Dynamic field theory (DFT)

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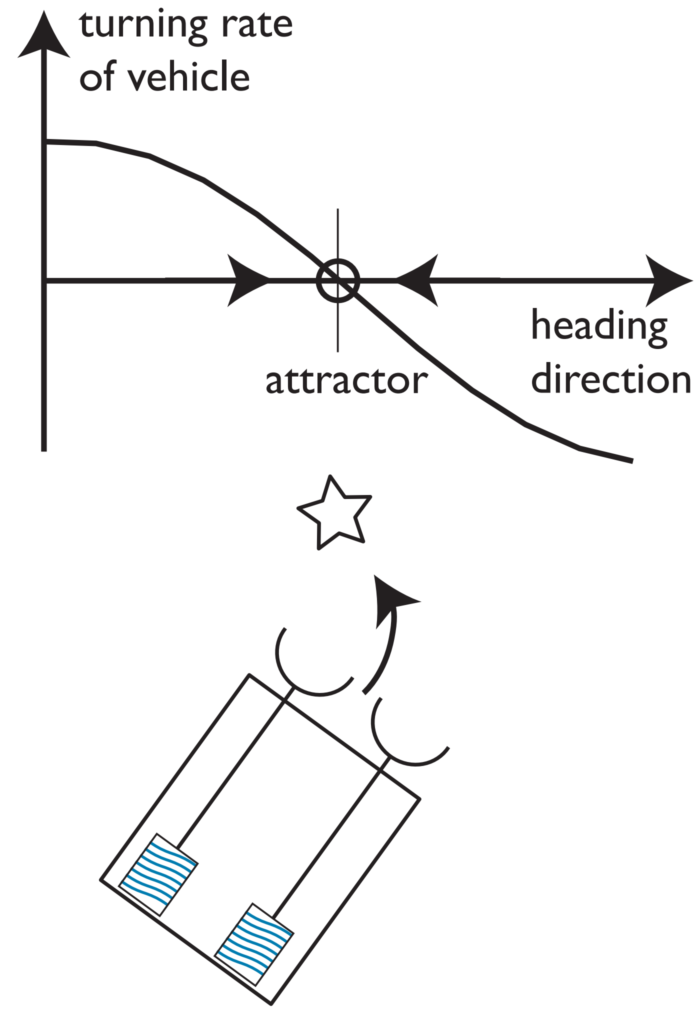
behavioral attractor dynamics

- generate time courses of behavioral variables to steer a system toward desired states while satisfying constraints



perception/cognition

- need perception and cognition to autonomous generated behavior:
  - detect targets, obstacles
  - estimate direction to target etc.
  - select objects, recognize objects, etc
- => perception = extract information about the world from sensory signals
- => cognition: plan actions, action sequences, motor goals, etc.

detection

- detection=decide if a particular signal/object etc is present
- examples:
    - target detection from radar signals
    - detection of communication signals from radio waves
- theoretical approaches:
    - signal detection theory, with varying amounts of prior information about signals and noise (models)
    - framework: statistical hypothesis testing

estimation

- estimation=determine the value of a continuously valued parameter from data, given the presence of a signal (which was detected)
- tracking: do some continuously in time, updating estimates…
- examples:
  - navigation: determine ego-position from distance sensors, maps, beacons
  - control: estimate parameters of plant
  - motion planning constraints: estimate pose and position of targets

estimation

- theoretical approaches
  - (optimal) estimation theory based on various amounts of a priori knowledge about the system
  - Optimal filtering, Kalman filtering, particle filters

classification

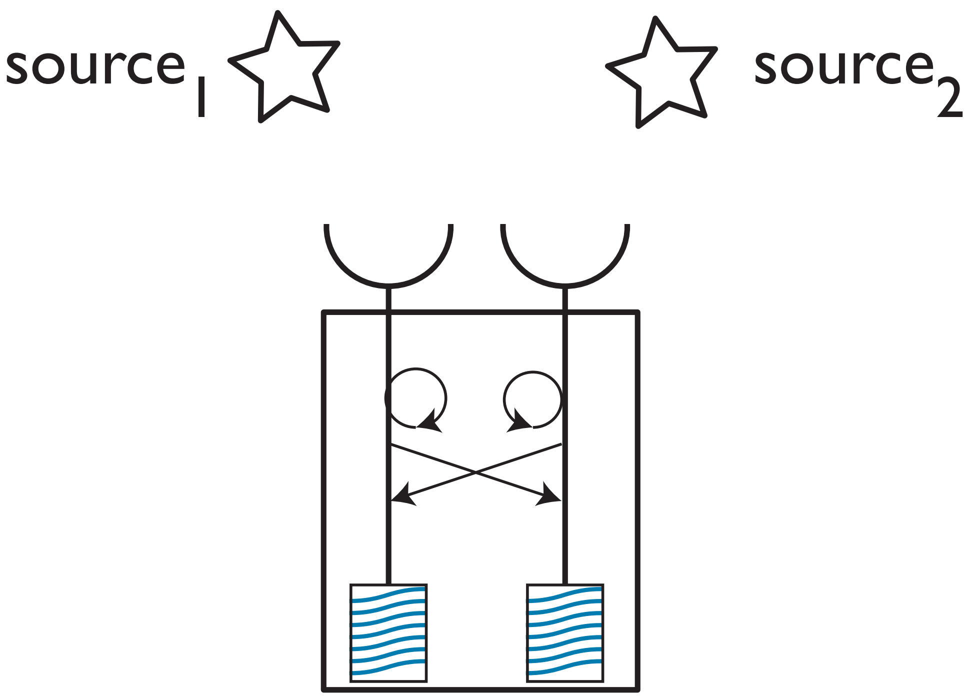
- classification=given that a signal has been detected, assign that signal to one class within a set of discrete classes
- examples:
  - binary classification (target yes or no)
  - decoding in (digital) telecommunication
  - recognition: letters, speech, objects, ...

classification

- theoretical approaches:
  - statistical hypothesis testing within metrics of feature/code space to separate distributions (discrimination)
  - (detection being a special case of classification)
  - neural networks, learning
  - statistical learning theory: support vector machines
  - link to coding: optimal code that maximize distances in code space between classes

The neural dynamics approach to perception and cognition: Dynamic Field Theory

- dimensions
- activation fields
- field dynamics: peaks, instabilities



Dimensions

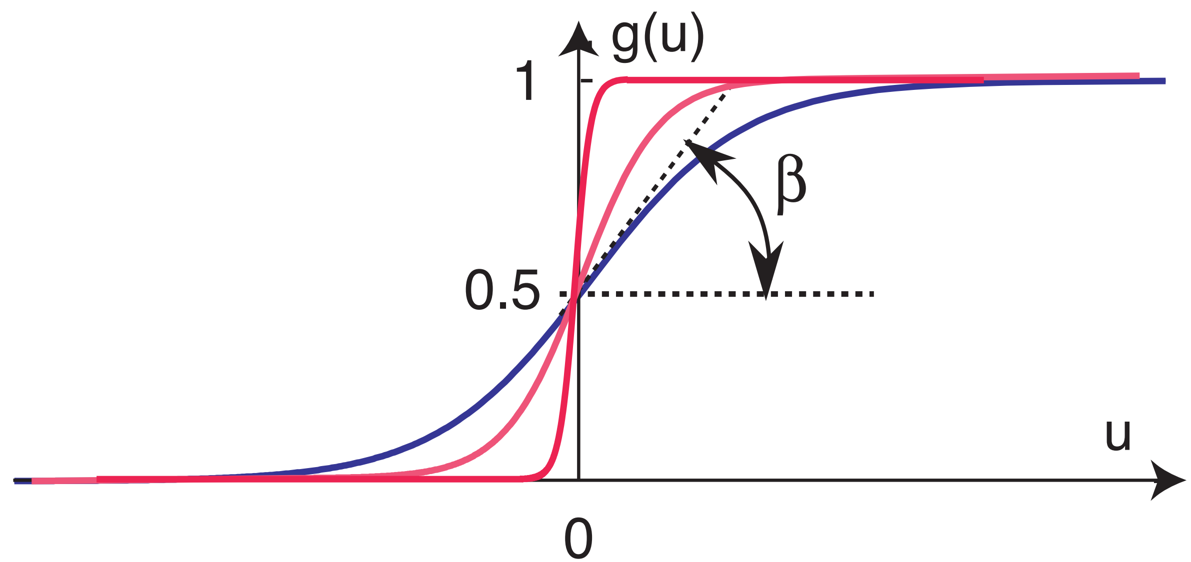
- different categories of behavior and percepts each form continua, embedded in spaces
  - e.g., the space of possible reaching movements: spanned by the direction in space of the hands velocity
  - e.g., the spaces of possible shapes, colors, poses of a segmented visual object

Activation

- activation: the notion of an “inner” state of a neural network that is used to mark what is significant about neural activity (=has impact)
  - membrane potential of neurons
  - spiking rate?
  - ... population activation… elaborated in lecture course of the WS on neural dynamics

