Neural Dynamics For Embodied Cognition

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Survey

- Session 1: Foundations
  - Neural dynamics/neural fields [Daniel Sabinasz]
  - Introduction to Cedar/Instabilities in DFT [Raul Grieben]
- Session 2: Dimensions/Binding [Raul Grieben]
  - Cedar architecture: visual search

Survey

- Session 3: Grounded Cognition [Daniel Sabinasz]
  - Cedar architecture: relational grounding
- Session 4: Sequence generation
  - Sequence generation/Embedding DFT [Raul Grieben]
  - Cedar architecture sequence generation [Daniel Sabinasz]

Roadmap

Session 4: Sequence generation/Discussion

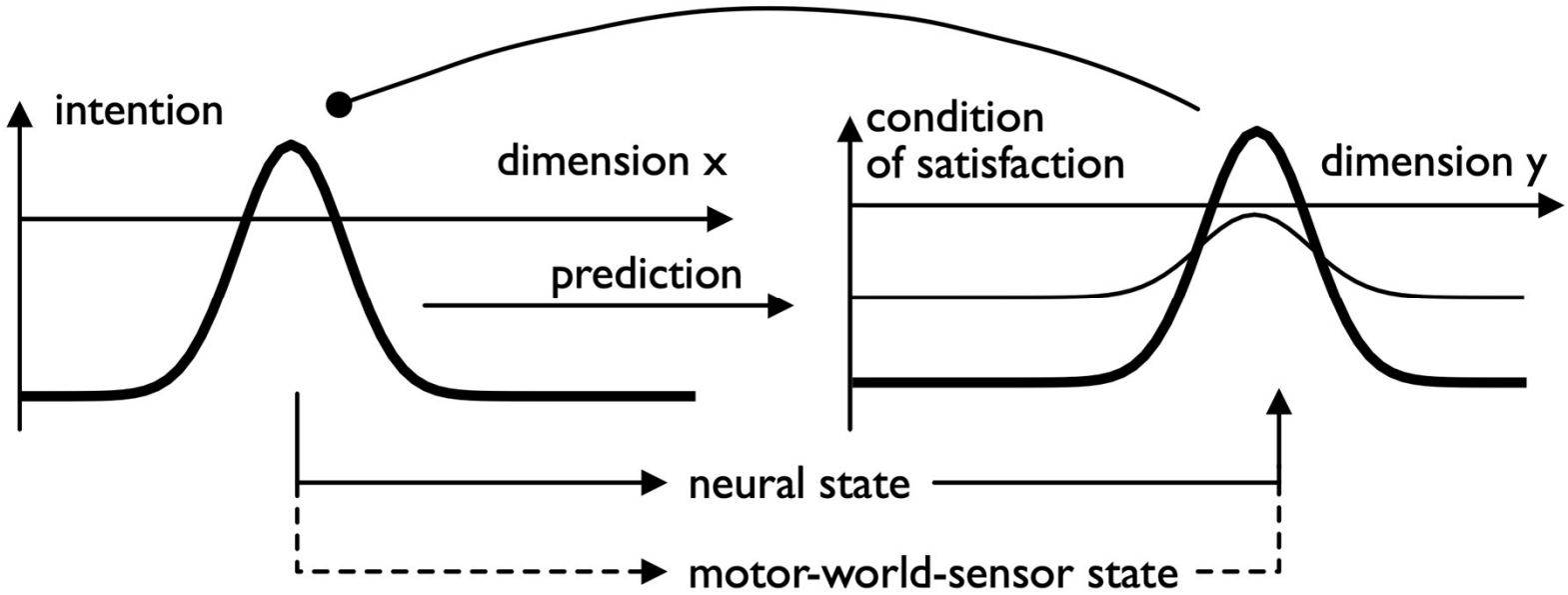
- Sequence generation: problem and example
- Condition of satisfaction
- Who to activate next?
- Demonstration of sequence generation
- Embedding DFT in the literature

Sequential processes

- How may neural attractors lead to the sequences of processing steps/actions that characterize higher cognition and behavior?

Sequential processes

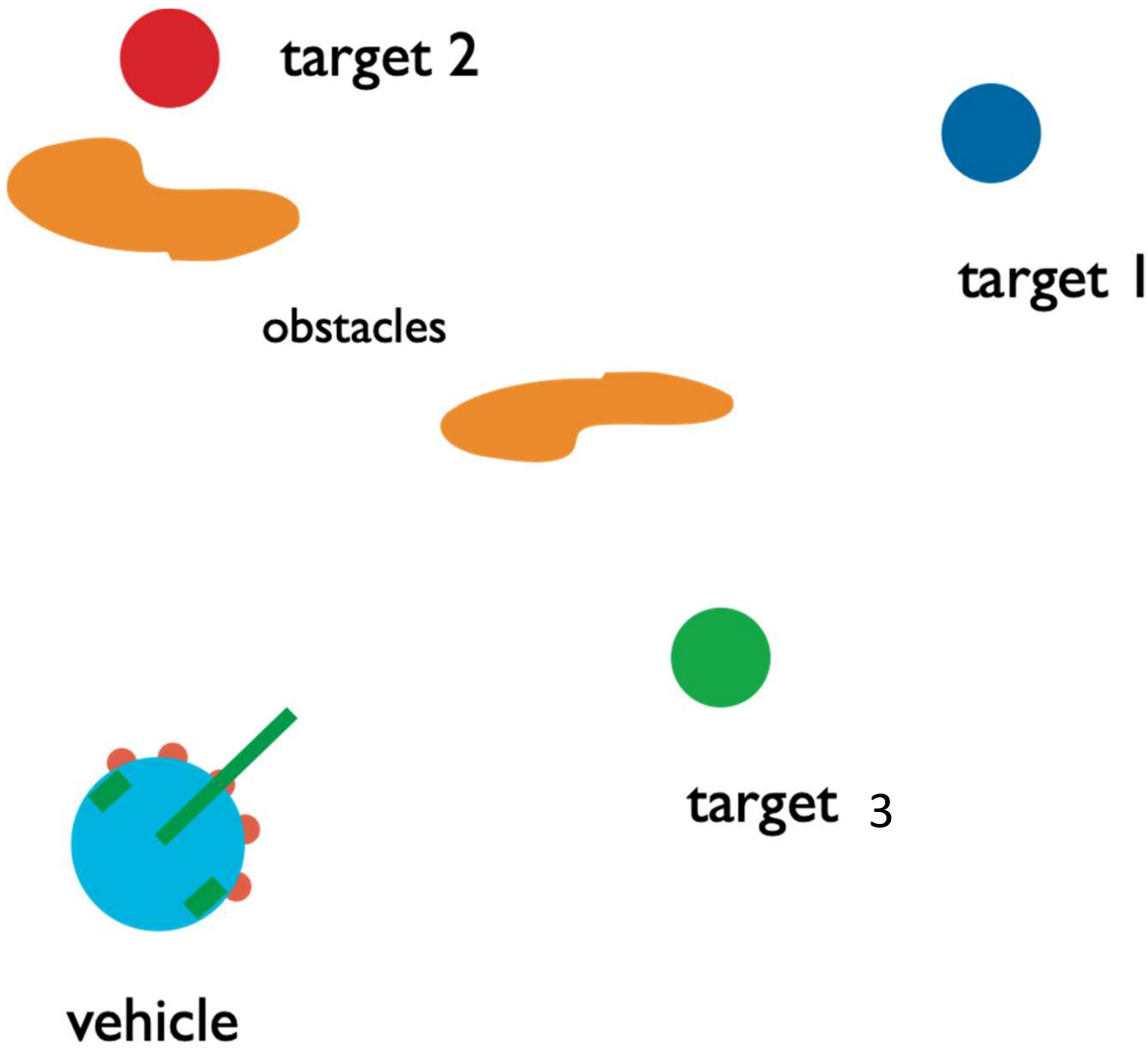
- the neural attractor = intention predicts its condition of satisfaction
- matching input detected => detection instability
- inhibits intention… => transition



[Sandamirskaya … 2010-2016]

Sequence of physical acts

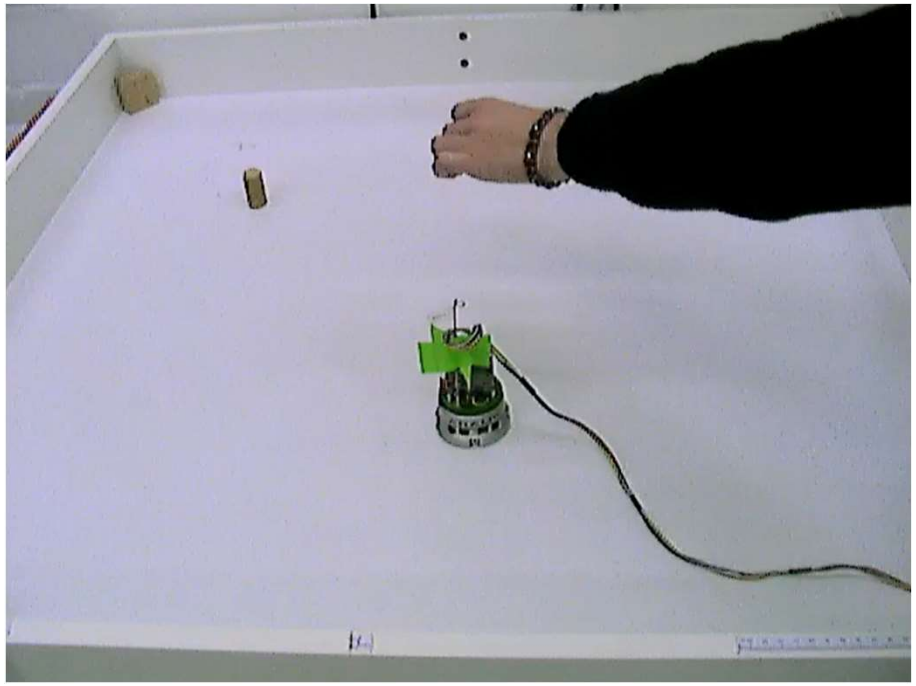
- task: search for objects of a given color in a given order
  - 1 blue
  - 2 red
  - green
- stably couple to objects once they are detected
- ignore objects when their turn has not yet come (distractors)



Implementation as an imitation task

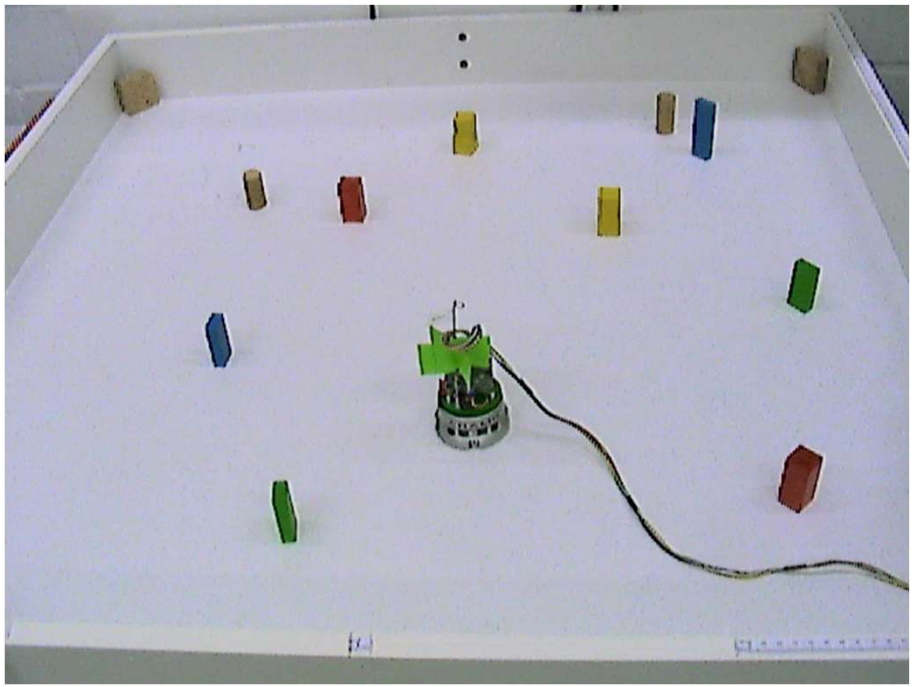
- learn a serially ordered sequence from a single demonstration

