Dynamic Field Theory

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Discrete “neurons”

- or activation variables: how do they arise? How do they sample sensory/motor spaces...
- no evidence that neural discreteness matters for behavior

Continuity in space

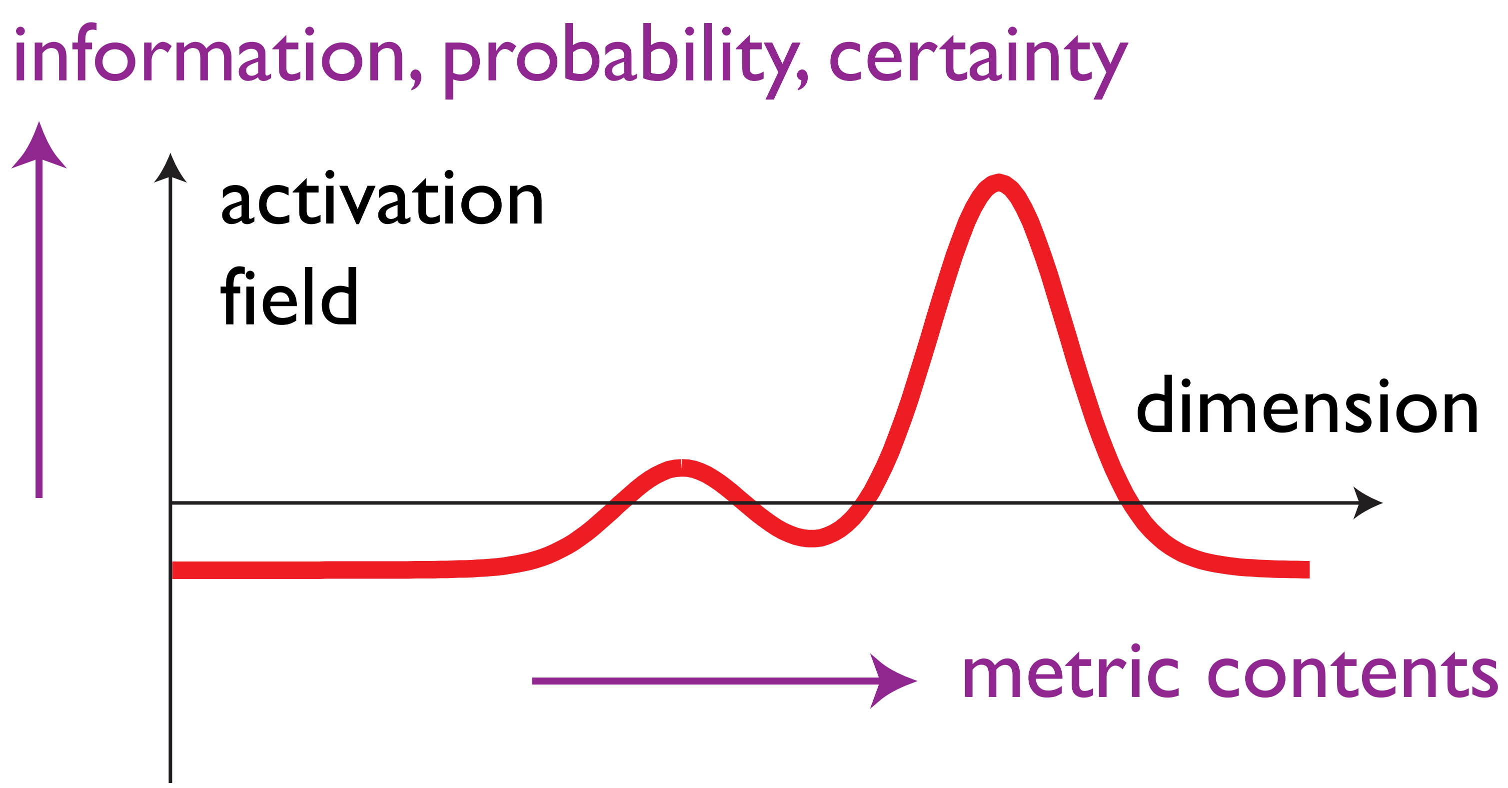
- hypothesis: behavior is embedded in continua
  - the space of possible behaviors, e.g. space of movements, percepts, timing structures
  - neuronal substrate is continuous (maps, broad tuning)
- (=> need to understand how categorical behavior may emerge from such continua)

Dynamical Field Theory: space

- in DFT, continuous spaces are dimension over which activation fields are defined
  - homologous to sensory surfaces, e.g., visual or auditory space (retinal, allocentric, ...)
  - homologous to motor surfaces, e.g., saccadic end-points or direction of movement of the end-effector in outer space
  - feature spaces, e.g., localized visual orientations, color, impedance, ...
  - abstract spaces, e.g., ordinal space, along which serial order is represented

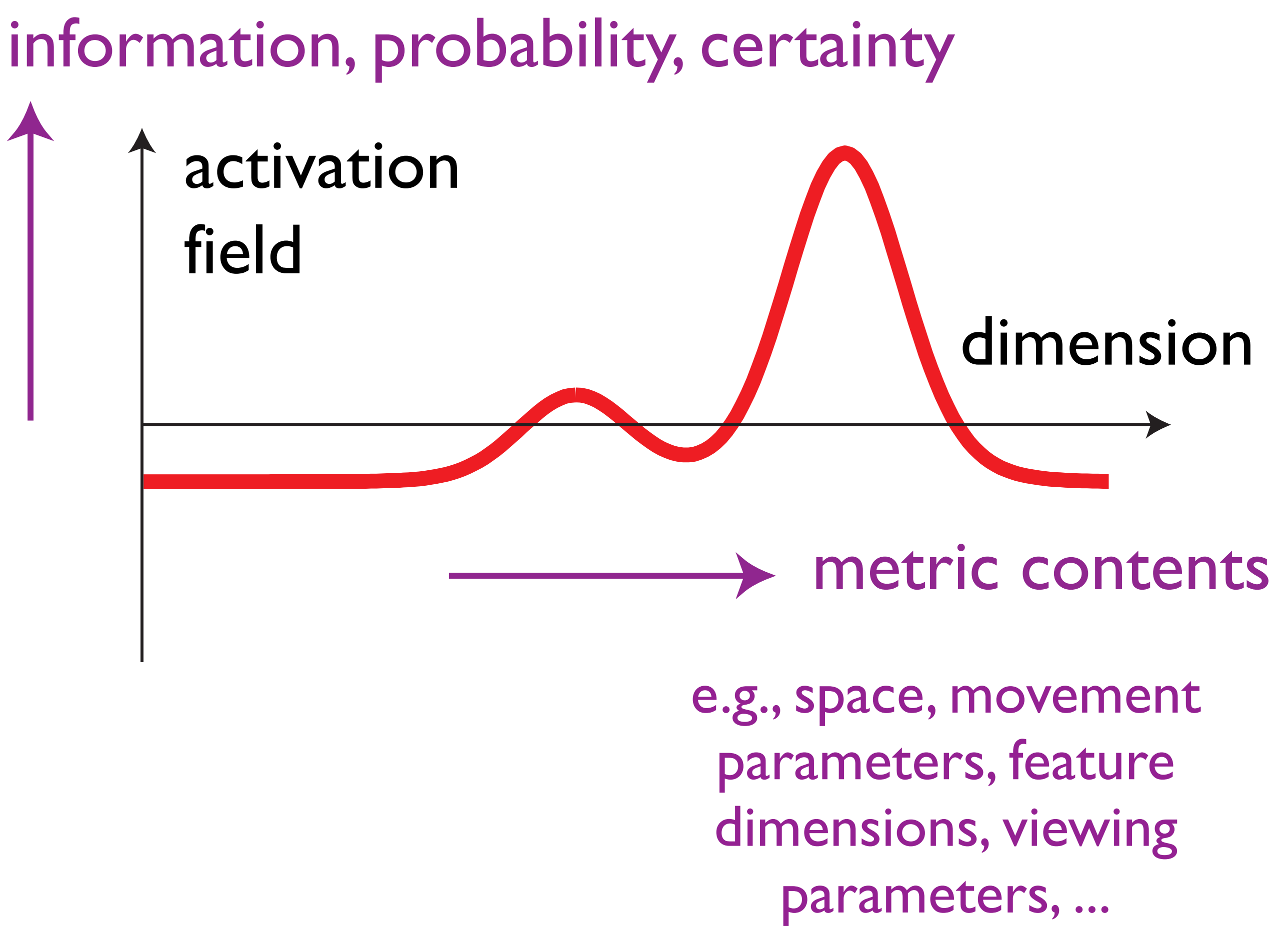
Dynamical Field Theory: space

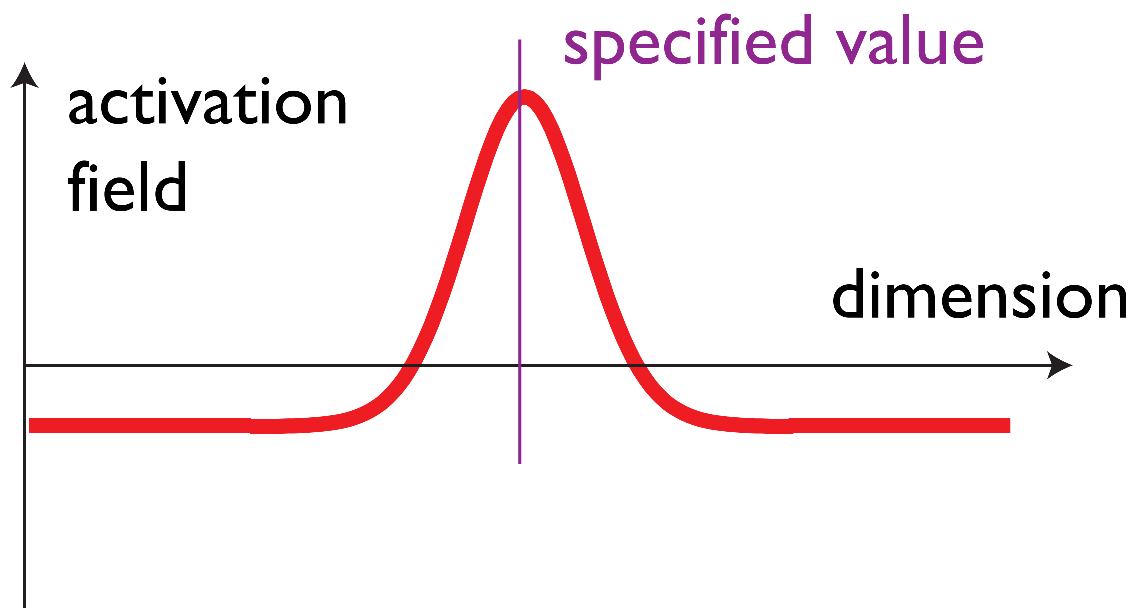
- fields: continuous activation variables defined over continuous spaces

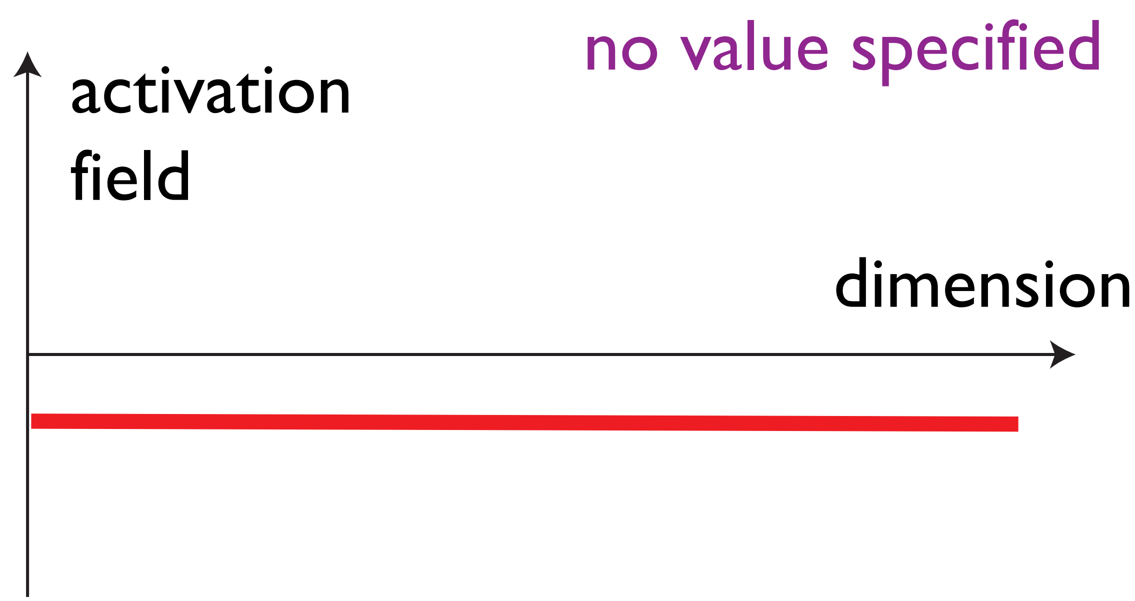


e.g., retinal space, movement parameters, feature dimensions, viewing parameters, ...

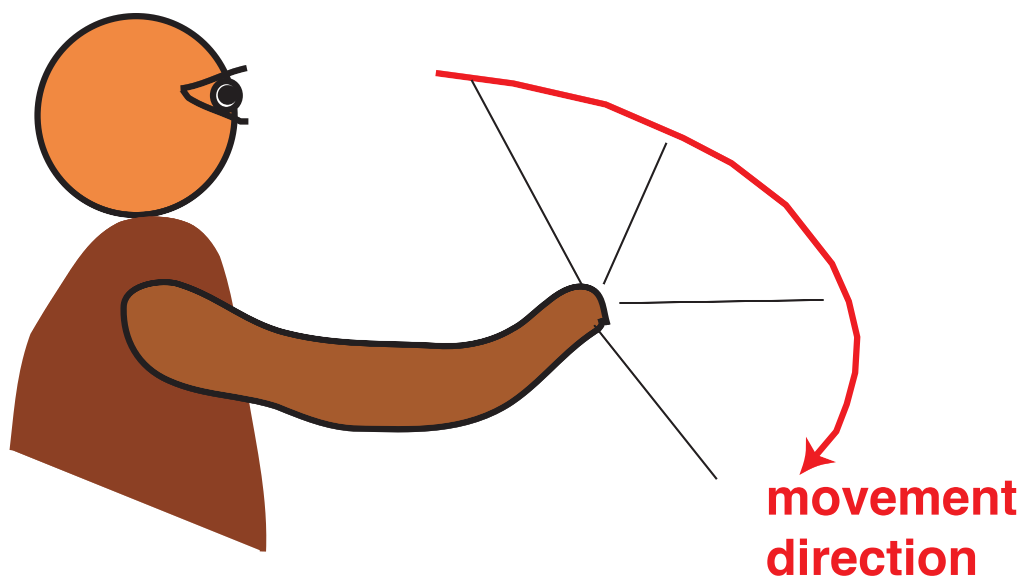
activation fields

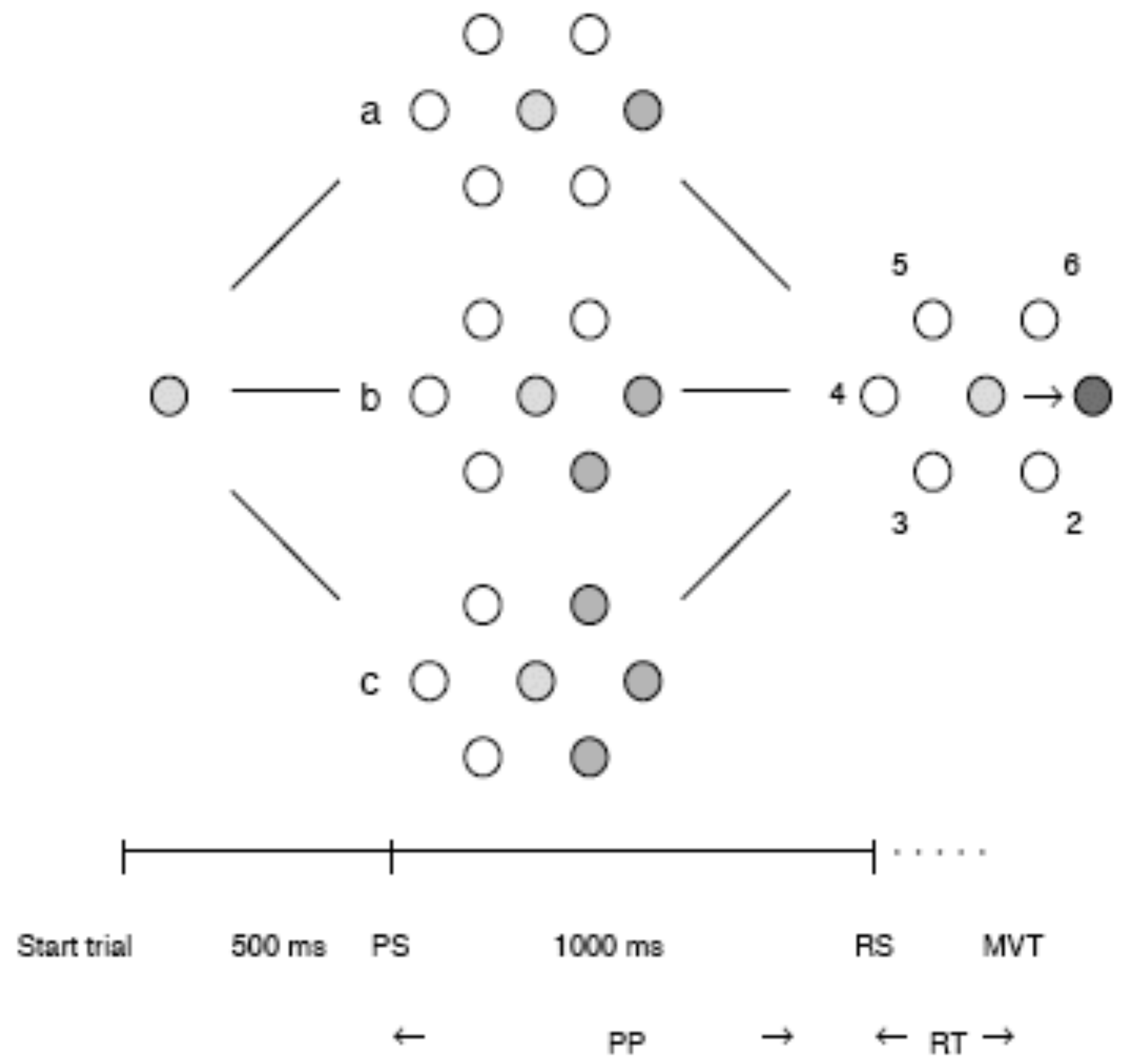






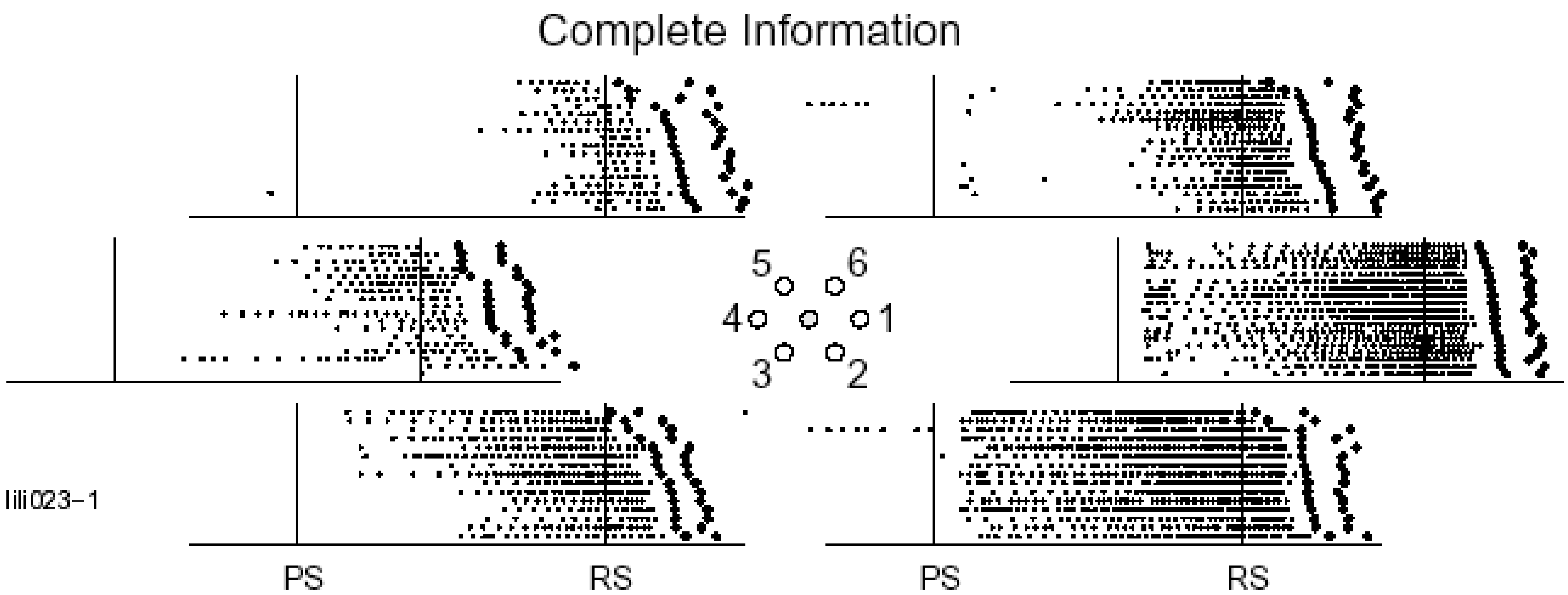
Neurophysiological grounding of DFT example: movement planning





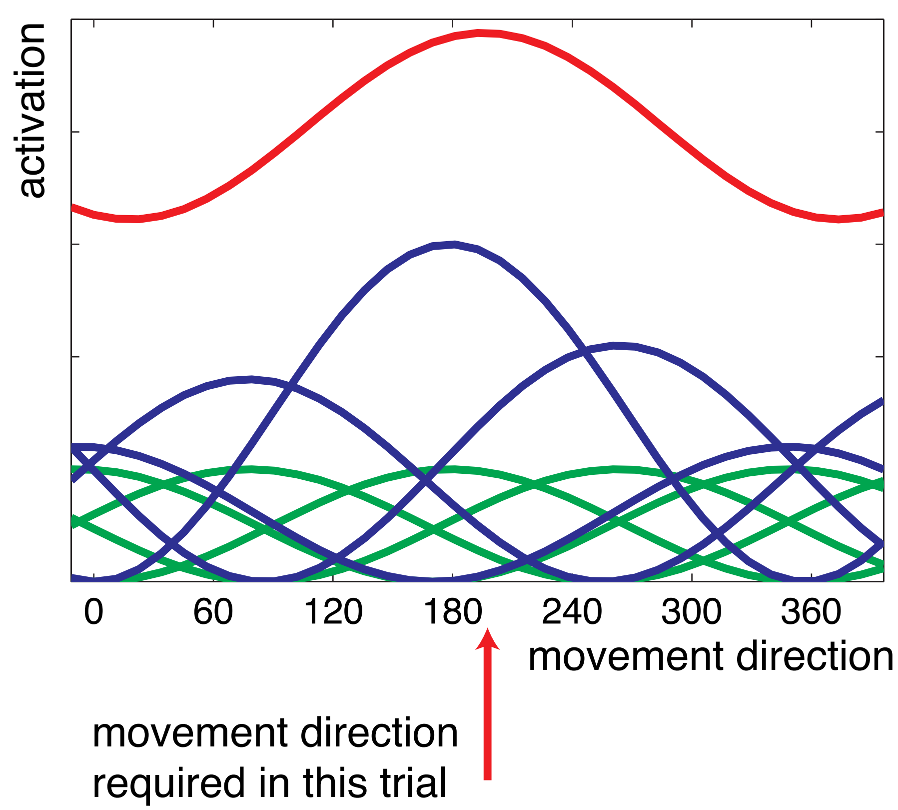
Bastian, Riehle, Schöner, 2003

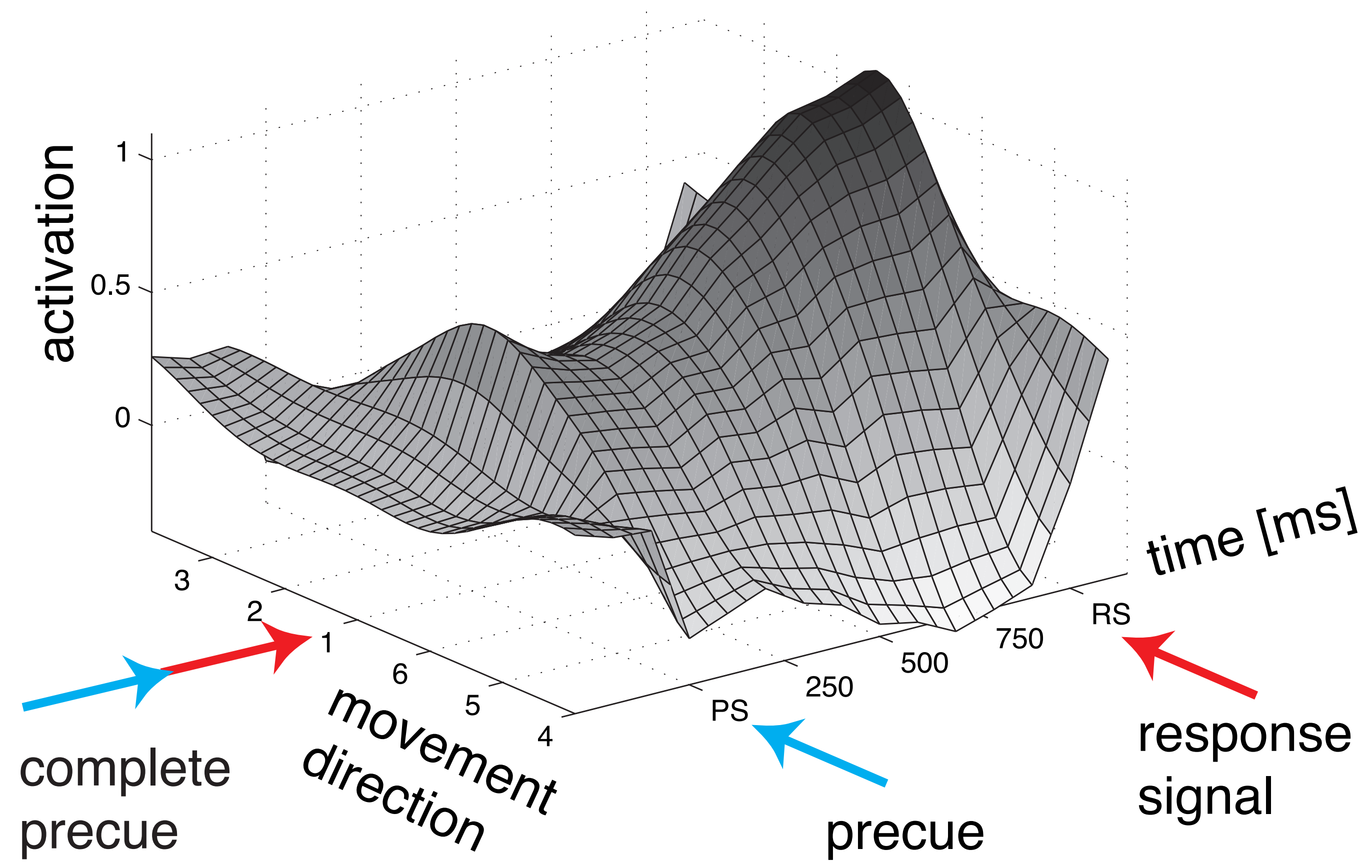
- tuning of cells in motor and premotor cortex to direction of end-effector movement path



