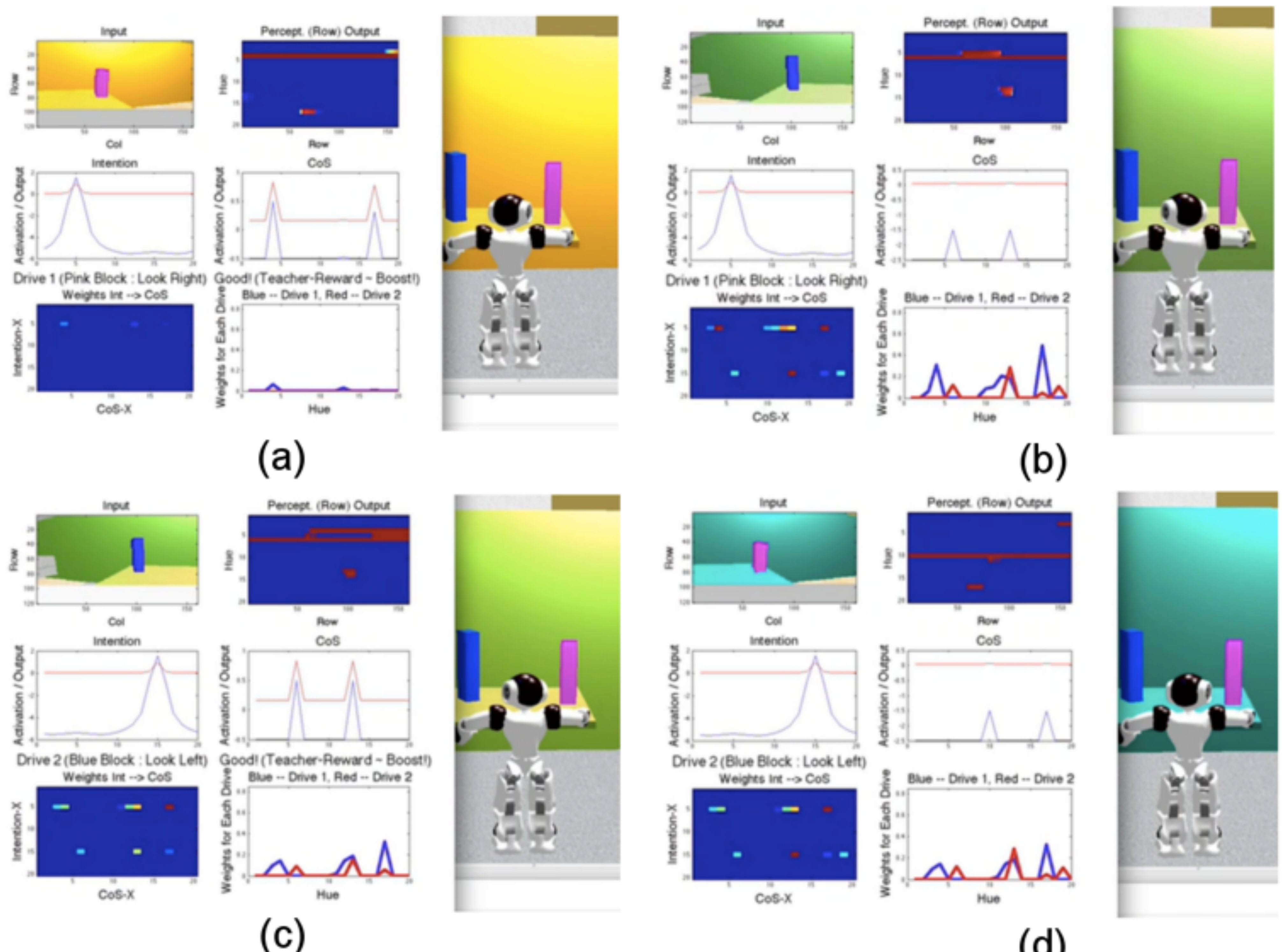
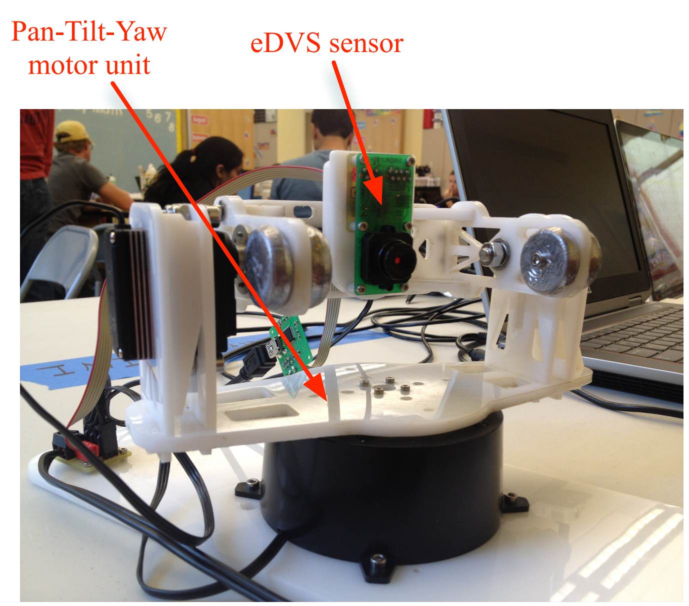