yellow-red-green-blue-red



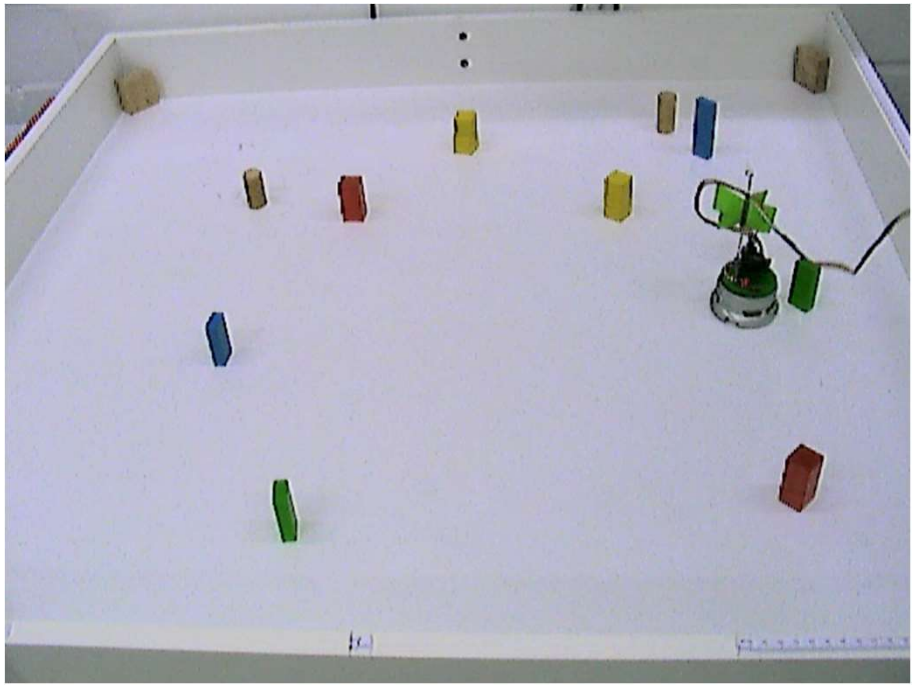
- perform the serially ordered sequence with new timing

yellow-red-green-blue-red

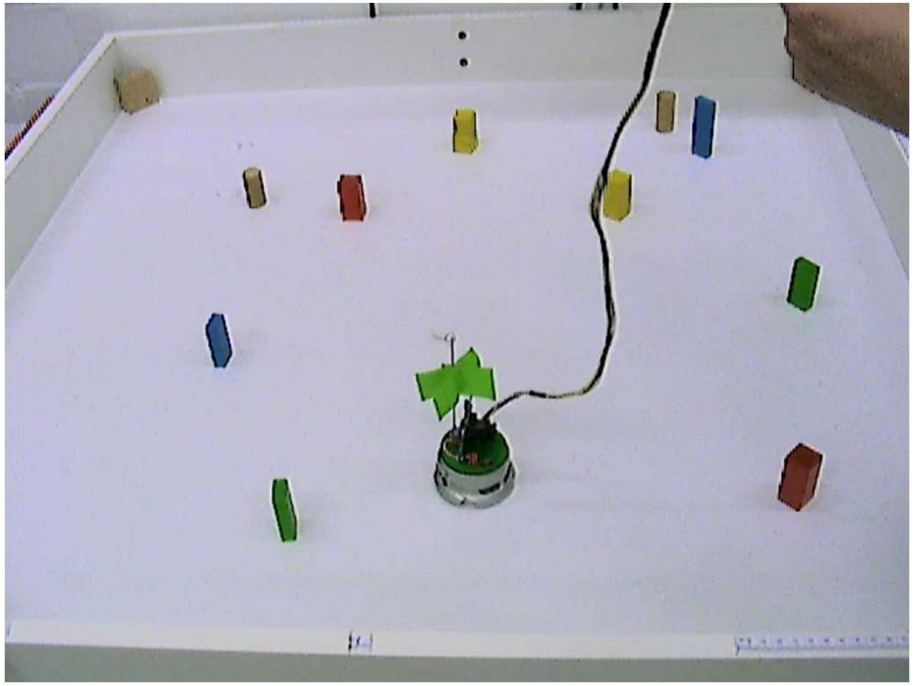


[Sandamirskaya, Schöner: *Neural Networks* 23:1163 (2010)]

red a distractor

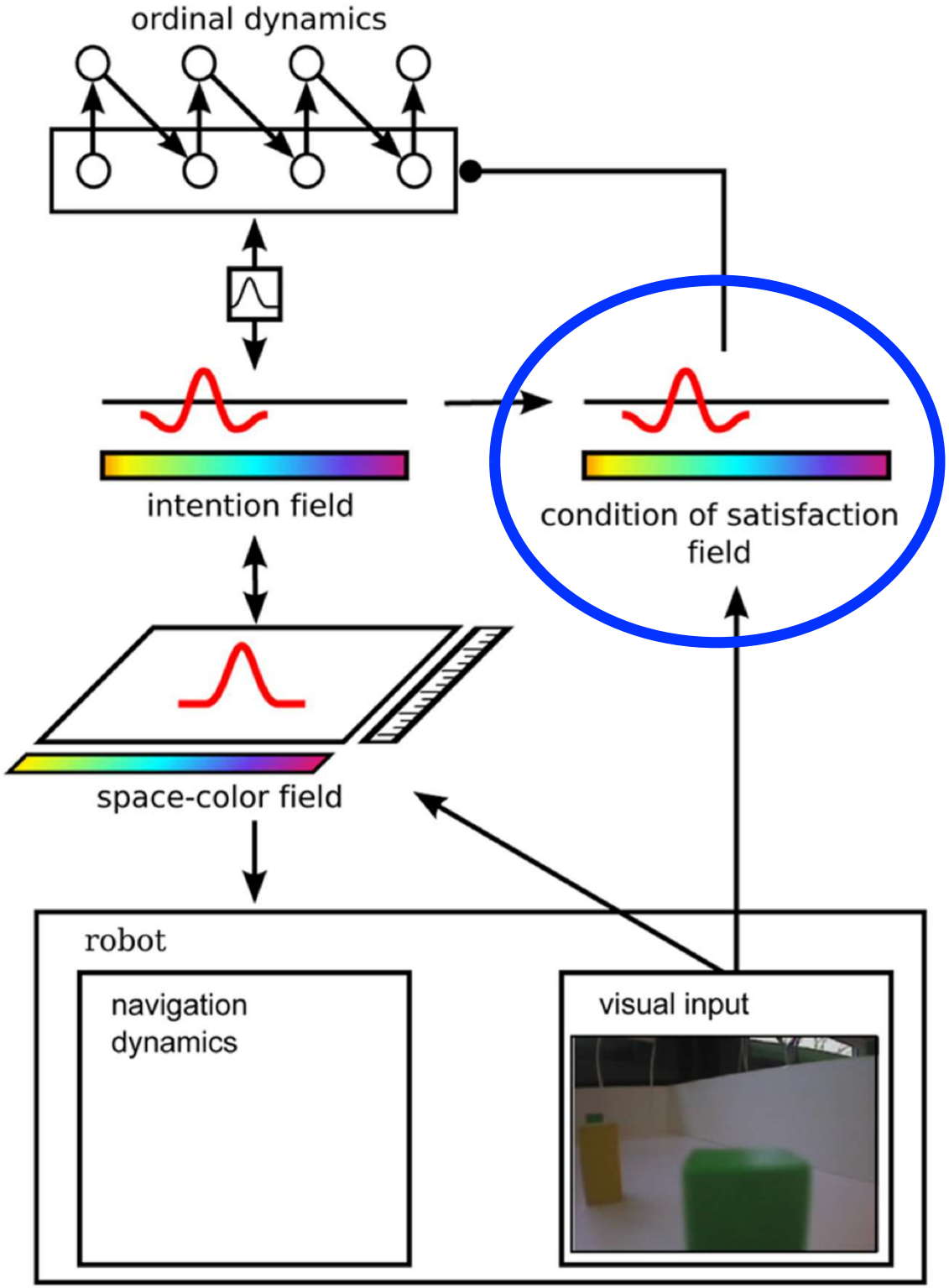


red a target



[Sandamirskaya, Schöner: *Neural Networks* 23:1163 (2010)]

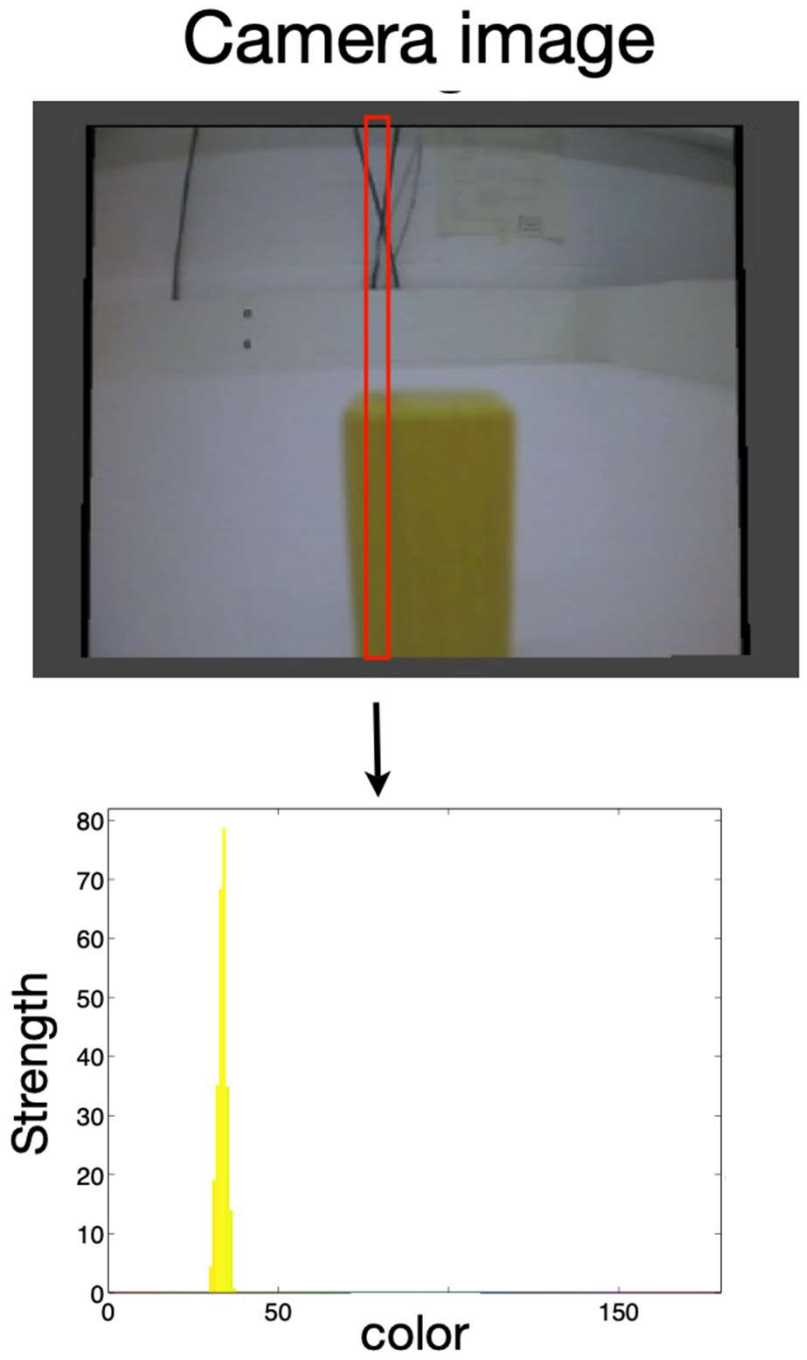
Condition of Satisfaction (CoS)



[Sandamirskaya, Schöner: *Neural Networks* 23:1163 (2010)]