Distribution of Population Activation (DPA)

Distribution of population activation =
$\sum_{\text{neurons}}$ tuning curve * current firing rate



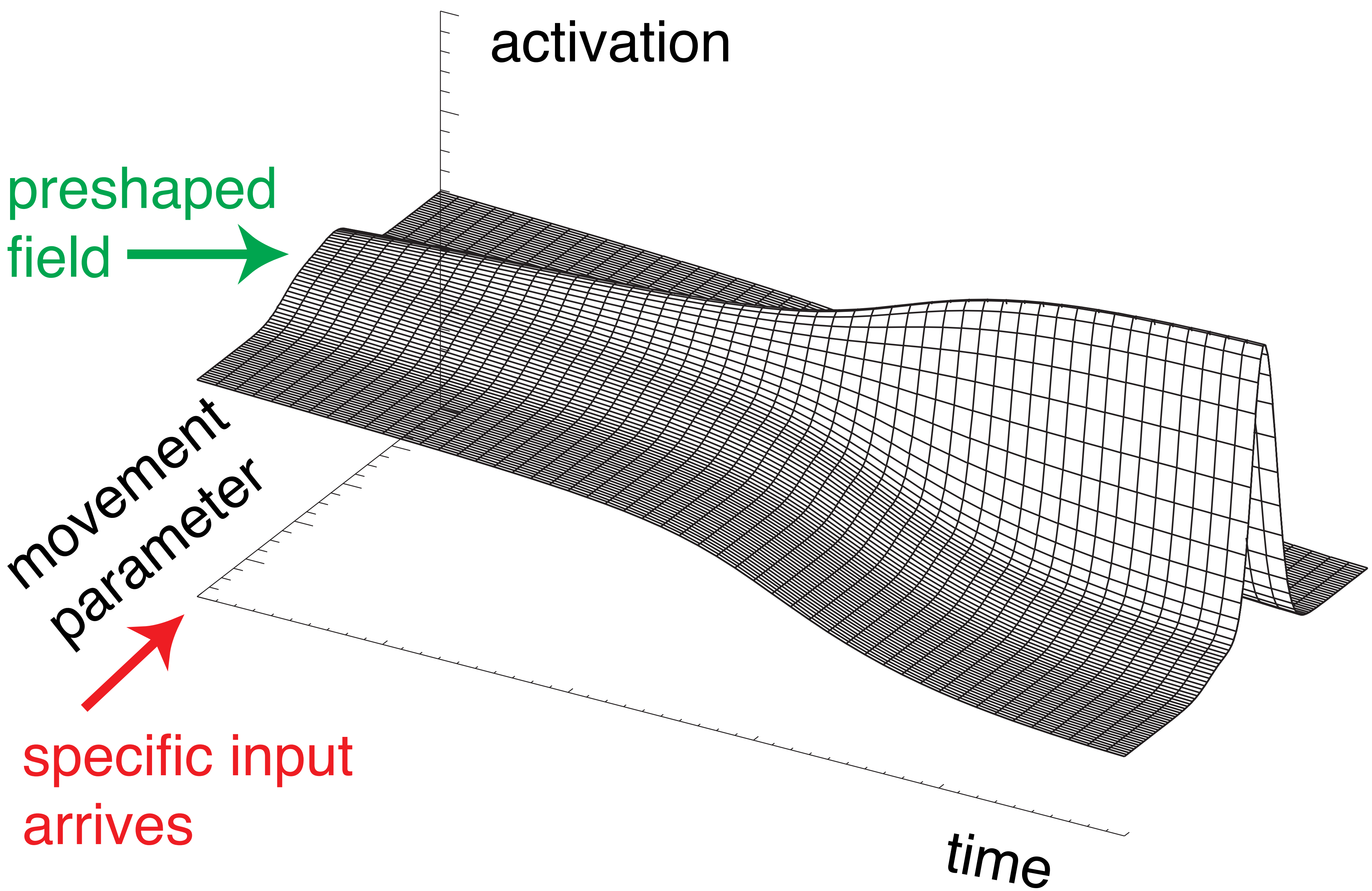


[Bastian, Riehle, Schöner, 2003]

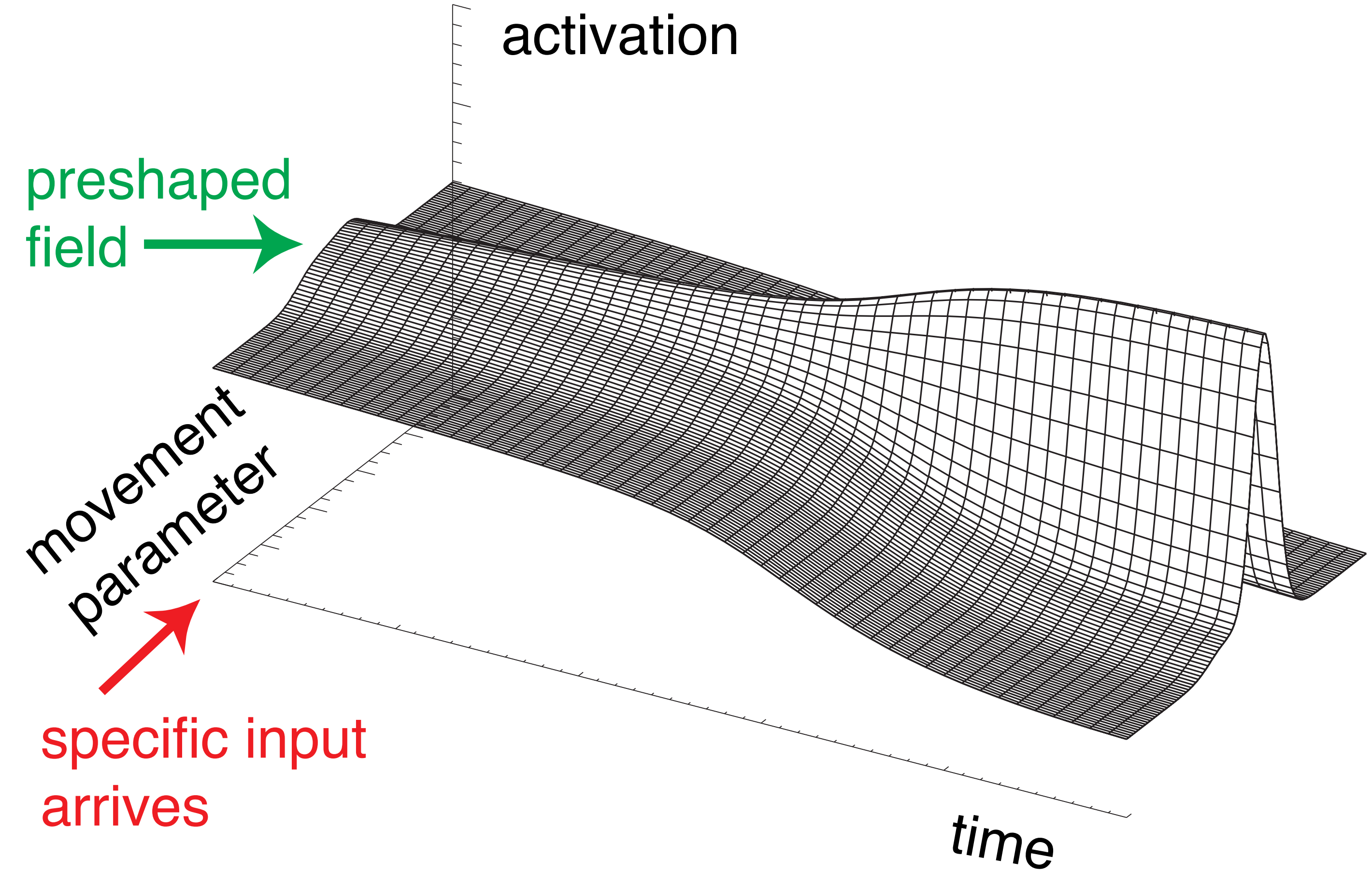
Distributions of Population Activation are abstract

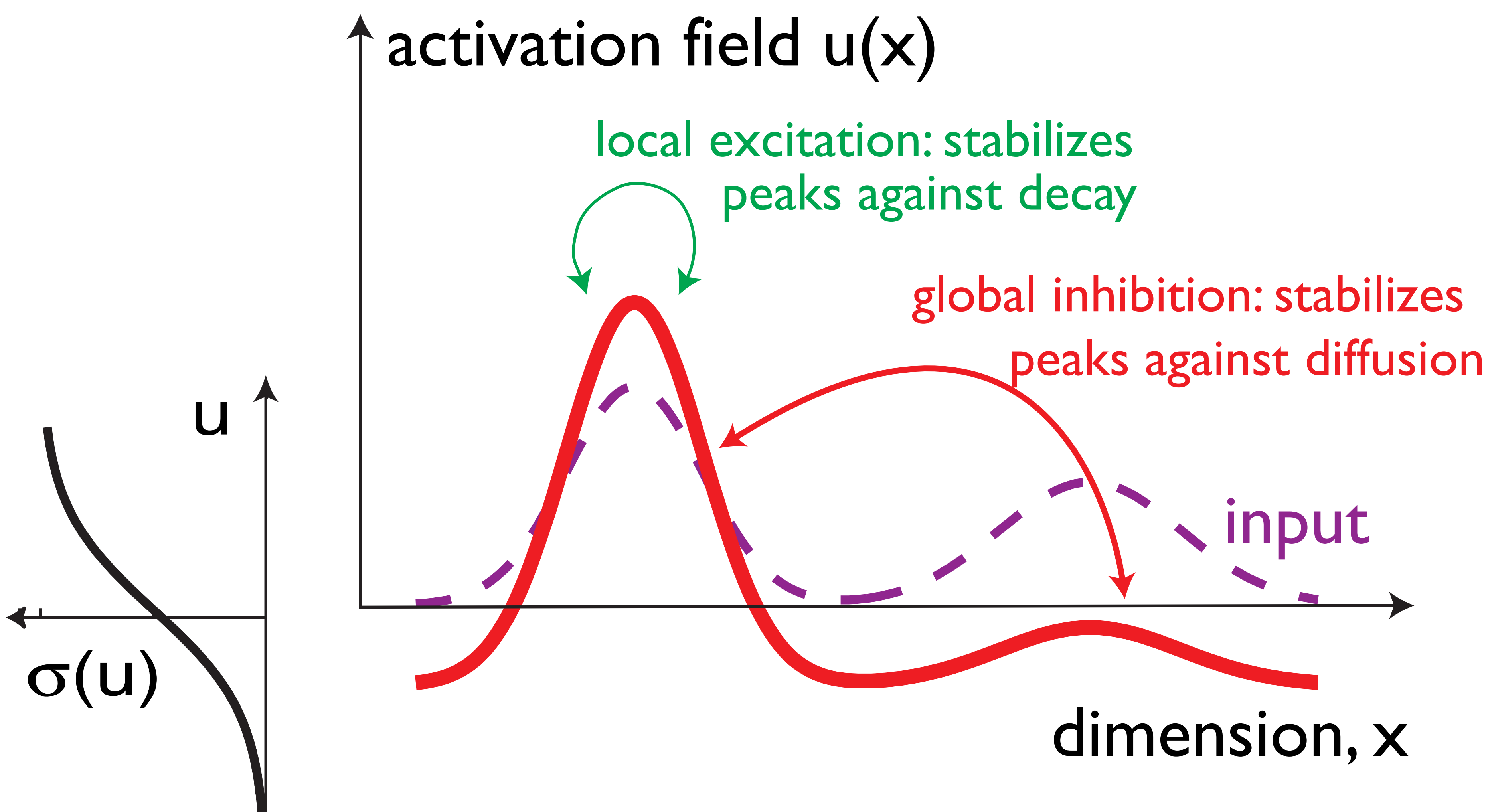
- neurons are not localized within DPA!
- cortical neurons really are sensitive to many dimensions
  - motor: arm configuration, force direction
  - visual: many feature dimensions such as spatial frequency, orientation, direction...
- => DPA is a projection from that high-dimensional space onto a single dimension

evolution of activation fields in time: neuronal dynamics



the dynamics such activation fields is structured so that localized peaks emerge as attractor solutions





mathematical formalization

Amari equation

$$\tau \dot{u}(x,t) = -u(x,t) + h + S(x,t) + \int w(x-x')\sigma(u(x',t))\, dx'$$

where

- time scale is τ
- resting level is $h < 0$
- input is $S(x,t)$
- interaction kernel is

$$w(x-x') = w_i + w_e \exp\left[-\frac{(x-x')^2}{2\sigma_i^2}\right]$$

- sigmoidal nonlinearity is

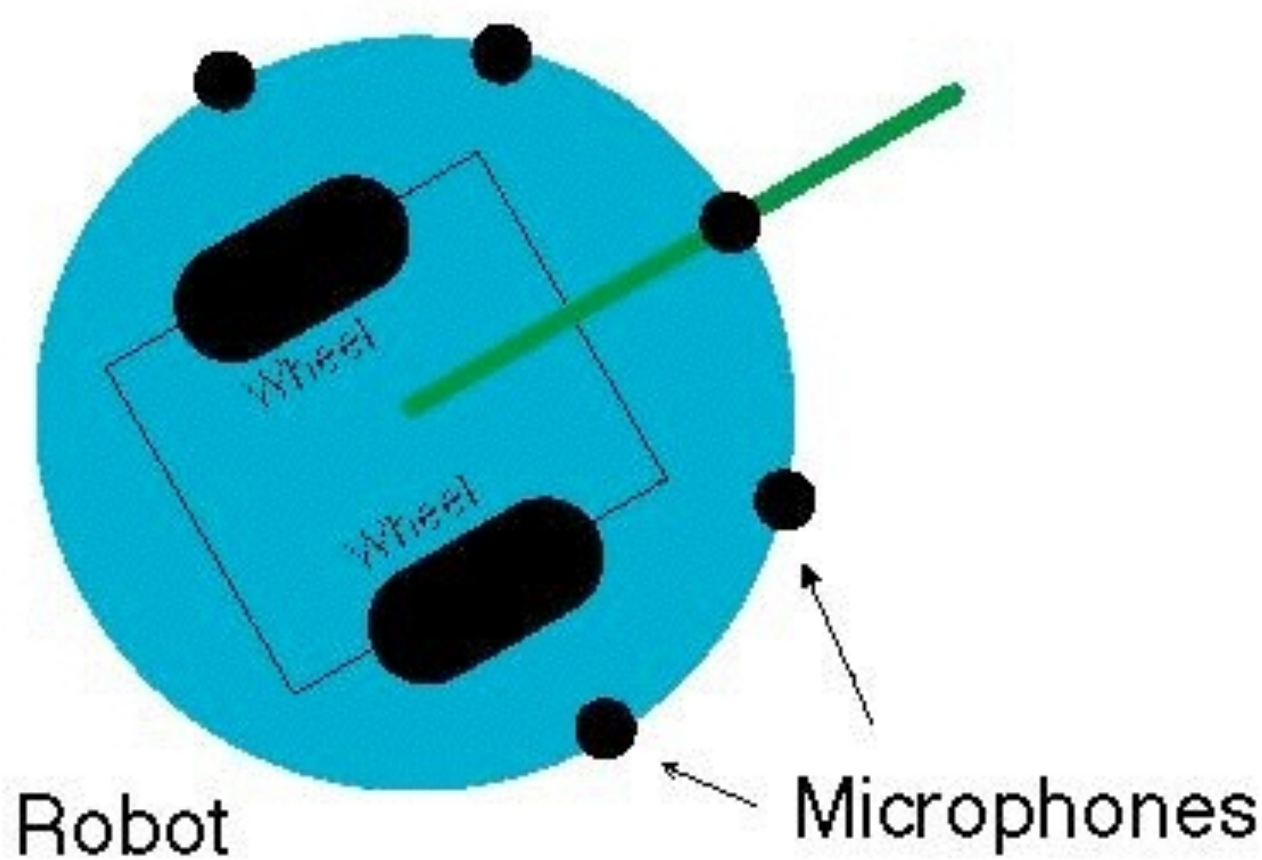
$$\sigma(u) = \frac{1}{1+\exp[-\beta(u-u_0)]}$$

=> simulations

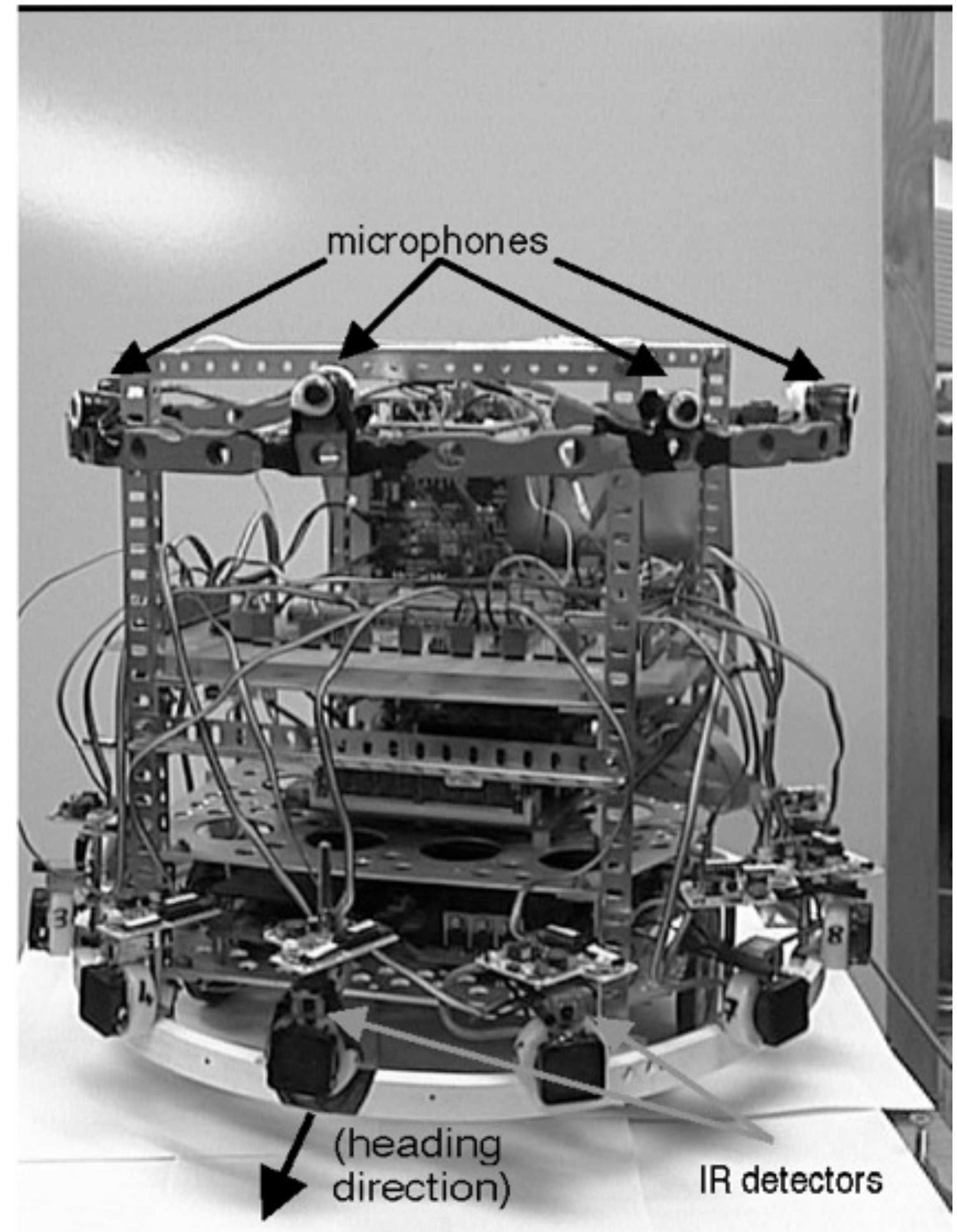
solutions and instabilities

- input driven solution (sub-threshold) vs. self-stabilized solution (peak, supra-threshold)
- detection instability
- reverse detection instability
- selection
- selection instability
- memory instability
- detection instability from boost

Illustration: linking to sensors

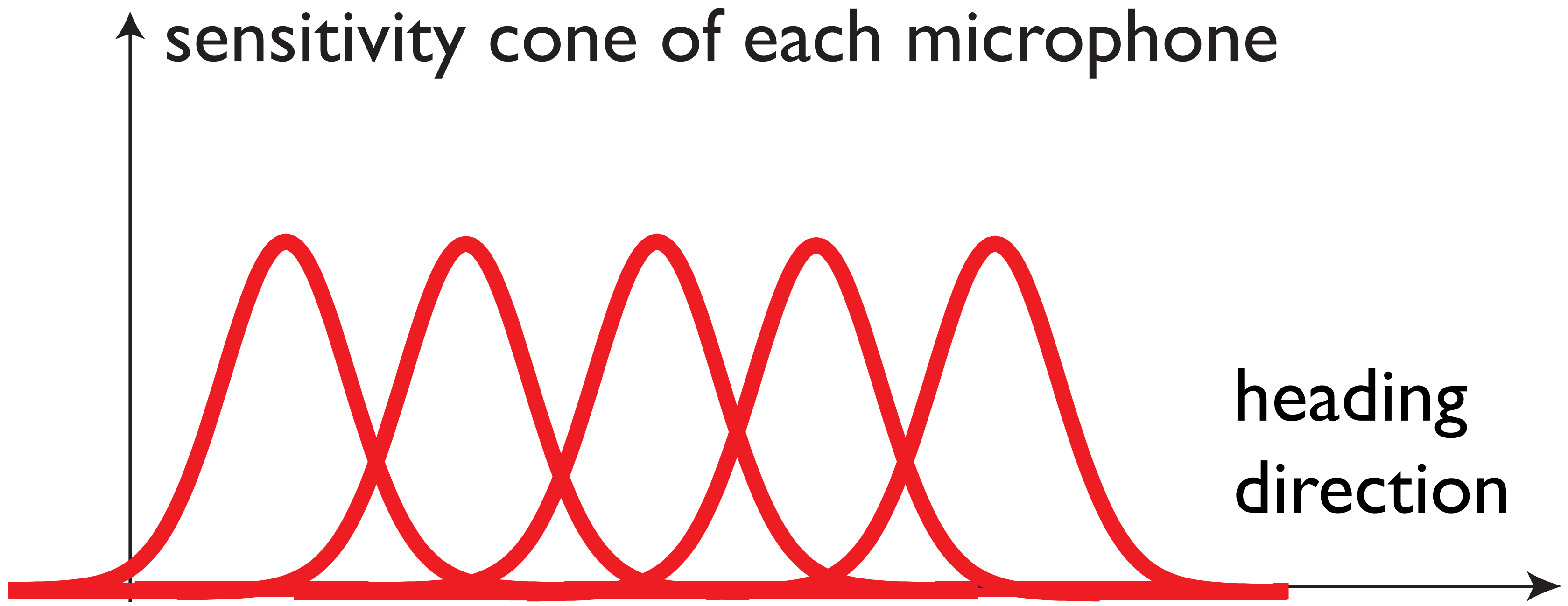


[from Bicho, Mallet, Schöner, Int J Rob Res,2000]