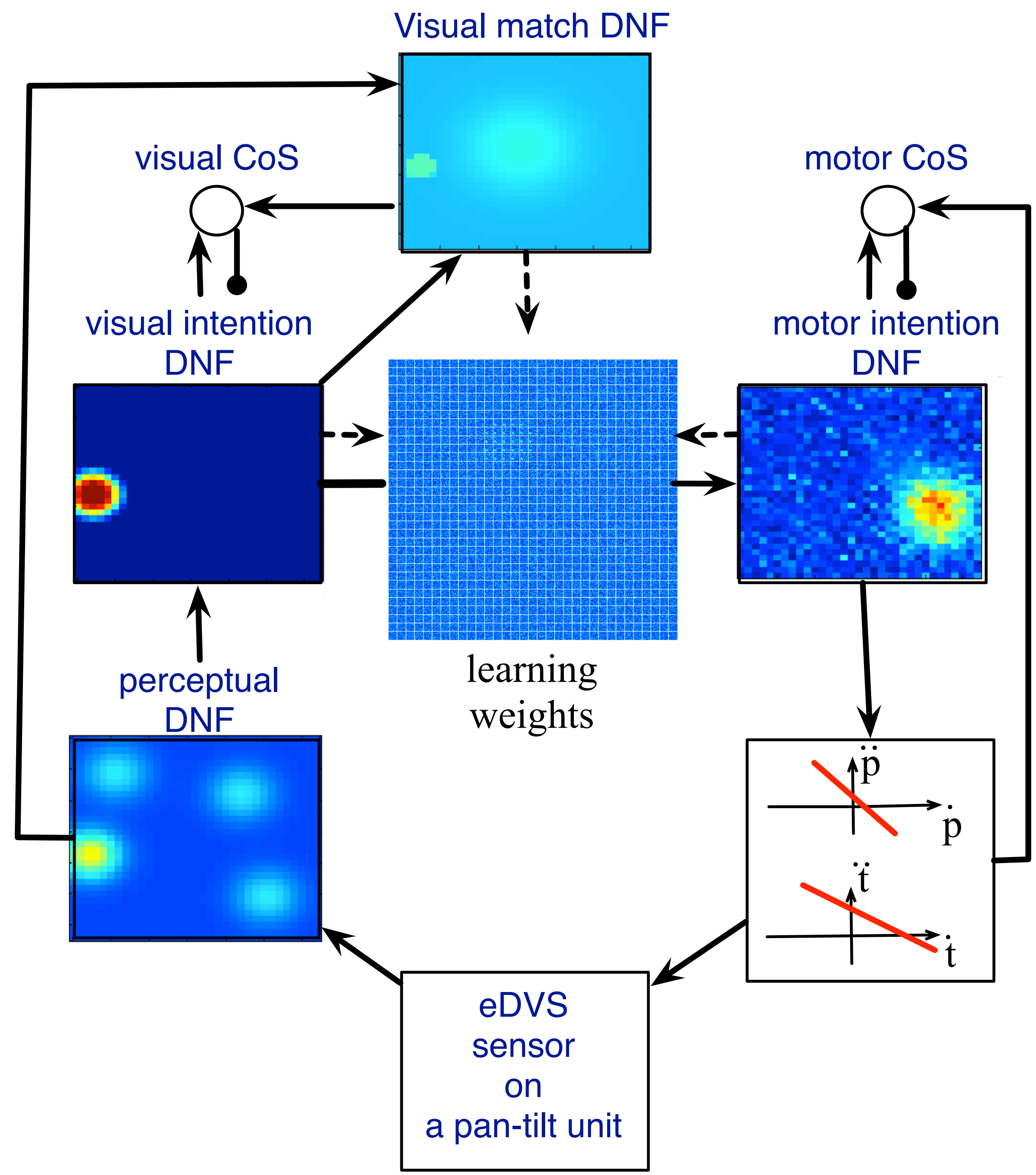