Visual input

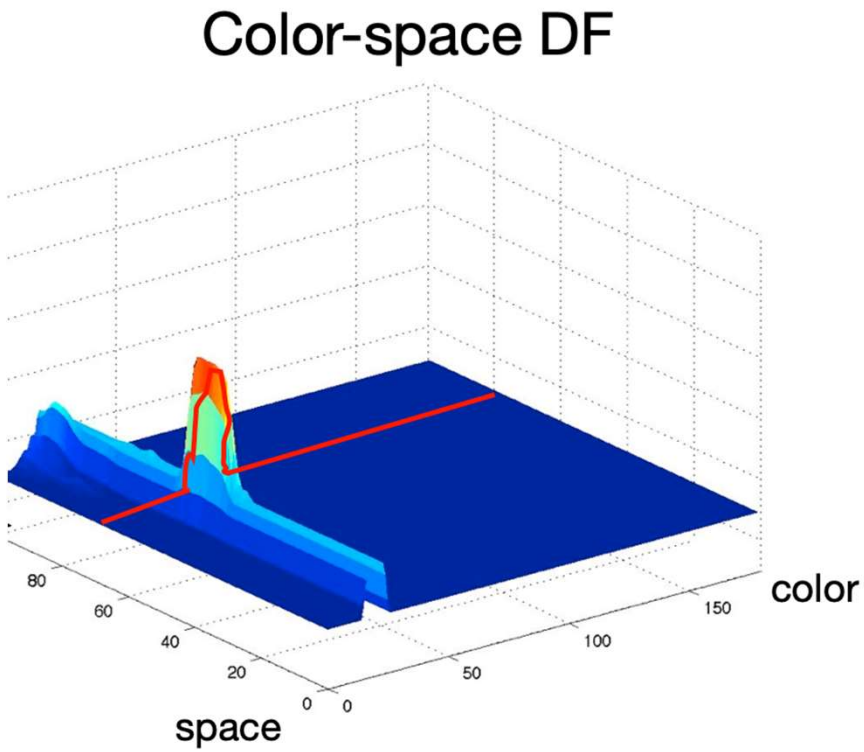
- 2D visual input
  - horizontal space
  - color
- “intensity” of 2D input from color histogram at each horizontal location



Visual search

- intention=color cue provides ridge input into space-color field
- when that ridge overlaps with 2D space-color input => peak formed

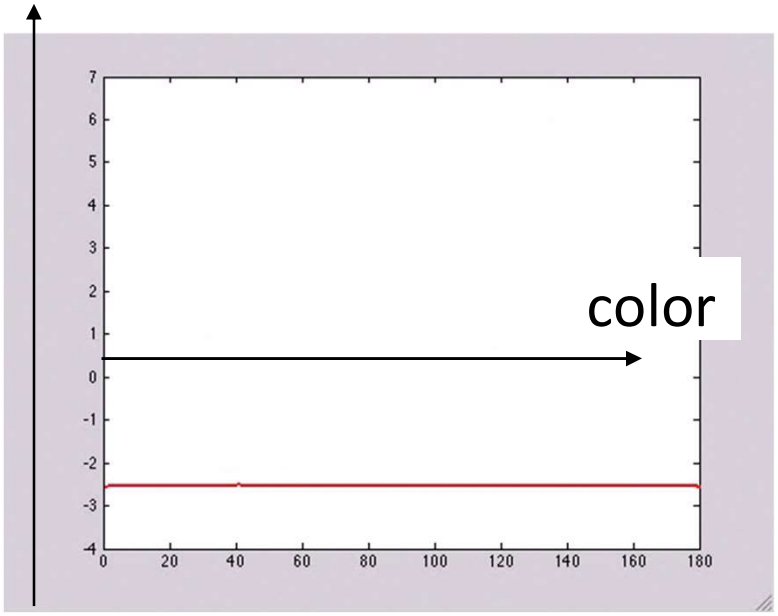
search cue



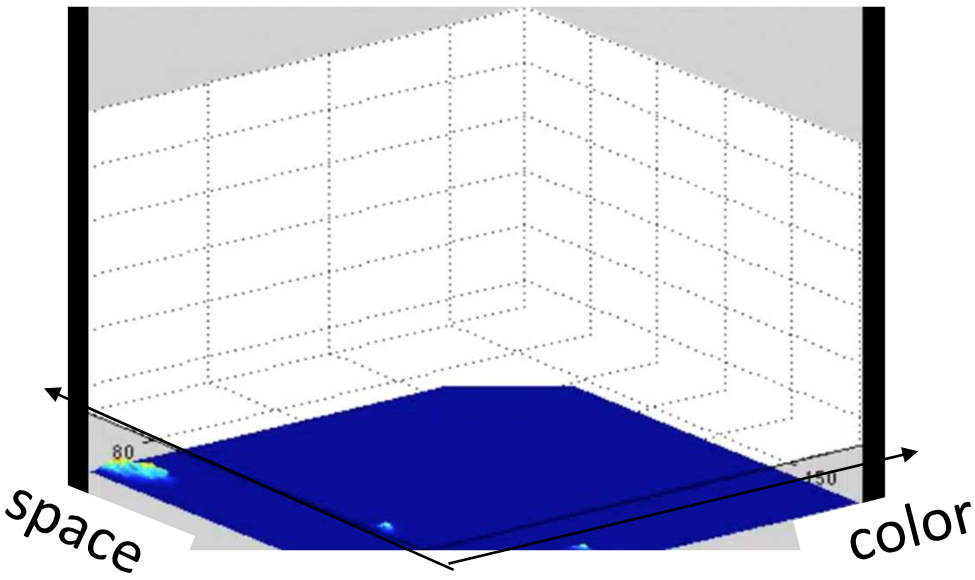
ordinal stack

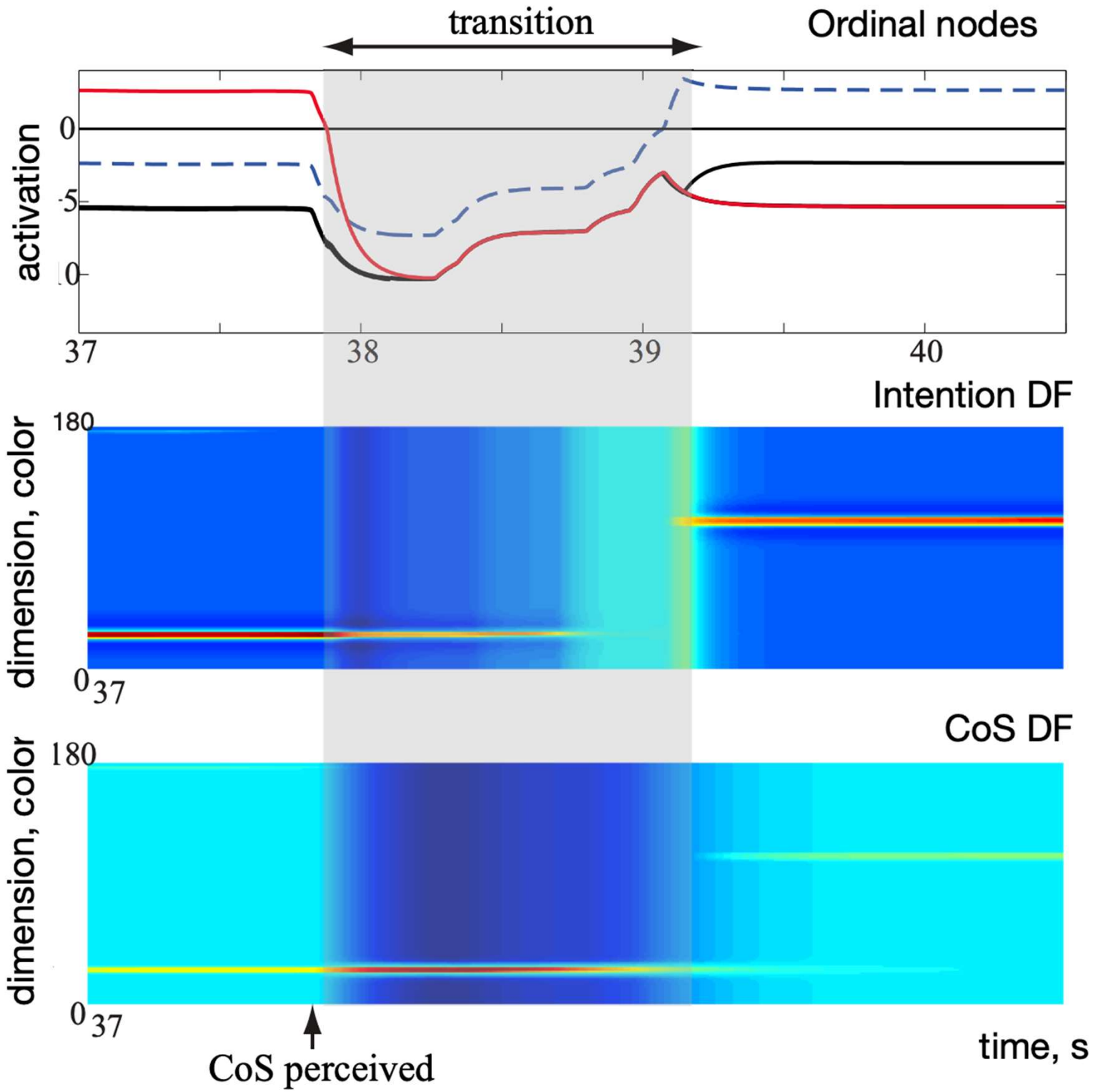
condition of satisfaction (CoS)