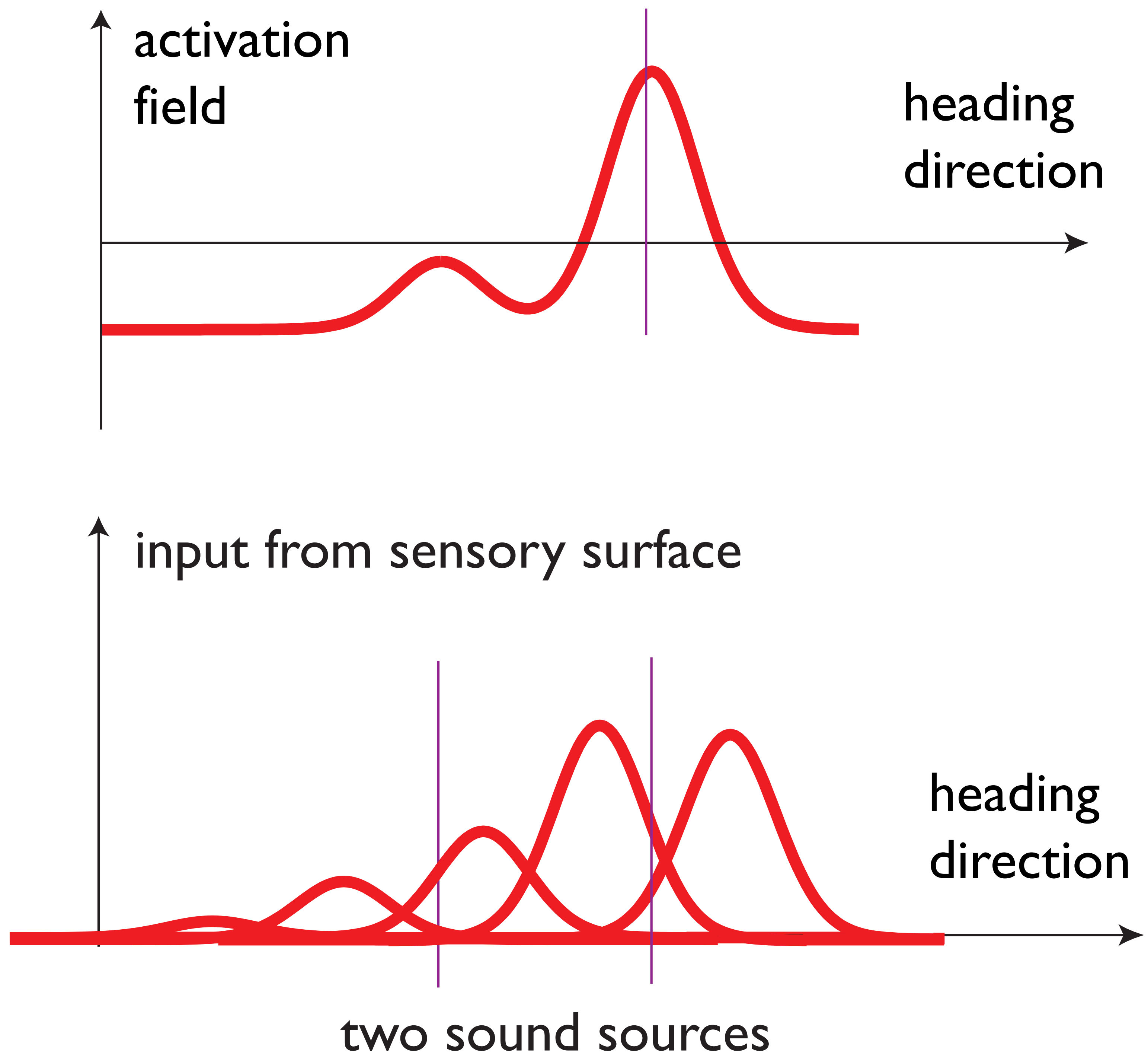


Sensory surface

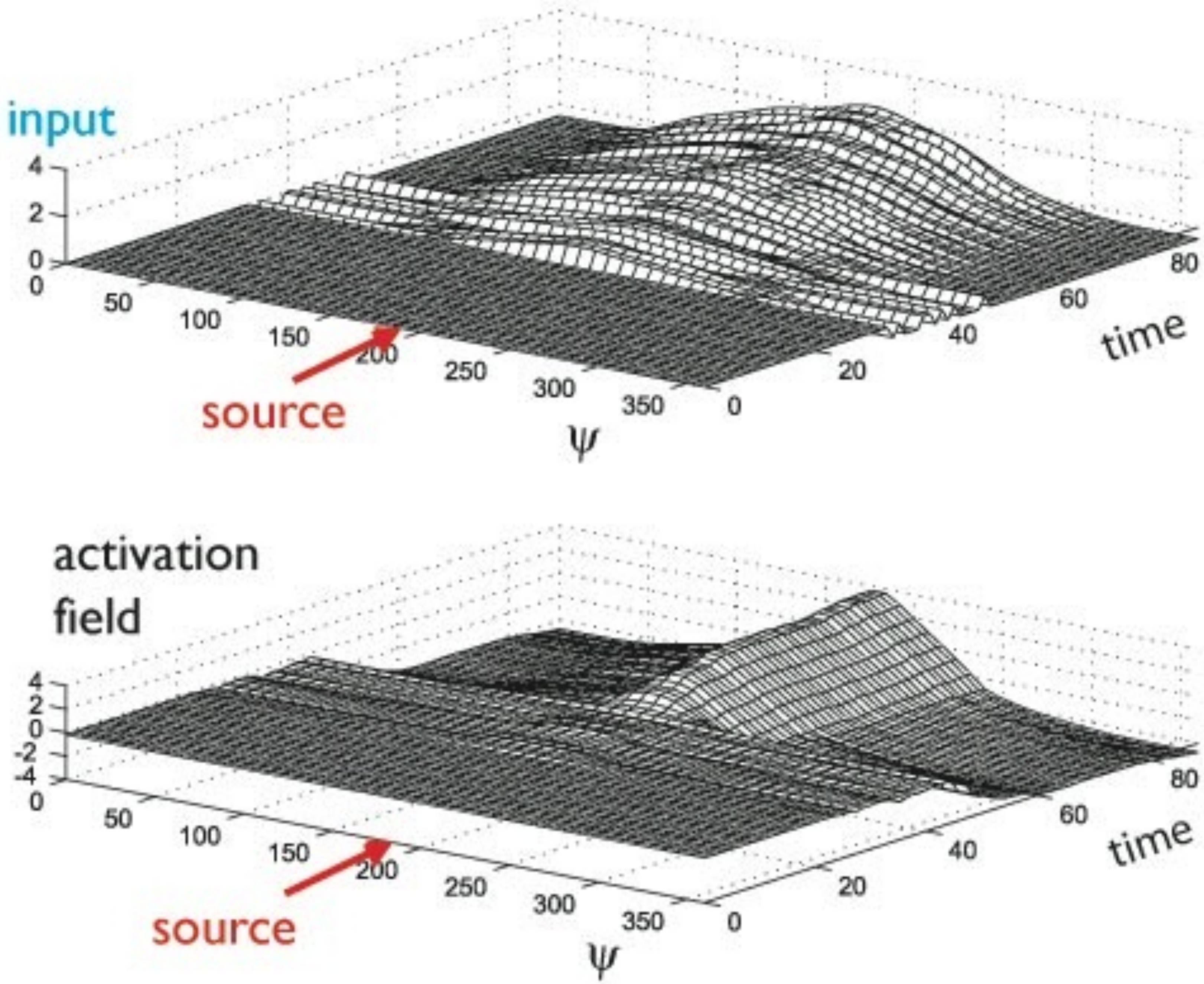
- each microphone samples heading direction



- each microphone provides input to the field



Detection instability induced by increasing intensity of sound source



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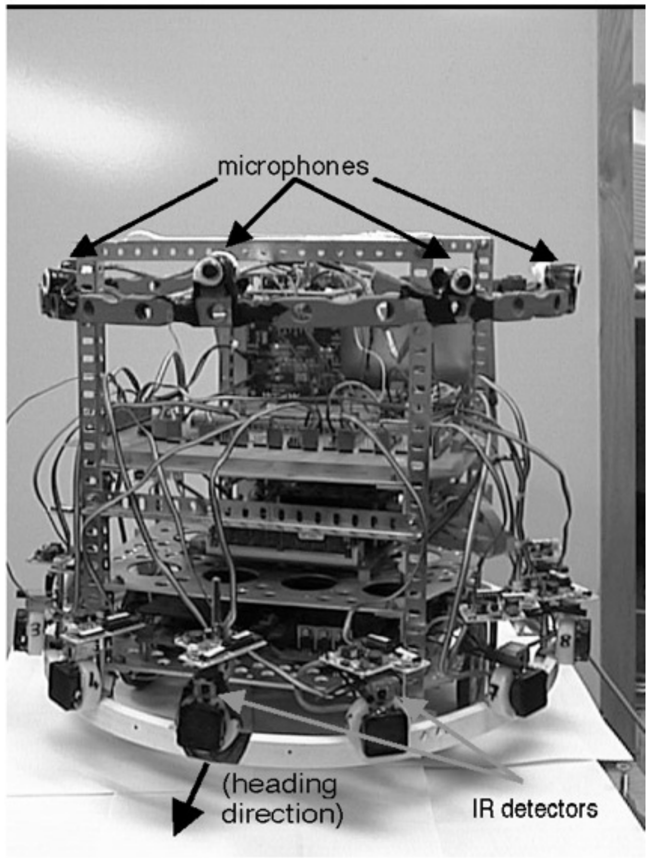
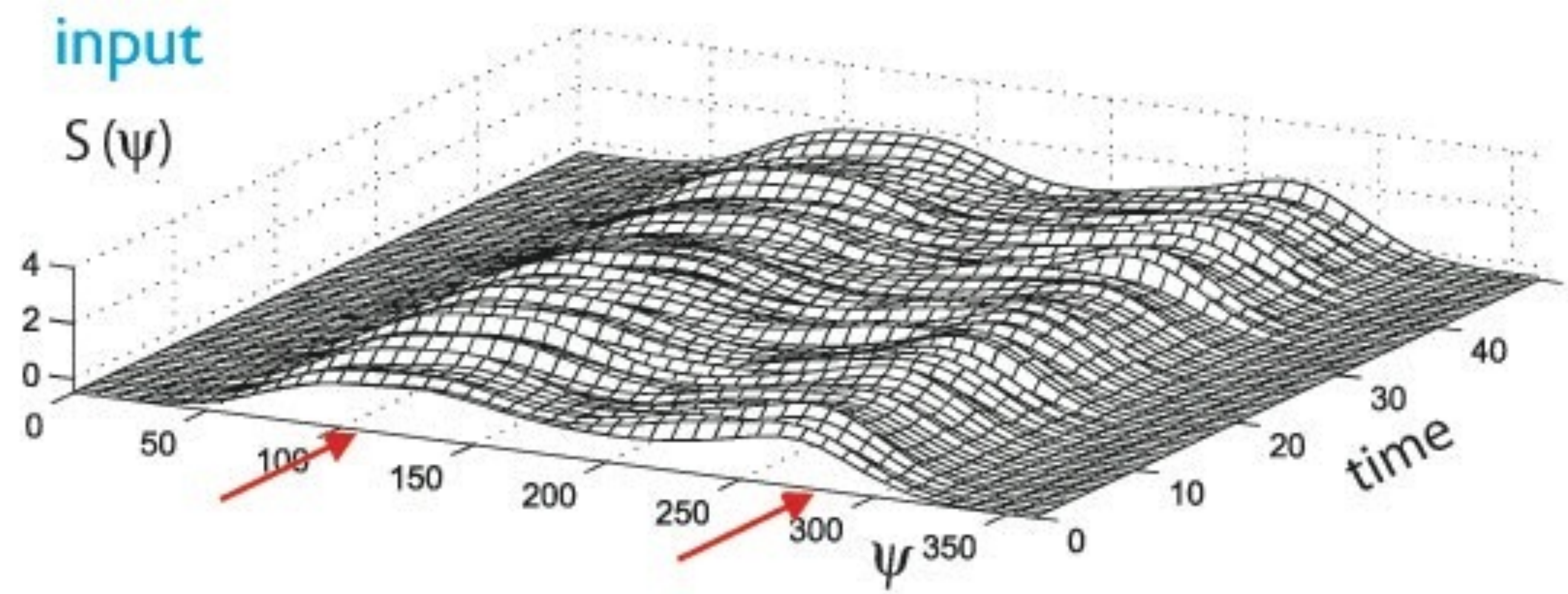
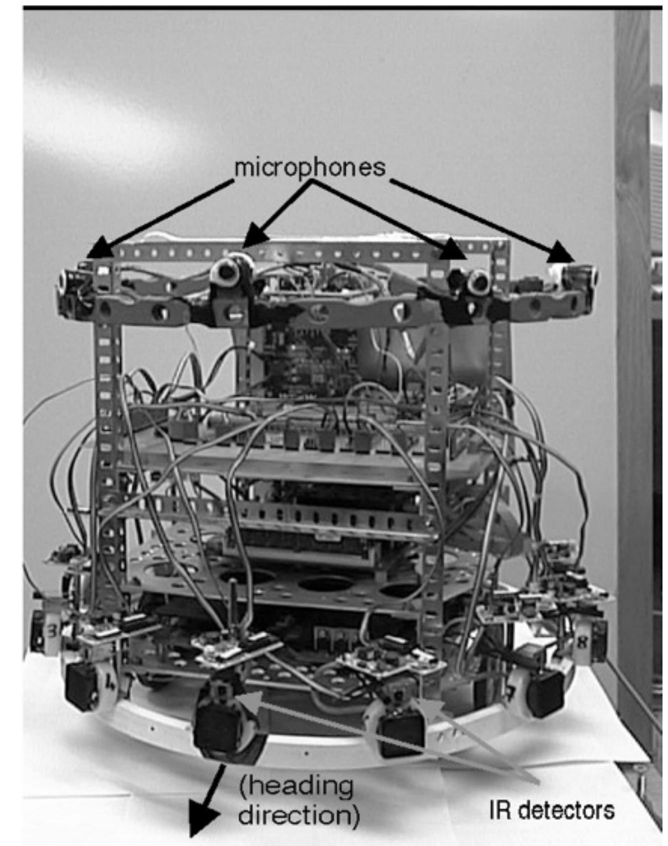
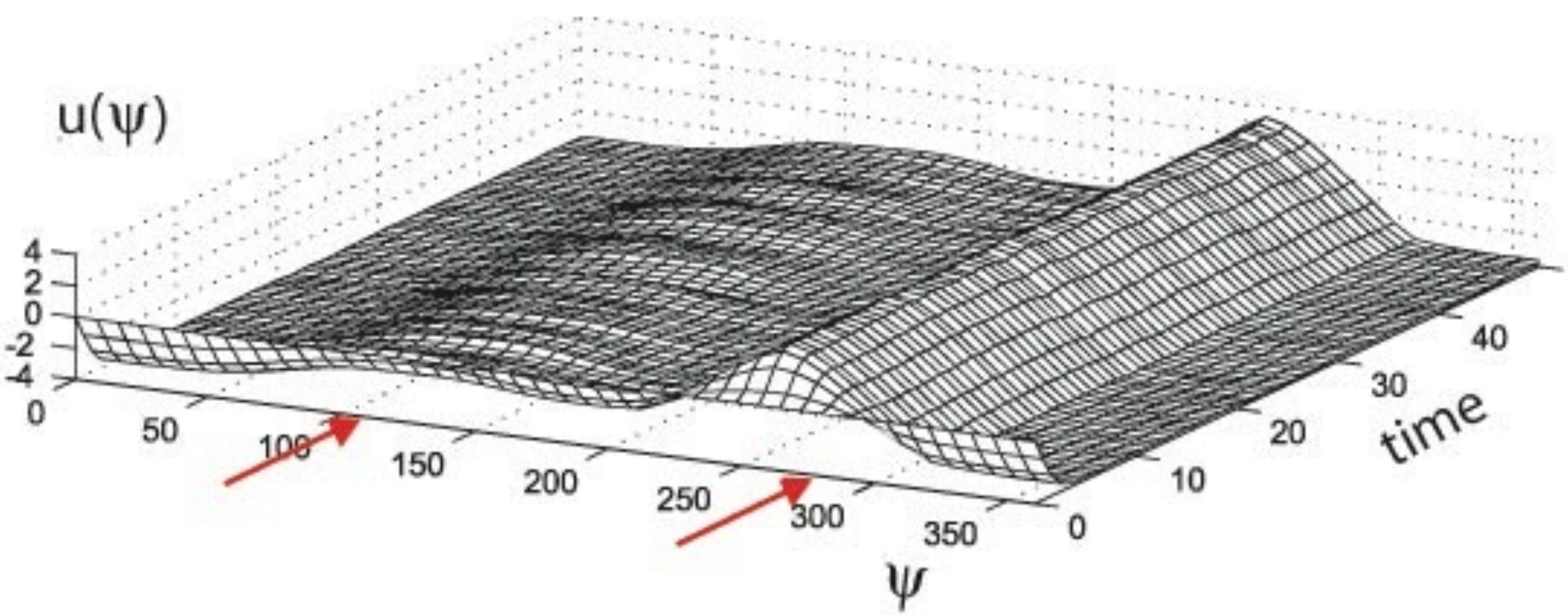


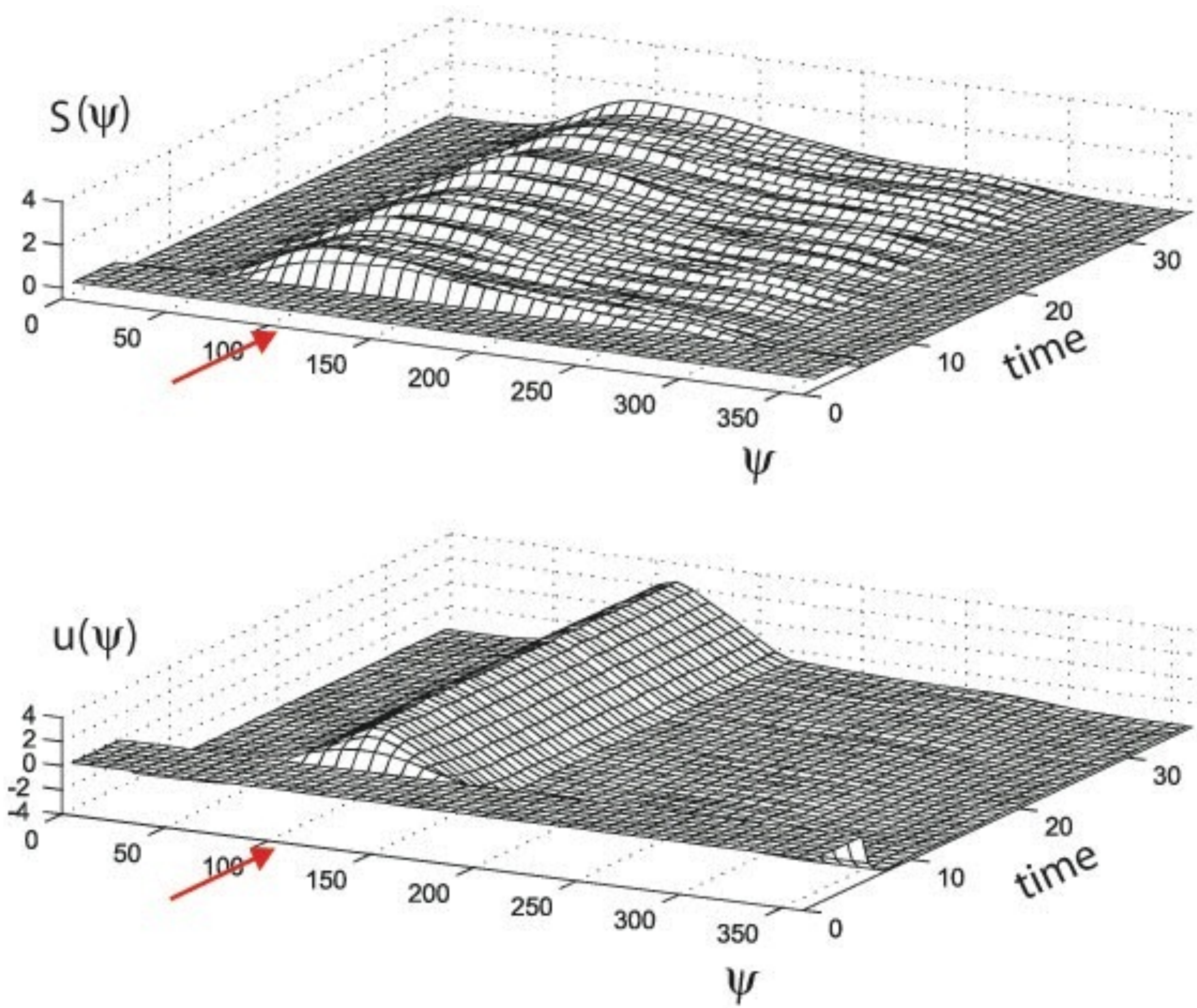
Target selection in the presence of two sources



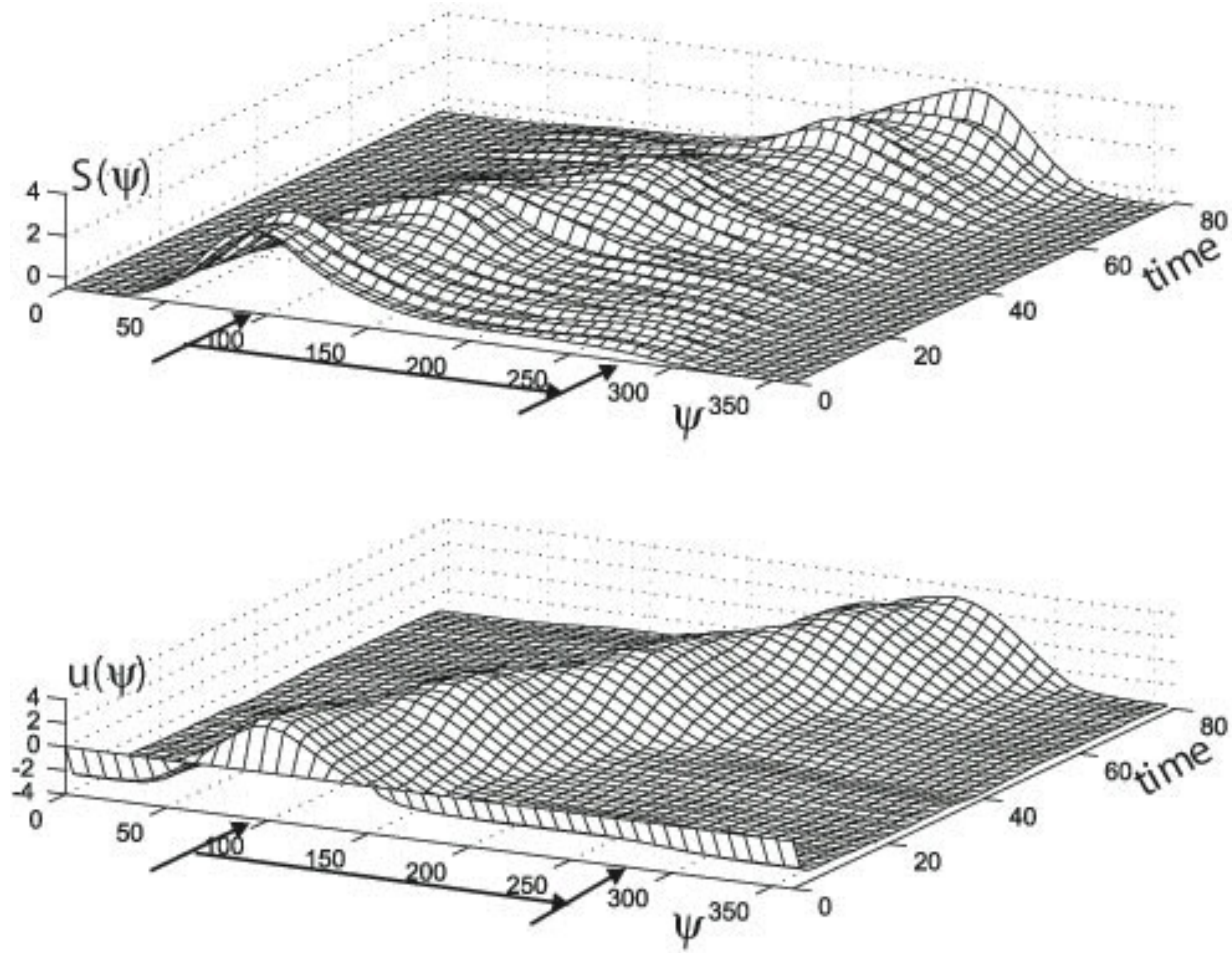




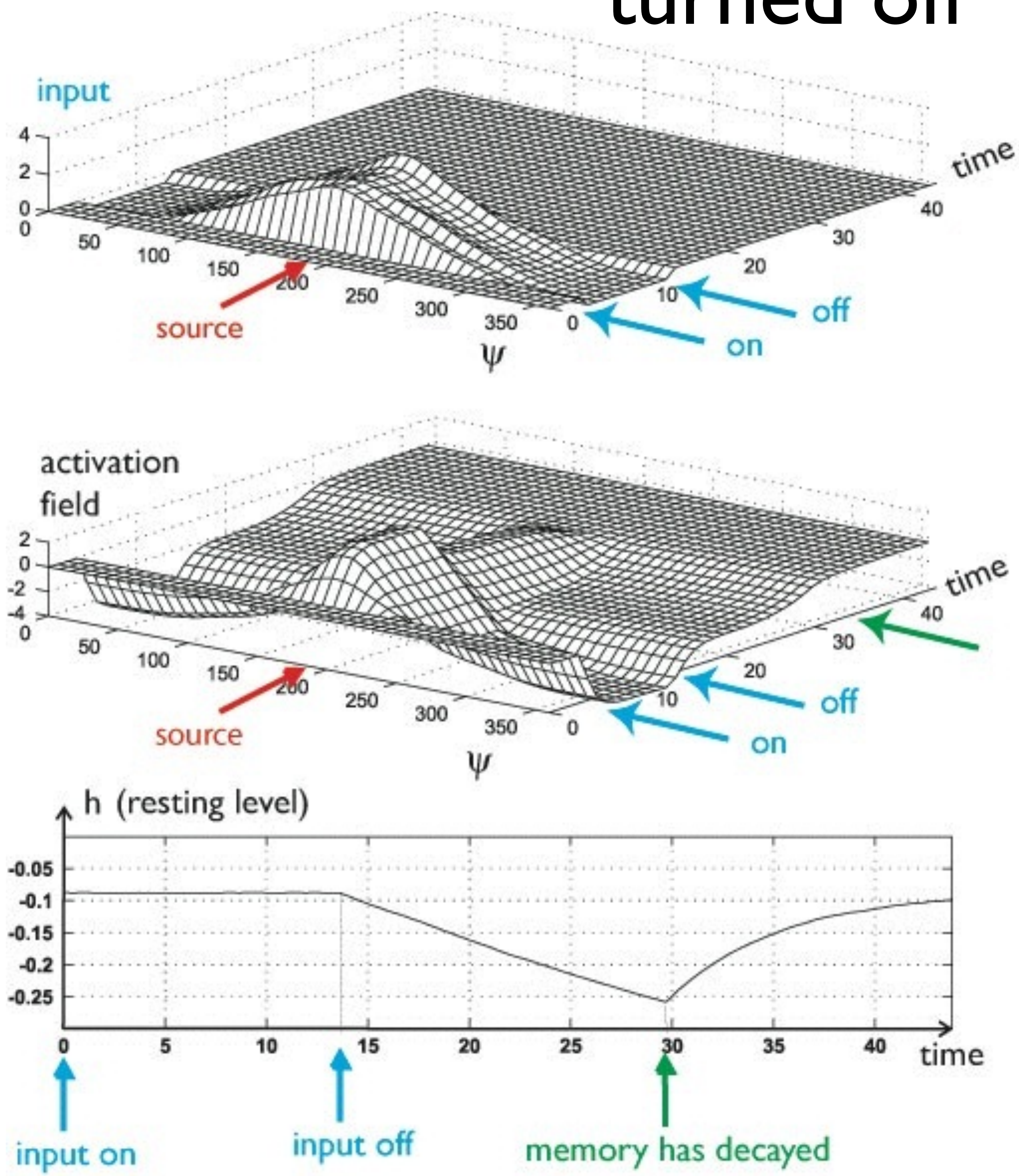
Robust estimation in the presence of outliers