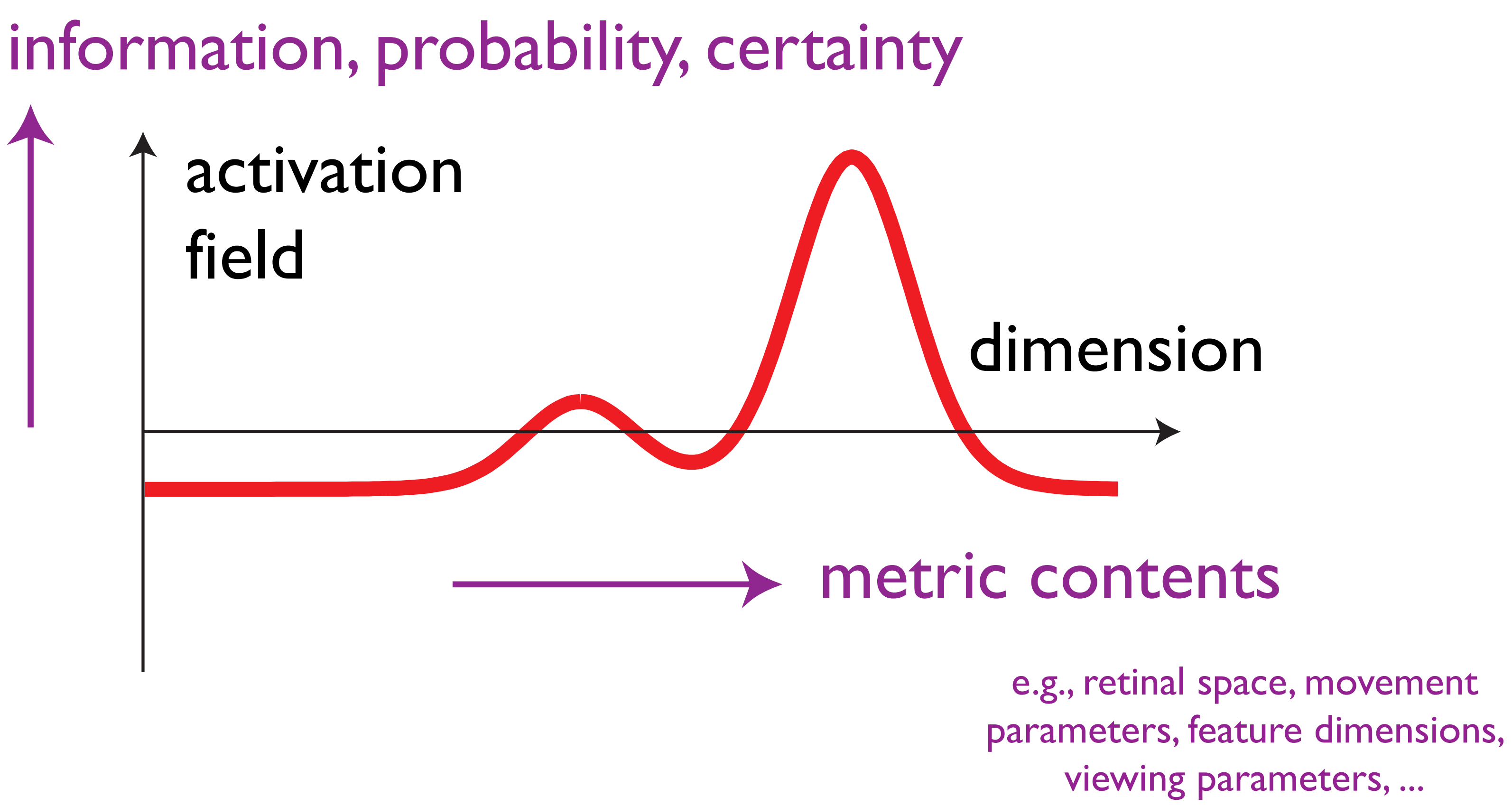
Activation

- activation: a real number that characterizes the inner state of a "neuron", and abstracts from biophysical details
  - low levels of activation: state of the "neuron" is not transmitted to other systems (e.g., to motor systems)
  - high levels of activation: state is transmitted to other systems
  - => sigmoidal threshold function



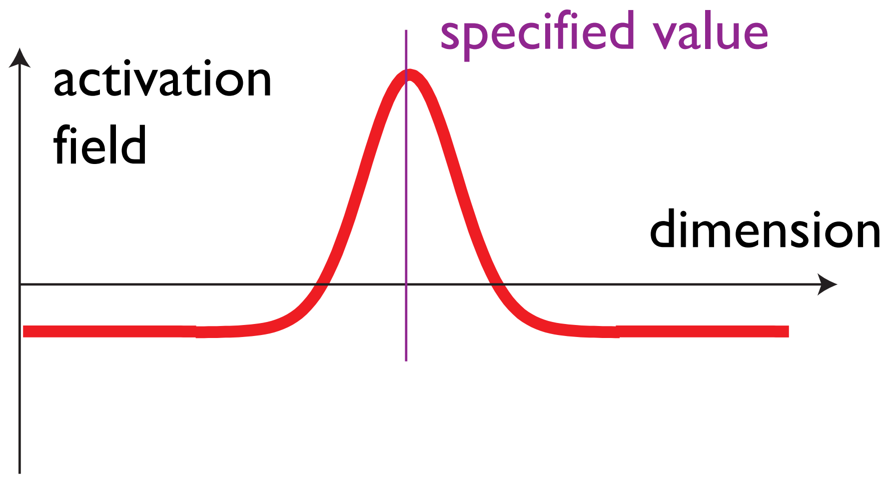
Activation fields

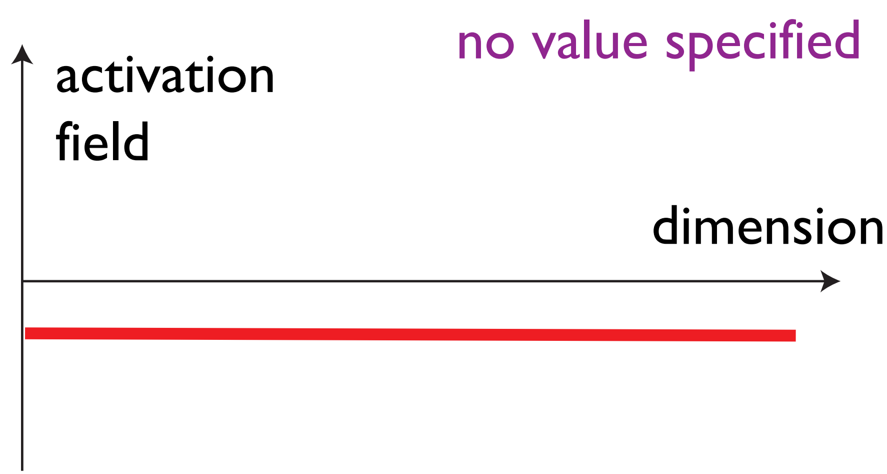
- combine activation and dimensions



Activation fields

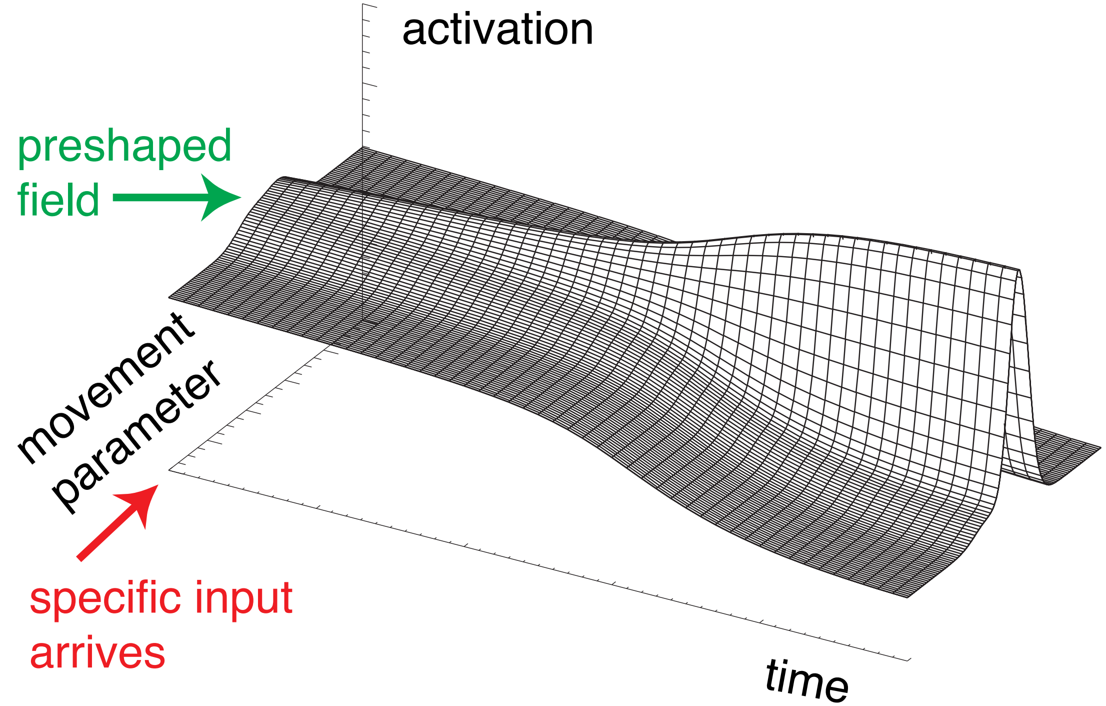
- may represent different states of affairs:
  - localized activation peak: a specific value along the dimension is specified and information about the dimension is thus available
    - had been detected/instantiated
    - and has been estimated/planned
  - flat, sub-threshold activation: no information is available, no value is specified

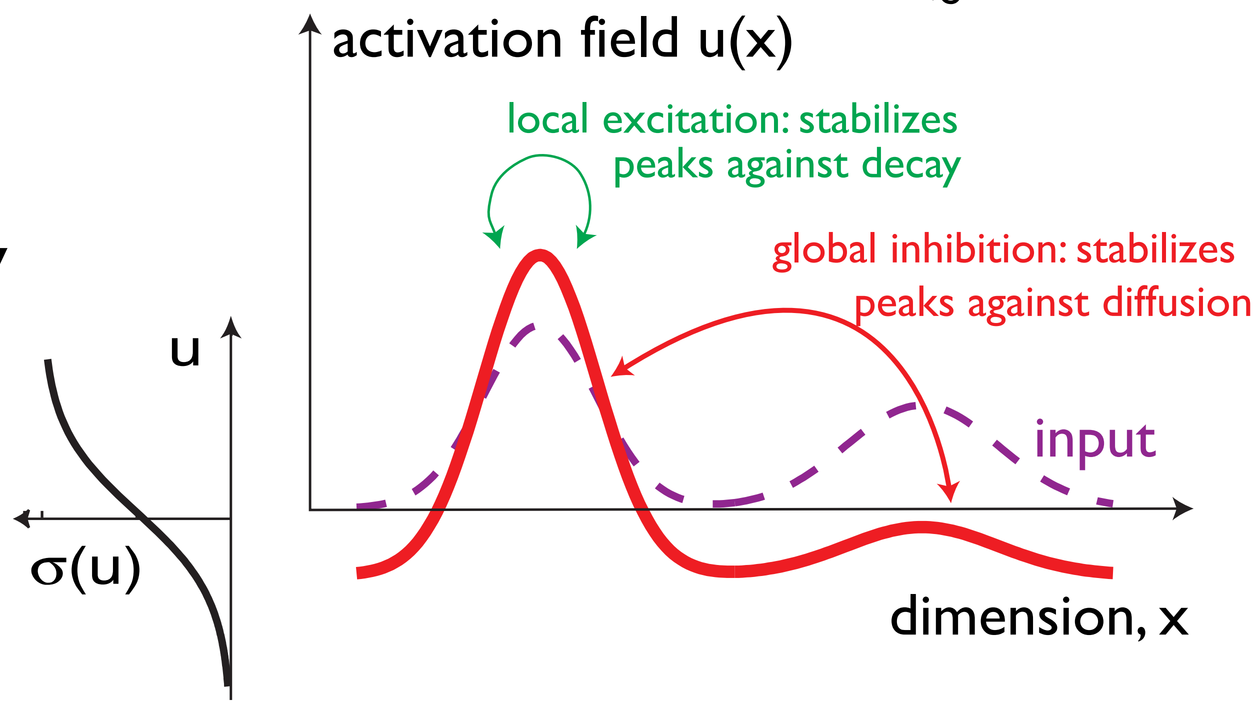




The dynamics activation fields

- field dynamics combines input
- with strong interaction:
  - local excitation
  - global inhibition
- => generates stability of peaks