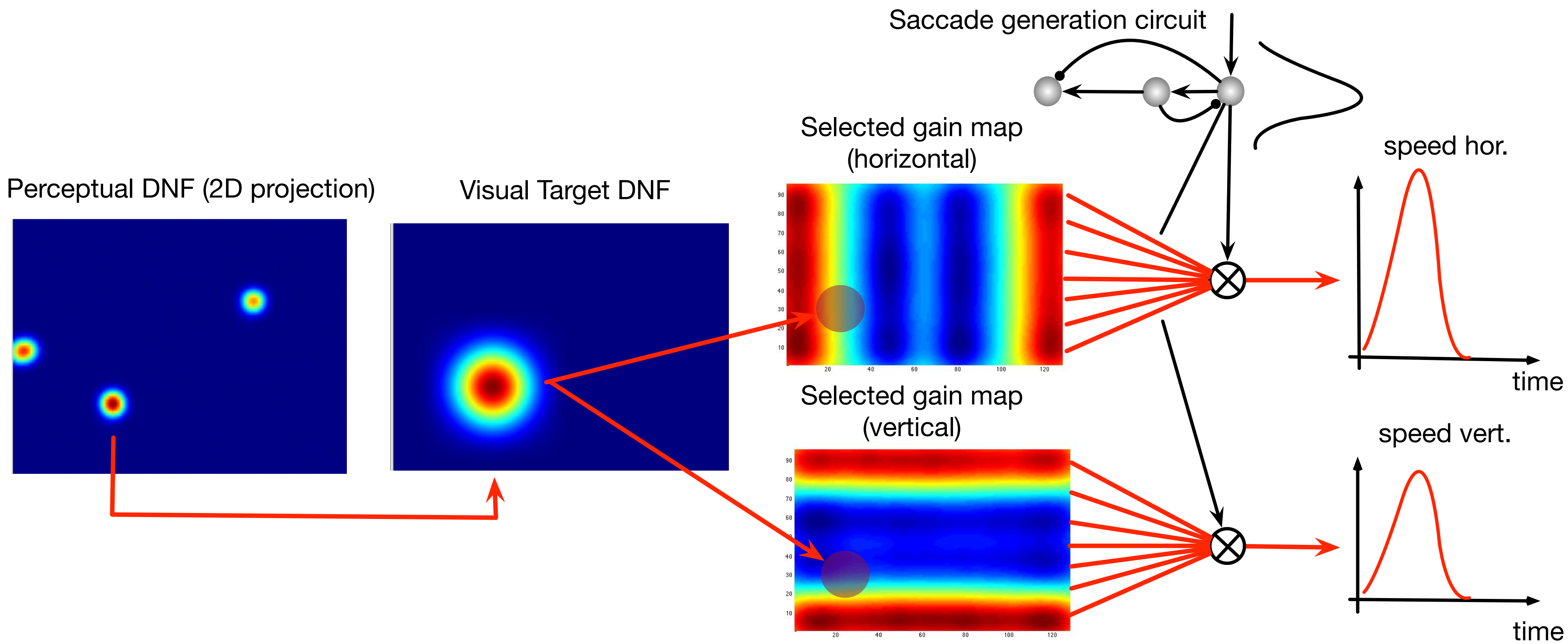
Preshape and adaptive weights

$$\tau_l \dot{T}(x,y,k,l) = \lambda \int f(u_{match}(x,y))dxdy \cdot \Big(-T(x,y,k,l) + f(u_{vis}(x,y)) \times f(u_{mot}(k,l)) \Big)$$