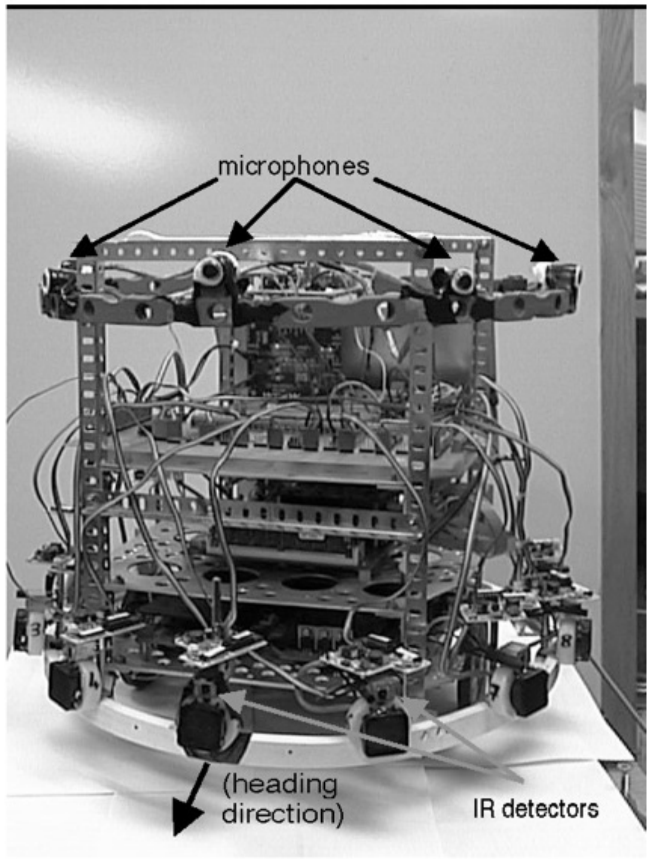


Tracking when sound source moves



Memory (and forgetting) when sound source is turned off

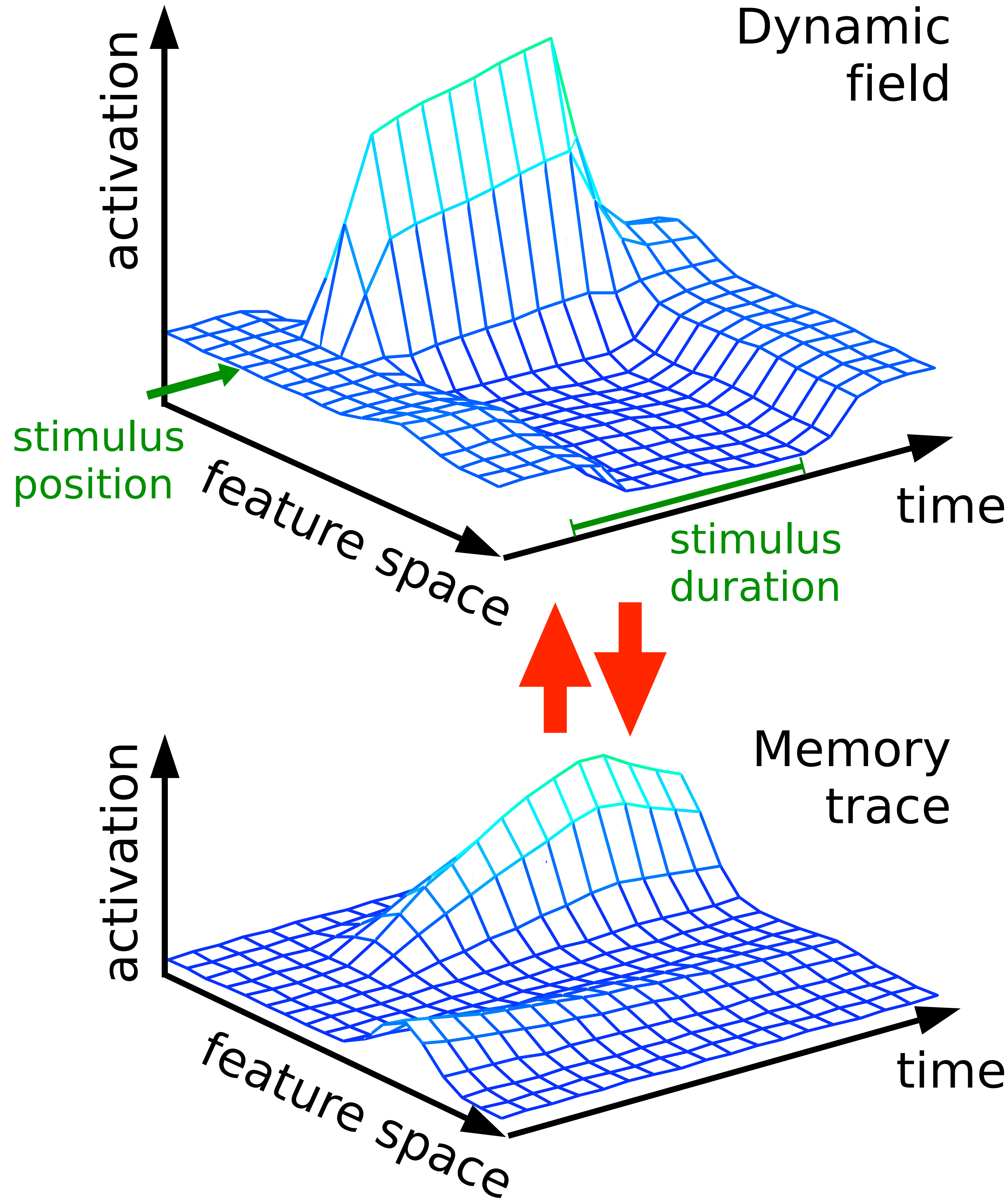




[from Bicho, Mallet, Schöner: Int J Rob Res 19:424(2000)]

Illustration of instabilities

simplest form of learning: the memory trace

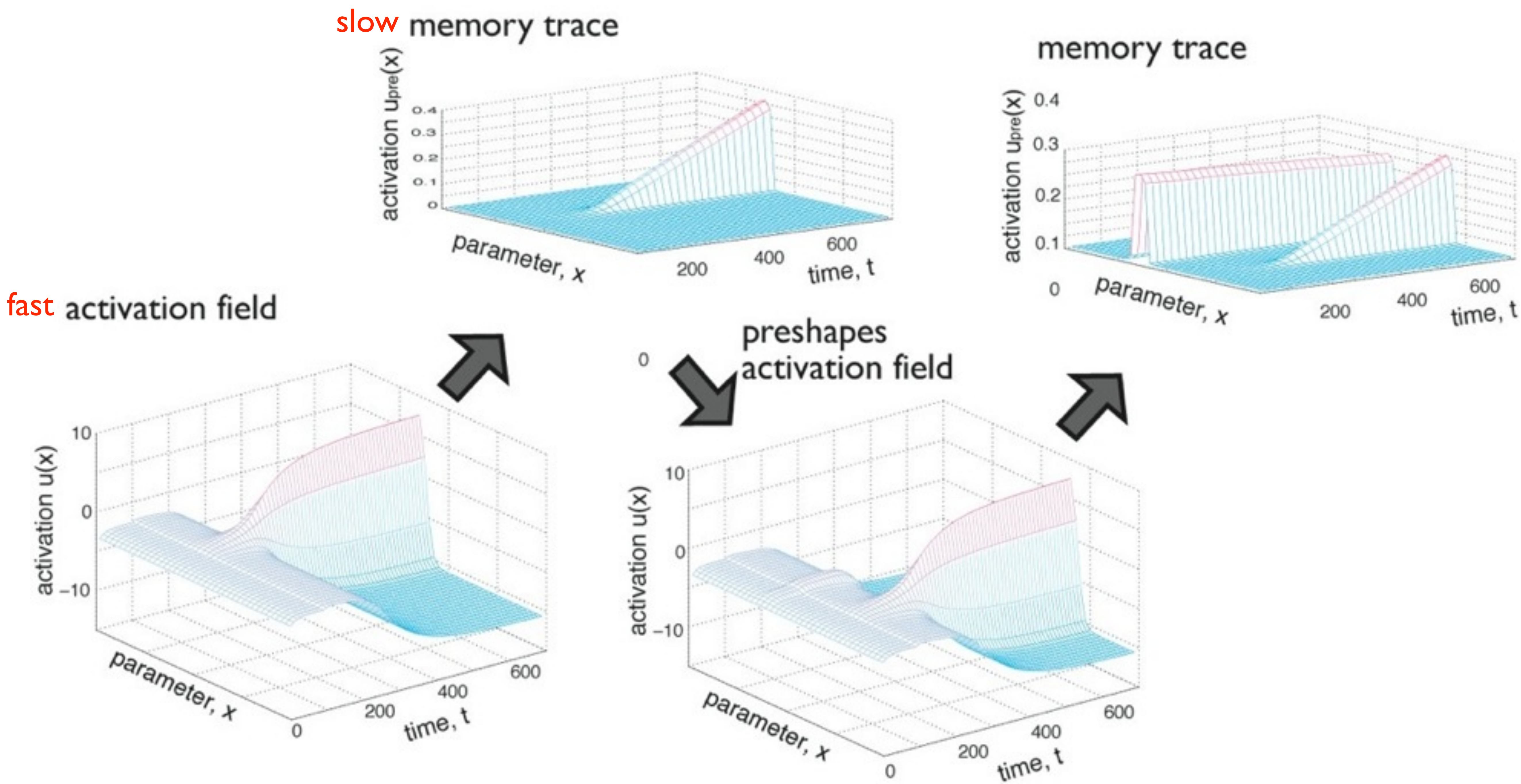


- William James: habit formation as the simplest form of learning
  - (habituation: same for inhibition)

mathematics of the memory trace

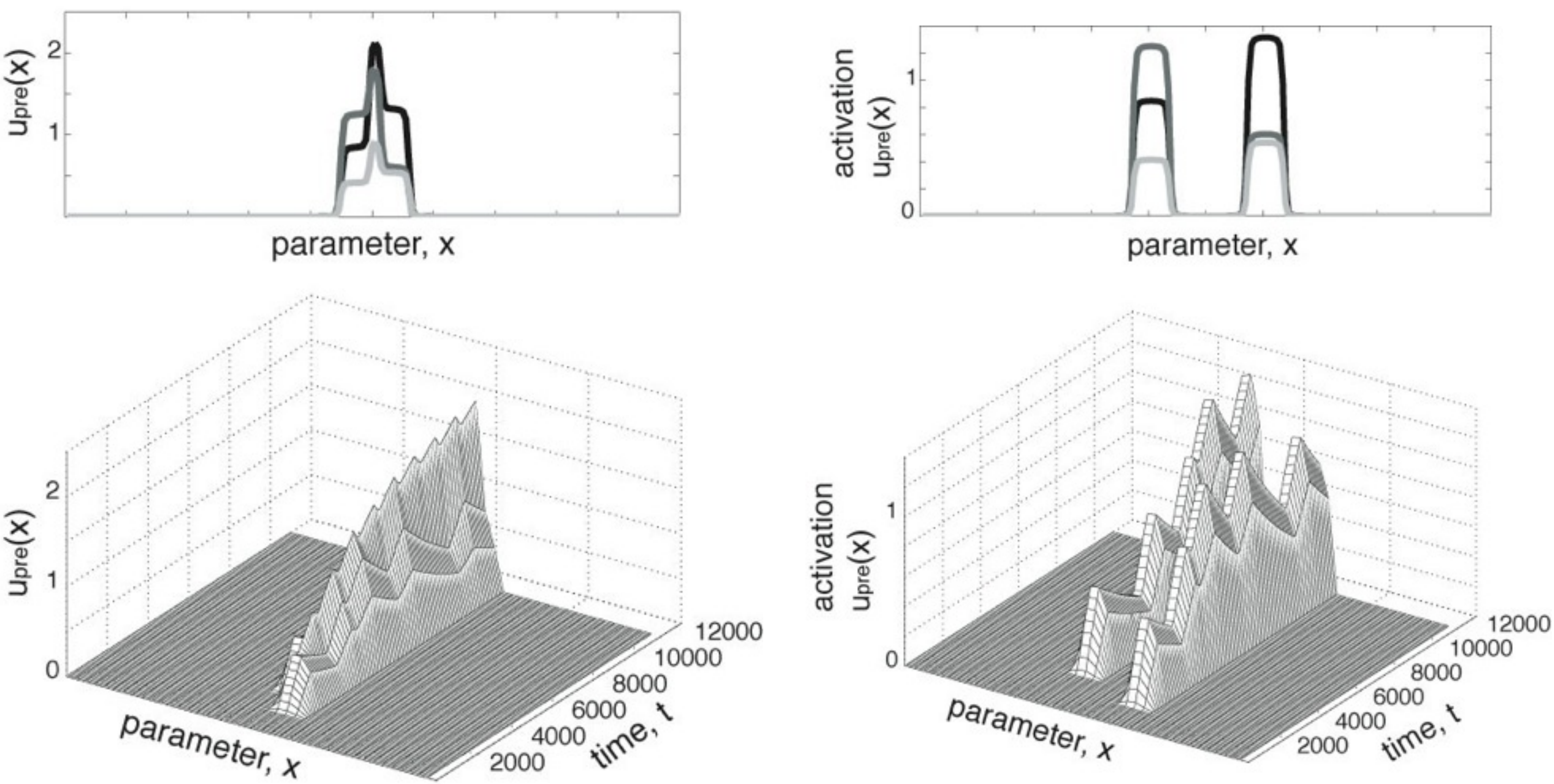
$$
\begin{aligned}
\tau \dot{u}(x,t) &= -u(x,t) + h + S(x,t) + u_{\mathrm{mem}}(x,t) \\
&+ \int dx' \; w(x-x') \; \sigma(u(x')) \\
\tau_{\mathrm{mem}} \; \dot{u}_{\mathrm{mem}}(x,t) &= -u_{\mathrm{mem}}(x,t) \\
&+ \int dx' \; w_{\mathrm{mem}}(x-x')\sigma(u(x',t))
\end{aligned}
$$

- memory trace only evolves while activation is excited
- potentially different growth and decay rates



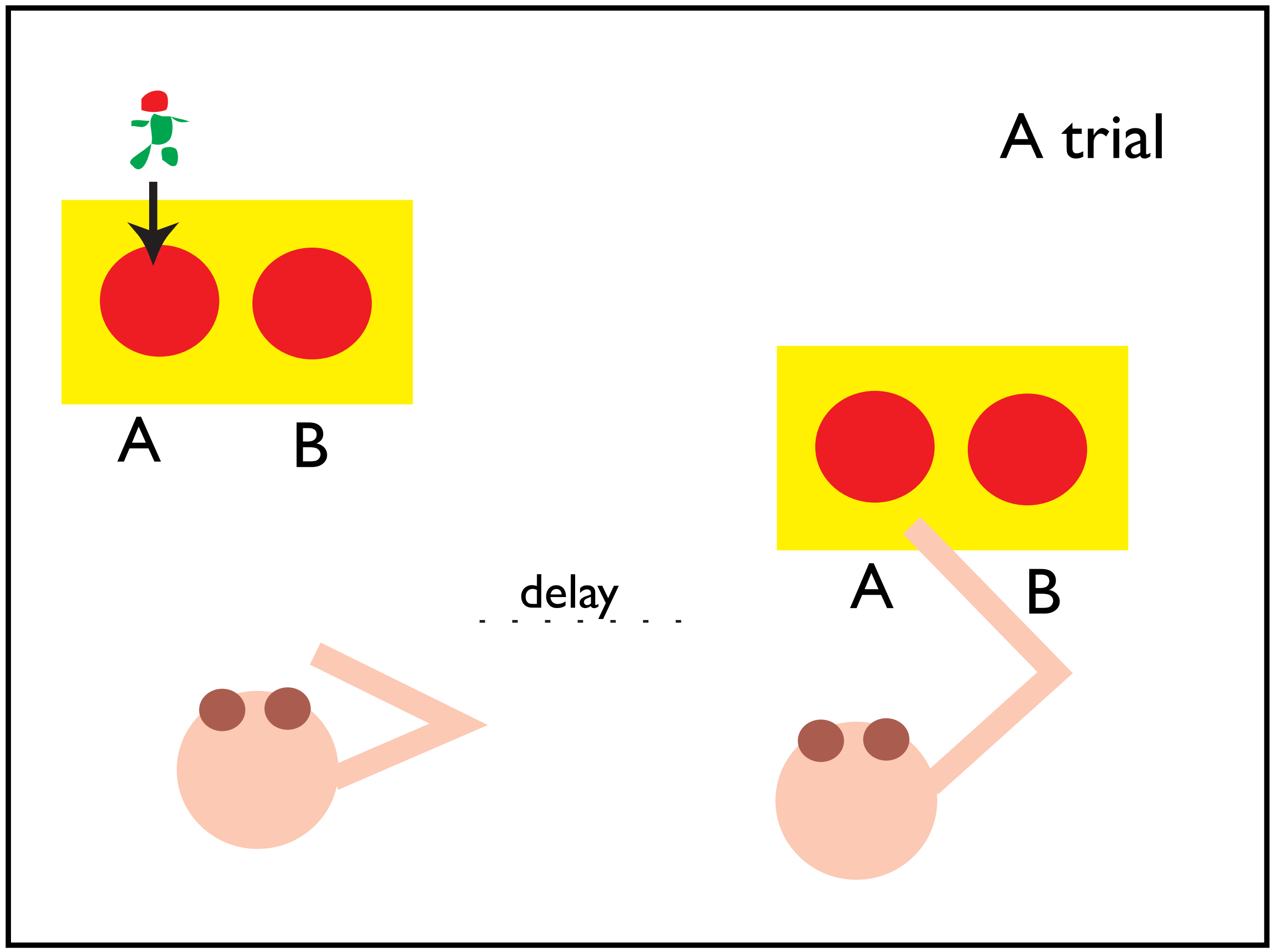
Wilimzig, Schöner 2006

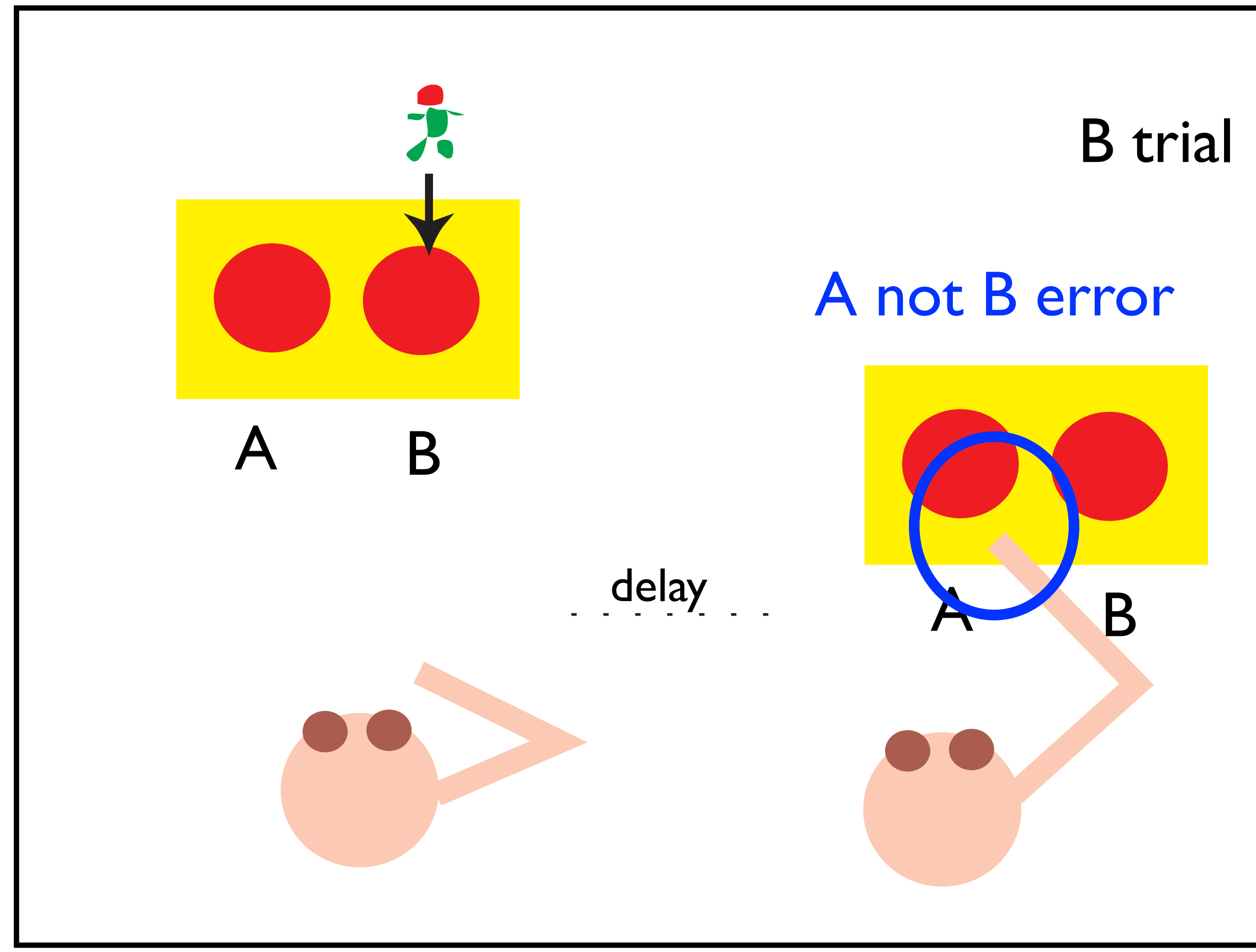
categories may emerge ...



Wilimzig, Schöner 2006

Piaget's A not B paradigm: "out-of-sight -- out of mind"

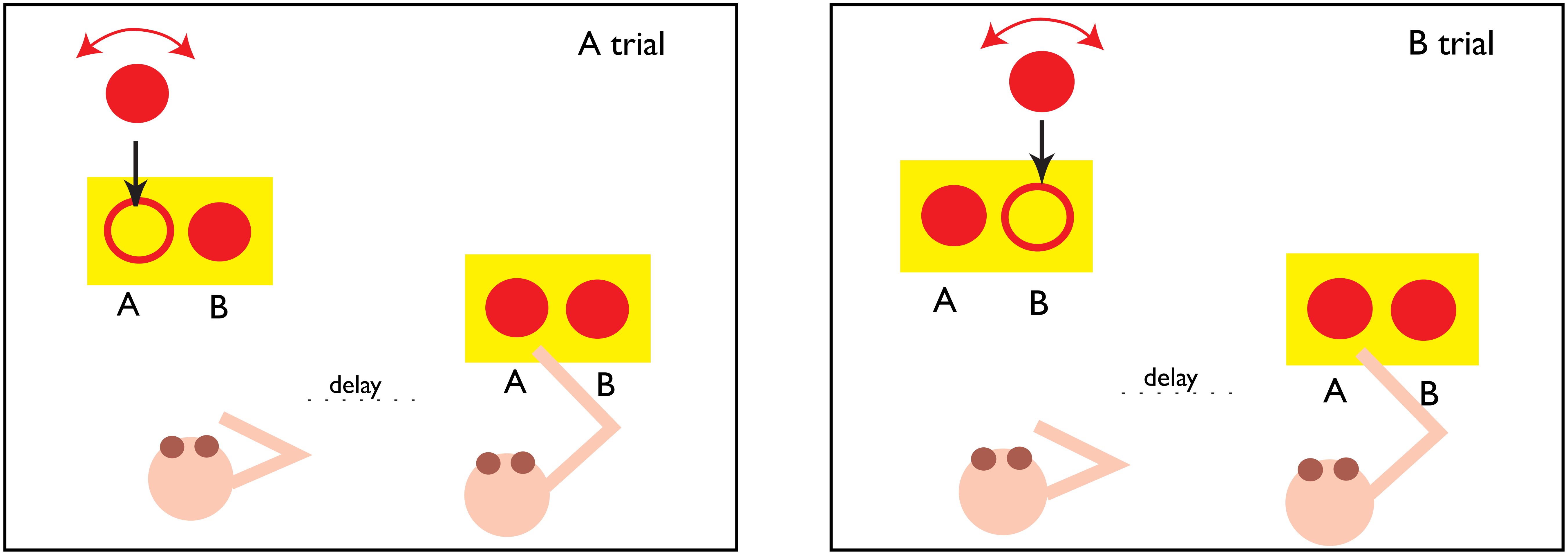




Toyless variant of A not B task

[Smith, Thelen et al.: Psychological Review (1999)]

Toyless variant of A not B task reveals that A not B is essentially a decision task!