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

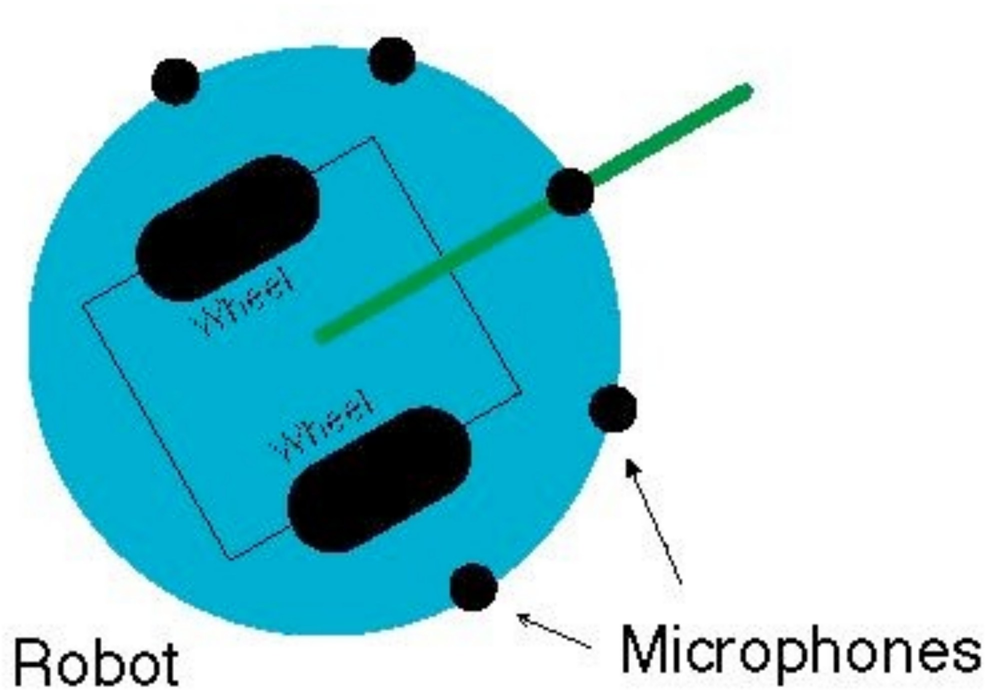
$$\sigma(u) = \frac{1}{1+\exp[-\beta(u-u_0)]}$$

=> simulations

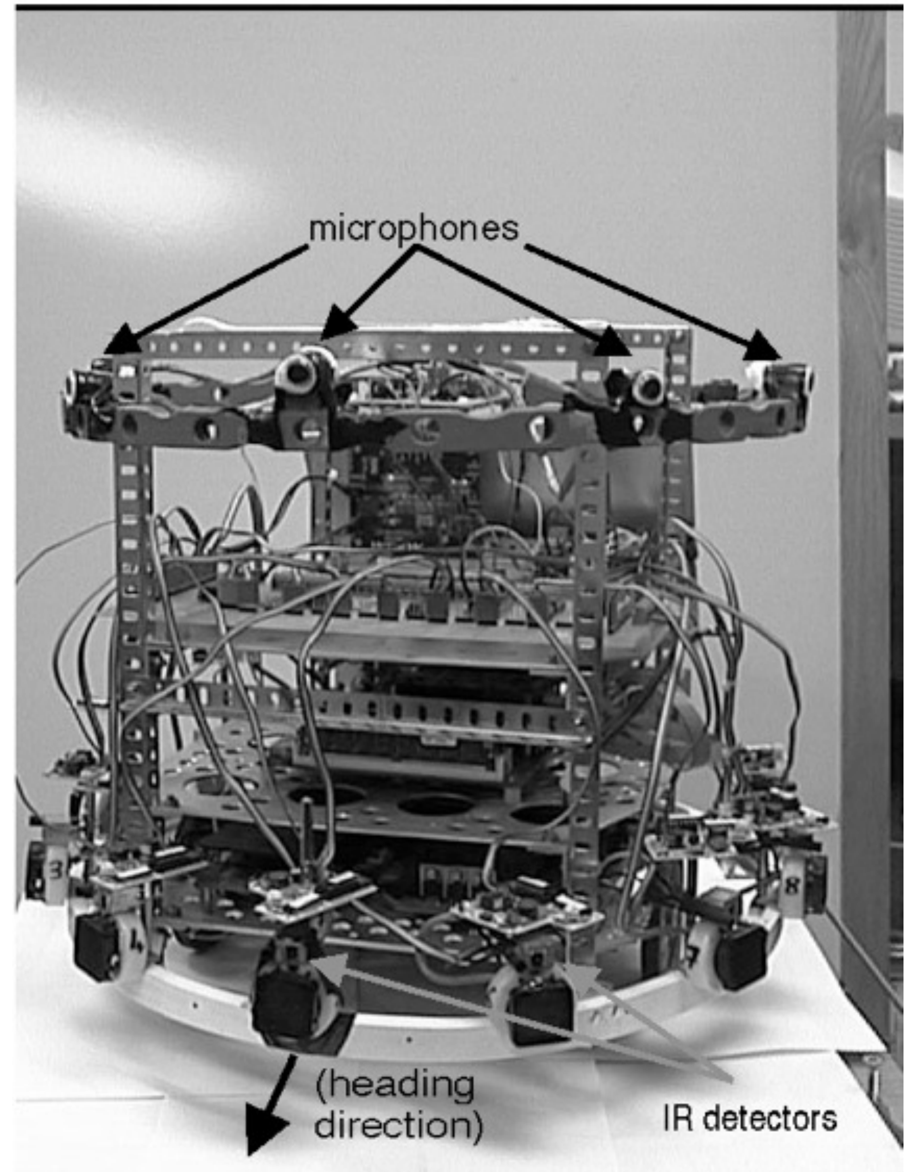
=>

- attractor states
  - input driven solution (sub-threshold)
  - self-stabilized solution (peak, supra-threshold)
- instabilities
  - detection instability (from localize input or boost)
  - reverse detection instability
  - selection instability
  - memory instability

Vehicle

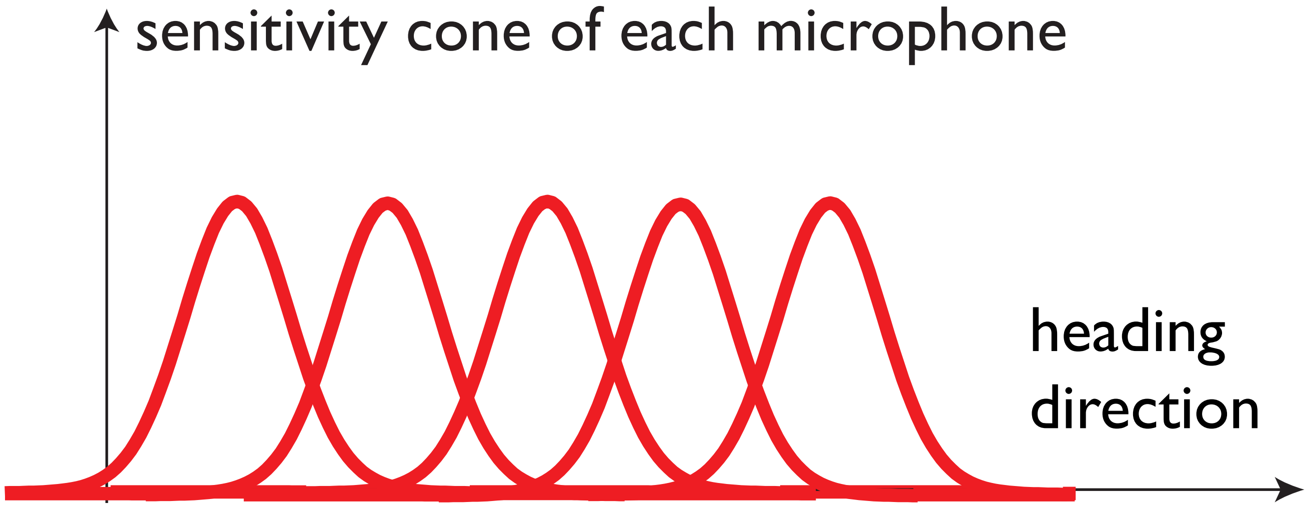


[from Bicho, Mallet, Schöner, Int J Rob Res,2000]