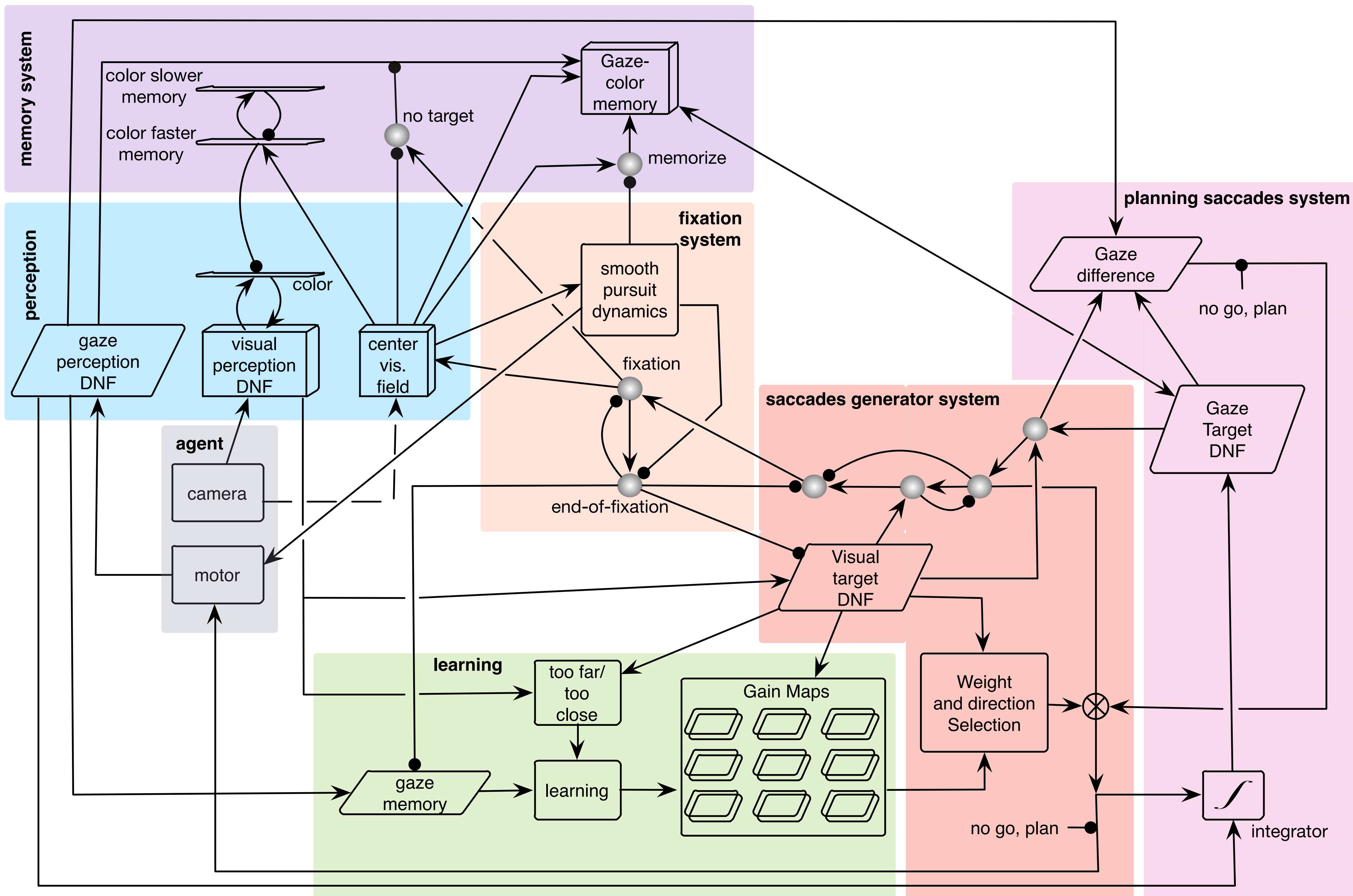


Error-driven Gain-Map Adaptation



$$\tau \dot{G}(x, y, p, t) = c_{\text{on}} \cdot err_{\text{sign}} \cdot T(x, y) \cdot M(p, t)$$

