Dynamic Field Theory: Part 3: the dynamic instabilities

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the dynamics such activation fields is structured so that localized peaks emerge as attractor solutions.
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
the detection instability helps stabilize decisions

threshold piercing

detection instability

![threshold piercing graph](image1)

![detection instability graph](image2)
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)
emergence of time-discrete events

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

Luminance (cd/m²)

Left Position

Right Position

1

2

L1

Lm

L2

Lb
Detection instability

Background-Relative Luminance Change (BRLC)

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

\[ \text{Background-Relative Luminance Change (BRLC)} = \frac{L_1 - L_2}{L_m - L_b} \]
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. (1997) third experiment. The proportion of trials with switches from the perception of motion to the perception of non-motion, and vice versa, describes a function of the BRLC value when a descending 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 sub-threshold (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
overcoming fixation

- detection can be like selection: initiating an action means terminating the non-action=fixation or posture

- example: saccade initiation

[Wilimzig, Schneider, Schöner, 2006]
initiation vs. fixation

Such models account for the gap-step-overlap effect

[Kopecz, 95]
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

Figure 2. Typical scanpath while a subject searched for changes. The original picture was in colour. The change that occurred in this picture was a vertical displacement of the railing in the background to the level of the man’s eyes. In this record the change was detected at the moment that the observer blinked for the fourth time. The positions of the eye when the blinks occurred are shown as white circles. The last “effective” blink marked “E” occurred when the eye was in the region of the bar. [O’Reagan et al., 2000]
saccade generation

[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)

[figure: Wilimzig, Schneider, Schöner, Neural Networks, 2006]
2 layer Amari model

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

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

Figure 16 Wilimzig, Schneider, Schöner, Neural Networks, 2006
fixation and 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

response

RT
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
- movement parameter
- time
- activation
- task input
- specific input

Graph showing: movement parameter vs. time with activation as the third dimension, demonstrating the notion of preshaping.
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

\[ \text{preshape } (x) \\Rightarrow \text{umax}(t) \]

[Erhagen, Schöner, Psych Rev 2002]
metric effect

- predict faster response times for metrically close than for metrically far choices

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

[McDowell, Jeka, Schöner]
boost-induced detection instability

activation

preshape

boost

self-excited activation peak
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

[Wilimzig, Schöner, 2006]

when preshape dominates
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..