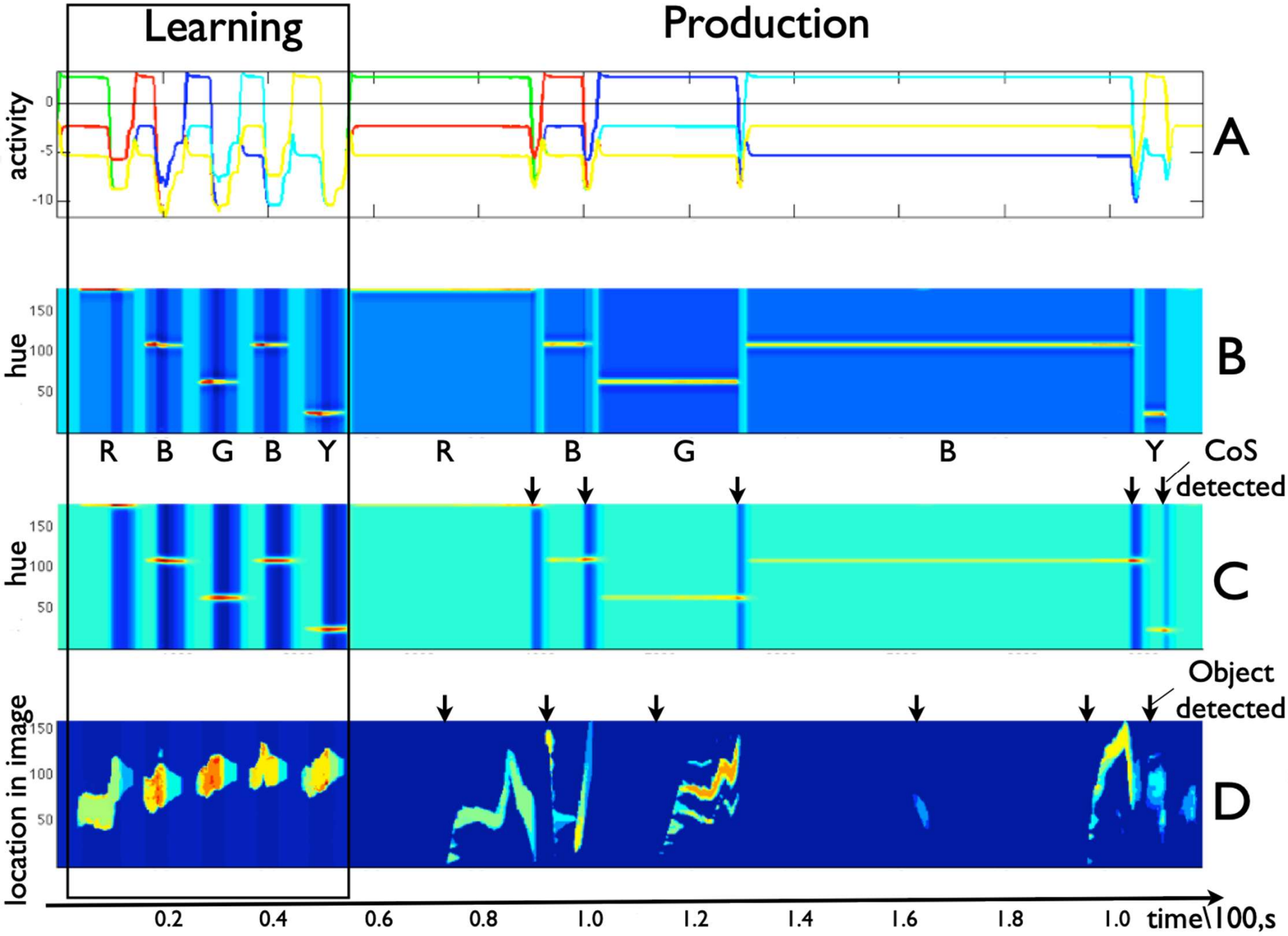
intentional state



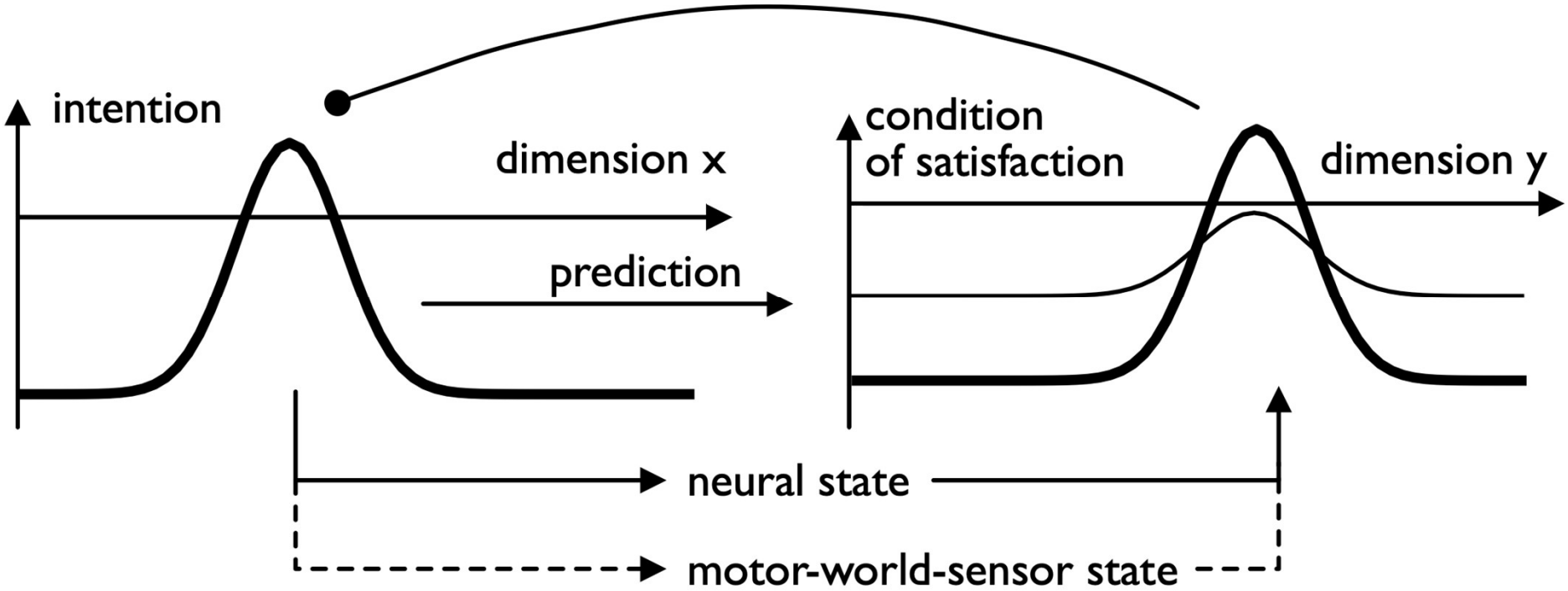
2D color-space field




transition
Ordinal nodes
activation
0
-5
0
37
38
39
40
Intention DF
dimension, color
180
0
37
CoS DF
dimension, color
180
0
37
CoS perceived
time, s

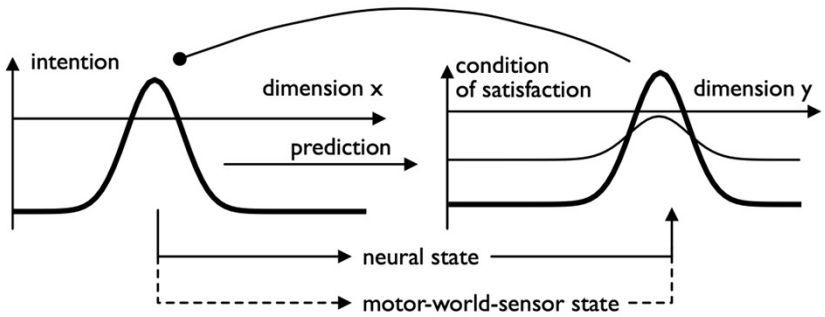

Learning
Production
activity
0
-5
-10
A
hue
150
100
50
B
R B G B Y R B G B Y
CoS detected
hue
C
Object detected
location in image
D
0.2 0.4 0.6 0.8 1.0 1.2 1.4 1.6 1.8 1.0
time\100,s

Mathematical mechanism



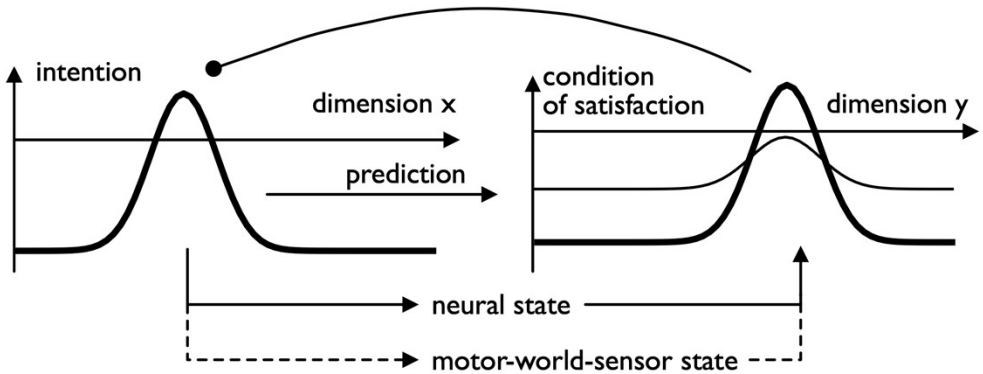
Sequence of instabilities

- the CoS is pre-shaped by the intention field, but is in the sub-threshold state
- until a matching input pushes the CoS field through the detection instability
- the CoS field inhibits the intention field that goes through a reverse detection instability
- the removal of input from the intention to the CoS field induce a reverse detection instability
- both fields are sub-threshold



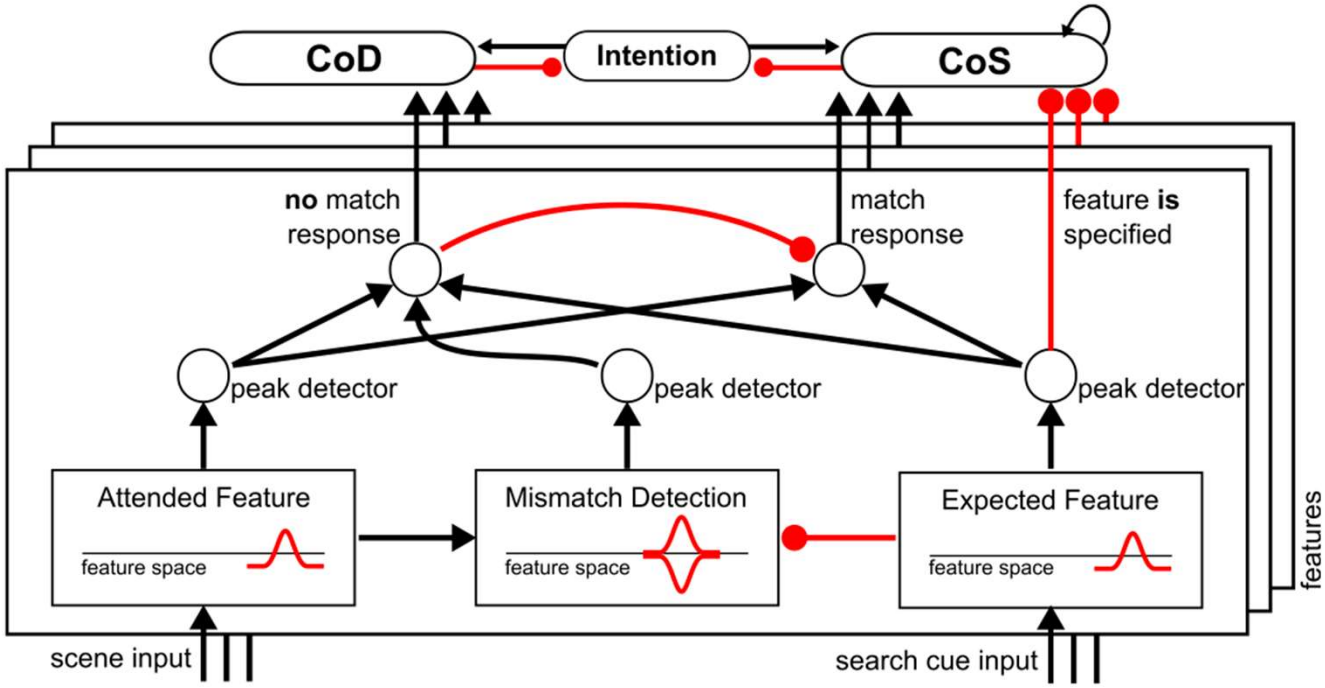
CoS and efference copy

- one could think of the “prediction” implied in the CoS as being a form of efference copy
- that does act inhibitorily…
- but it does so on the (motor)intention, not on the perception of the outcome that is predicted!



Generalization

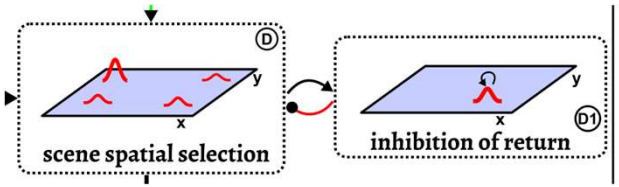
- match-detection => CoS
- mis-match (or change) detection => CoD (condition of dissatisfaction)



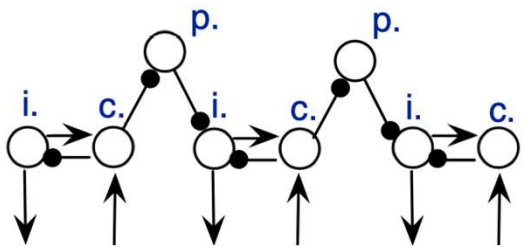
[Grieben, Schöner, *CogSci* 2021]

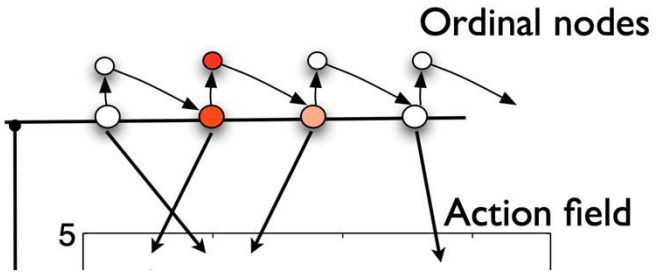
How is the next state selected?