Error-driven Gain-Map Adaptation



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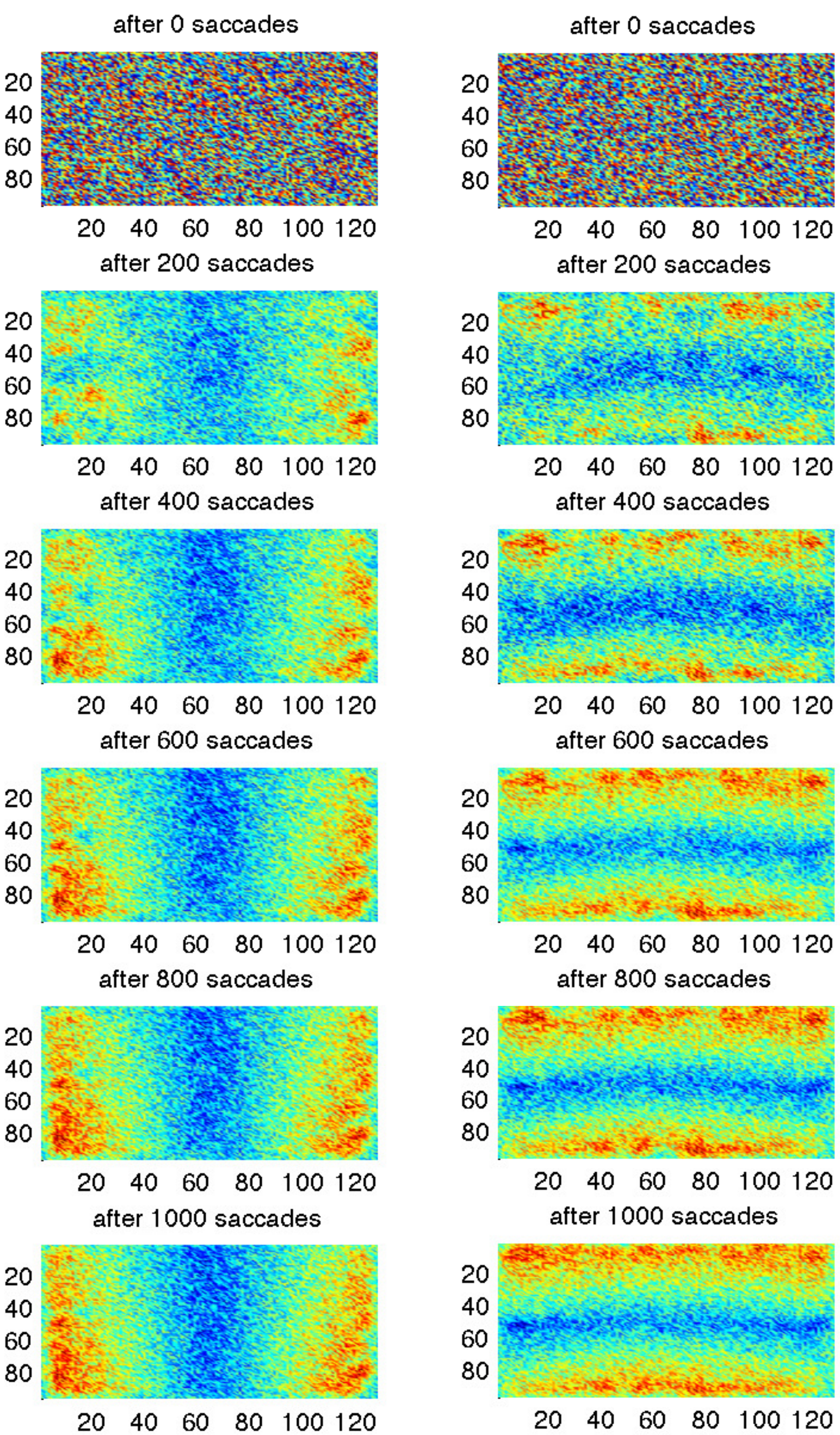

