Dynamic Field Theory: Part 2: dynamics of activation fields

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activation fields

information, probability, certainty

activation field

dimension

metric contents

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

activation field

dimension

specified value

activation field

no value specified

dimension
evolution of activation fields in time: neuronal dynamics

- preshaped field
- movement parameter
- specific input arrives
- time
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 \( \tau \)
- 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

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

\[ (B2.2) \]

where \( (\! - \! - 1) / 2 \) is the half-width of the kernel. The sum extends to indices outside the original range of the field (e.g., for \( m = 0 \) at \( \! = - \! )

But that doesn't cause problems because we extended the range of the field as shown in Figure 2.18. Note again that to determine the interaction effects for the whole field, this computation has to be repeated for each point \( \! \).

In COSIVINA all these problems have been solved for you, so you don't need to worry about figuring out the indices in Equations like B2.2 ever again!

Figure 2.18

Top: The supra-threshold activation, \( (\! \) \), of a field is shown over a finite range (from 0 to 180° deg).

Second from top: The field is expanded to twice that range by attaching the left half of the field on the right and the right half on the left, imposing periodic boundary conditions.

Third from top: The kernel has the same size as the original field and is plotted here centered on one particular field location, \( \! \).

Bottom: The matching portions of supra-threshold field (red line) and kernel (blue line) are plotted on top of each other. Multiplying the values of these two functions at every location returns the black line. The integral over the finite range of the function shown in black is the value of the convolution at the location \( \! = \! \).
Relationship to the dynamics of discrete activation variables

\[ u(x) \]

\[ s(x) \]

Self-excitation

Mutual inhibition

Self-excitation
=> 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
Detection instability

- **Input**
- **Sub-threshold hill**
- **Self-excited peak**
the detection instability helps stabilize decisions

threshold piercing

detection instability

![Graph of threshold piercing](image1.png)

![Graph of detection instability](image2.png)
the detection instability helps stabilize decisions

- self-stabilized peaks are macroscopic neuronal states, capable of impacting on down-stream neuronal systems

( unlike the microscopic neuronal activation that just exceeds a threshold )
the detection instability also explains how a
time-continuous neuronal dynamics may create macroscopic, time-discrete events
behavioral signatures of detection decisions

detection in psychophysical paradigms is rife with hysteresis

but: minimize response bias
Detection instability in the detection of Generalized Apparent Motion.
Detection instability

\[ L_m = \frac{L_1 + L_2}{2} \]

Background-Relative Luminance Change (BRLC)

\[ \text{BRLC} = \frac{L_1 - L_2}{L_m - L_b} \]
Detection instability

- hysteresis of motion detection as BRLC is varied (while response bias is minimized)

Figure 5. Hysteresis effect observed by gradually increasing or gradually decreasing the background relative luminance contrast (BRLC) for a participant in Hock et al.'s (1997) third experiment. The proportion of trials with switches from the perception of motion to the perception of non-motion, and vice versa, a region of function of the BRLC value at which a descending or ascending sequence of BRLC values ends. (Note the inversion of the axis on the right.)

Which there were switches during trials with a particular end-point BRLC value was different, depending on whether that aspect ratio was preceded by an ascending (vertical axis on the left side of the graph) or a descending sequence of BRLC values (the inverted vertical axis on the right side of the graph). For example, when the end-point BRLC value was 0.5, motion continued to be perceived without a switch to non-motion for 90% of the descending trials, and non-motion continued to be perceived without a switch to motion for 58% of the ascending trials. Perception therefore was bistable for this BRLC value and other BRLC values near it; both motion and non-motion could be perceived for the same stimulus, the proportion of each depending on the direction of parameter change. It was thus confirmed that the hysteresis effect obtained for single-element apparent motion was indicative of perceptual hysteresis, and was not an artifact of 'inferences from trial duration'.

7. Near-Threshold Neural Dynamics

The perceptual hysteresis effect described above indicates that there are two stable activation states possible for the motion detectors stimulated by generalized apparent motion stimuli, one suprathreshold (motion is perceived) and the other subthreshold (motion is not perceived). Because of this stabilization of near-threshold activation, motion and non-motion percepts both can occur for the same stimulus (bistability), and both can resist random fluctuations and stimulus changes that would result in frequent switches between them.