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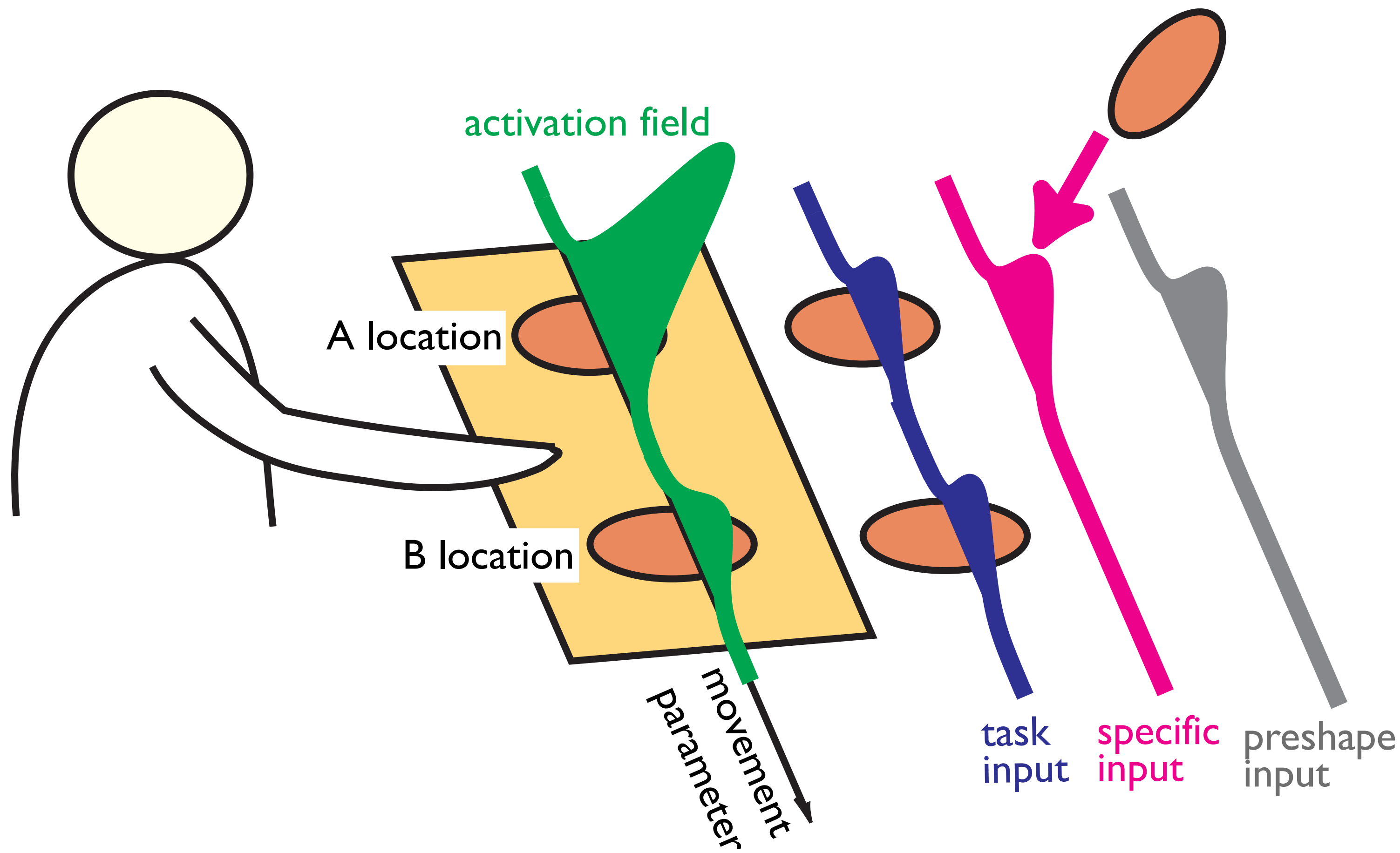
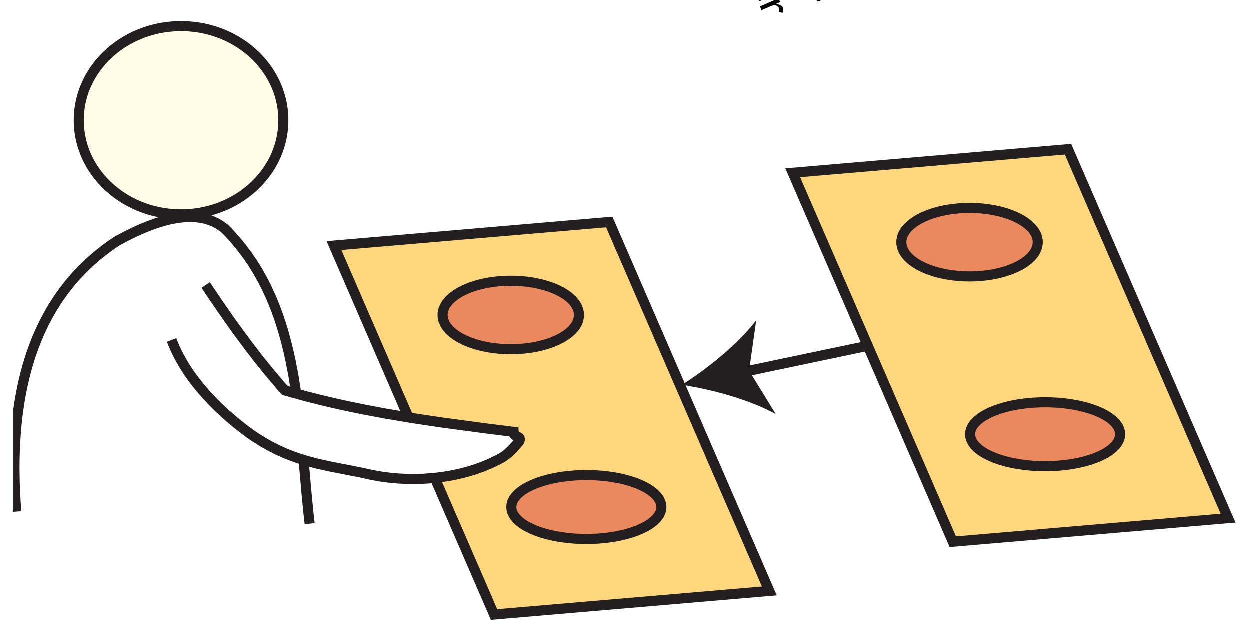


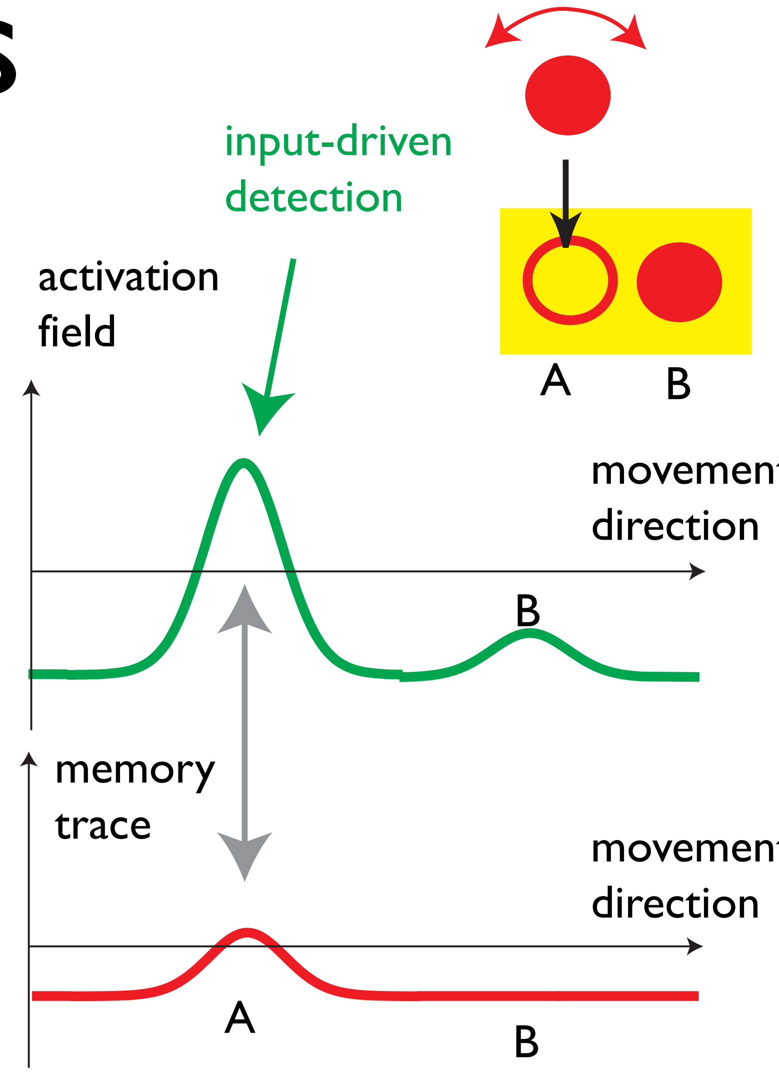
[Thelen, et al., BBS (2001)]



[Dinveva, Schöner, Dev. Science 2007]

Instabilities

- detection: forming and initiating a movement goal
- selection: making sensori-motor decisions
- (learning: memory trace)
- boost-driven detection: initiating the action
- memory instability: old infants sustain during the delay, young infants do not



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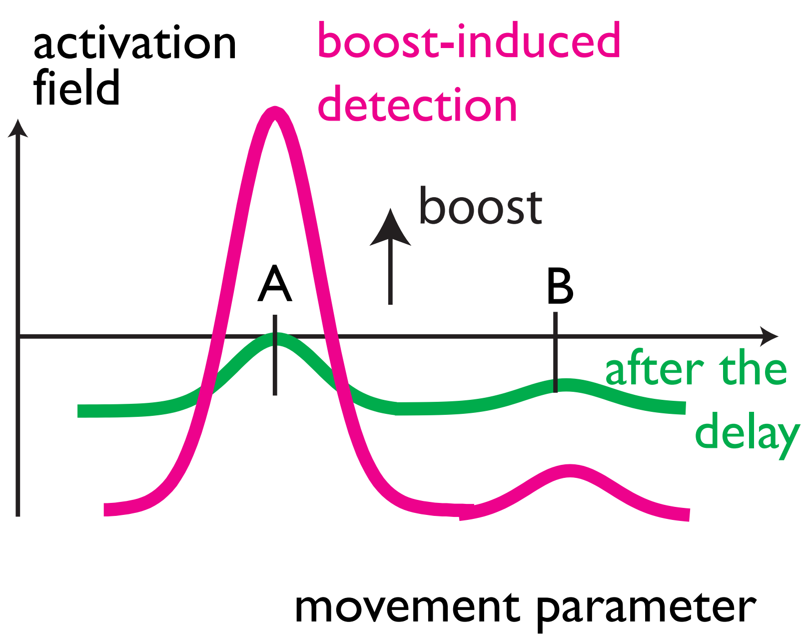

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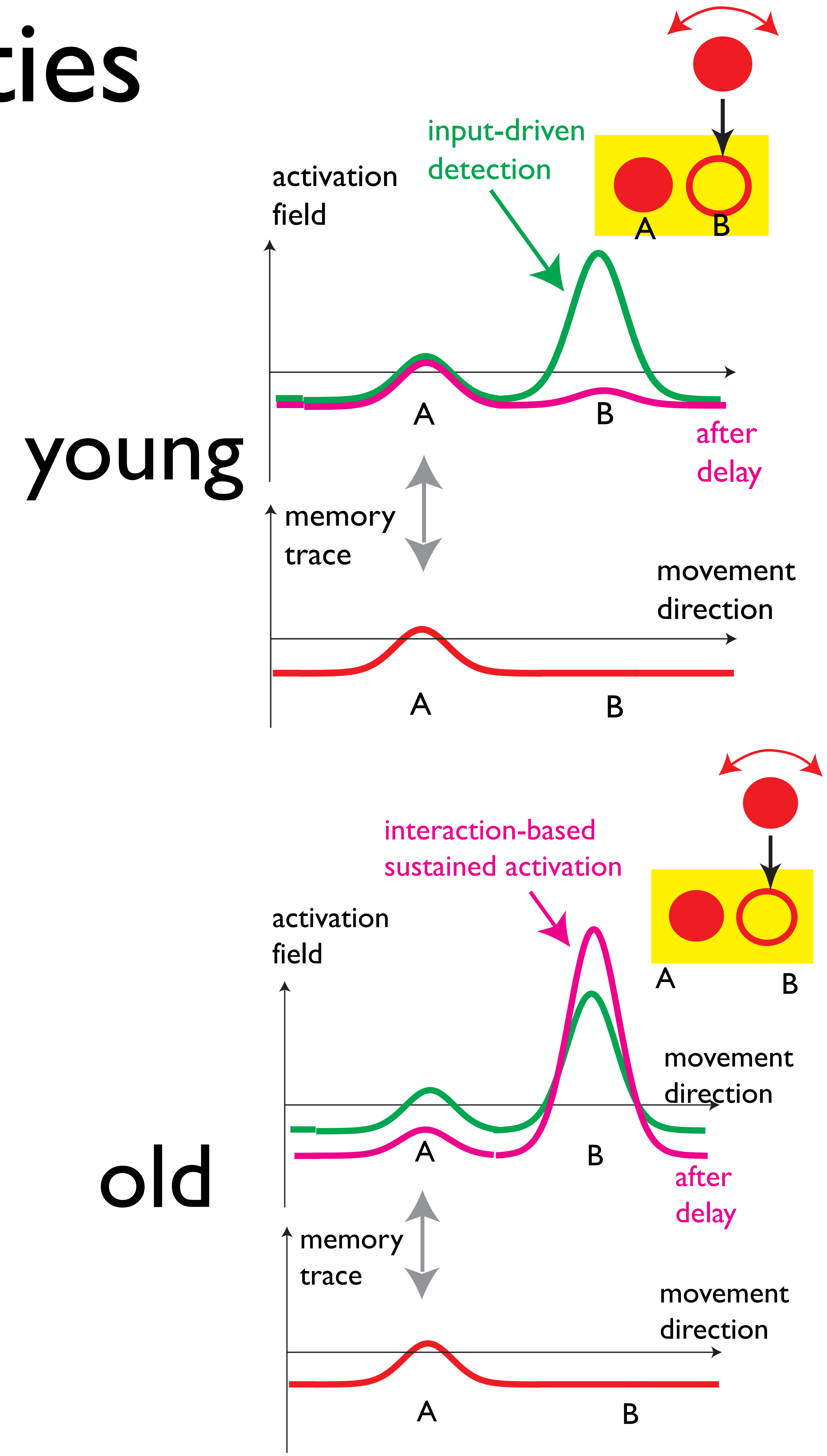
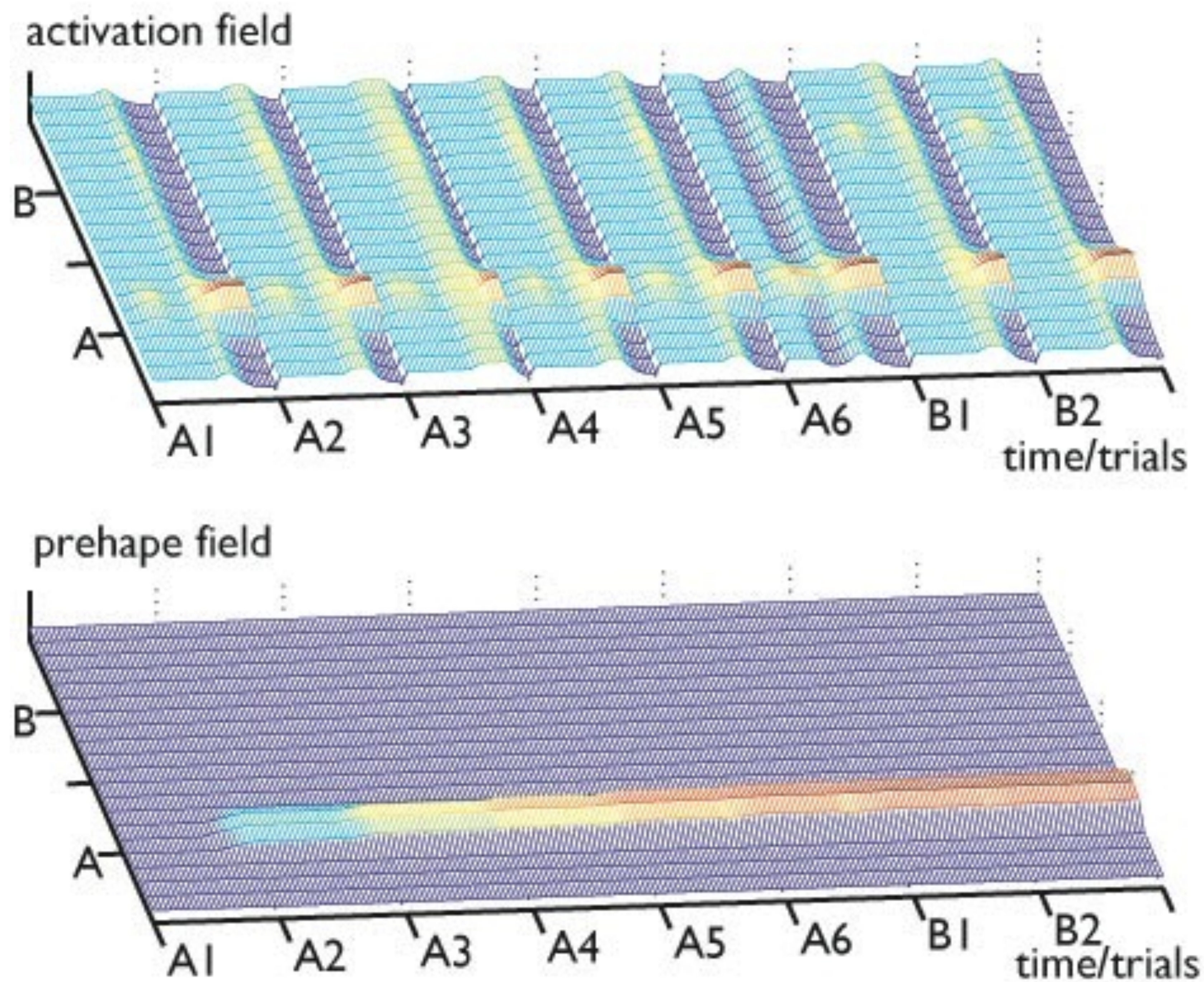


DFT of infant perseverative reaching



[Dinveva, Schöner, Dev. Science 2007]

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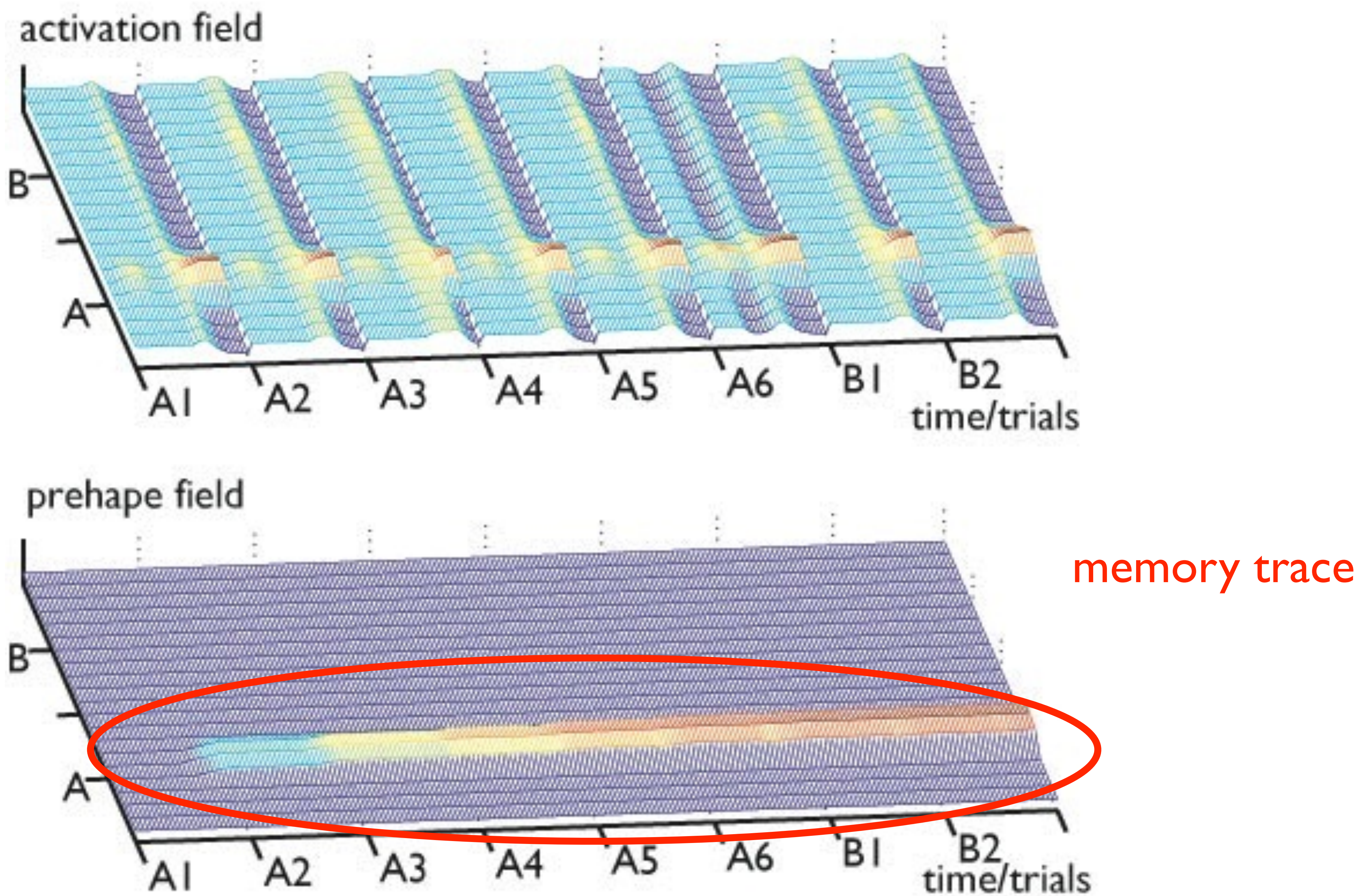

[Dinveva, Schöner, Dev. Science 2007]