- once the current state has been deactivated…
- 3 notions (~Henson Burgess 1997)



- 1 gradient-based selection
- 2 chaining
- 3 positional representation

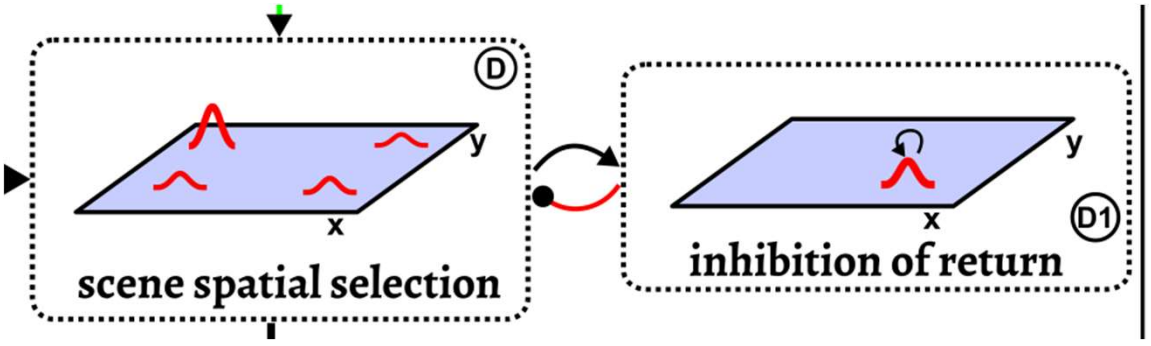




Gradient-based

- a field/set of nodes is released from inhibition once the current state is deactivated…
- a new peak/node wins the selective competition based on inputs…
  - e.g. salience map for visual search
  - e.g. overlapping input from multiple fields..
- return to previous states avoided by inhibition of return

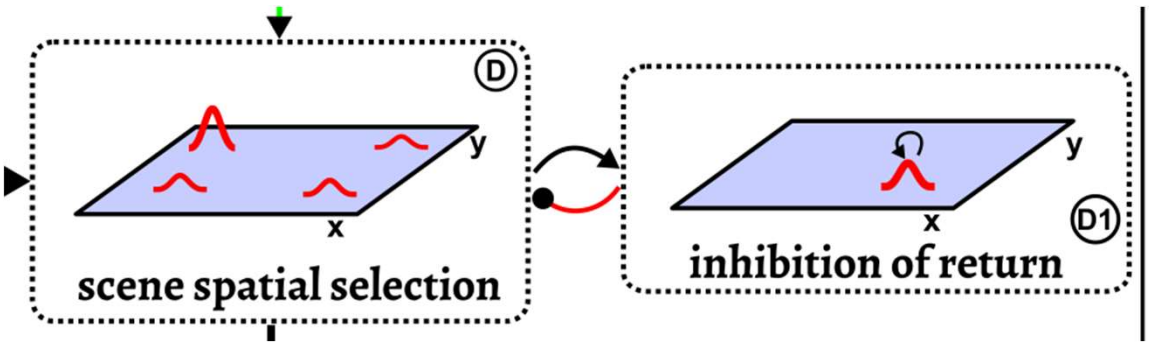
[Grieben, Schöner, *CogSci* 2021]



Gradient-based

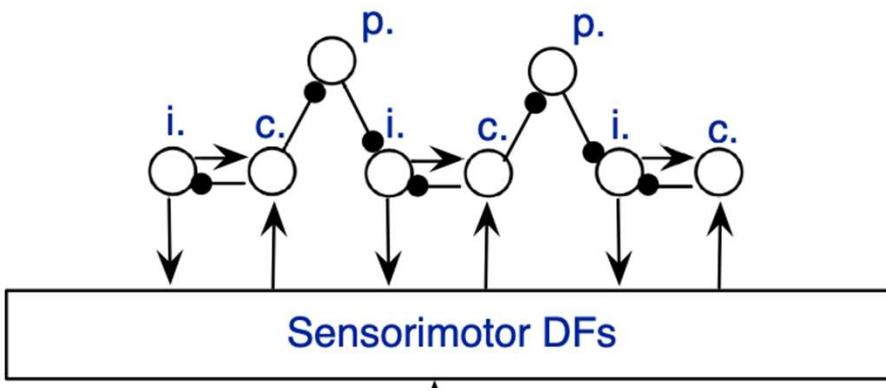
- this is used in many of the DFT architectures
  - visual search
  - relational grounding
  - mental mapping

[Grieben, Schöner, *CogSci* 2021]



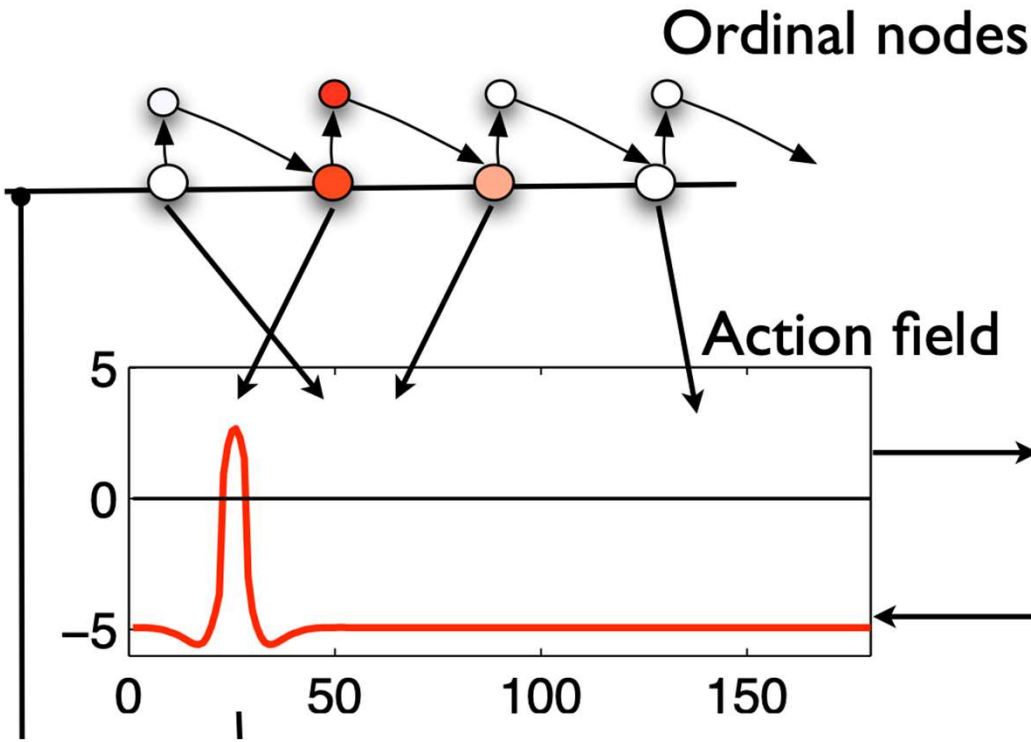
Chaining

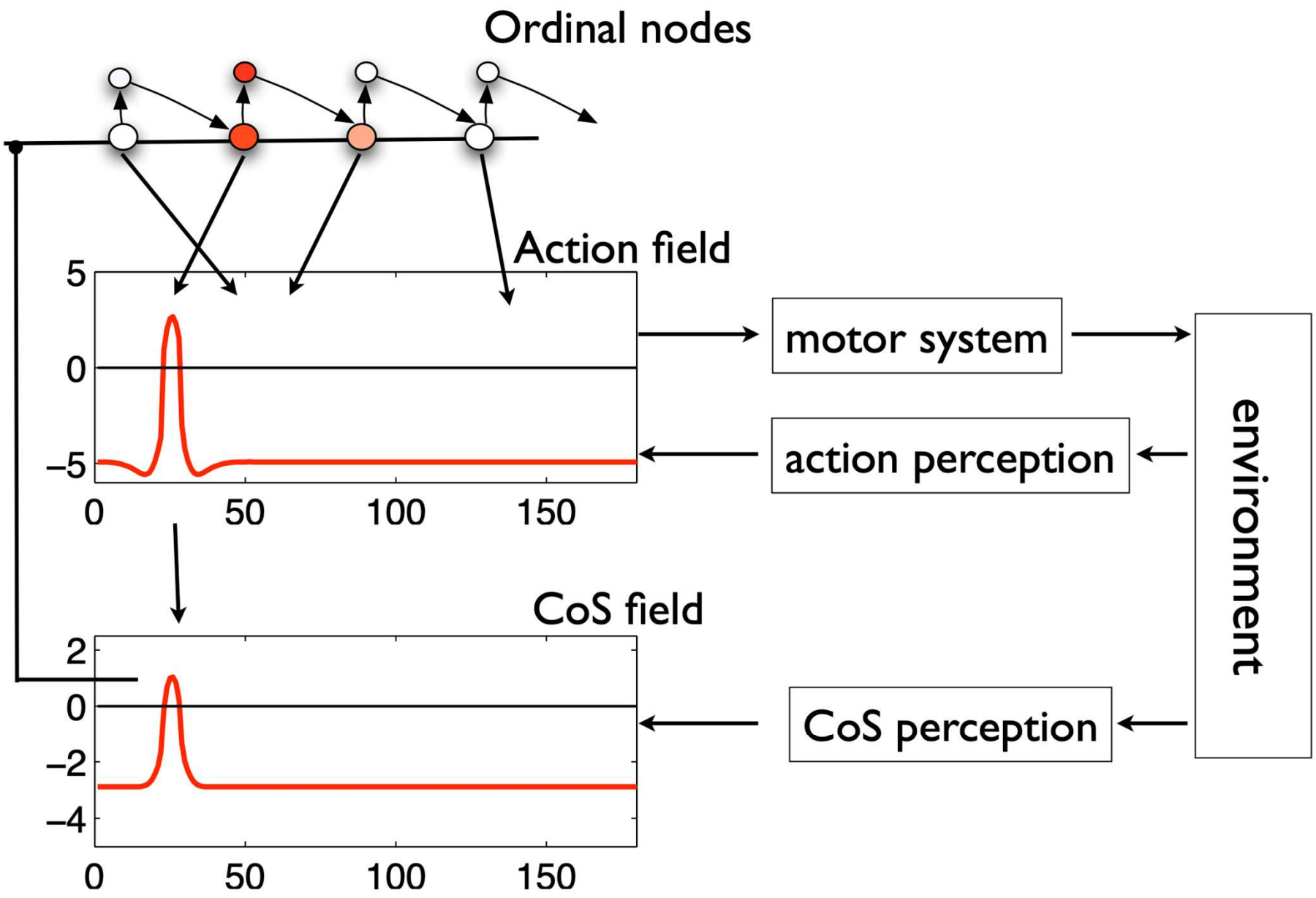
- for fixed sequences…
  - e.g. reach-grasp
  - fixed order of mental operations… e.g. ground reference object first, then target object
- less flexible (e.g.. when going through the same state with different futures)
- could be thought to emerge with practice/habit from the positional system



Positional representation

- a neural representation of ordinal position is organized to be sequentially activated…
- the contents at each ordinal position is determined by neural projections from each ordinal node…