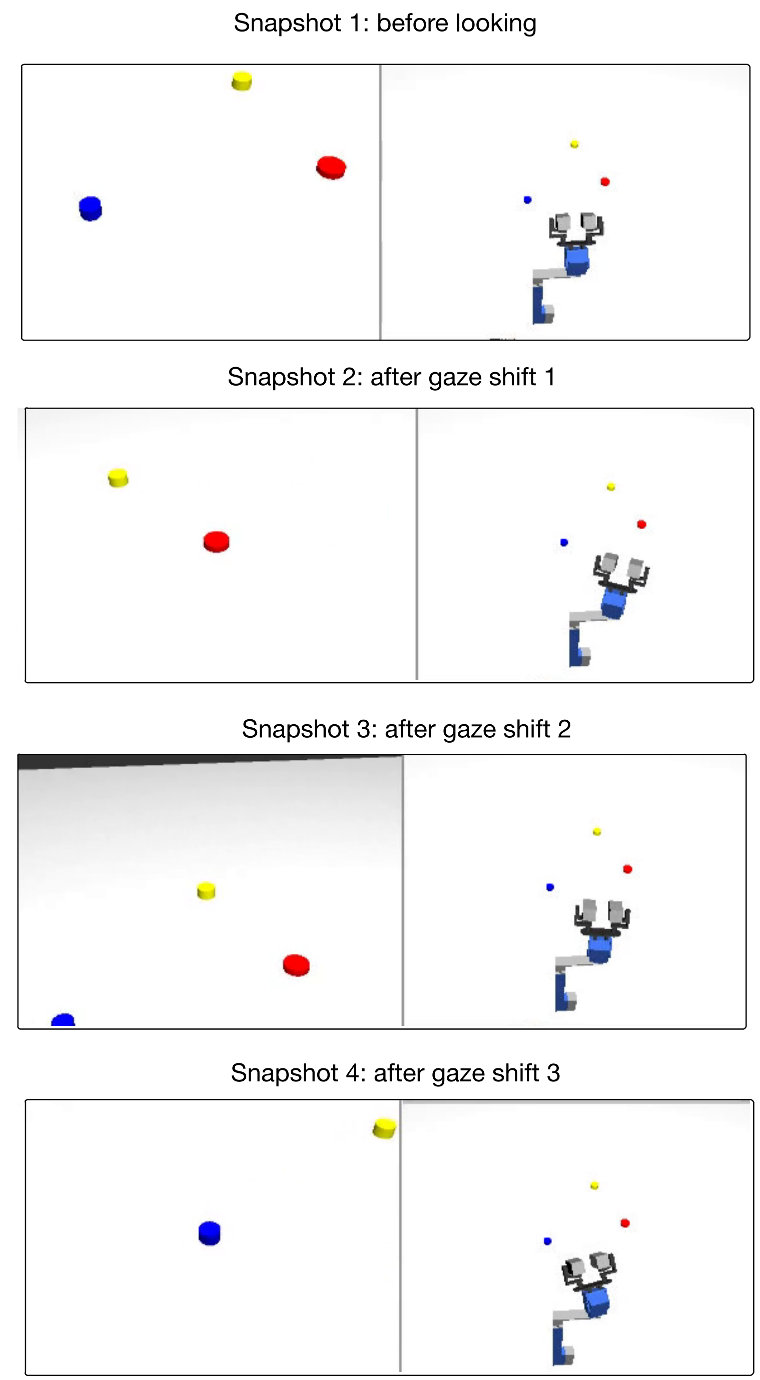

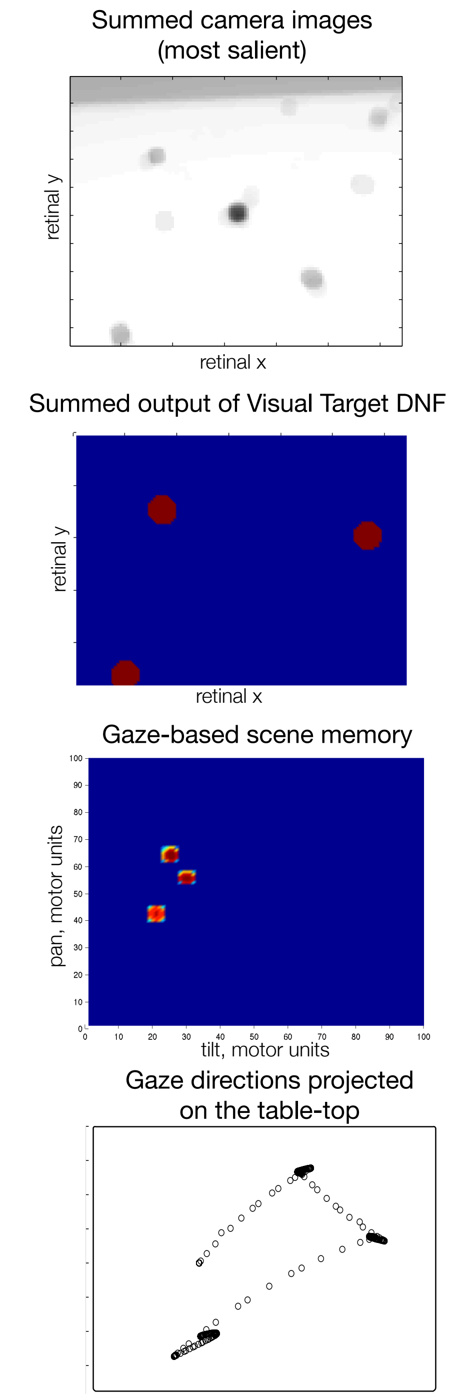

What was not considered here….

- Learning lateral connections in DNFs
  - SOMs
  - RBF
  - Asymmetrical inhomogeneous connections (memory trace in the interaction kernel)
- Predictive learning

Conclusions

- Structure is needed for learning; structure and behaviour co-evolve, bootstrap each other
    - representations for intentions, CoS, and CoD
    - sensorimotor representations
- Environment, in which learning unfolds, matters
- Teacher guidance may be needed to learn complex behaviours

(More) Questions?

Thanks!