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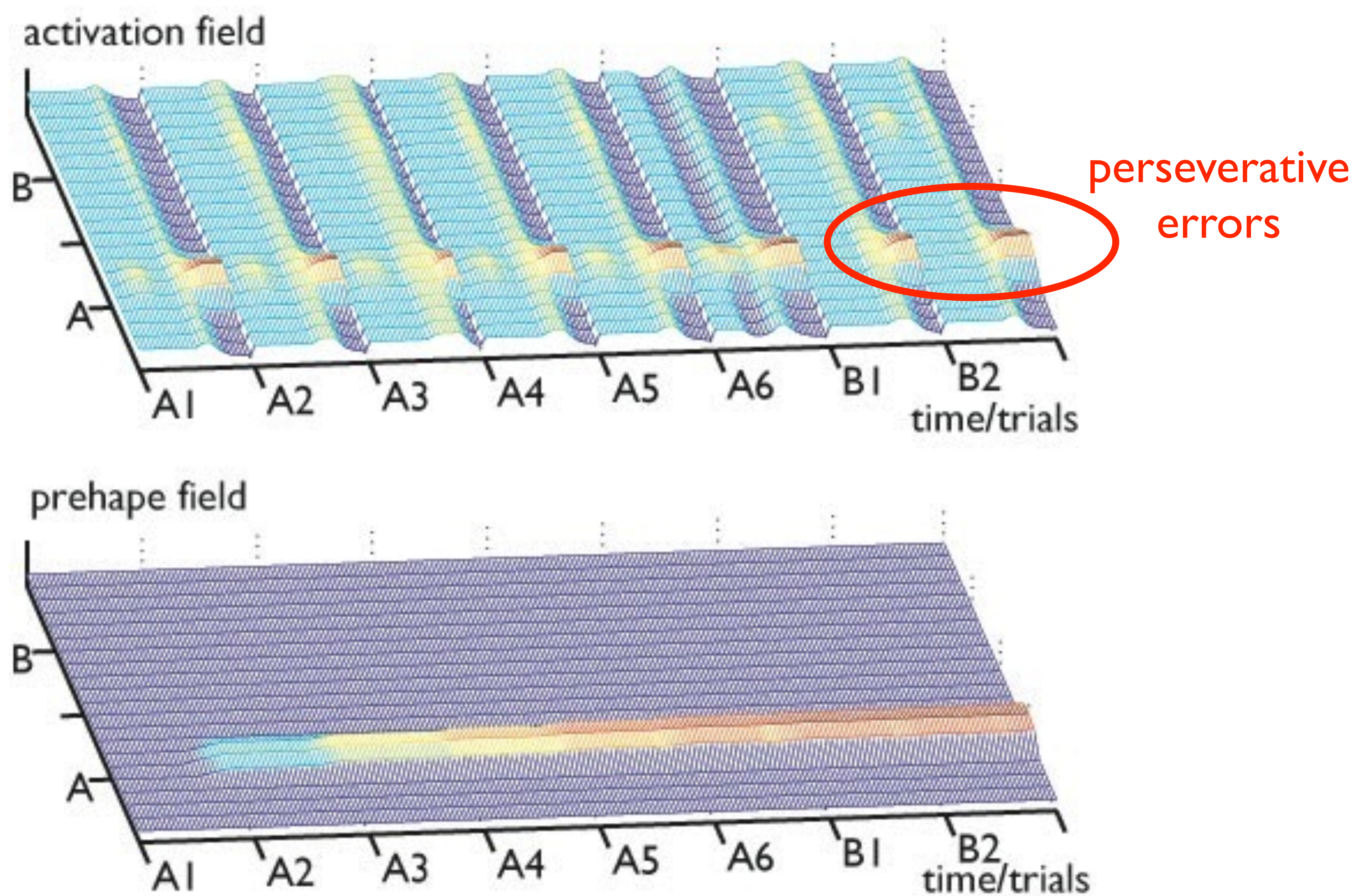
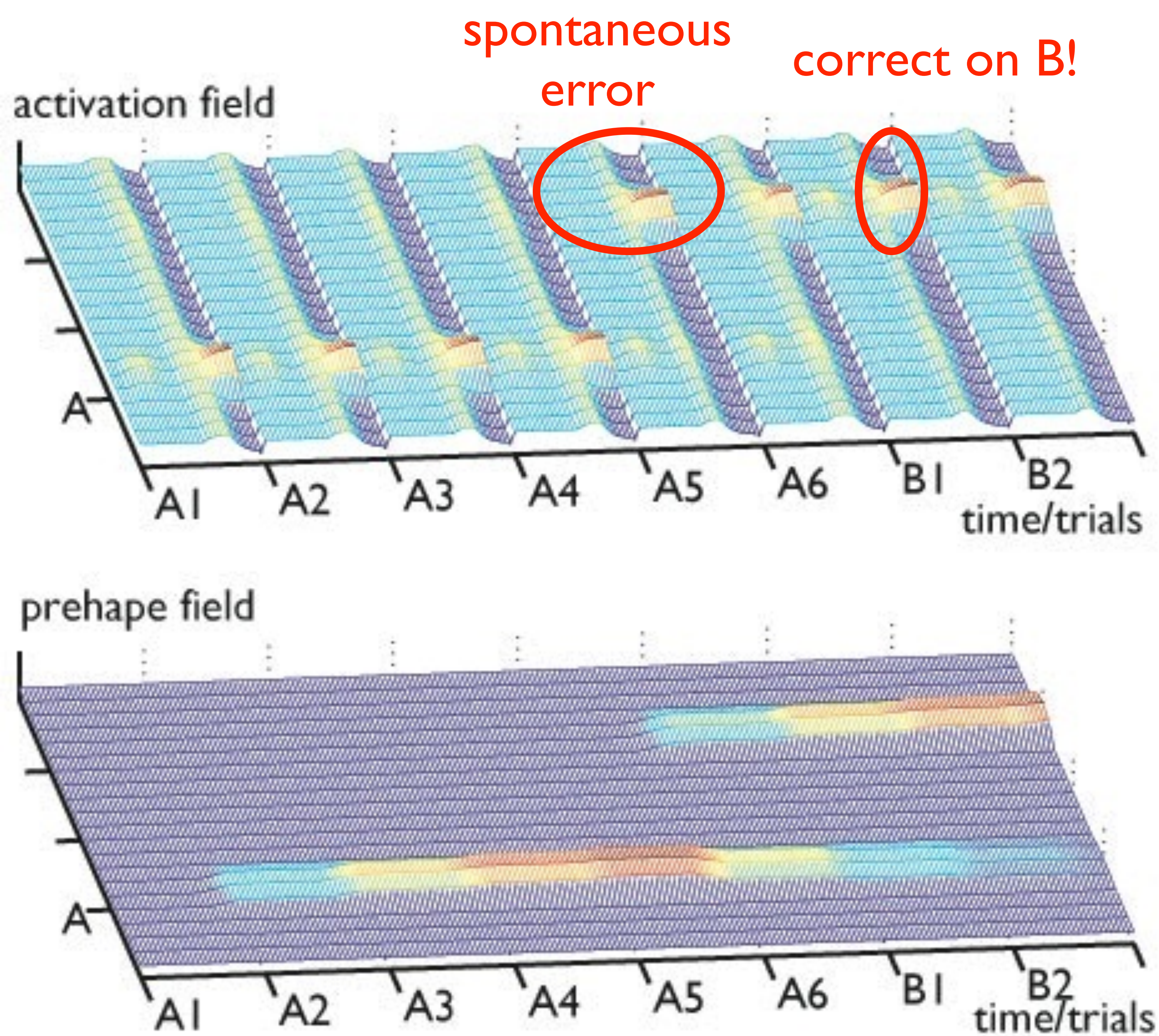


[Dinveva, Schöner, Dev. Science 2007]

DFT of infant perseverative reaching

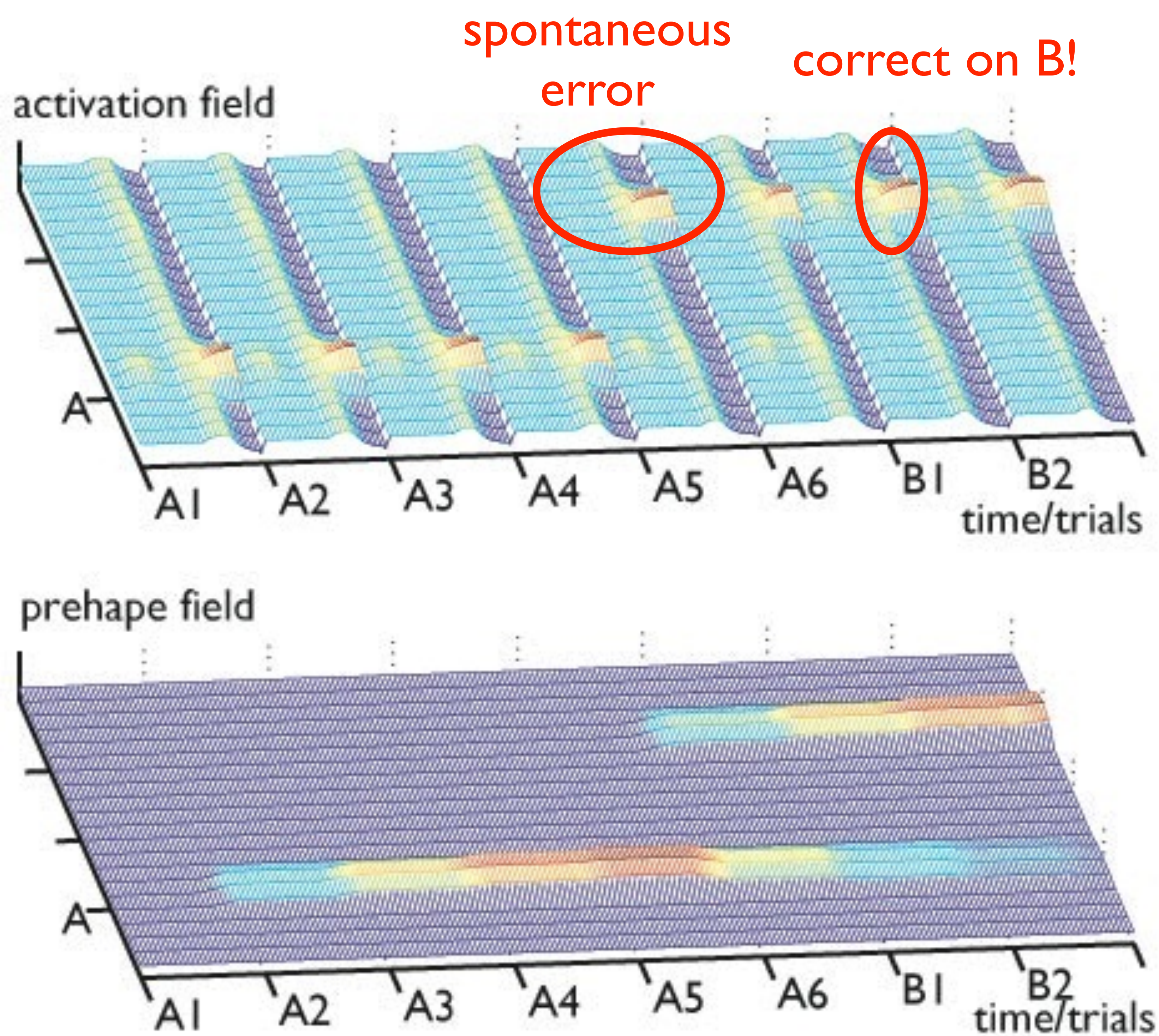
- in spotaneous errors, activation arises at B on an A trial
- which leads to correct reaching on B trial



[Dinveva, Schöner, Dev. Science 2007]

DFT of infant perseverative reaching

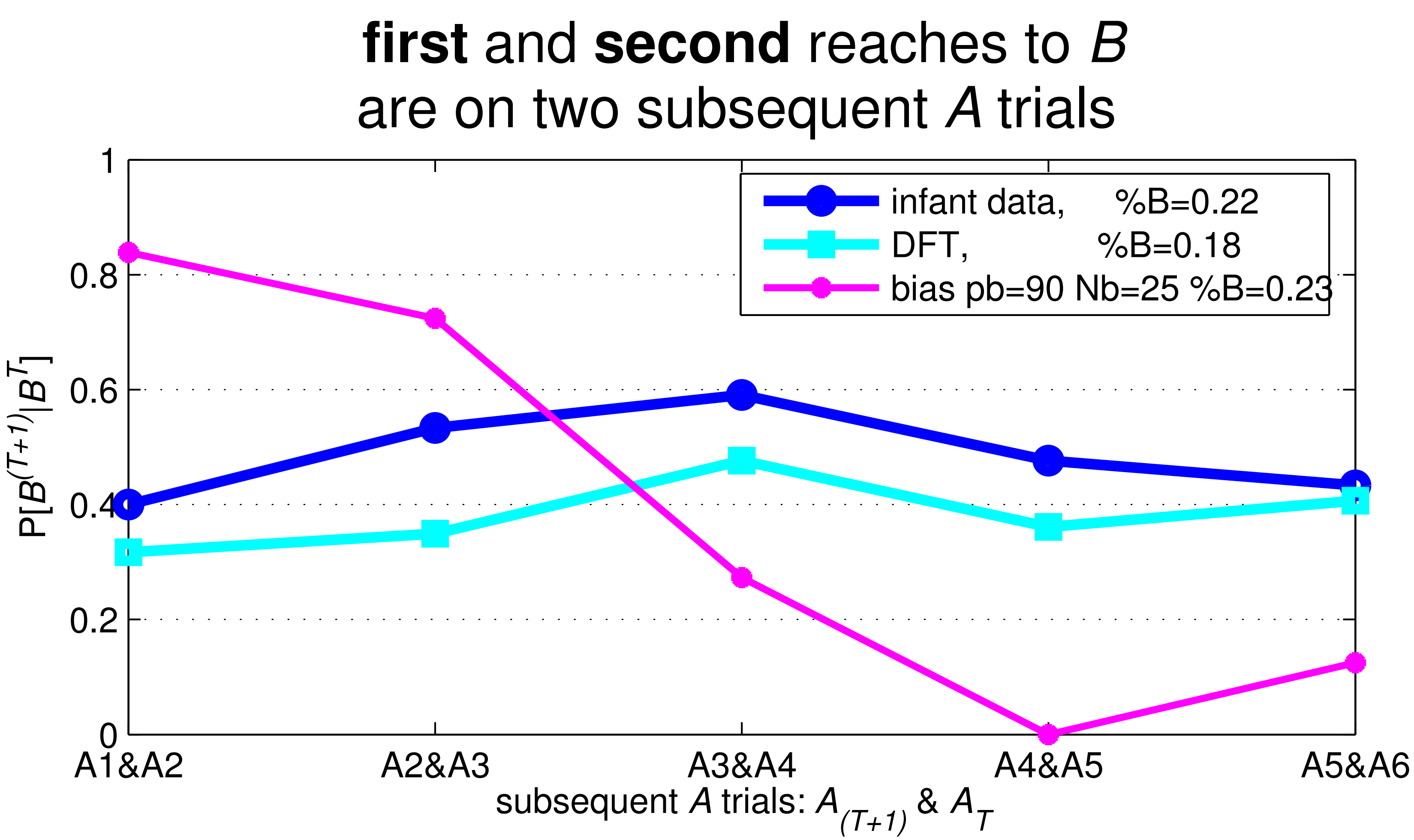
- that is because reaches to B on A trials leave memory trace at B



[Dinveva, Schöner, Dev. Science 2007]

DFT of infant perseverative reaching

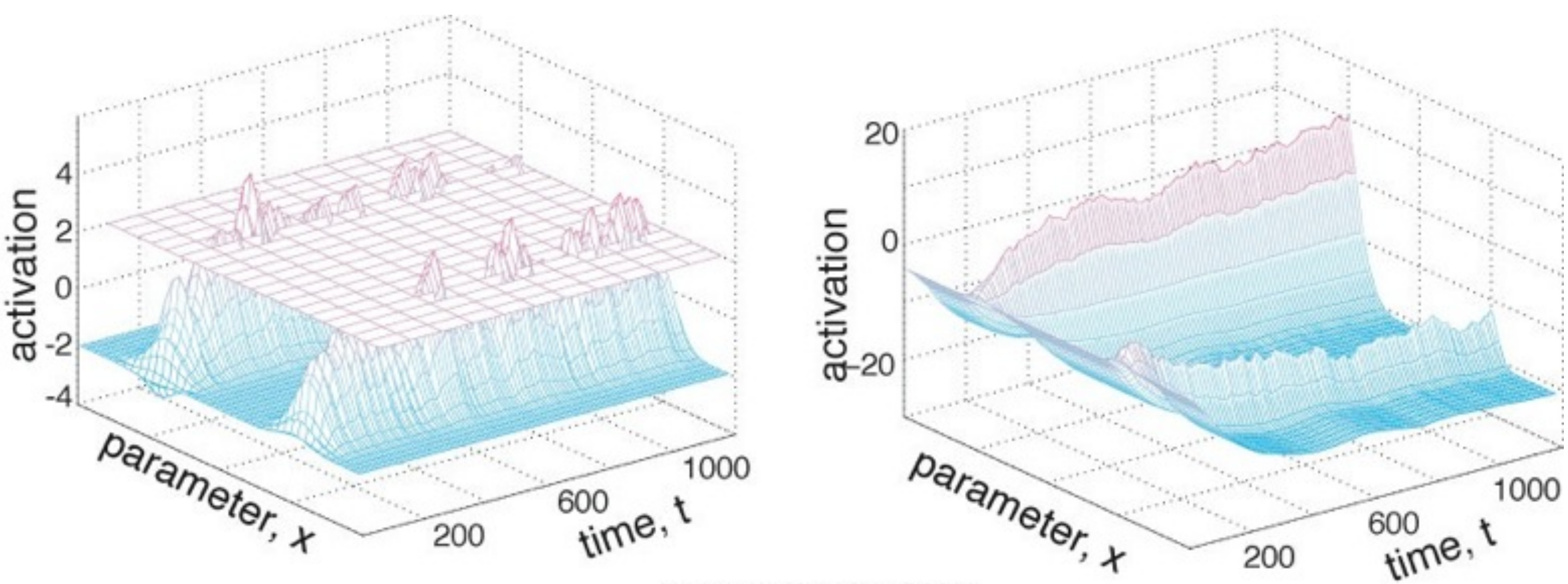
- spontaneous errors promote spontaneous errors



[Dinveva, Schöner, Dev. Science 2007]

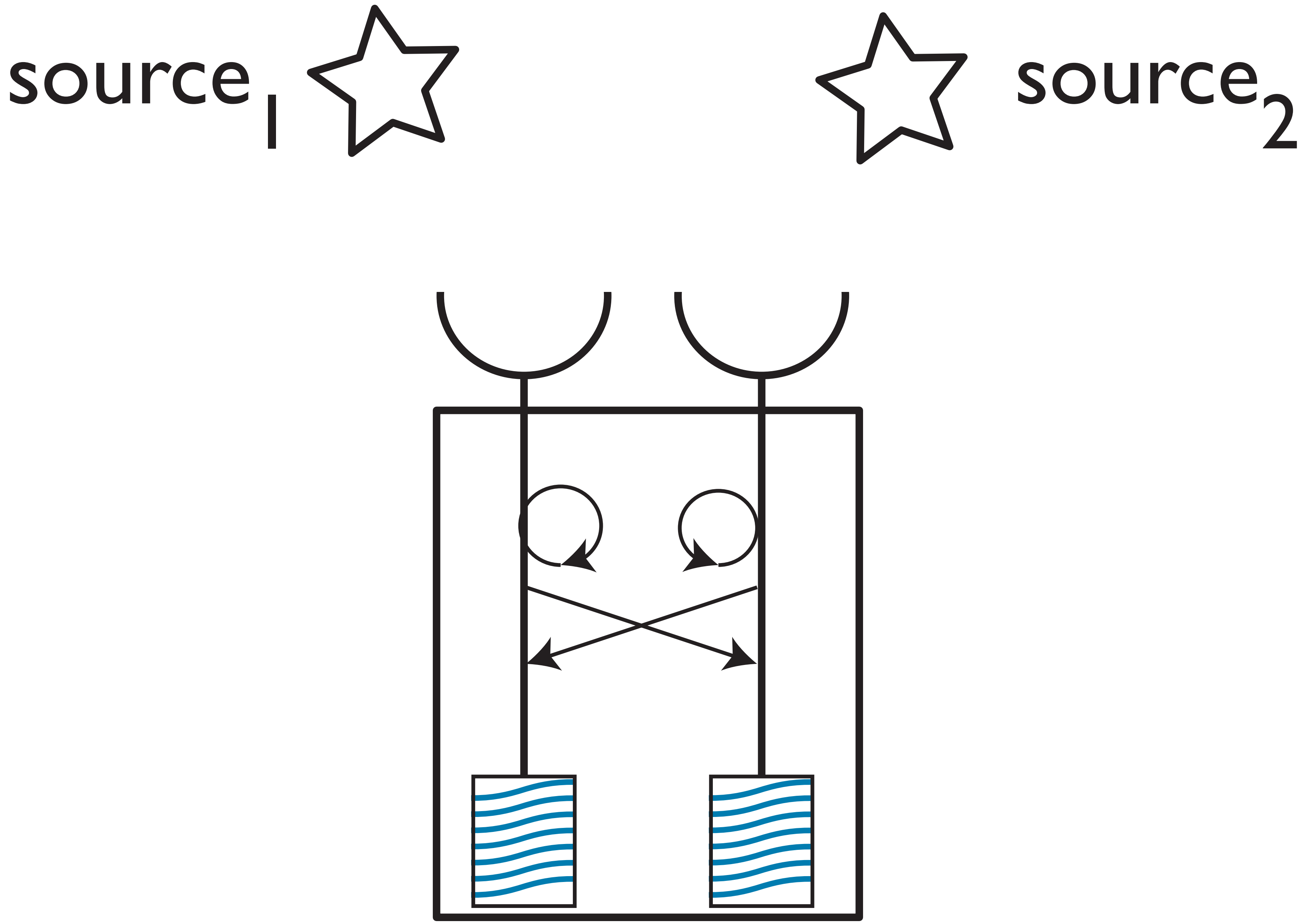
DFT is a neural process model

- that makes the decisions in each individual trial, by amplifying small differences into a macroscopic stable state
- and that's how decisions leave traces, have consequences



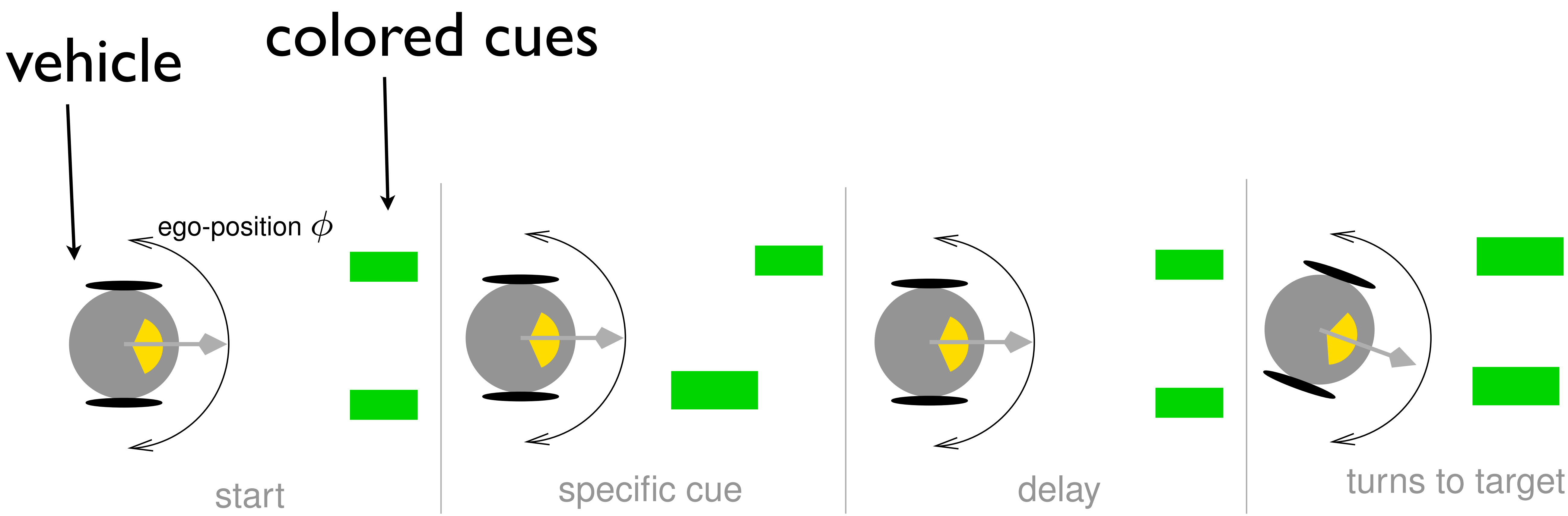
[Wilimzig, Schöner, 2006]

Combining neural and behavioral dynamics



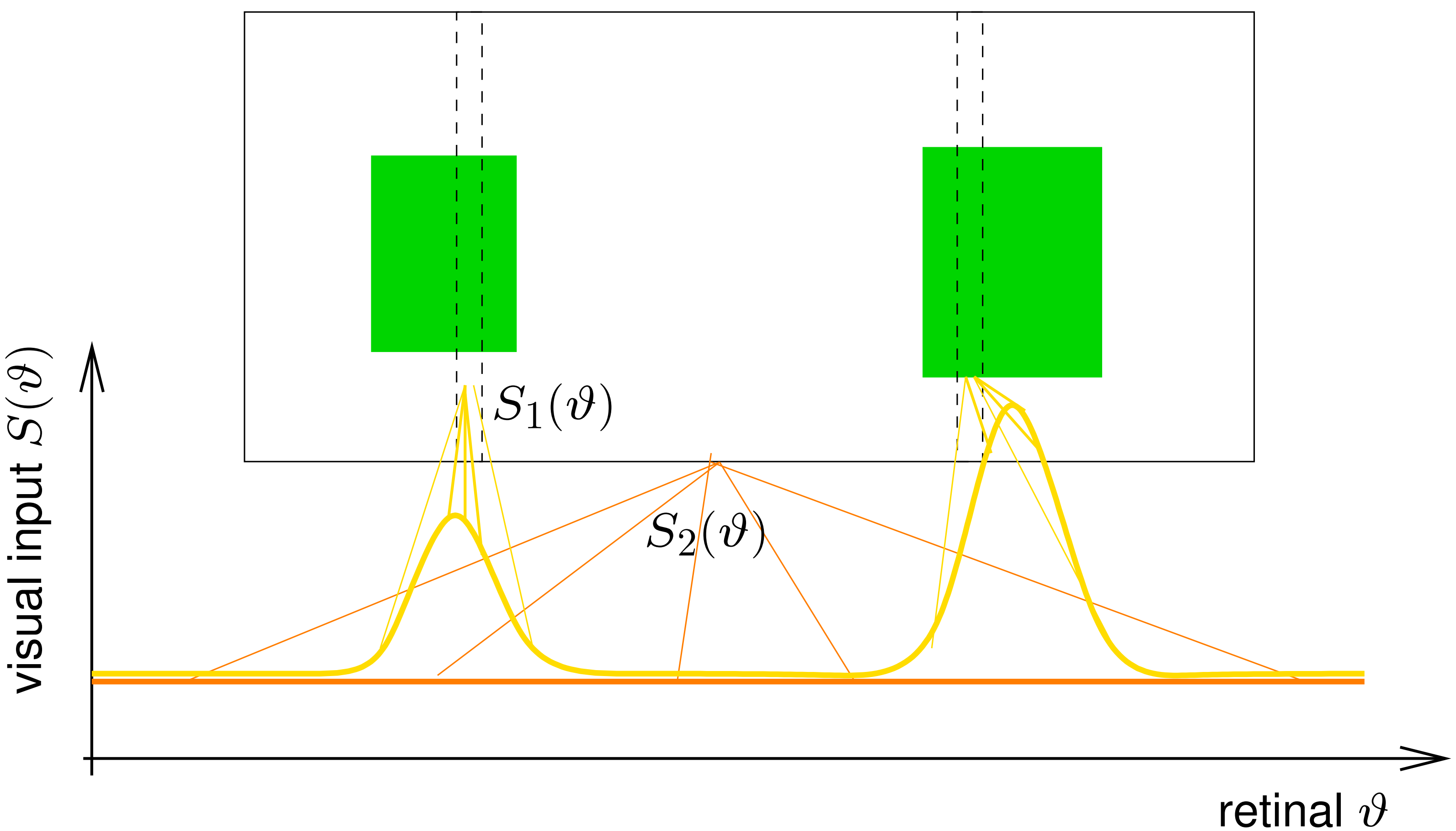
Embodied A not B

- implementing the A not B model on a autonomous robot with continuous link to sensory and motor surfaces...