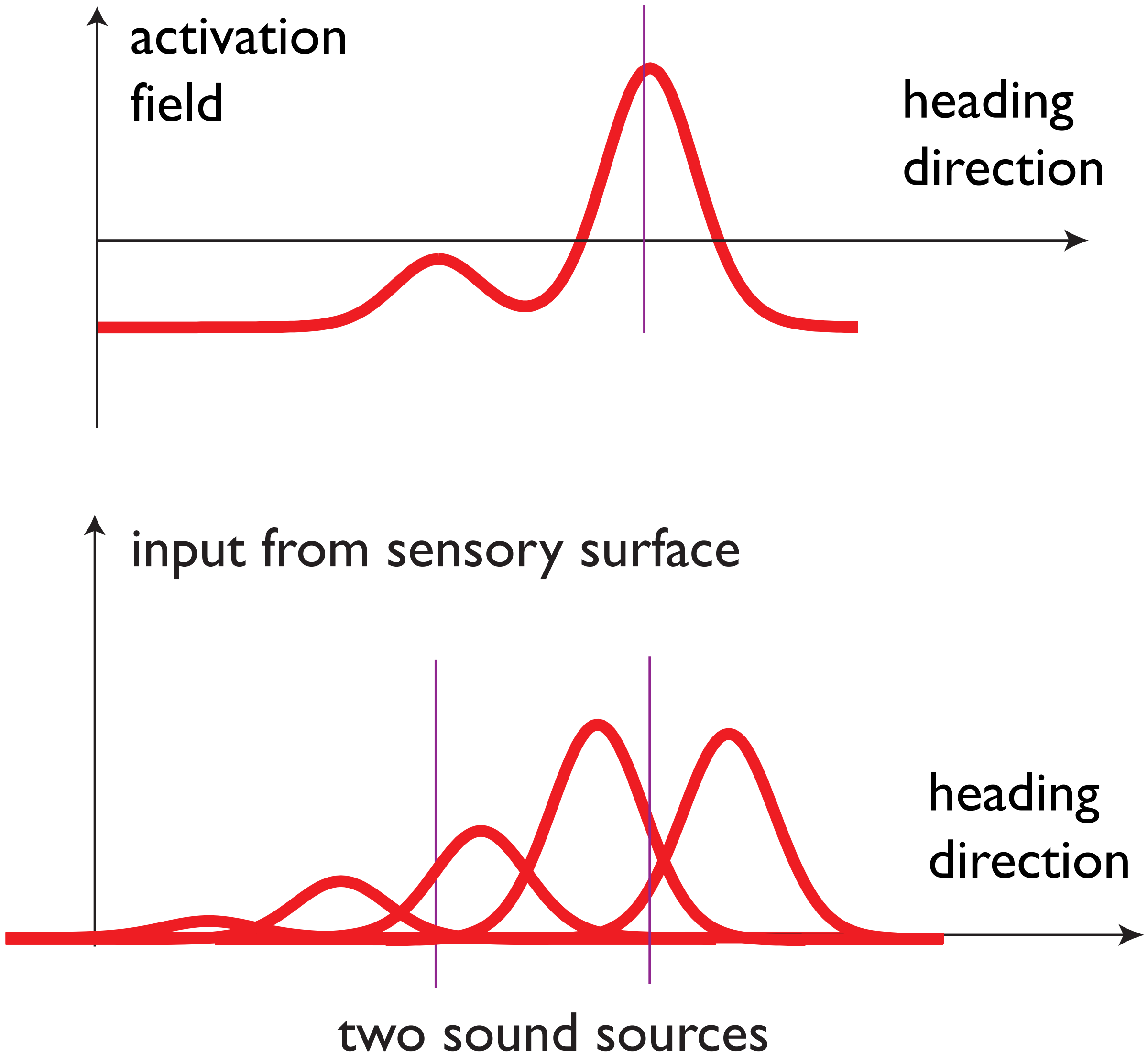


sensory surface

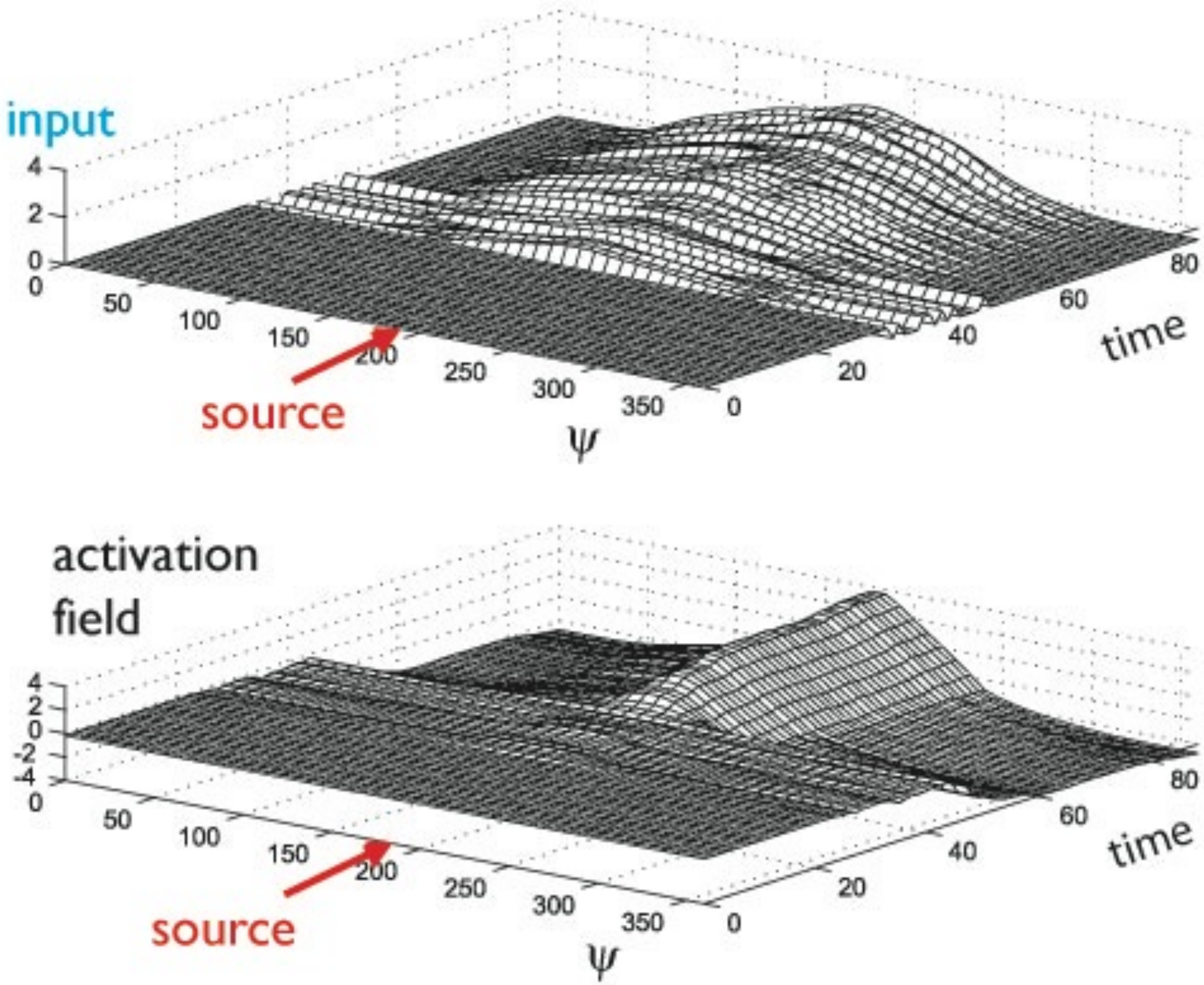
- each microphone samples heading direction

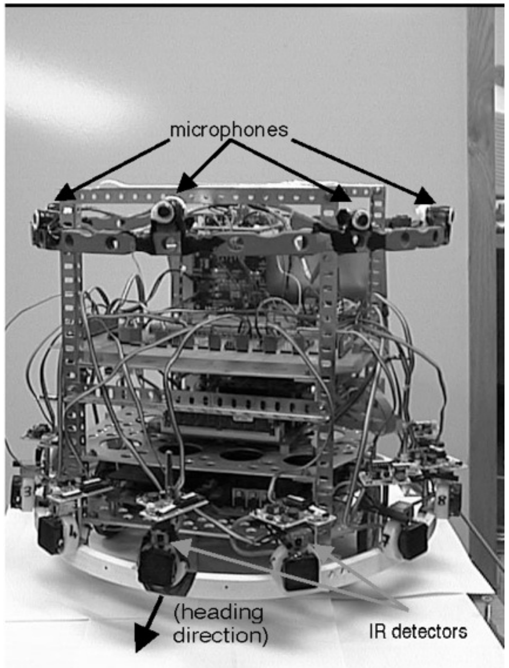


and provides input to the field



detection instability on a phonotaxis robot



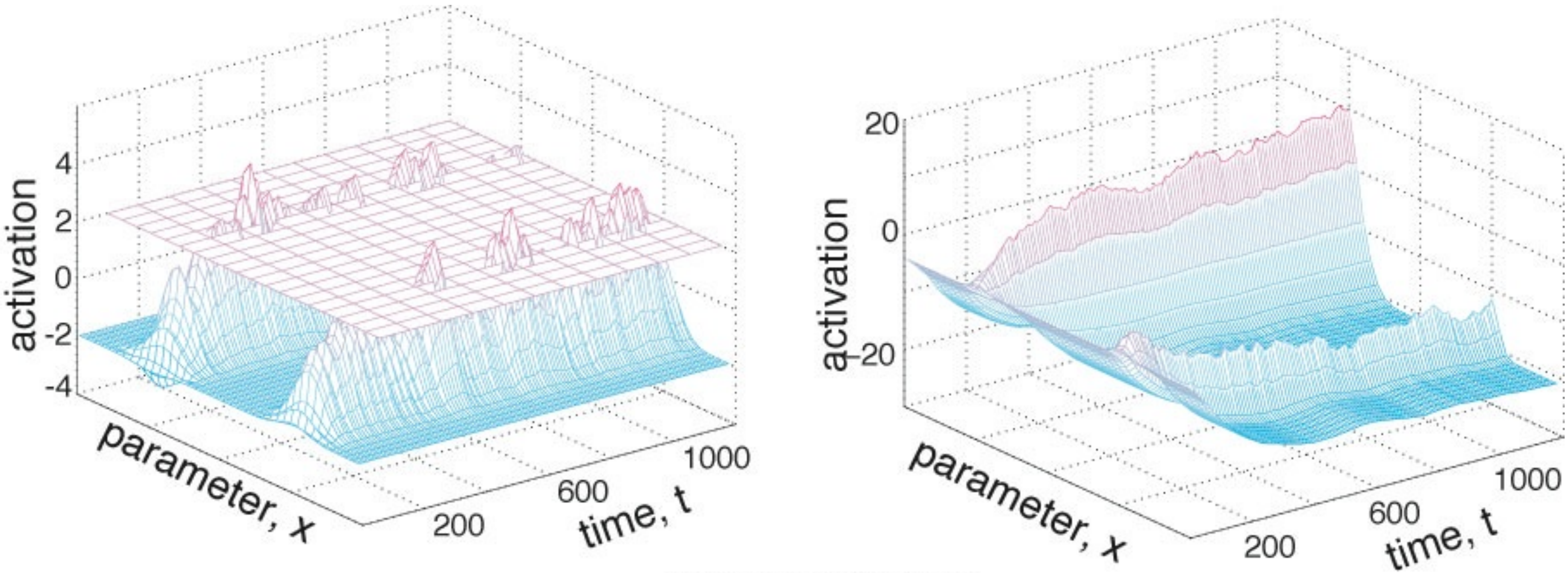


[from Bicho, Mallet, Schöner: Int. J. Rob. Res., 2000]

emergence of time-discrete events

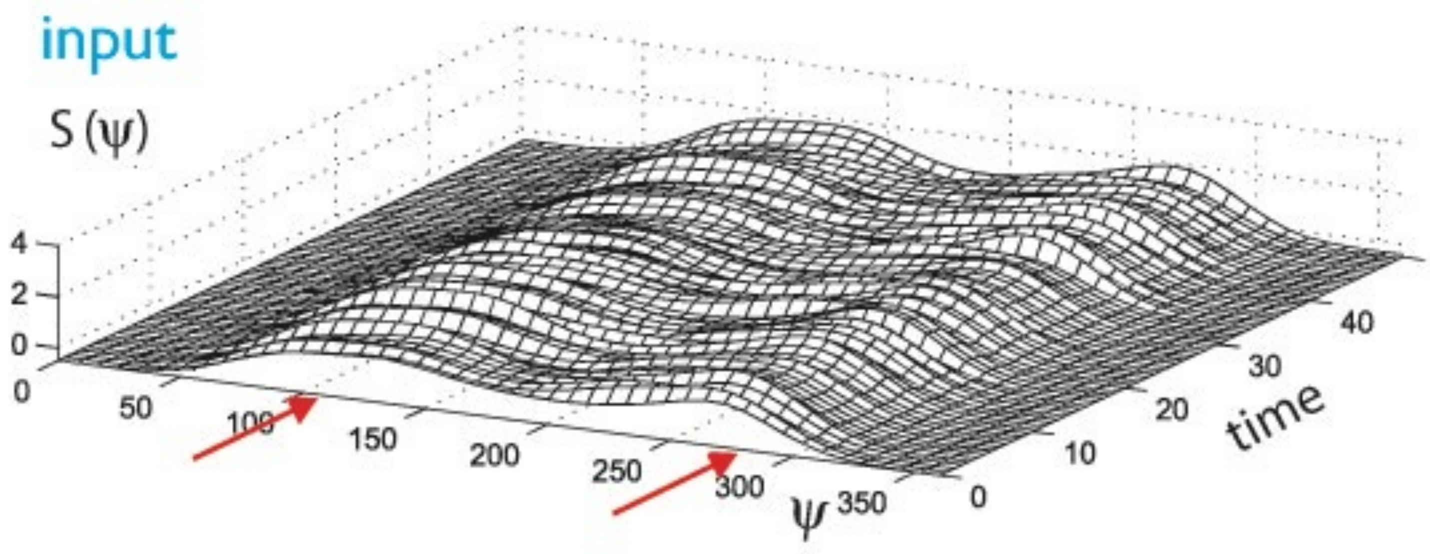
- the detection instability also explains how a time-continuous neuronal dynamics may create macroscopic, time-discrete events