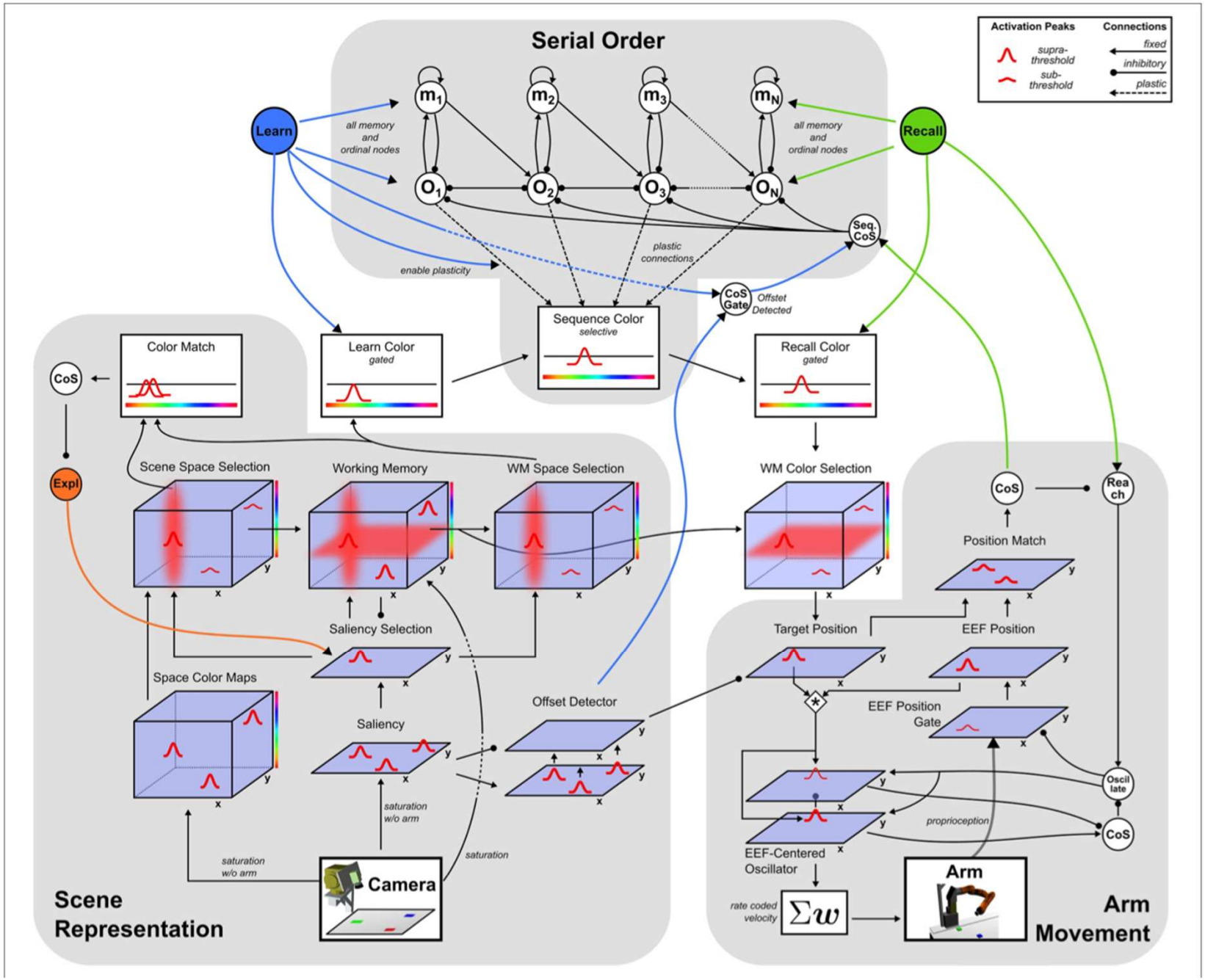


[Sandamirskaya, Schöner: Neural Networks 23:1163 (2010)]

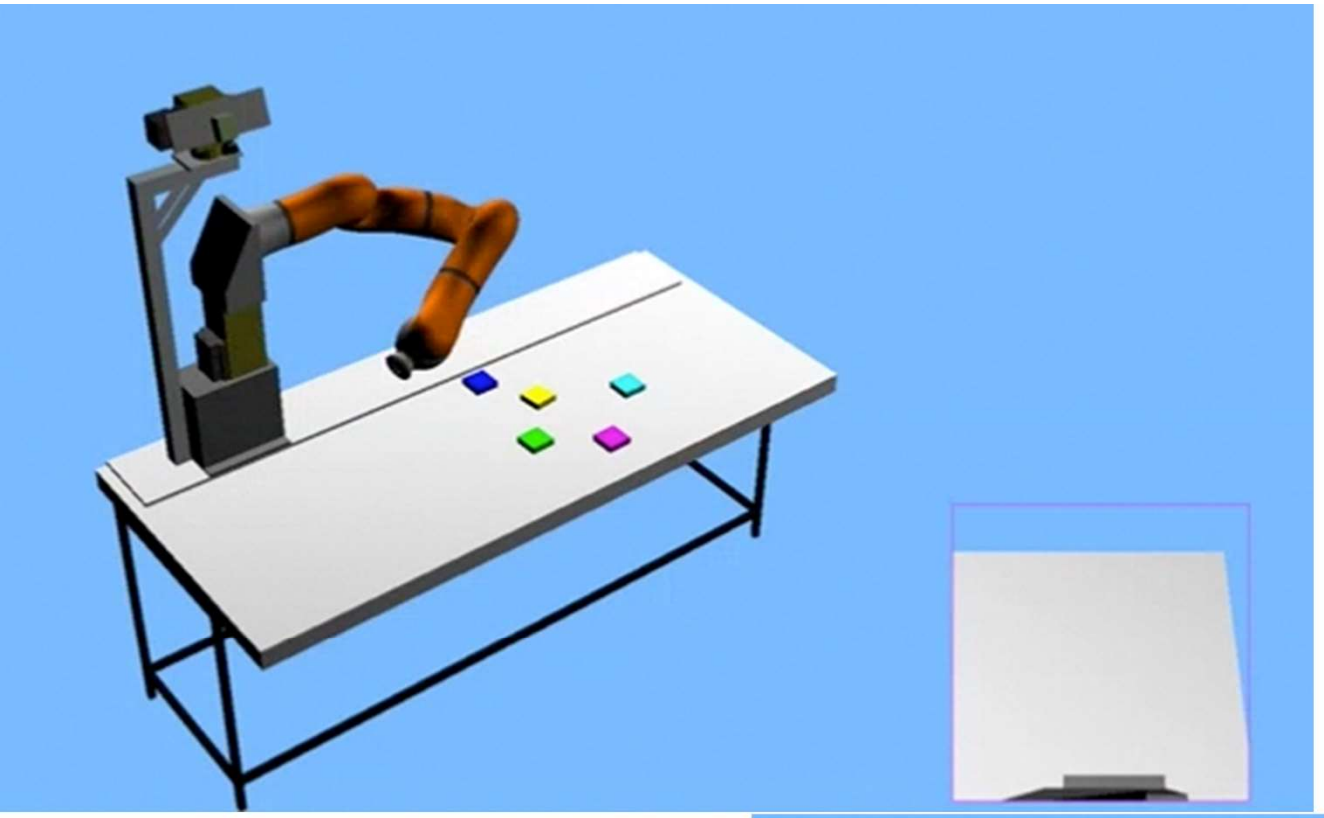
Positional representation

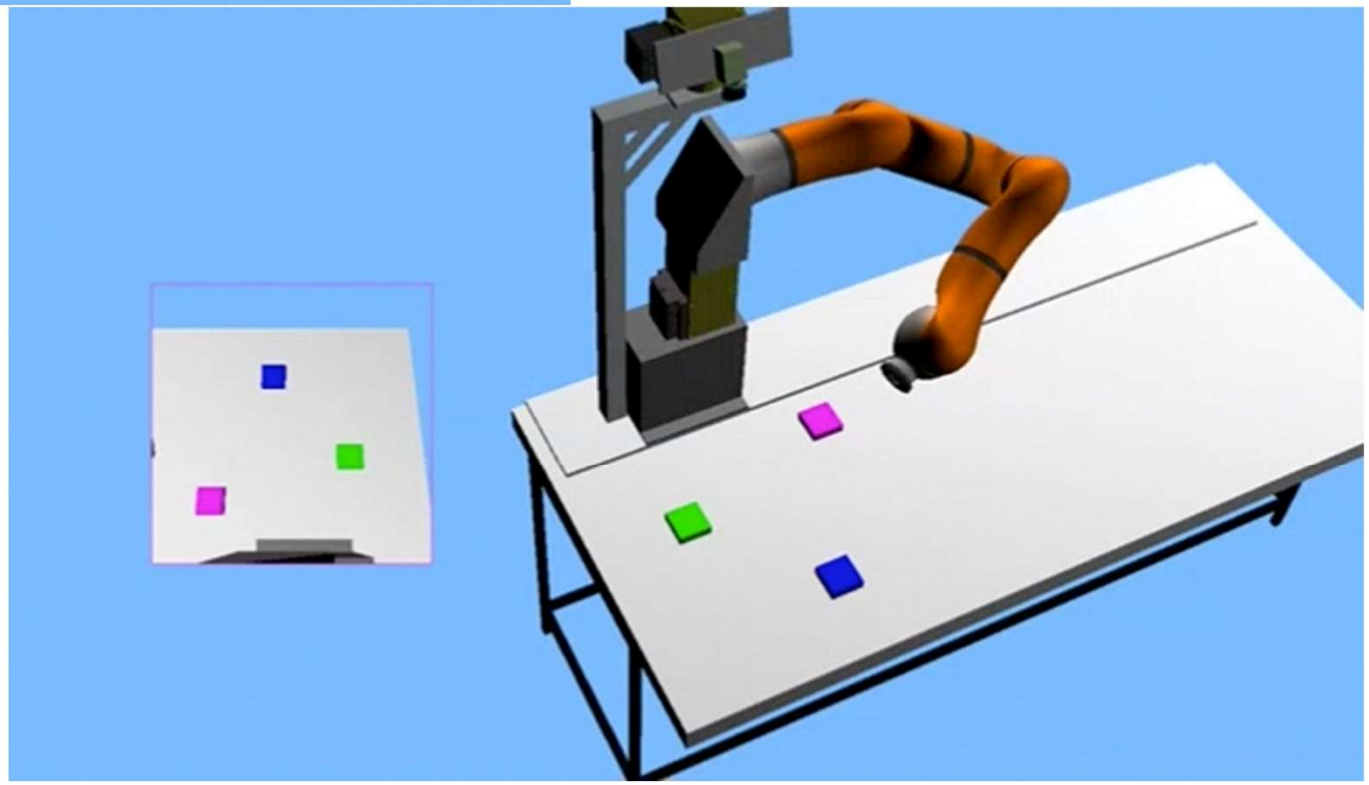
- essentially chaining with flexible contents
- good for fast learning of sequences…
  - e.g. imitation
  - a Hippocampus function?
- but: must have potential synaptic links to many representations…
- => such ordinal systems must exist for sub-representations… embodiment effects…

Serial order demonstrated/enacted



[Tekülve et al., Frontiers in Neurorobotics (2019)]





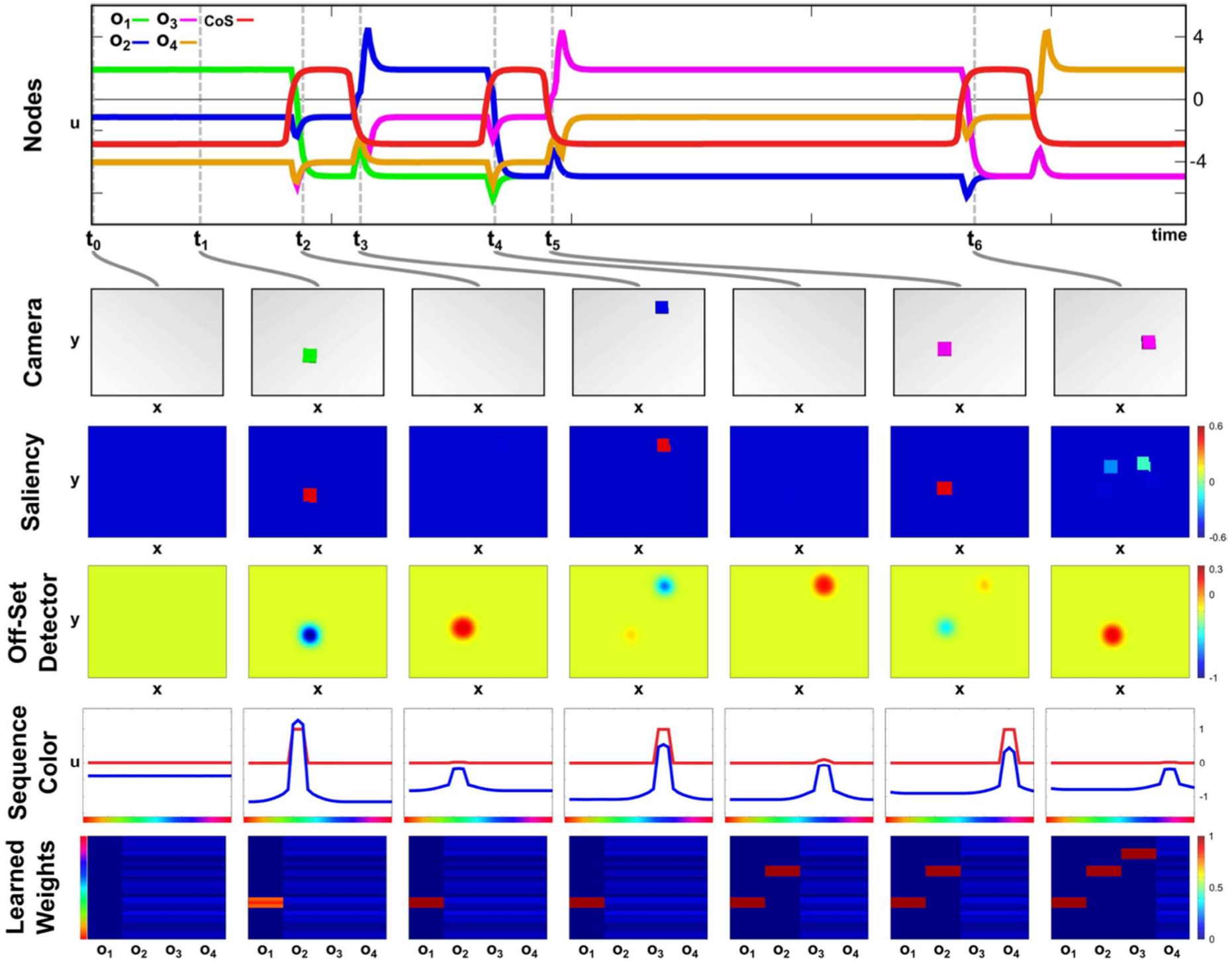


FIGURE 5 | Time course of learning a three element sequence with varying presentation time.