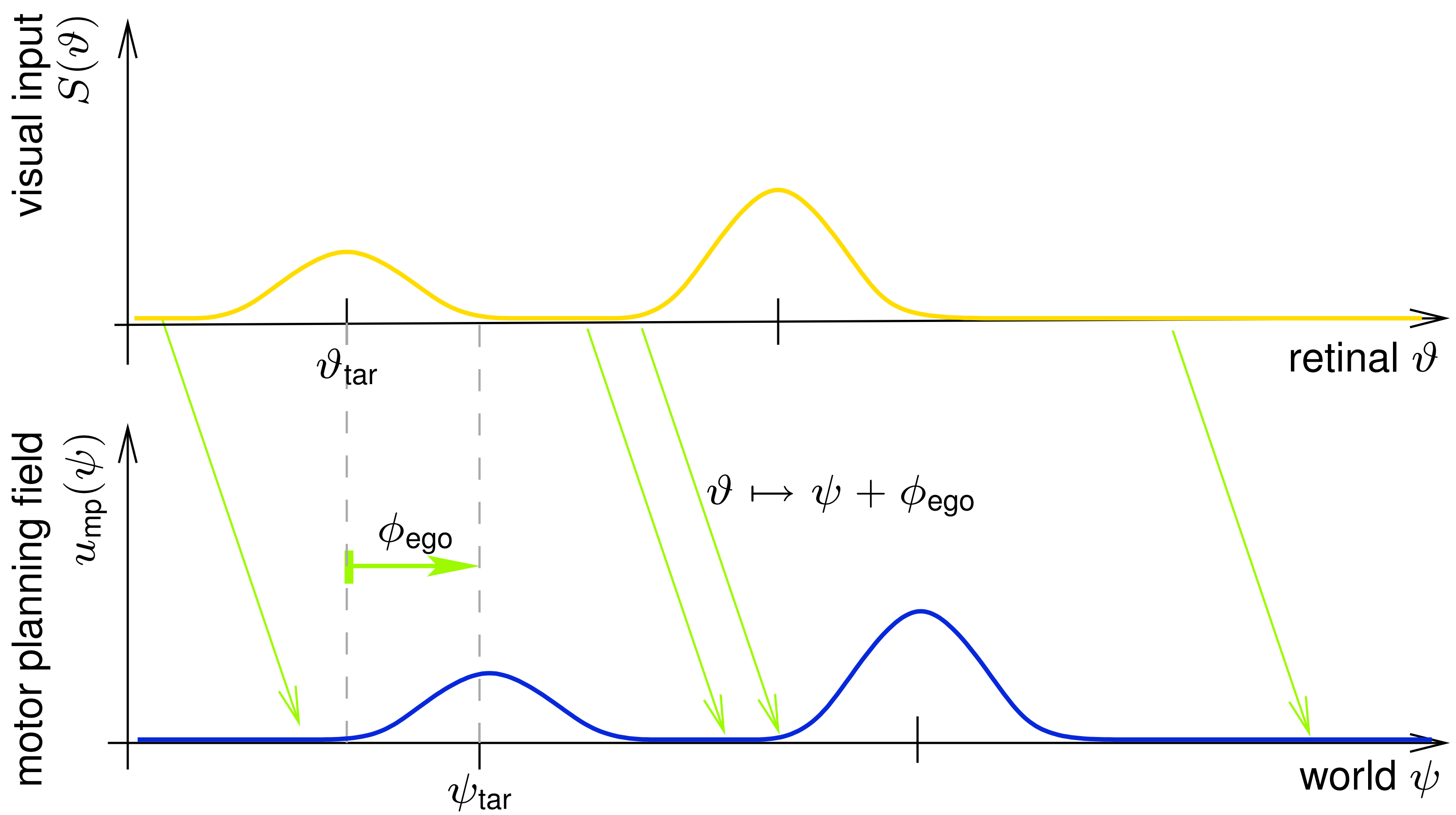
Visual input

- color-based segmentation
- summing color pixels within color slot along the vertical
- spatially filter at two resolutions



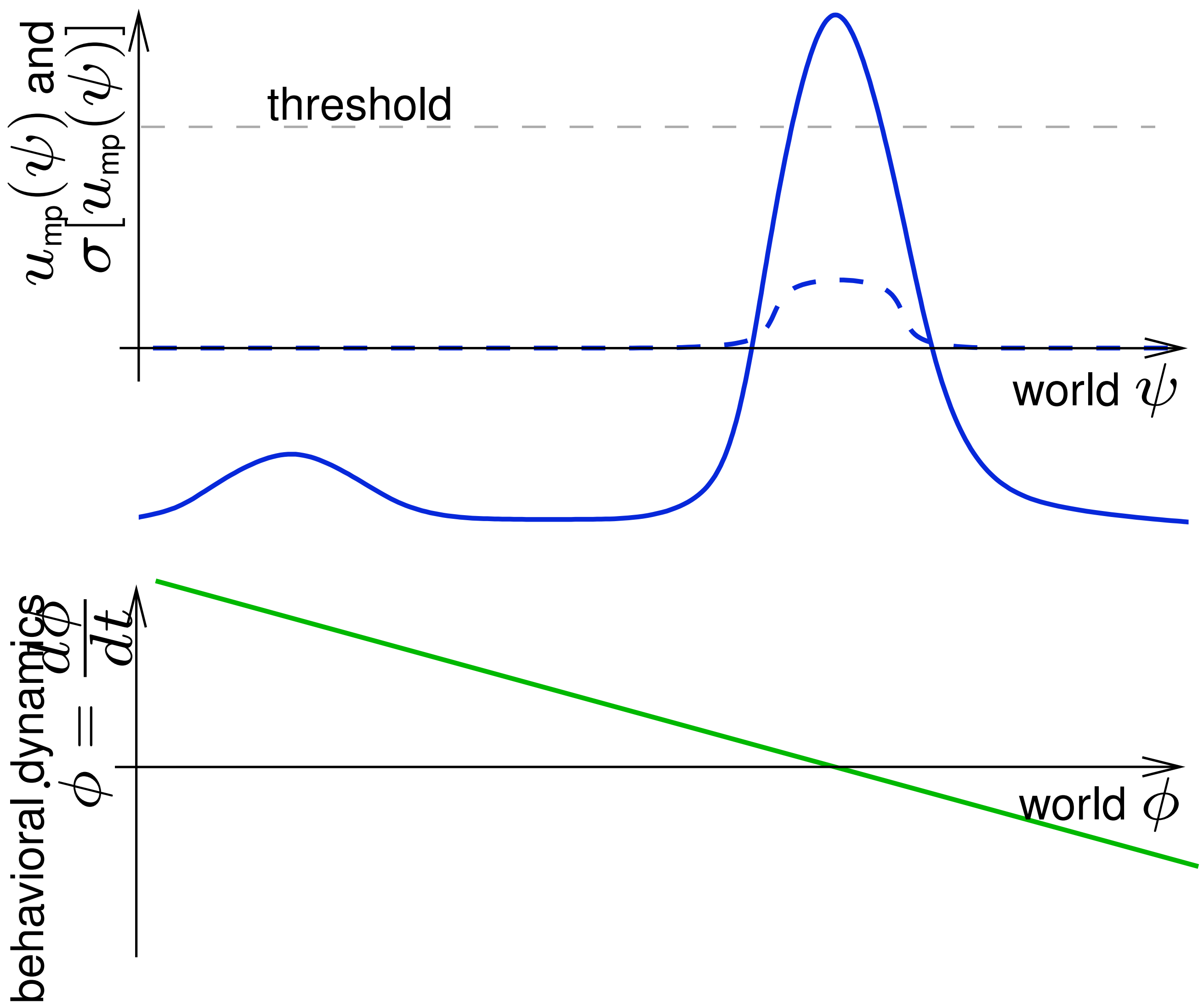
Dynamic field

- defined over direction in the world
- (requires coordinate transform from retina based on dead-reckoning)



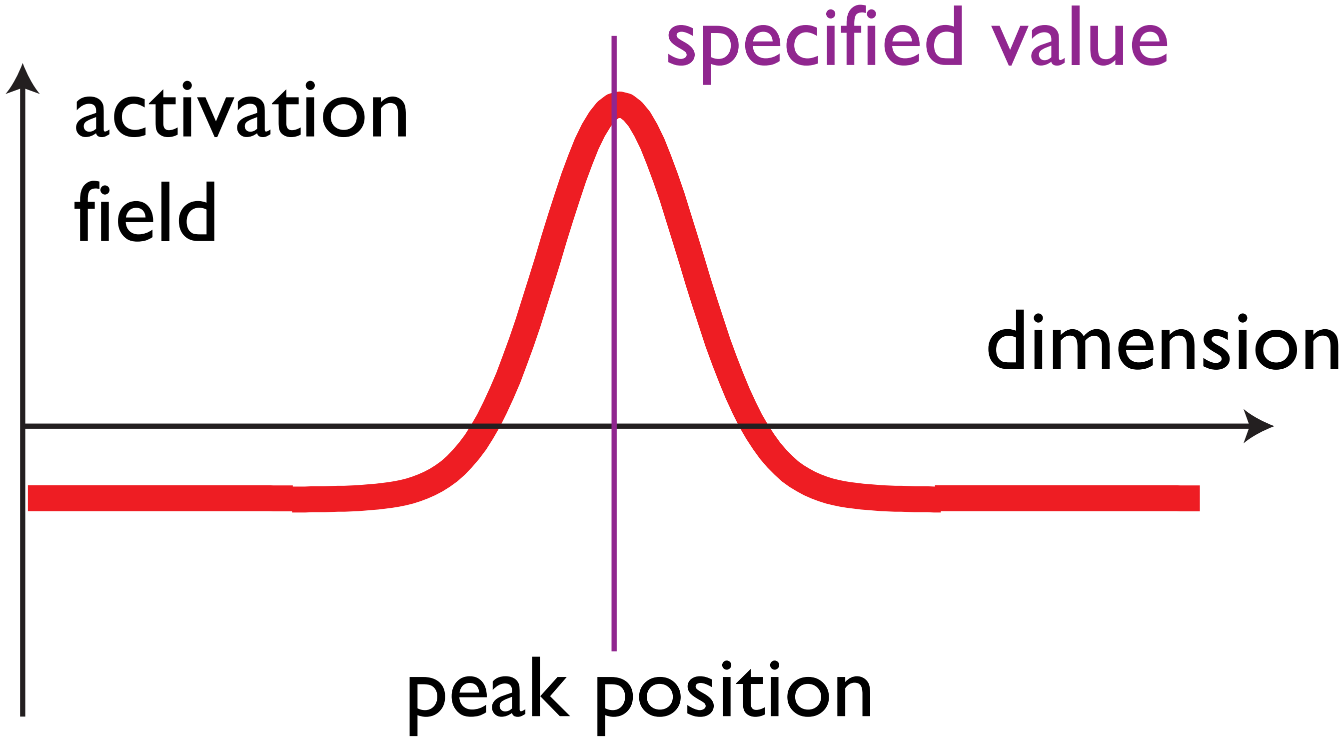
Motor dynamics

- couple peak in direction field into dynamics of heading direction as an attractor



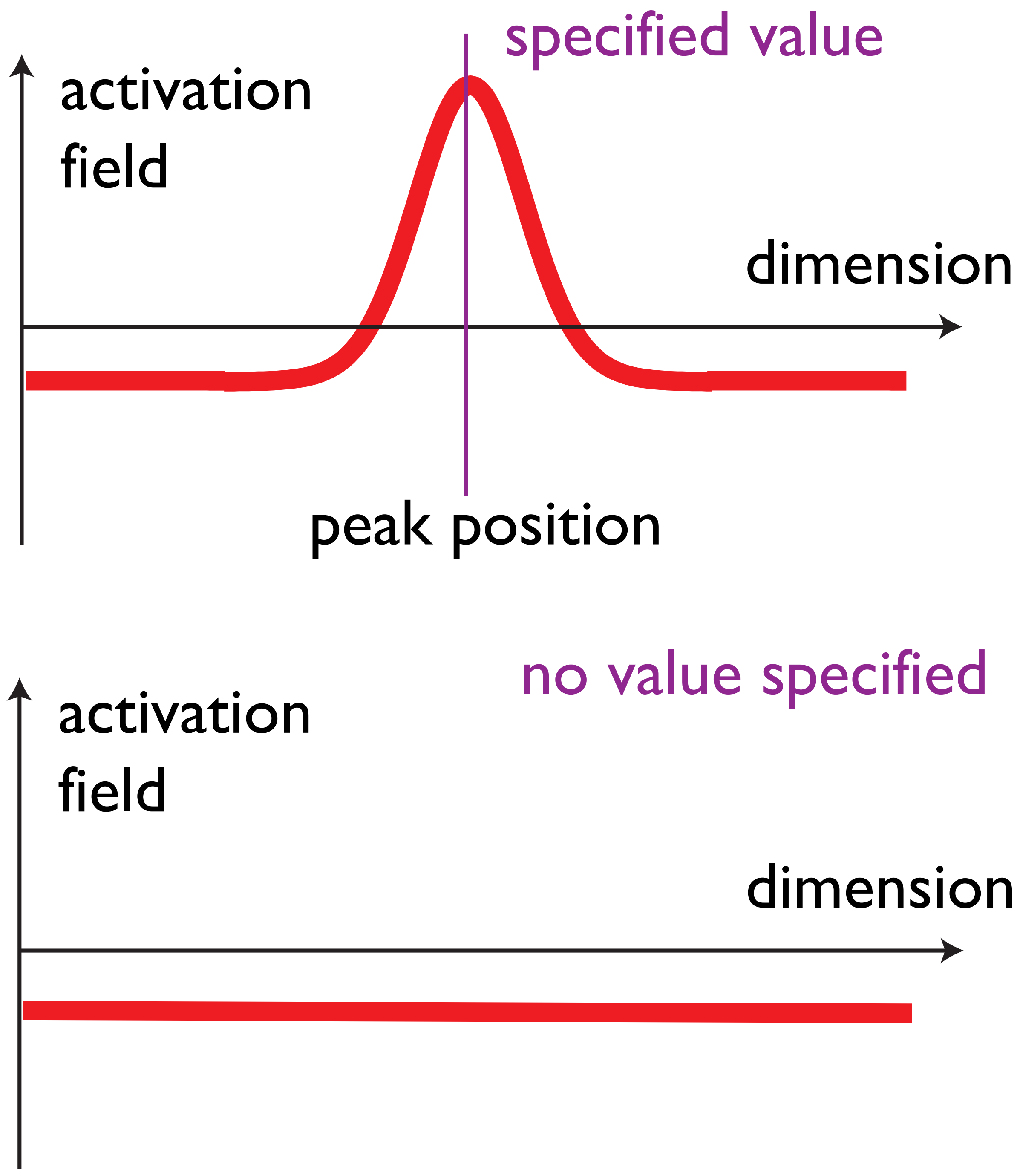
“Read-out” by generating attractor dynamics for motor system

- peak specifies value for a dynamical variable that is congruent to the field dimension



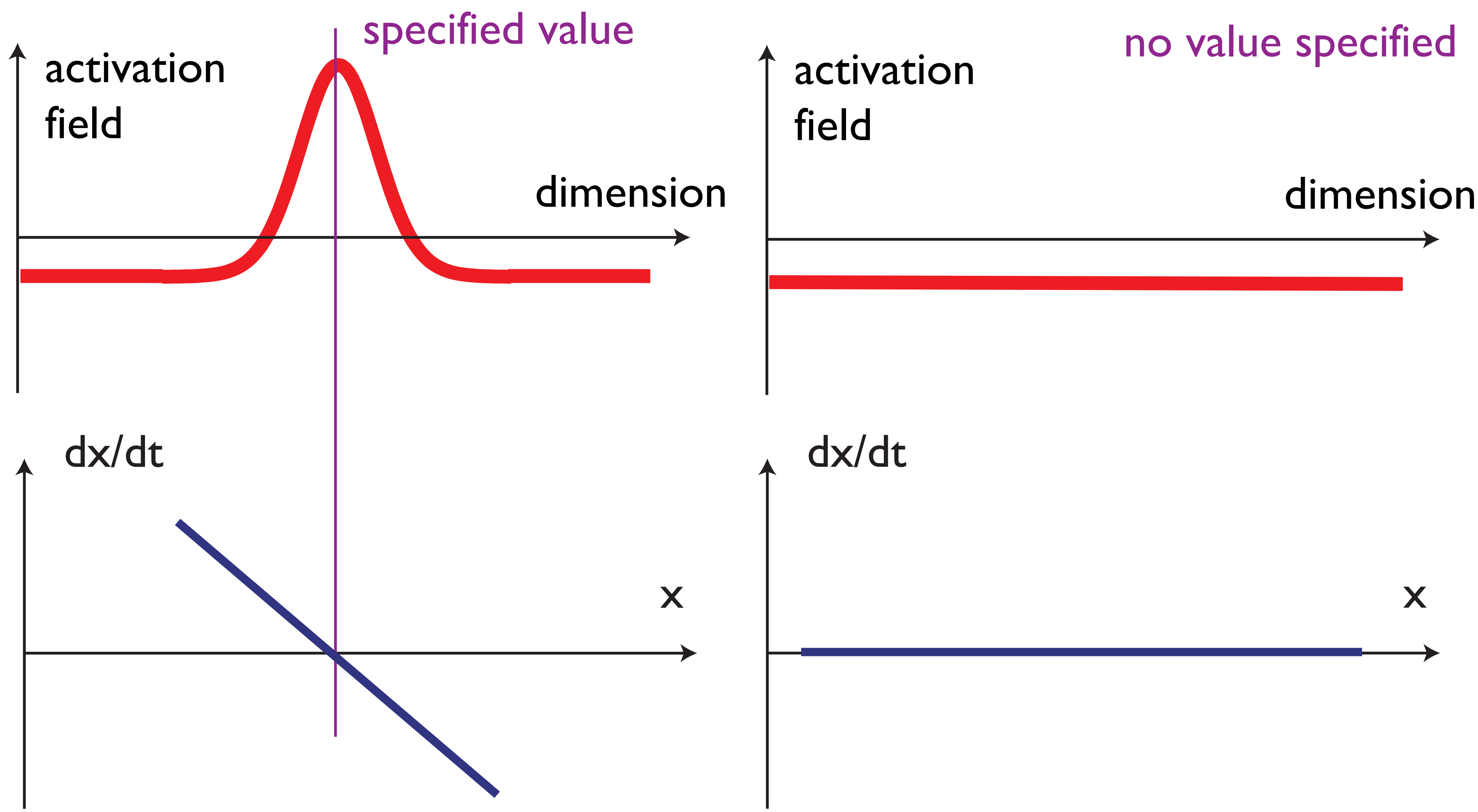
- treating sigmoided field as probability: need to normalize
    - => problem when there is no peak: devide by zero!

$$x_{\text{peak}} = \frac{\int dx' \ \sigma(u(x',t))x'}{\int dx' \ \sigma(u(x',t))}$$



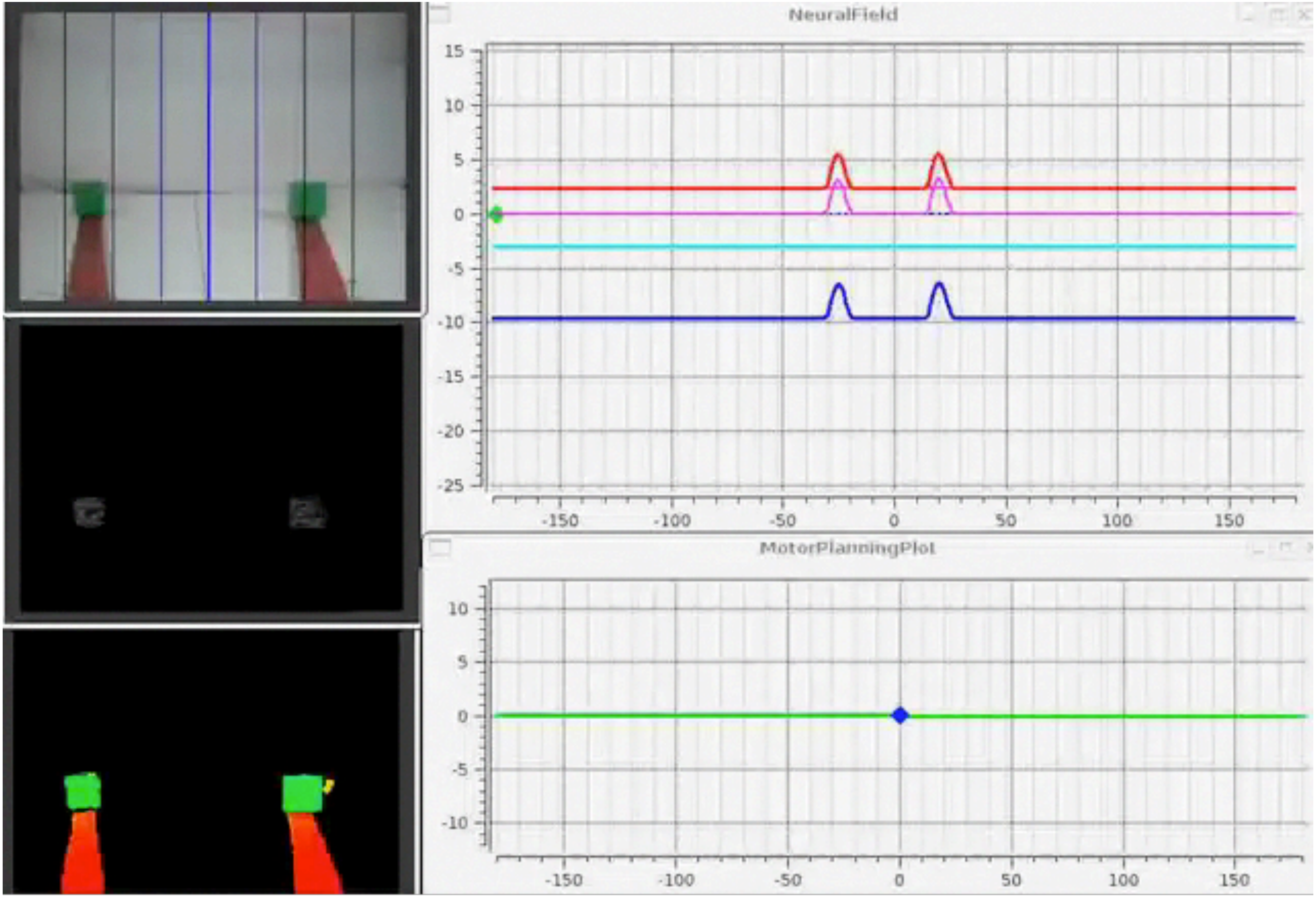
instead:

