Dynamic Field Theory: Selection Decisions

Gregor Schöner
gregor.schoener@ini.rub.de
Recall from last lecture …
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
Psychophysical evidence for the detection instability

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, are plotted as a function of the BRLC value at which the change occurred. (Note the inversion of the axis on the right.)

There were switches during trials with a particular end-point BRLC value 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

[Wilimzig, Schöner, 2006]
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

[after: Ottes et al., Vis. Res. 25:825 (85)]

[after Kopecz, Schöner: Biol Cybern 73:49 (95)]
... so far we assumed

that a single population of activation variable mediates both the excitatory and the inhibitory coupling required to make peaks attractors

\[
\text{activation field } u(x)
\]

\[
\sigma(u)
\]

local excitation: stabilizes peaks against decay

global inhibition: stabilizes peaks against diffusion

input

dimension, x
But: Dale’s law

- says: every neuron forms with its axon only one type of synapse on the neurons it projects onto
- and that is either excitatory or inhibitory

This is not actually possible!
inhibitory coupling is mediated by inhibitory interneurons that are excited by the excitatory layer and in turn inhibit the inhibitory layer.
2 layer Amari fields

\[
\tau_u \dot{u}(x,t) = -u(x,t) + h_u + s(x,t) + \int k_{uu}(x - x') g(u(x',t))dx' - \int k_{uv}(x - x') g(v(x',t))dx'
\]

\[
\tau_v \dot{v}(x,t) = -v(x,t) + h_v + \int k_{vu}(x - x') g(u(x',t))dx'
\]

with projection kernels

\[
k_{uu}(x - x') = c_{uu} \cdot \exp\left(-\frac{(x - x')^2}{2\sigma_{uu}^2}\right)
\]
simulation
the fact that inhibition arises only after excitation has been induced has observable consequences in the time course of decision making:

- initially input-dominated
- early excitatory interaction
- late inhibitory interaction

[figure: Wilimzig, Schneider, Schöner, Neural Networks, 2006]
time course of selection

early: input driven

intermediate: dominated by excitatory interaction

te=25 ms

te=10 ms

late: inhibitory interaction drives selection

[figure: Wilimzig, Schneider, Schöner, Neural Networks, 2006]
early fusion, late selection

Figure 16 Wilimzig Schneider Schöner

[figure: Wilimzig, Schneider, Schöner, Neural Networks, 2006]
fixation and selection

figure: Wilimzig, Schneider, Schöner, Neural Networks, 2006
2 layer fields afford oscillations

* => simulation

* (oscillatory states for enhanced coupling among fields)

* (generic nature of oscillations)
studying selection decisions in the laboratory

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

imperative
signal = go signal

response

task set

RT

time
the task set

is the critical factor in such studies of selection: which perceptual/action alternative/choices are available...

- e.g., how many choices
- e.g., how likely is each choice
- e.g., how “easy” are the choices to recognize/perform

because the task set is known to the participant prior to the presentation of the imperative signal, one may think of the task set as a “preshaping” of the underlying representation (pre=before the decision)
notion of preshape

specific input

preshaped field

task input

movement parameter

activation

time
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

[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]
same metrics, different probability

different metrics, same probability

[preshaped activation field]

movement parameter

[high probability]

maximal activation

[low probability]

time

[from Erlhagen, Schöner: Psych. Rev. 2002]
[from McDowell, Jeka, Schöner, Hatfield, 2002]
detection-selection: 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]
boost-induced detection instability

activation

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
... emergence of categories?

If we understand, how such inhomogeneities come about, we understand the emergence of categories...
this supports categorical behavior

when preshape dominates

[Wilimzig, Schöner, 2006]
categorical responding

based on categorical memory trace and boost-driven detection instability
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 (1930s')
opposite to that predicted for input-driven detection instabilities:

metrically close choices show larger effect of probability

Wilimzig, Schöner, 2006