Time course of attention selection and building of scene memory

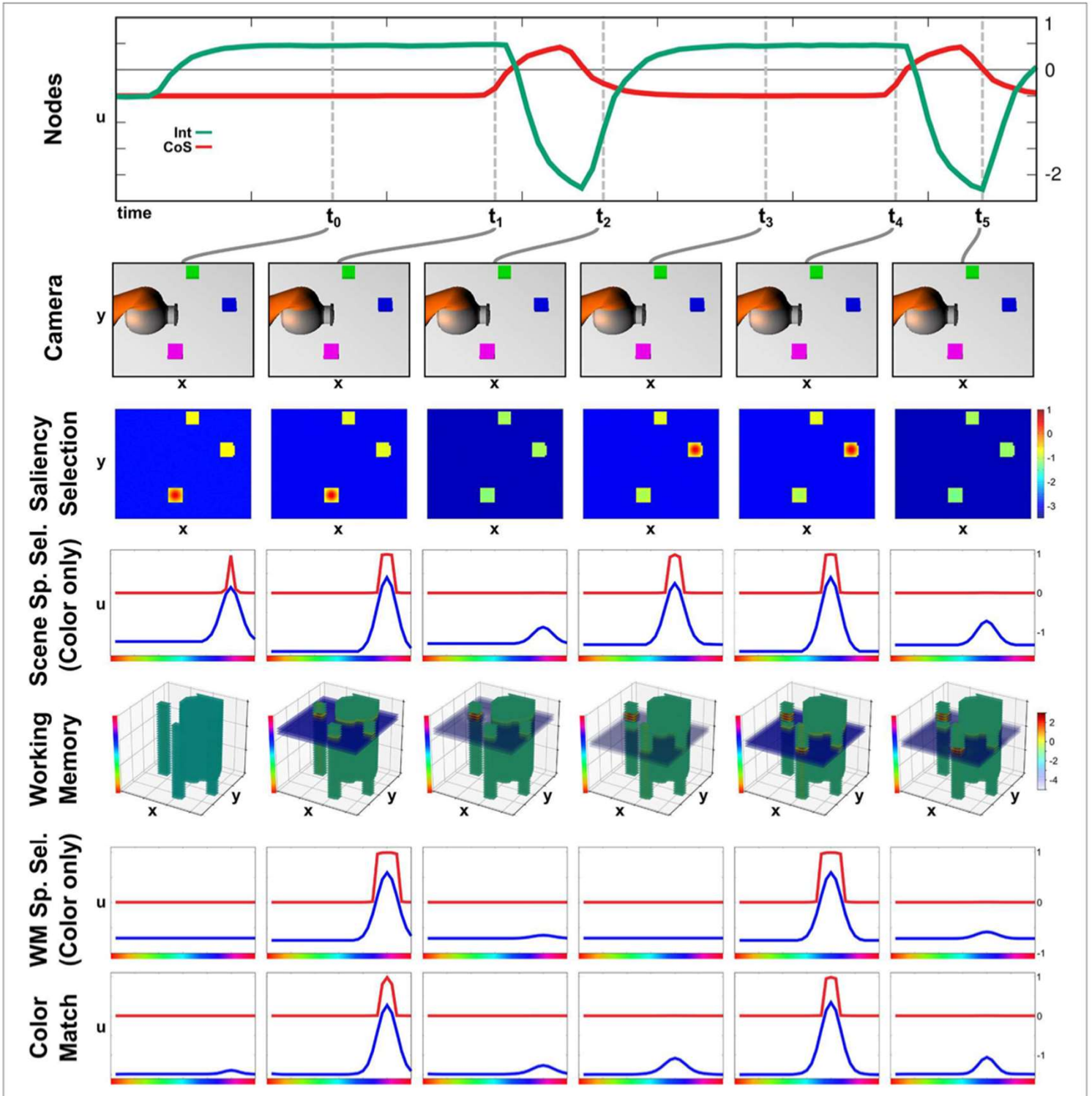


FIGURE 4 | Time course of building a scene memory.

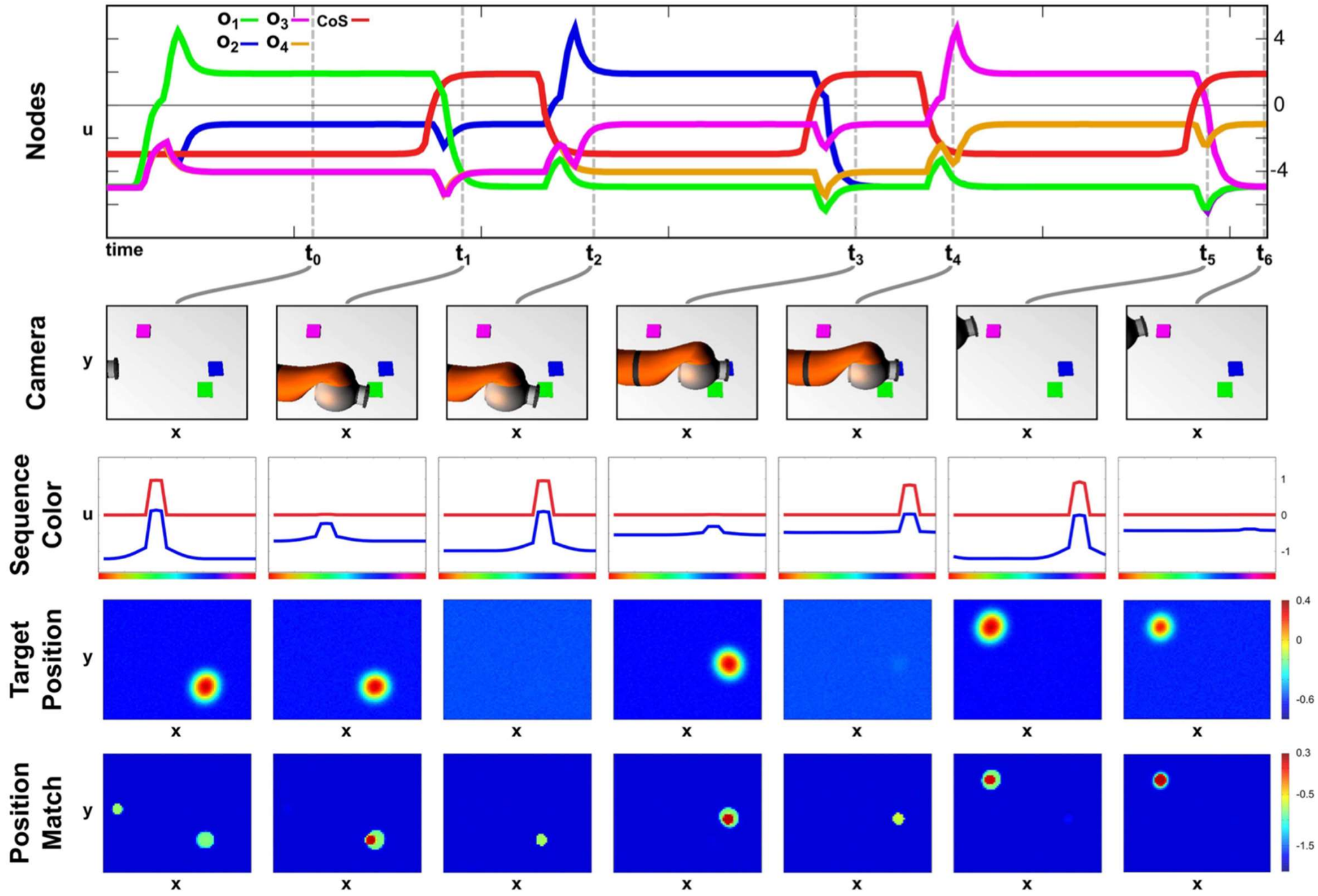
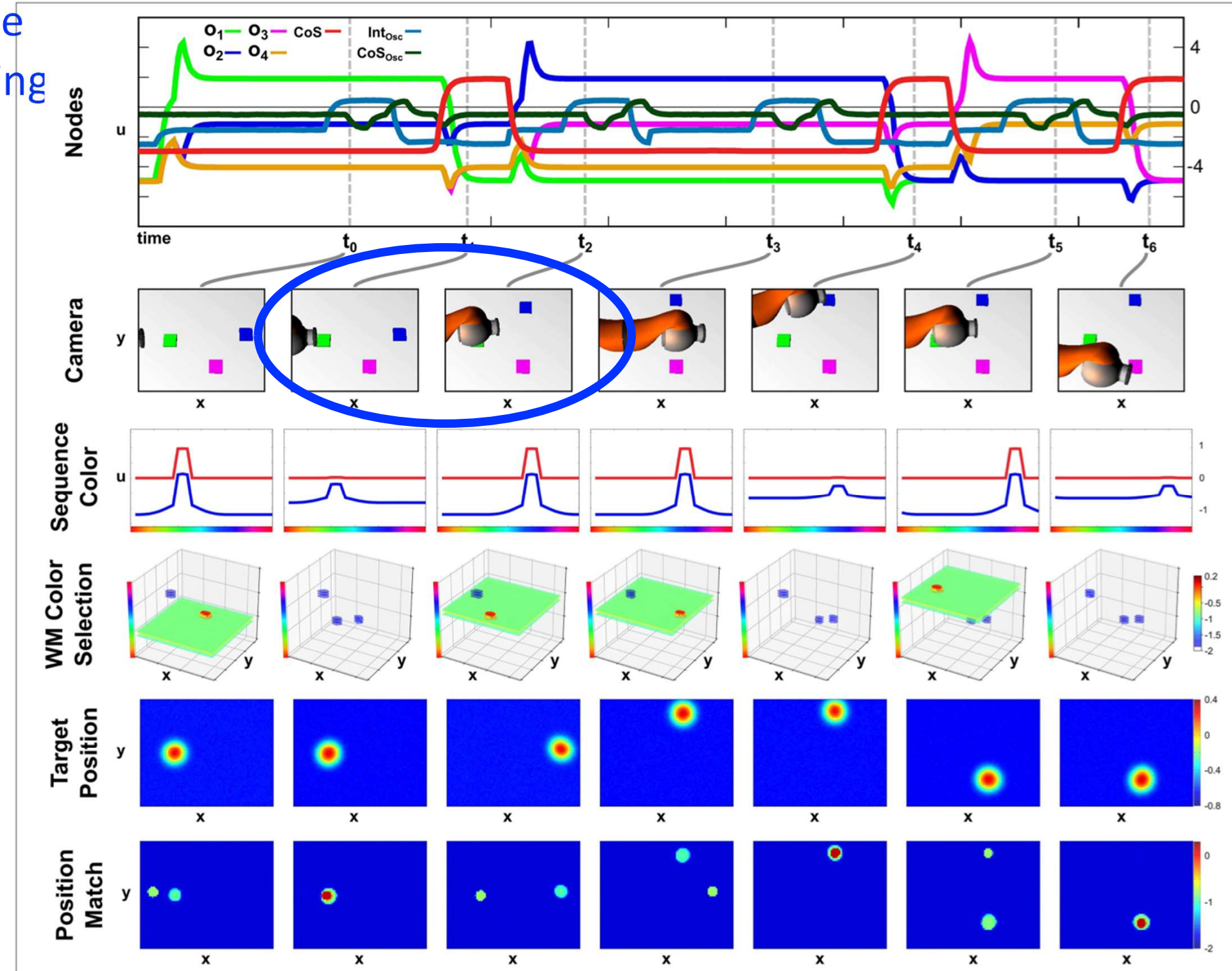