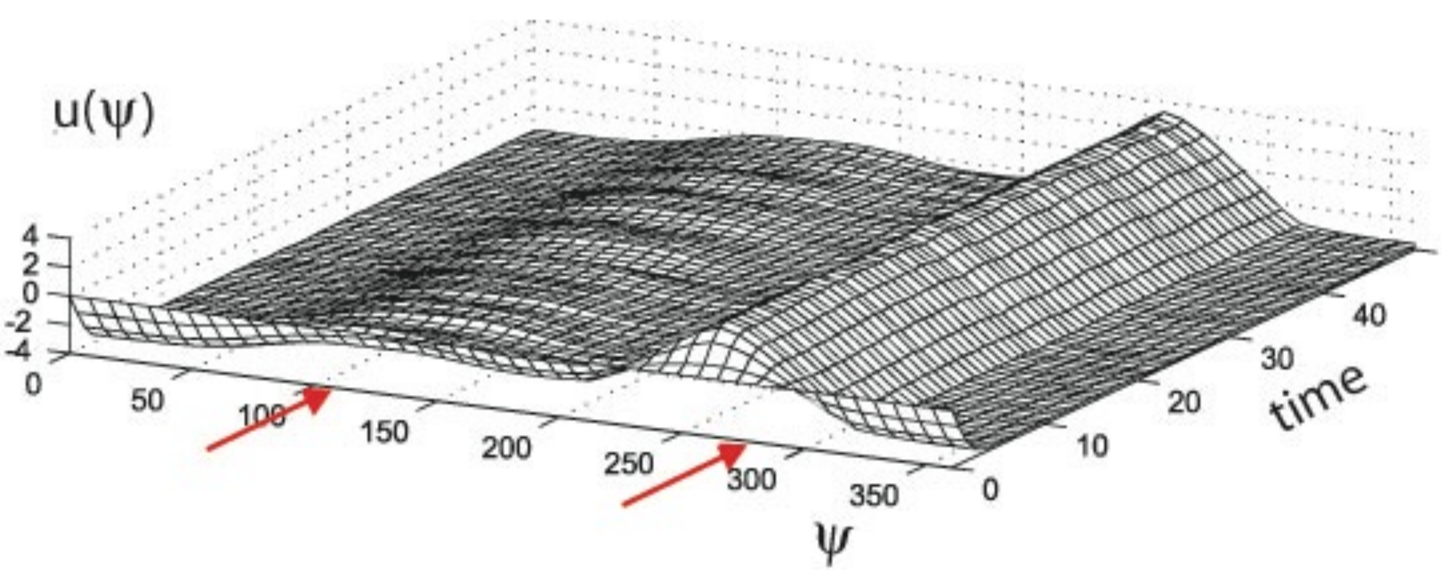
the selection instability stabilizes selection decisions

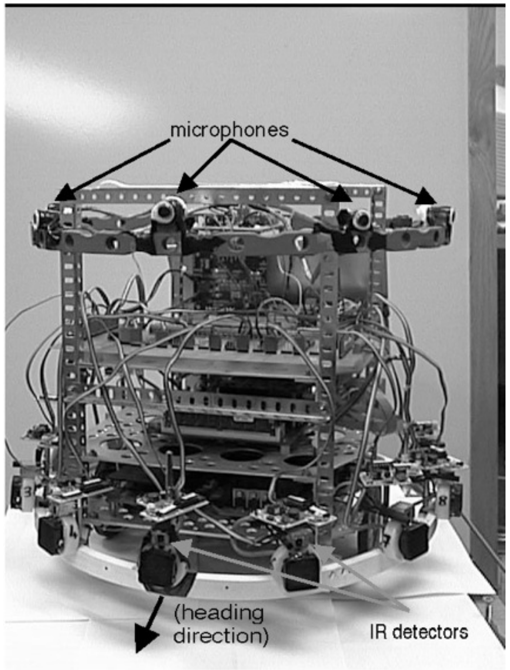


[Wilimzig, Schöner, 2006]