7.1. Why Stabilization Is Necessary

Whether an individual detector is activated by a stimulus or not, a random perturbation will with equal probability increase or decrease its activation. Assume it
selection
instability
stabilizing selection decisions
behavioral signatures of selection decisions

- In most experimental situations, the correct selection decision is cued by an “imperative signal” leaving no actual freedom of “choice” to the participant (only the freedom of “error”)

- Reasons are experimental

- When performance approaches chance level, then close to “free choice”

- Because task set plays a major role in such tasks, I will discuss these only a little later
one system of “free choice”

selecting a new saccadic location

[O’Reagan et al., 2000]
saccade generation

initial fixation
visual targets

activation field
activation field

input
input

targets
targets

saccadic end-point
saccadic end-point

bistable

after: Ottes et al., Vis. Res. 25:825 (85)
[after Kopecz, Schöner: Biol Cybern 73:49 (95)]
to comply with Dale’s law

and account for difference in time course of excitation (early) and inhibition (late)
2 layer Amari model

\[
\tau u(x, t) = -u(x, t) + h_u + S(x, t) + \int dx' \ c_{uu}(x - x') \ \sigma(u(x', t)) \\
- \int dx' \ c_{uv}(x - x') \ \sigma(v(x', t))
\]

\[
\tau v(x, t) = -v(x, t) + h_v + \int dx' \ c_{vu}(x - x') \ \sigma(u(x', t))
\]

\[
c_{ij}(x - x') = c_{i,j,\text{strength}} \ \exp \left[ -\frac{(x - x')^2}{2\sigma_{ij}^2} \right] . \quad \sigma(u) = \frac{1}{1 + \exp[-\beta u]} .
\]
time course of selection

early: input driven
intermediate: dominated by excitatory interaction
late: inhibitory interaction drives selection

Wilimzig, Schneider, Schöner, Neural Networks, 2006
early fusion, late selection

Wilimzig, Schneider, Schöner, Neural Networks, 2006
studying selection decisions in the laboratory

using an imperative signal...
reaction time (RT) paradigm

imperative signal = go signal

task set

RT

time

response
that is the critical factor in most studies of selection!

for example, the classical Hick law, that the number of choices affects RT, is based on the task set specifying a number of choices

(although the form in which the imperative signal is given is varied as well...) 

how do neuronal representations reflect the task set?
notion of preshape

specific input arrives

preshaped field

specific input

preshaped field

1.0

activation

time

movement parameter

input

0.0

0.0

1.0

0.0

0.4

movement parameter

task

input
weak preshape in selection

- specific (imperative) input dominates and drives detection instability

[Wilimzig, Schöner, 2006]
using preshape to account for classical RT data

- Hick’s law: RT increases with the number of choices

[Figures showing graphs and plots related to Hick's law and preshape]
The metric effect predicts faster response times for metrically close than for metrically far choices.

[from Schöner, Kopecz, Erlhagen, 1997]
experiment: metric effect

[McDowell, Jeka, Schöner]
same metrics, different probability

[Graph showing preshaped activation field with arrows indicating movement parameter, and two graphs below showing high and low probability for maximal activation over time, with a note: [from Erlhagen, Schöner: Psych. Rev. 2002]]
[from McDowell, Jeka, Schöner, Hatfield, 2002]
boost-induced detection instability

activation

dimension

preshape

boost

self-excited activation peak

preshape

boost
boost-driven detection instability

- inhomogeneities in the field existing prior to a signal/stimulus that leads to a macroscopic response="preshape"

- the boost-driven detection instability amplifies preshape into macroscopic selection decisions
this supports categorical behavior

- when preshape dominates

[Wilimzig, Schöner, 2006]
weak preshape in selection

- specific (imperative) input dominates and drives detection instability

[Wilimzig, Schöner, 2006]
distance effect

- common in categorical tasks

- e.g., decide which of two sticks is longer... RT is larger when sticks are more similar in length
interaction metrics-probability

- opposite to that predicted for input-driven detection instabilities:
  - metrically close choices show larger effect of probability

Wilimzig, Schöner, 2006
Memory instability

- Self-excited peak
- Sub-threshold attractor
- Self-sustained peak
“space ship” task probing spatial working memory

[Schutte, Spencer, JEP:HPP 2009]
repulsion from midline/landmarks

[Schutte, Spencer, JEP:HPP 2009]
DFT account of repulsion: inhibitory interaction with peak representing landmark

[Simmering, Schutte, Spencer: Brain Research, 2007]
Working memory as sustained peaks

- implies metric drift of WM, which is a marginally stable state (one direction in which it is not asymptotically stable)

- => empirically real..