FIGURE 6 | Time course of recalling a three element sequence through pointing at colored objects.

online updating

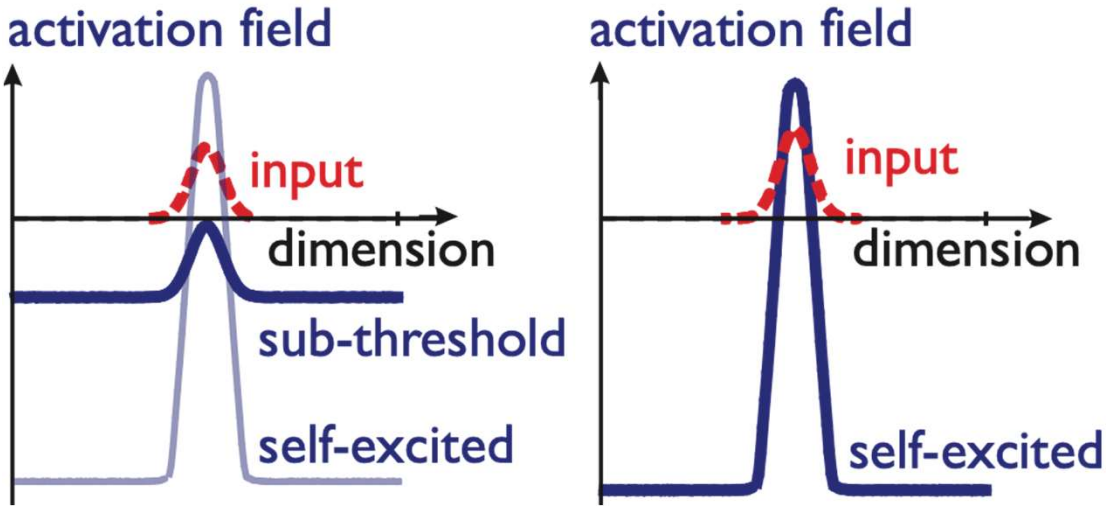


Why do neural dynamic architectures work?

- 1) Why is the dynamic regime (“selection”, “working memory”, “detection”, “match” etc.) of a component field invariant as we couple it into a larger architecture?
- 2) Why is the content (the feature space over which fields are defined, the content of a concept node) of a component field invariant as we couple it into a larger architecture?

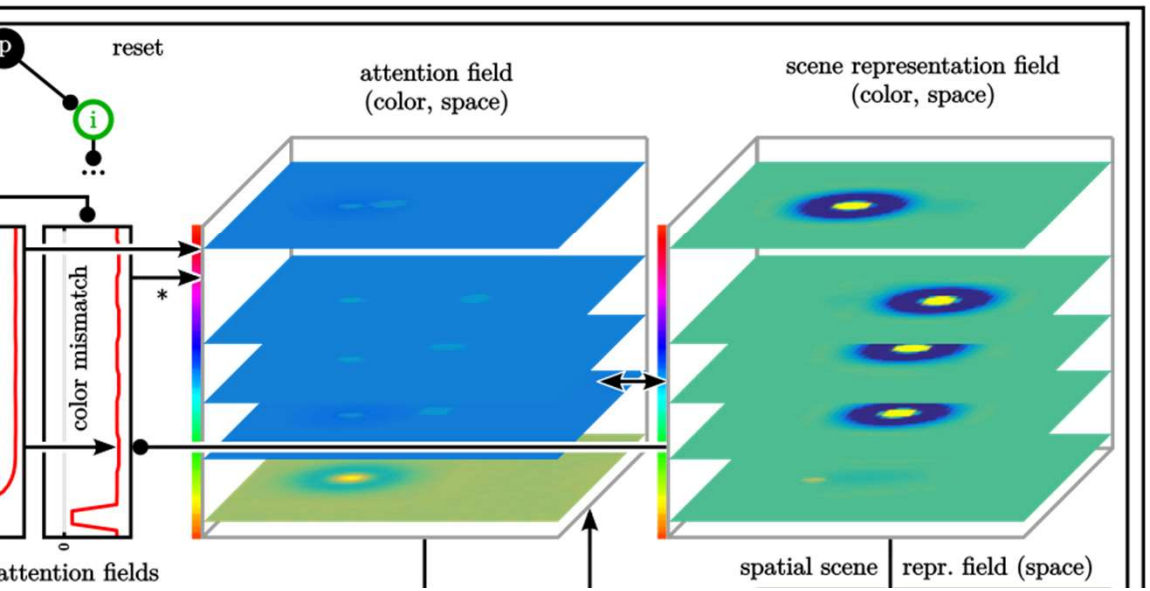
1) Why is the dynamic regime invariant?

- stability => structural stability = invariance of solutions under change of the dynamics
- => dynamic modularity: fields retain their dynamic regime as activation elsewhere varies



2) Why is the content invariant?

- coupling among fields must preserve the fields' dimensions: "non-synesthesia principle"
- informational modularity (encapsulation)



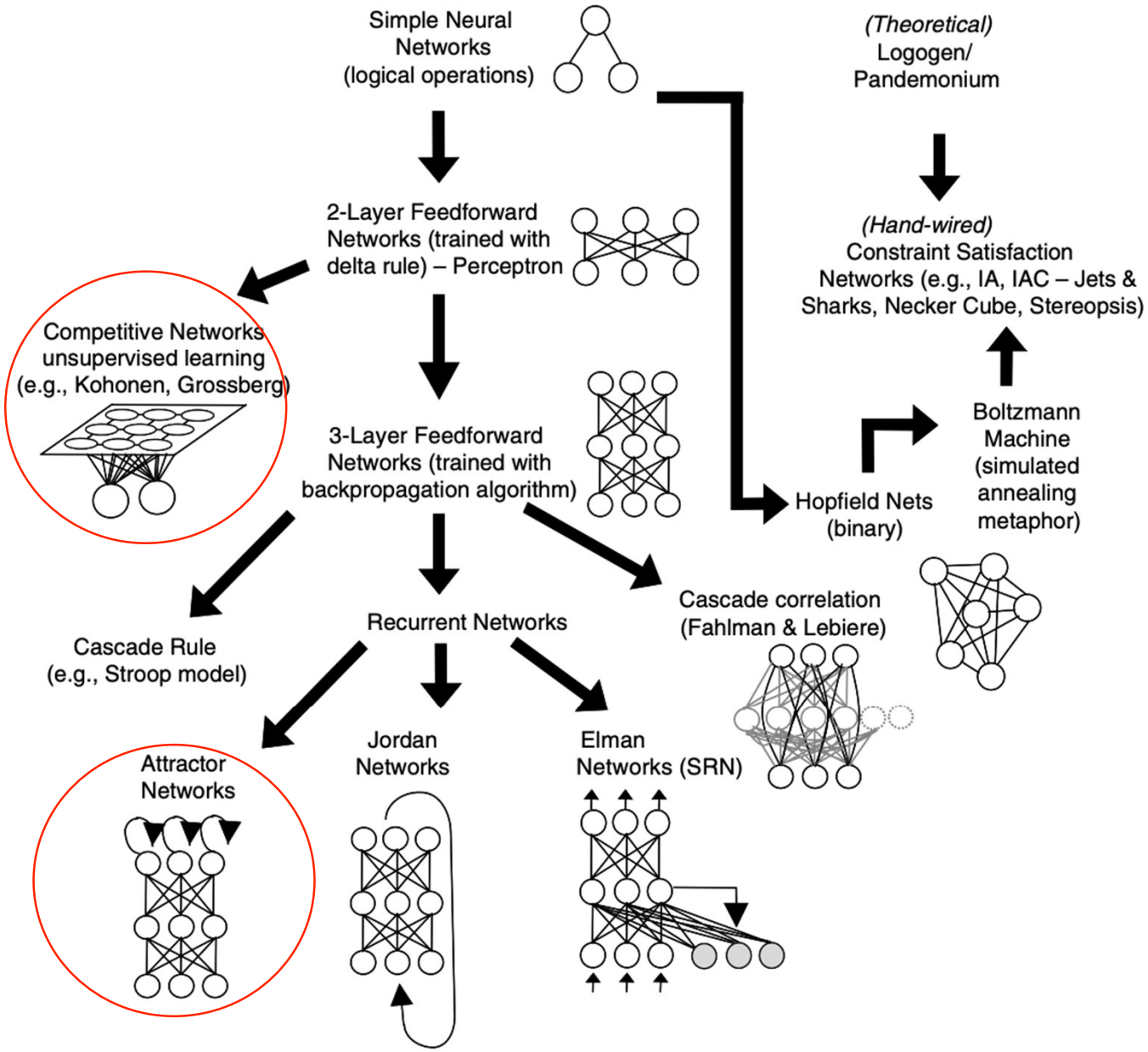
- neural dynamic architectures are specific = constrained by evolution and development

Embodiment hypothesis

- cognition does not necessarily activate motor systems
- cognition inherits the dynamic properties of sensory-motor cognition:
  - continuous state, continuous time, stability ..
  - continuous/intermittent link to the sensory and motor surfaces is *possible*
- => cognition is generated in the specific embodied cognitive architectures that emerged from evolution/development

DFT vs connectionism/NN

- DFT models are neural network models in the most general sense…
- sharing level of description (activation, sigmoid)



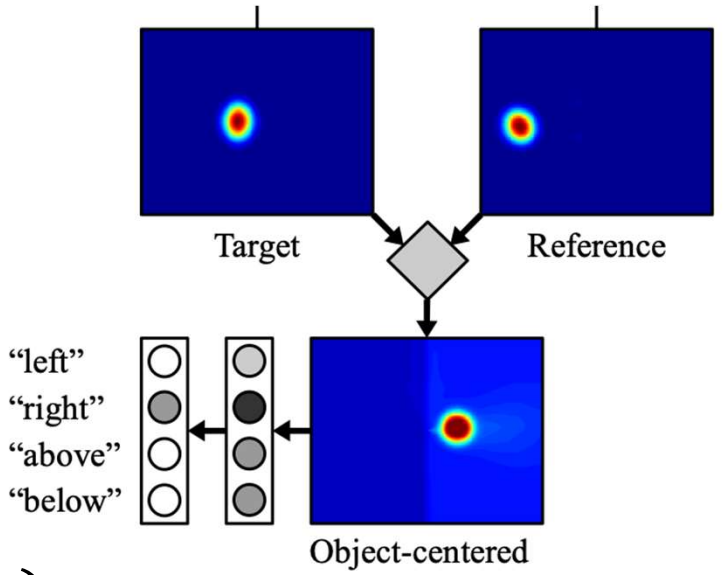
[Thomas, McClelland, 2008]

DFT makes more specific commitments

- stability of functionally significant states
- populations as the level of description at which regularities of behavior/thinking can be understood
- instabilities as key elements of neural processing .. sequences
- => all autonomous cognition is based on localist representations
- => all cognitive representations are low-dimensional

DFT as a neural theory for higher cognition

- 1) all concepts are grounded
- 2) attentional selection, coordinate transformation, sequential processing … emulate “function calls”



$$\text{totheleftof} = f(\text{target}, \text{reference})$$

- 3) the sequences of processing steps emerge from dynamic

- => DFT=neurosymbolics