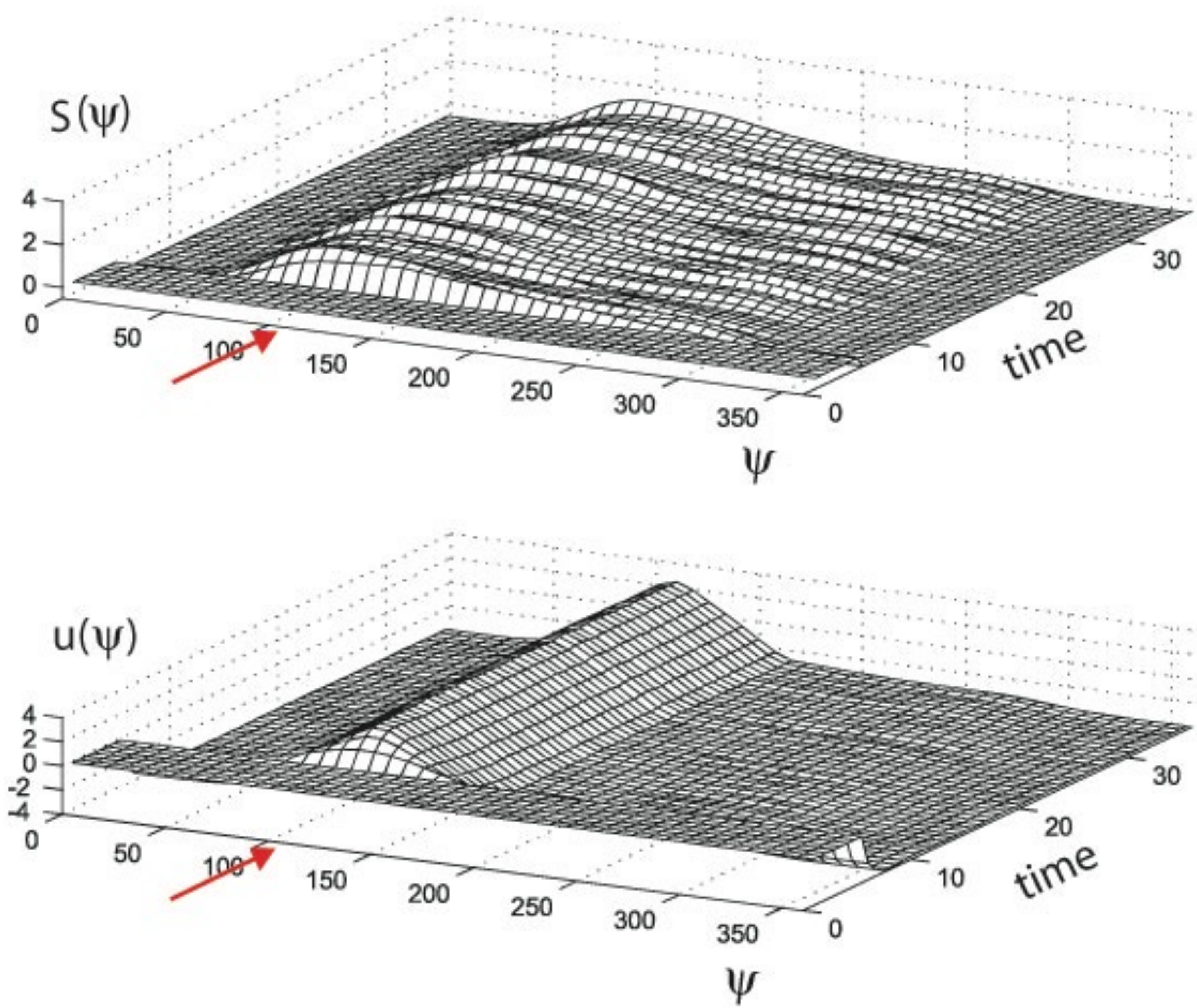
target selection on phonotaxis vehicle



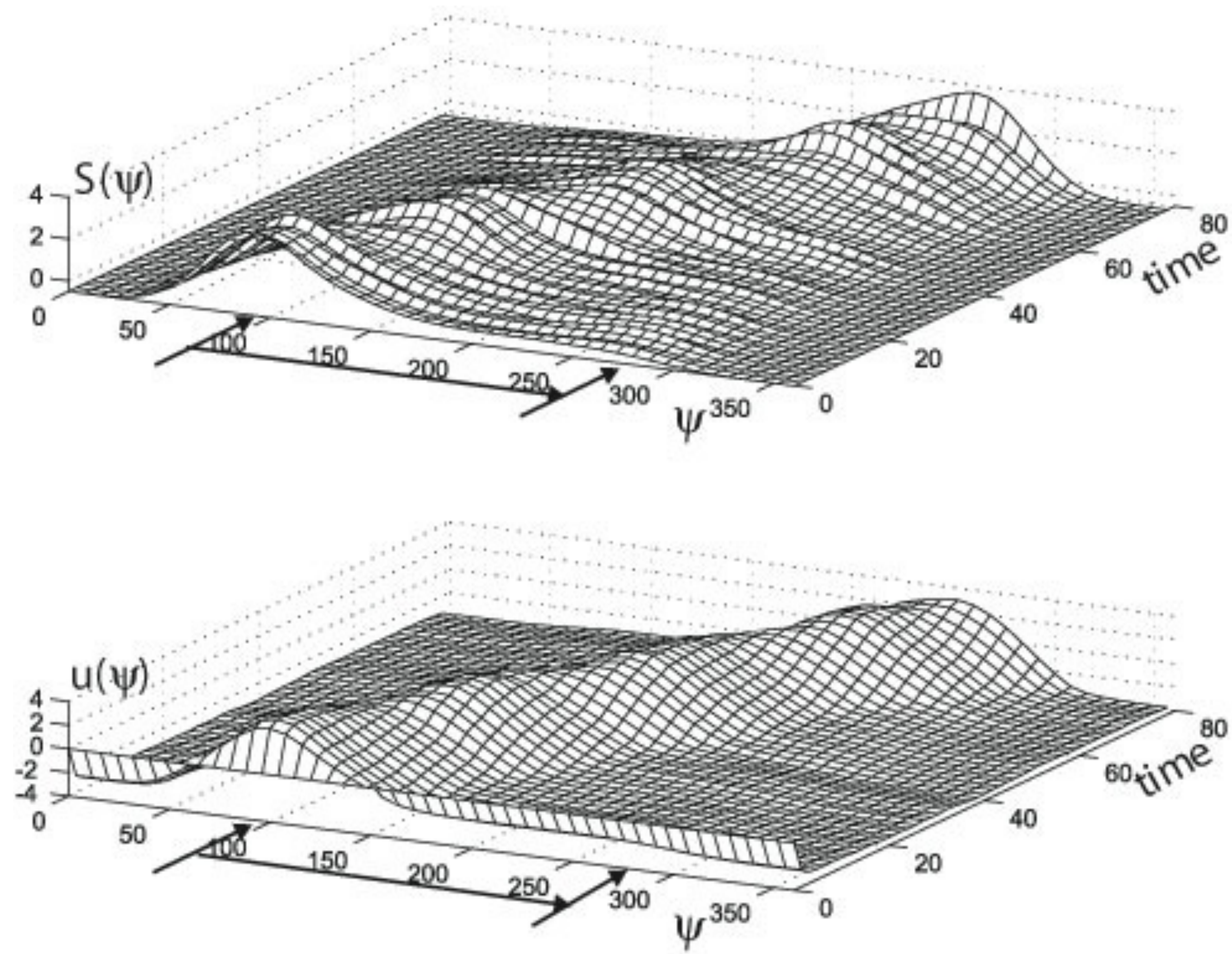




robust estimation



tracking


S(ψ)
4
2
0
0
50
100
150
200
250
300
350
ψ
0
20
40
60
80
time
u(ψ)
4
2
0
-2
-4
0
50
100
150
200
250
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ψ
0
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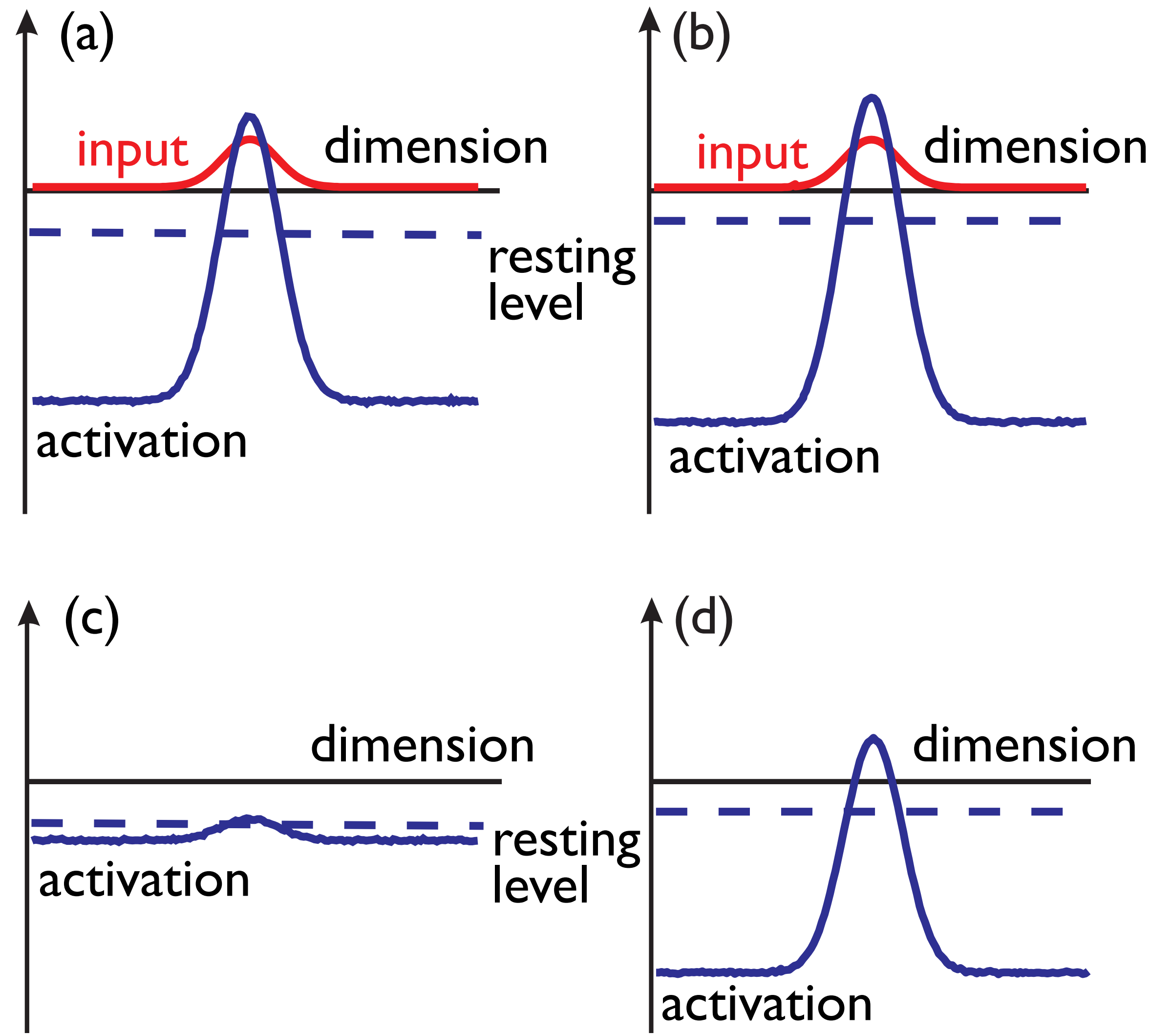
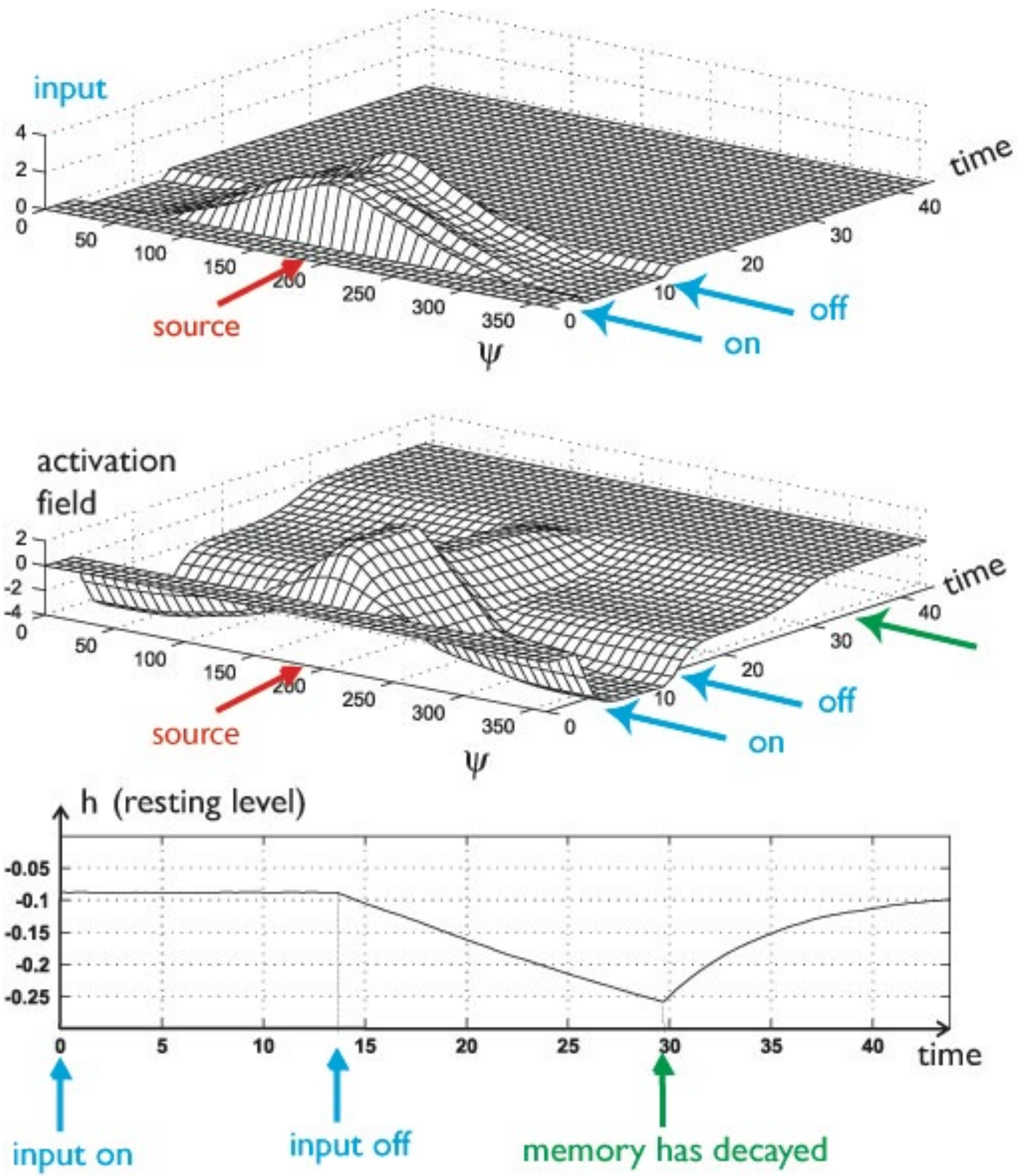
60
80
time

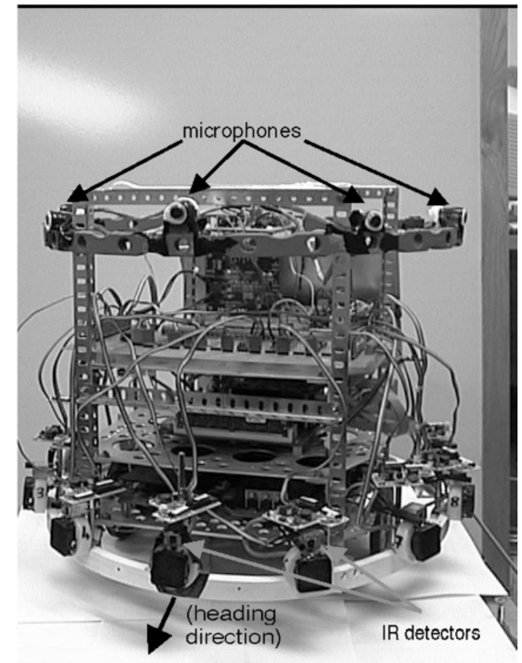
memory instability

- monostable "off" regime vs. bistable regime in which sustained activation provides working memory