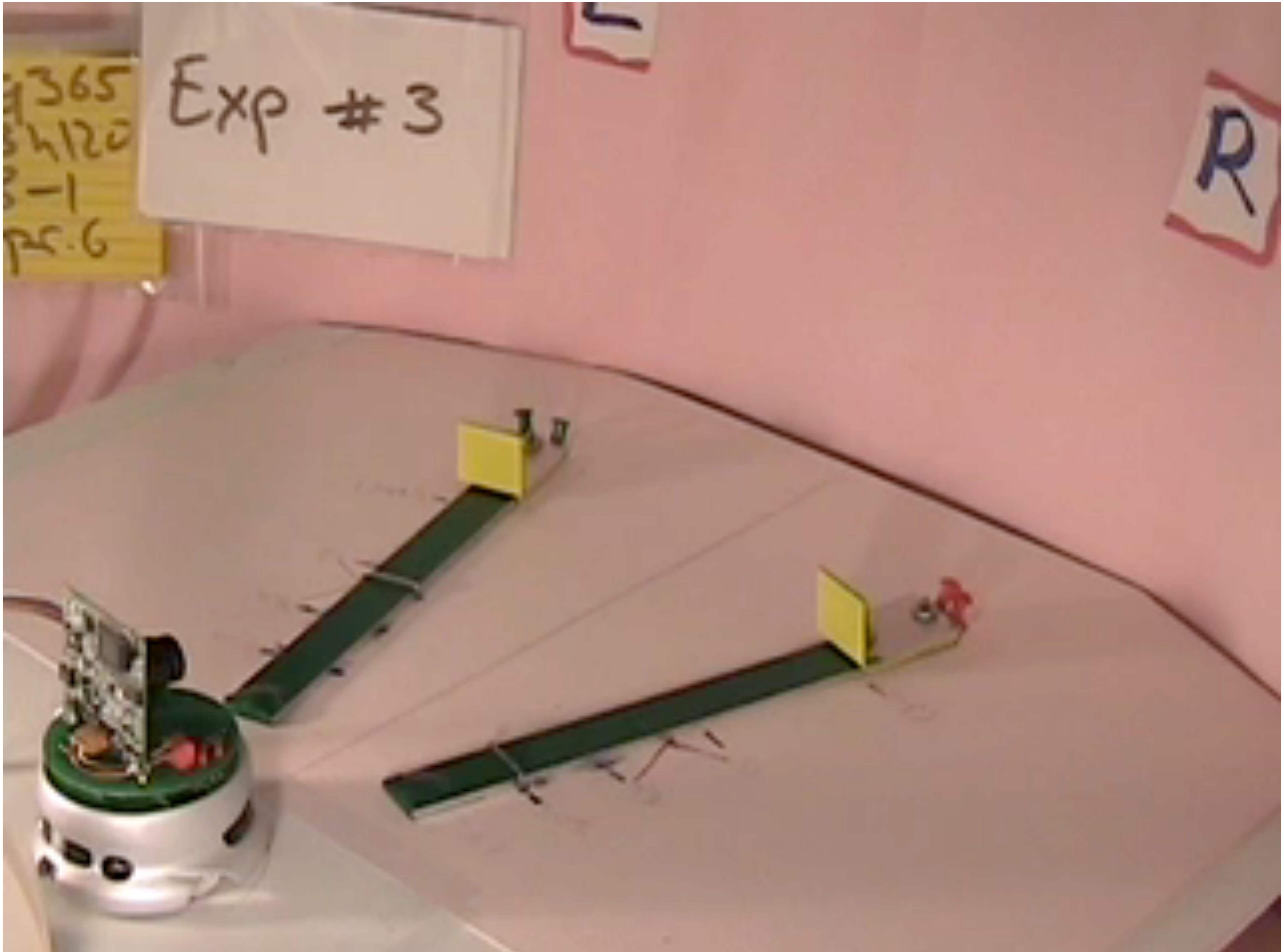
- create attractor



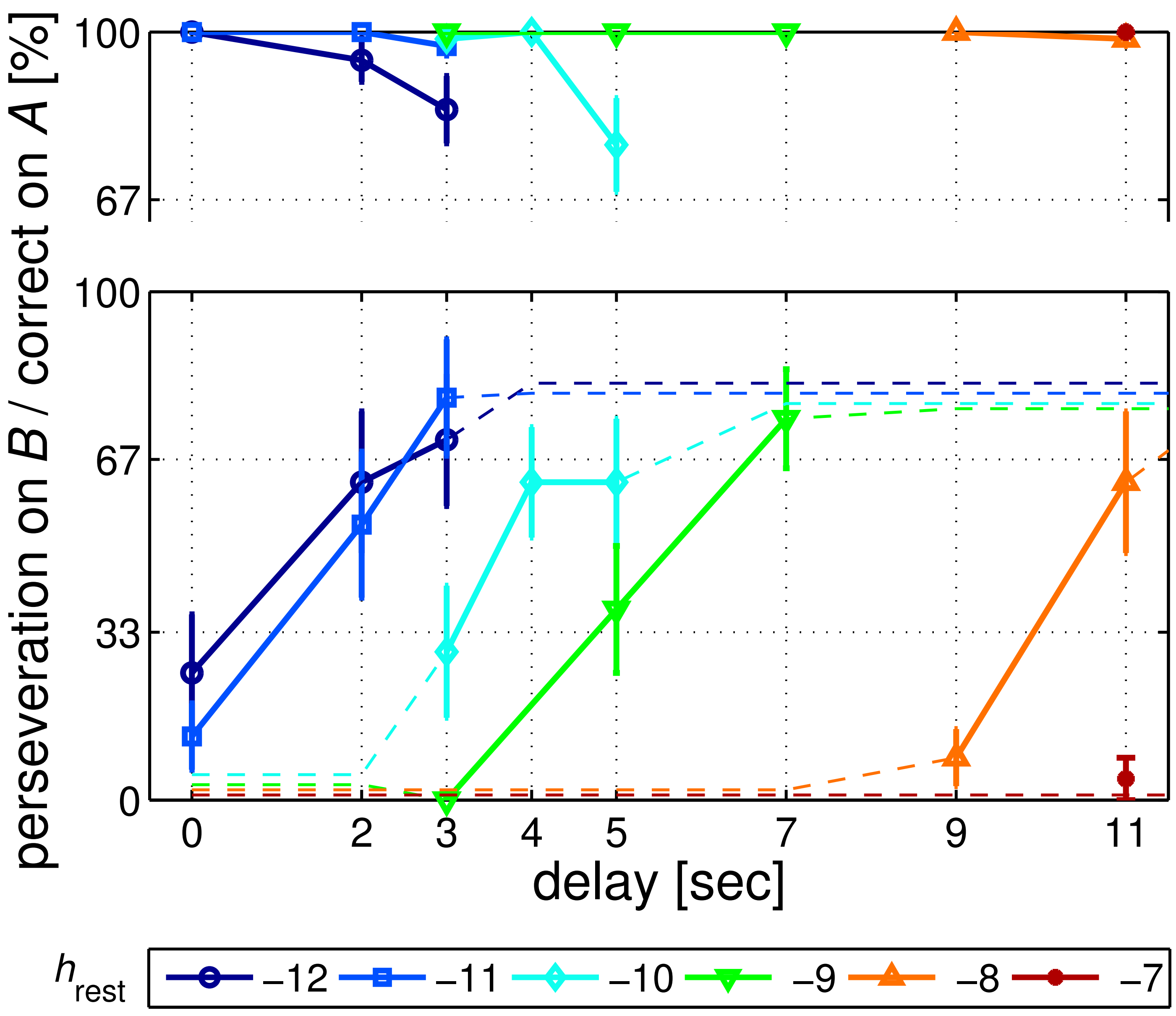
- solution: peak sets attractor
  - location of attractor: peak location
  - strength of attractor: summed supra-threshold activation

$$
\begin{aligned}
x_{\text{peak}} &= \frac{\int dx' \; \sigma(u(x',t))x'}{\int dx' \; \sigma(u(x',t))} \\
\dot{x} &= -\int dx' \; \sigma(u(x',t))\,(x - x_{\text{peak}}) \\
&= -\left[\int dx' \; \sigma(u(x',t)) \; x - \int dx' \; \sigma(u(x',t)) \; x_{\text{peak}}\right] \\
&= -\left[\int dx' \; \sigma(u(x',t)) \; x - \int dx' \; \sigma(u(x',t)) \; x'\right] \\
&= -\int dx' \; \sigma(u(x',t))\,(x - x')
\end{aligned}
$$


NeuralField
MotorPlanningPlot

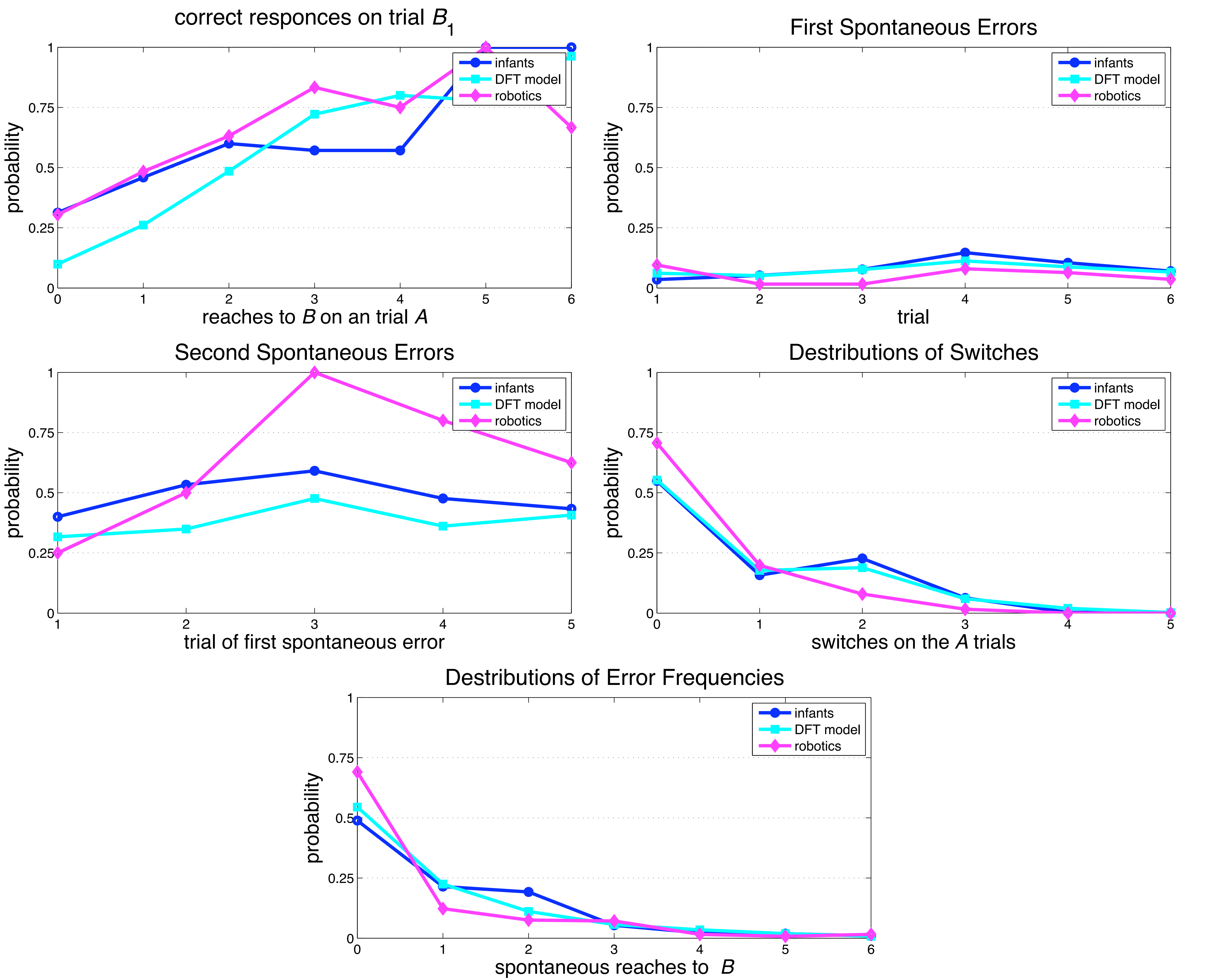

Exp #3
R

result: reproduce fundamental age-delay trade-off in A not B



young

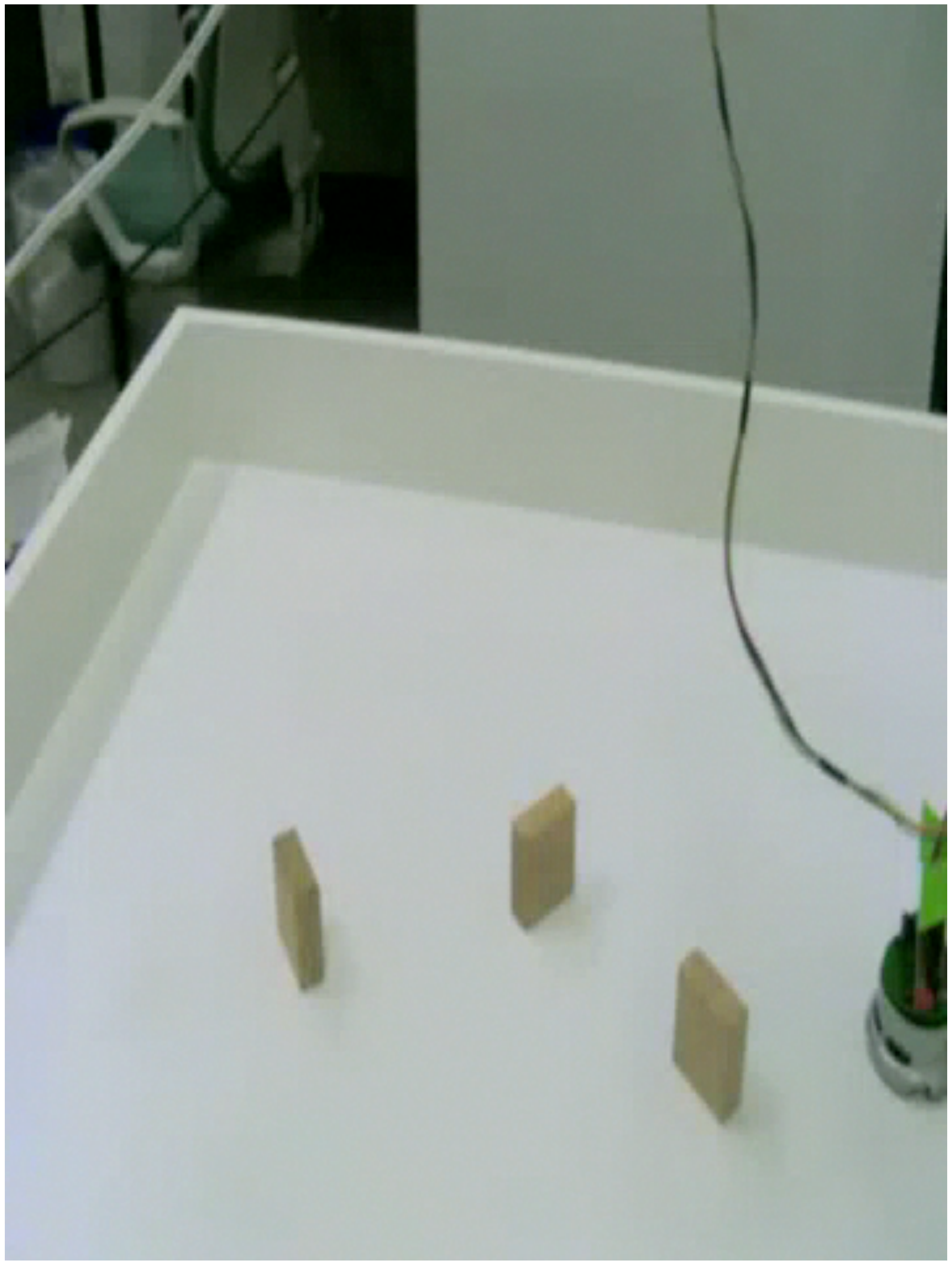
old



correct responces on trial B_1
probability
reaches to B on an trial A
infants
DFT model
robotics
First Spontaneous Errors
probability
trial
infants
DFT model
robotics
Second Spontaneous Errors
probability
trial of first spontaneous error
infants
DFT model
robotics
Destributions of Switches
probability
switches on the A trials
infants
DFT model
robotics
Destributions of Error Frequencies
probability
spontaneous reaches to B
infants
DFT model
robotics

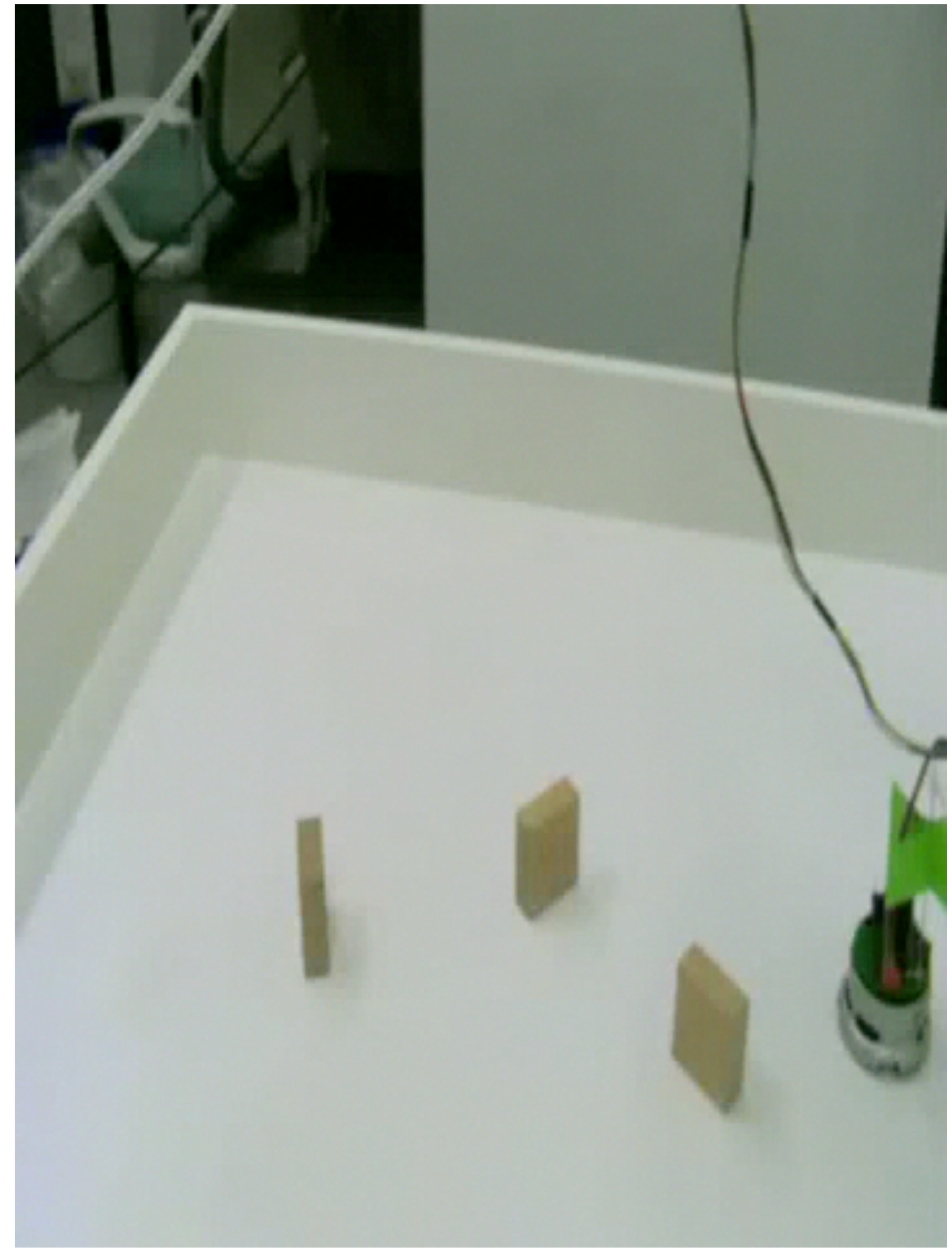
“young” robot

target



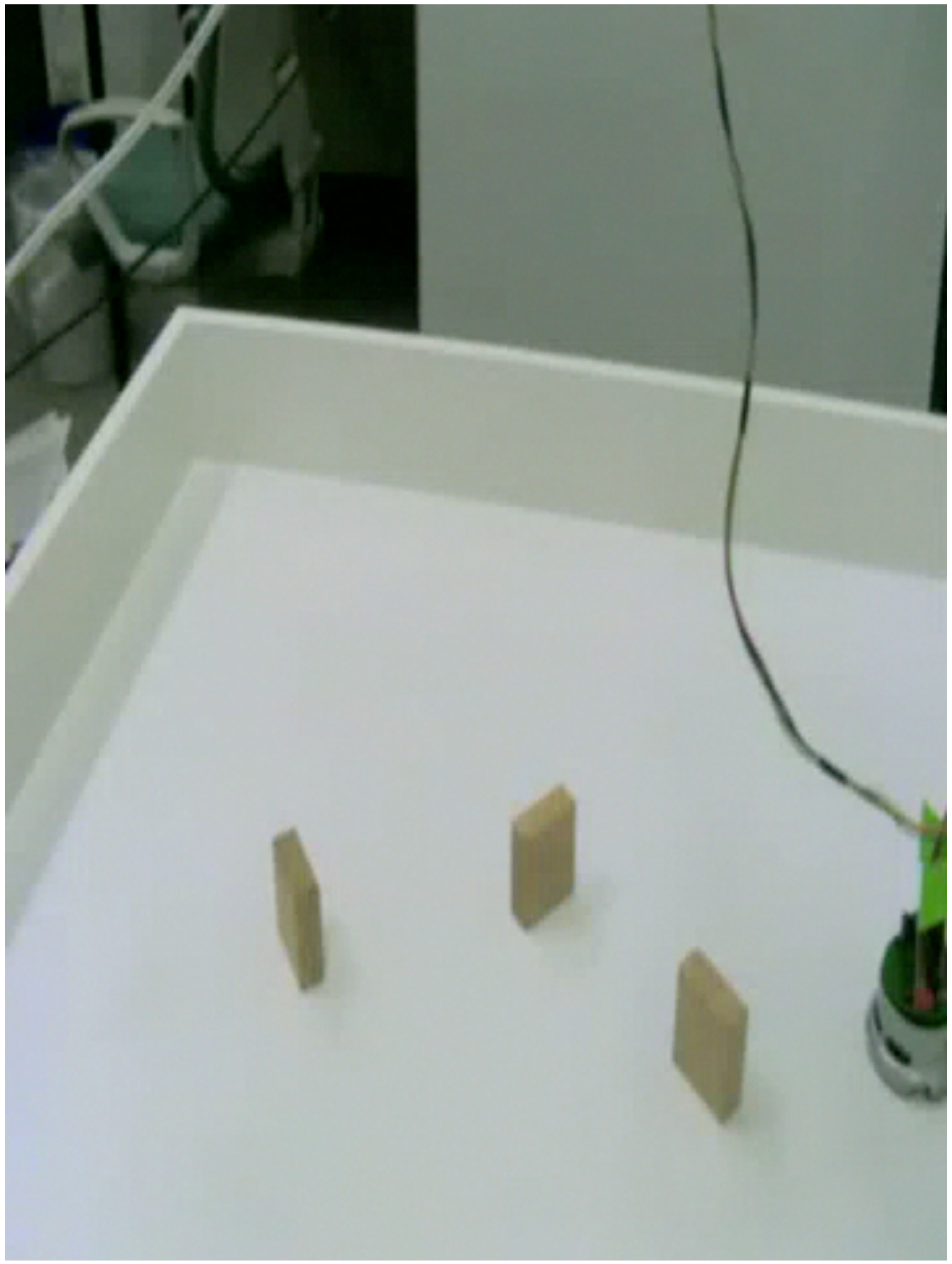
“old” robot

target



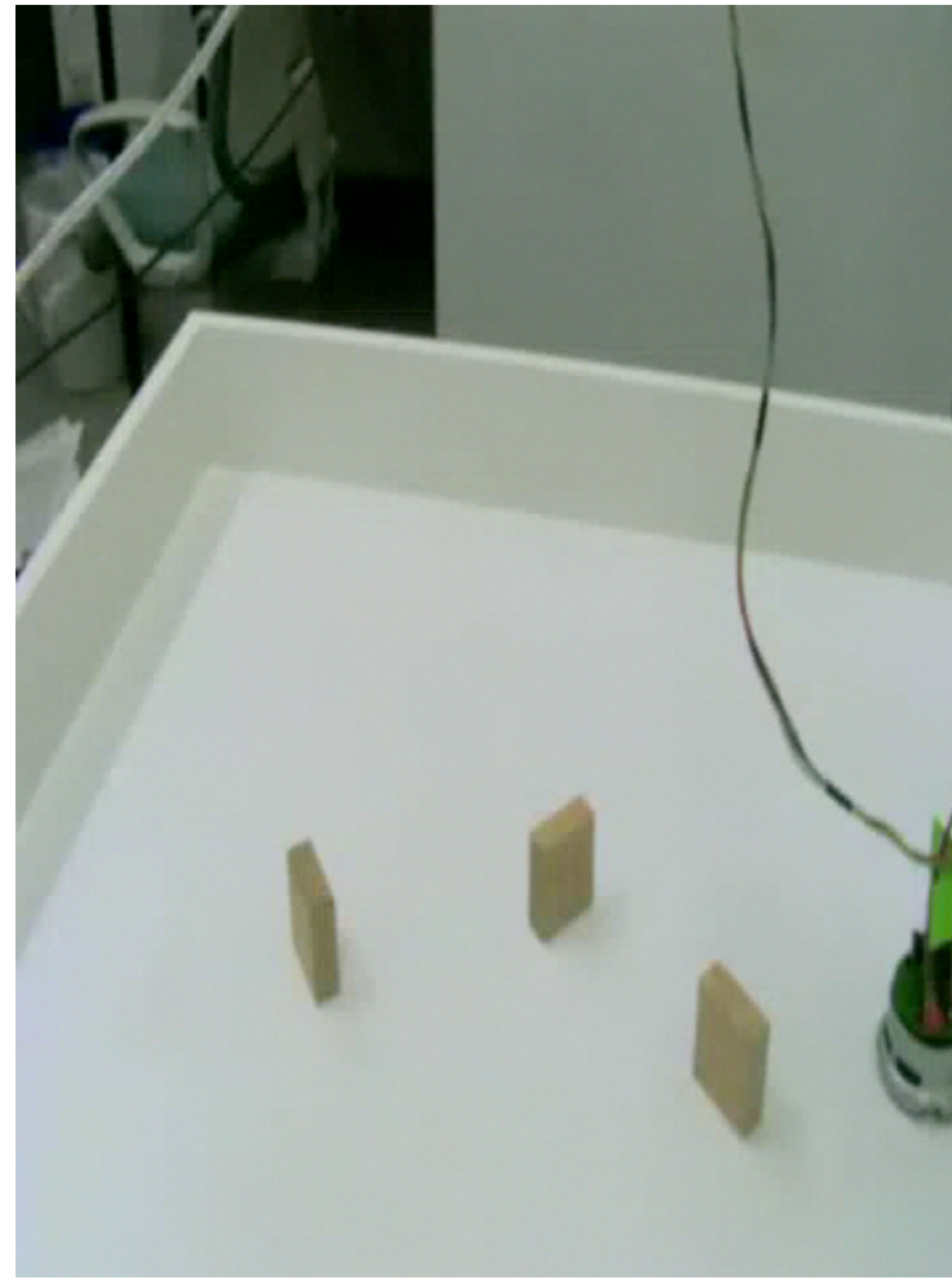
“young” robot

target



“young” robot with memory trace

target



DFT models can be embodied

- stabilization of decisions is critical
- (when we failed to do so, by just “reading out” the location with maximal activation after the delay, that location fluctuate from moment to moment leading to meandering of the robot in an averaged direction)

Conclusions

- action, perception, and embodied cognition takes place in continuous spaces. peaks = units of representation are attractors of the neural dynamics
- neural fields link neural representations to these continua
- stable activation peaks are the units of neural representation
- peaks arise and disappear through instabilities through which elementary cognitive functions (e.g. detection, selection, memory) emerge

The conceptual framework of DFT