memory & forgetting on phonotaxis vehicle



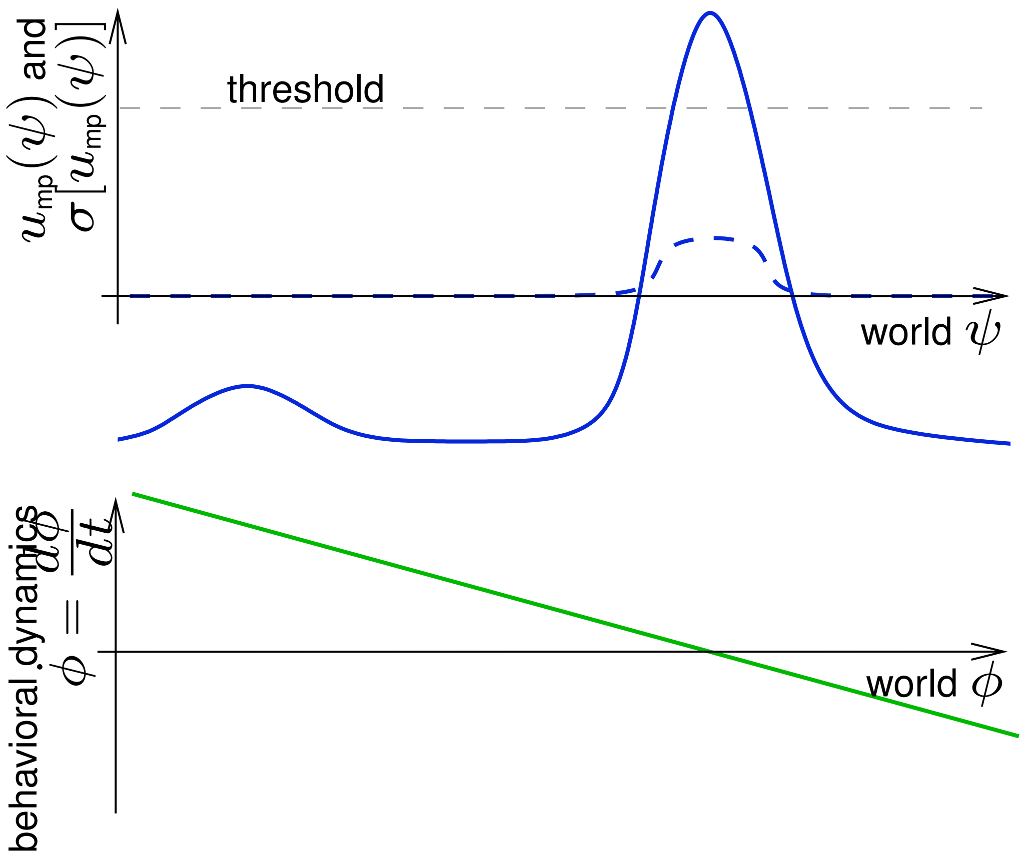


[from Bicho, Mallet, Schöner: Int J Rob Res 19:424(2000)]

a robotic demo of all of instabilities

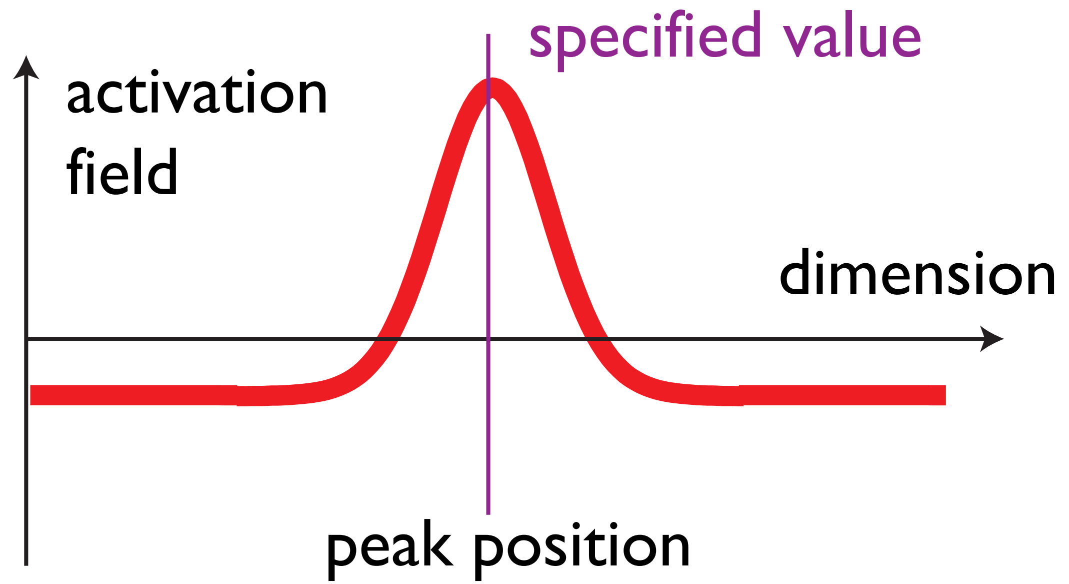
motor dynamics

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



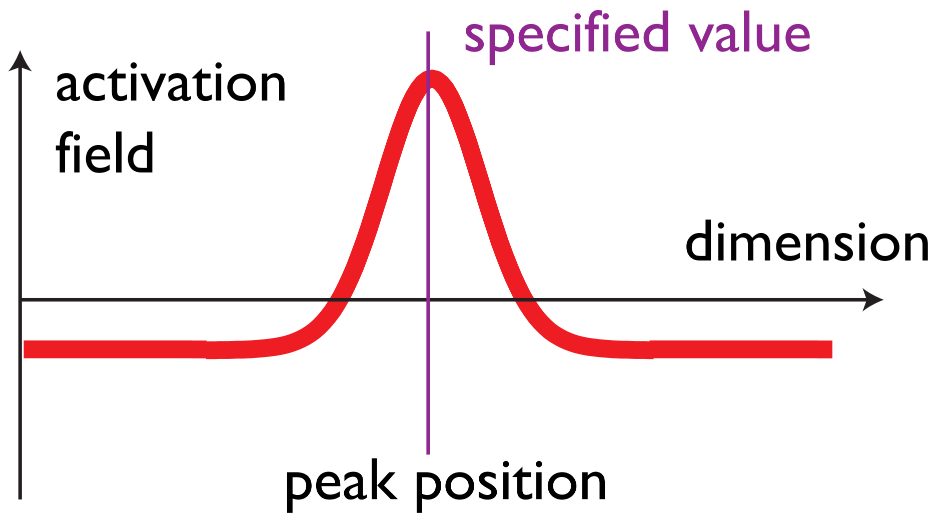
“Read-out” by generating attractor dynamics for motor system

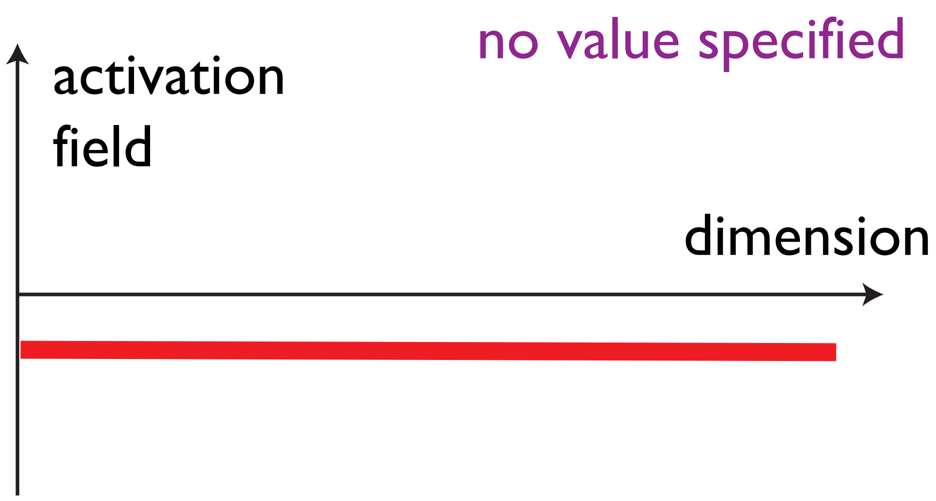
- peak specifies value for a dynamical variable that is congruent to the field dimension



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

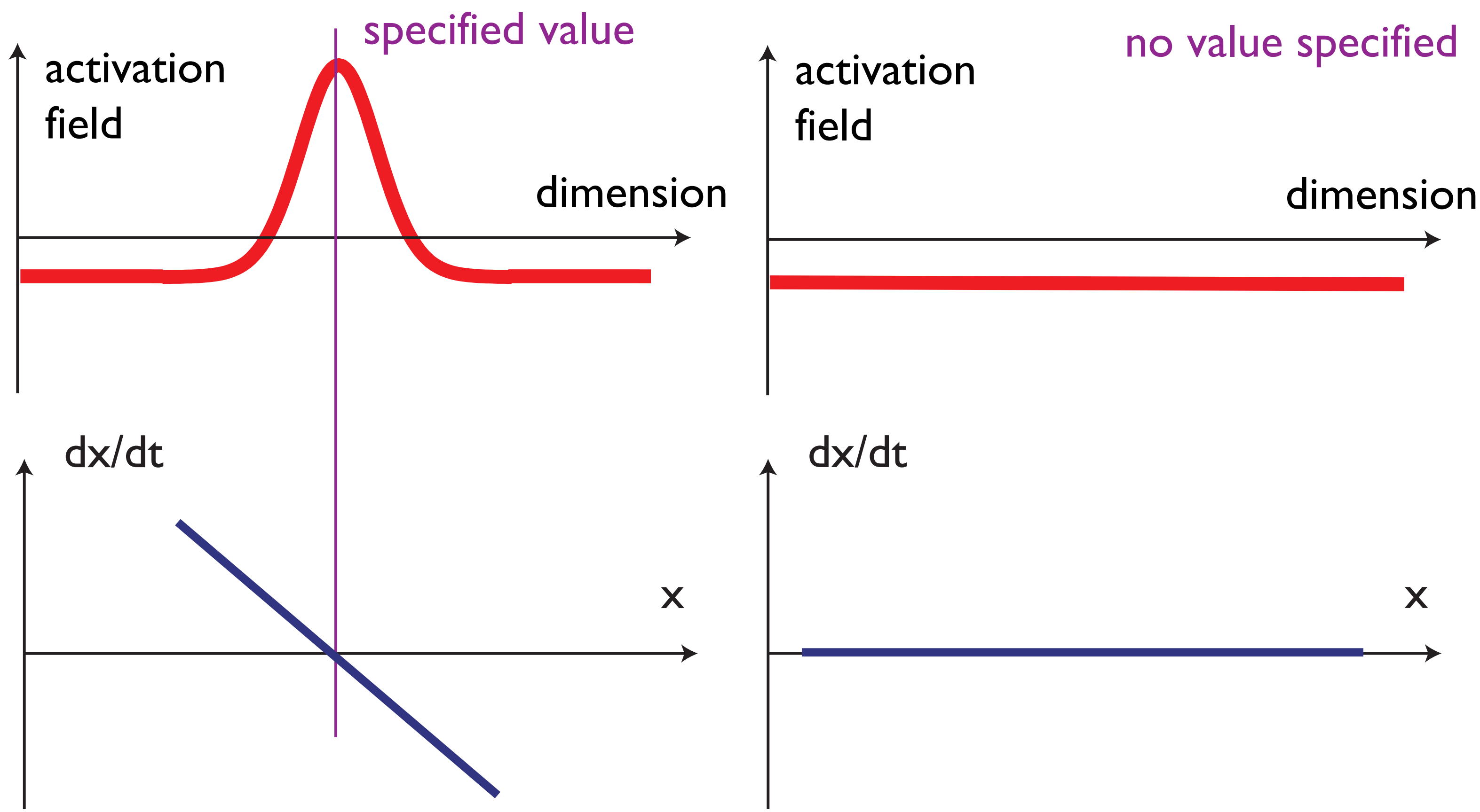
$$x_{\text{peak}} = \frac{\int dx' \ \sigma(u(x',t))x'}{\int dx' \ \sigma(u(x',t))}$$





instead:

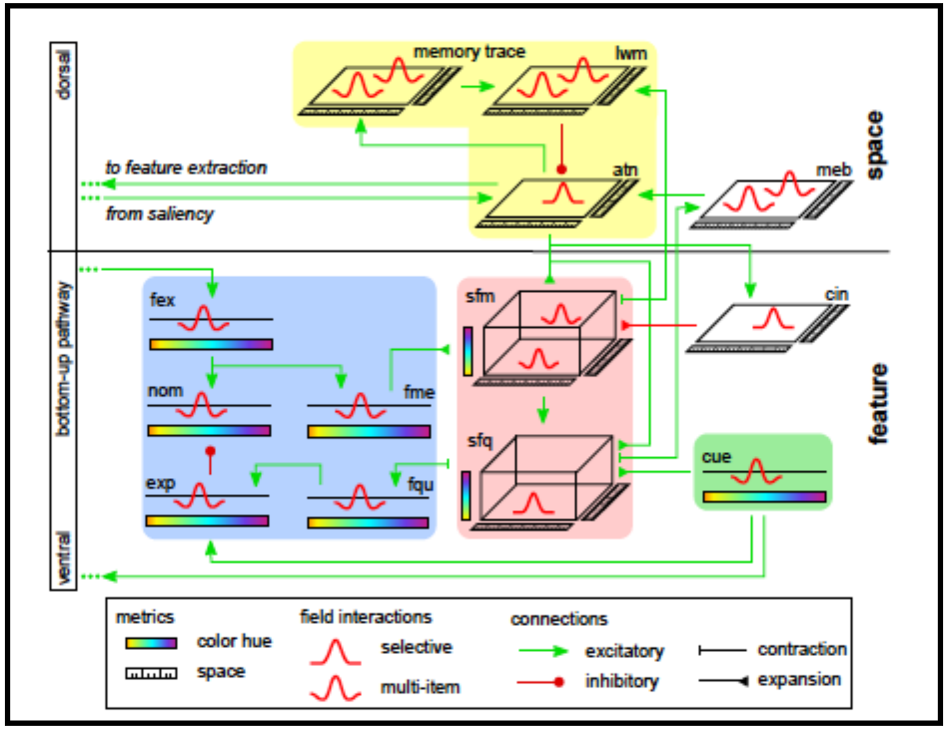
- create attractor



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

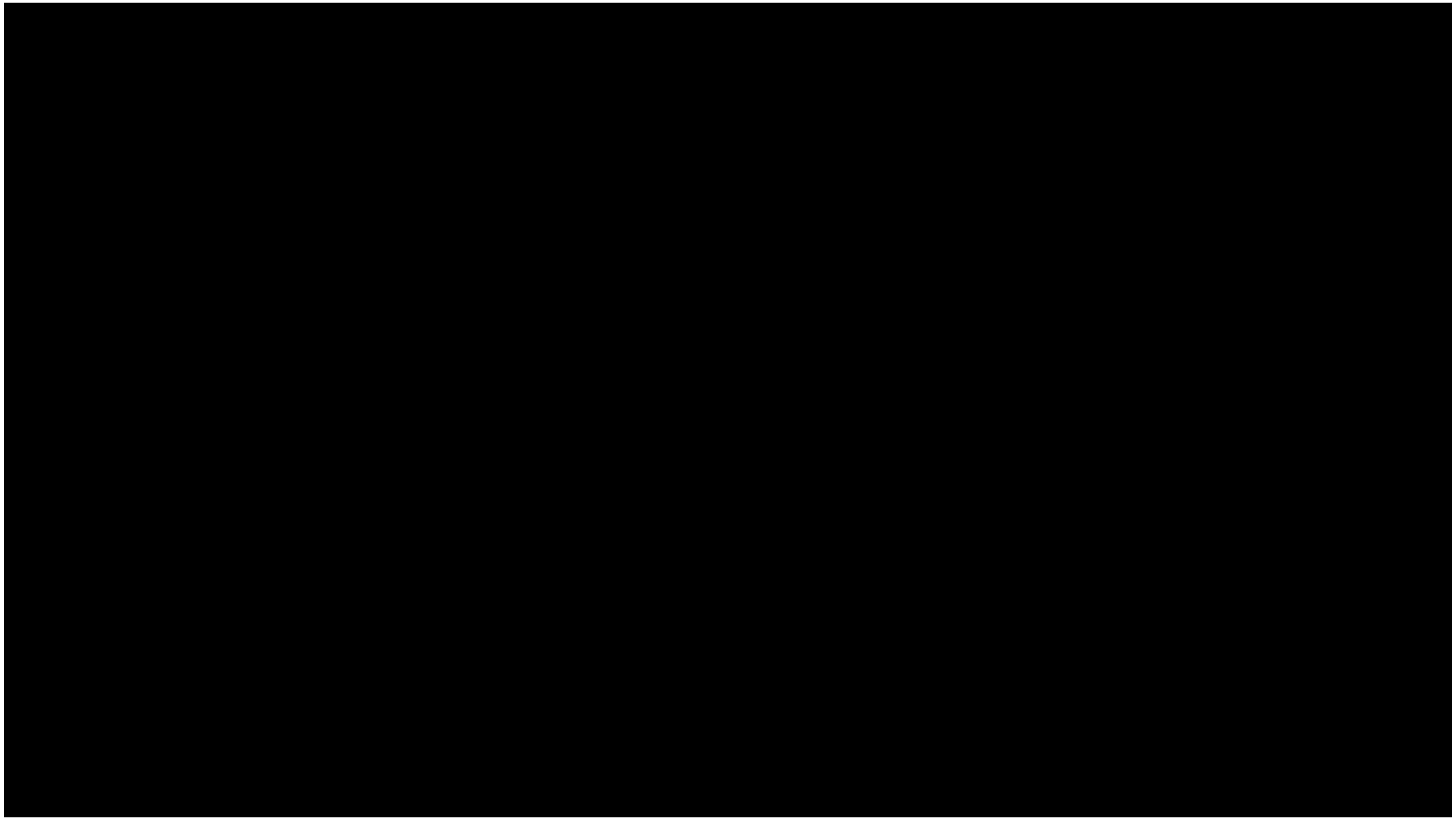
$$\begin{aligned}
x_{\text{peak}} &= \frac{\int dx' \; \sigma(u(x',t))x'}{\int dx' \; \sigma(u(x',t))} \\
\dot{x} &= -\int dx' \; \sigma(u(x',t)) \, (x - x_{\text{peak}}) \\
&= -\left[\int dx' \; \sigma(u(x',t)) \; x - \int dx' \; \sigma(u(x',t)) \; x_{\text{peak}}\right] \\
&= -\left[\int dx' \; \sigma(u(x',t))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

Scene Representation



Zibner 2015

Scene Representation



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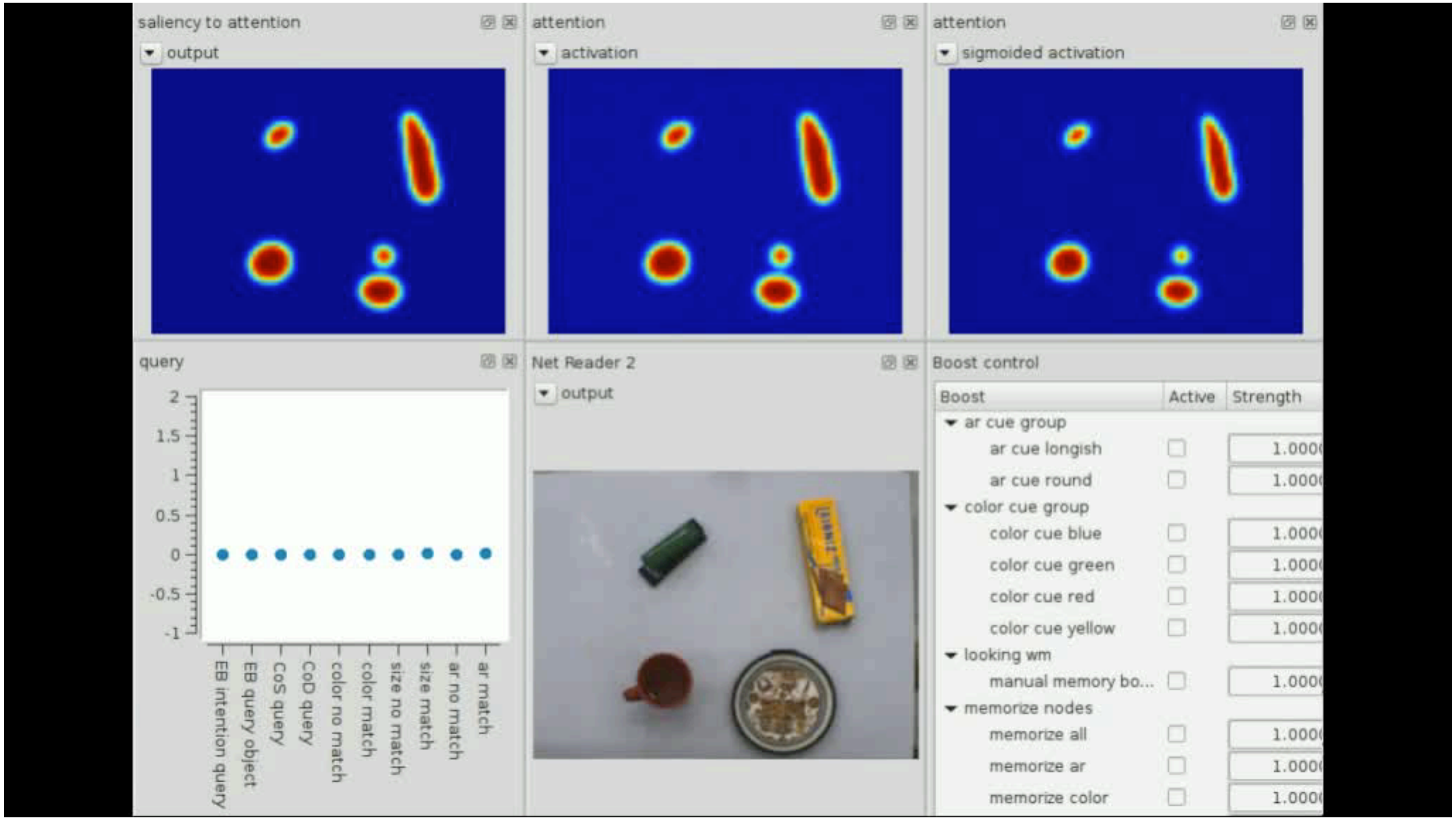
Scene Representation



Zibner 2015

Scene Representation

Zibner 2015