Dynamic Field Theory: Selection decisions

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Recall from last lecture …

- Attractor states in neural dynamic fields and their instabilities
  - self-stabilized peaks vs. sub-threshold activation patterns
  - detection and reverse detection instability
  - selection
  - working memory
  - boos-driven detection…
Detection instability

- just responding to input is a “decision” in which the “off” state becomes unstable and the system goes to the alternate “on” state

- that detection decision is self-stabilized… bistable regime.

- critical for the emergence of “events” at discrete times

- evidence for the detection instability from perceptual hysteresis

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*).

- When performance approaches chance level, this approximates *free choice*.

- Reasons are experimental (uncertainty, strategies…).

- (Task set plays a major role … to be discussed later.)
choice without imperative signal

selecting a new saccadic location

[O’Reagan et al., 2000]
saccadic selection

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

[after Kopecz, Schöner: Biol Cybern 73:49 (95)]
saccadic selection

- in reduced visual environment, selections become relatively reproducible...

- selection decisions depend on metrics of visual stimuli

- averaging vs. selection
saccadic selection

- time course of saccadic selection:
- transition from averaging to selection

[Ottes, Van Gisbergen, Eggermont, 1985]
saccadic selection

Understanding the time course of selection requires a re-examination of the theory.
... so far we assumed

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

Dynamic Field Theory and Its Links to Neurophysiology

Excitatory interactions have started firing. The delayed onset of inhibition means that an external stimulus may produce an initial overshoot of excitation, which then decreases as it is balanced by rising inhibition. This gives rise to a phasic-tonic response behavior in the excitatory neurons (although it is not the only cause of this pattern).

In the DF model, this connectivity and the resulting effects on the activation time course can be replicated by introducing separate layers for the excitatory and inhibitory subpopulations (Figure 3.13; see Box 3.5 for the formal description). The basic structure for the two-layer field is as follows:

The two layers, excitatory and inhibitory, are defined over the same feature space and are both governed by differential equations similar to those used in one-layer DFs. In the version considered here, only the excitatory layer receives direct external input. Excitatory interactions are implemented through connections of the excitatory layer onto itself, described by an interaction kernel (e.g., a Gaussian function). In addition, the excitatory layer also projects to and excites the inhibitory layer. These projections are topological; that is, a projection from any point along the feature space on the excitatory layer acts most strongly onto the same point in feature space on the inhibitory layer. The inhibitory layer, in turn, projects back to the excitatory layer in an inhibitory fashion (that is, it creates a negative input in that layer's field equation). Within the inhibitory layer, there are typically no lateral interactions.

The projections between the two layers can be described by interaction kernels, just like the lateral interactions. Note that the effective spread of inhibition is determined by properties of both the projection from the excitatory to the inhibitory layer and of the reverse projection. Let us assume, for instance, that all three projections in the two-layer field (from excitatory to excitatory, excitatory to inhibitory, and inhibitory to excitatory) are described by Gaussian kernels of the same width. Then the effective range of inhibition in the excitatory layer will be wider than the range of lateral excitation, because the inhibition is spread by two kernels instead of just one. In practice, the two-layer field is sometimes set up in such a way that the projection from the excitatory to the inhibitory field is purely local (point-to-point, without an interaction kernel). The kernel for the reverse projection is then made wider to produce the overall pattern of local excitation and surround inhibition. This is a simplification done to reduce the computational load and the number of parameters. It is not meant to reflect any neurophysiological property of the inhibitory neurons or the neural connectivity pattern.

The two-layer field shows a delayed onset of inhibition according to the same mechanism described earlier for the biological neural system. In particular, if an external input is applied to the system, it drives the activation in the excitatory layer, while the inhibitory layer initially remains unchanged. When the activation of the excitatory layer reaches the threshold of the output function, the interactions start to come into effect. The lateral interactions within the excitatory layer drive activation further up locally, and at the same time the activation of the inhibitory layer is increased.

[chapter 3 of the book]
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
Implications

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

intermediate: dominated by excitatory interaction

early: input driven

late: inhibitory interaction drives selection

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

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

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

- \(\Rightarrow\) 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

time

RT
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
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

[Graph showing the relationship between RT and the number of choices, with data points and a line of best fit.]

[Erlhagen, 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

[Diagrams showing preshaped activation field and movement parameter with arrows indicating high and low probability for different metrics, same probability.]

different metrics, same probability

[Diagrams showing preshaped activation field and movement parameter with arrows indicating high and low probability for different metrics, same probability.]

[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
- 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
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')
interaction metrics-probability

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

Wilimzig, Schöner, 2006
Time course of selection decisions: Behavioral evidence for the graded and continuous evolution of decision making

Timed movement initiation paradigm

- Imperative stimulus
- Imposed SR interval
- Move on 4th to tone

[Ghez and colleagues, 1988 to 1990's]
[Favilla et al. 1989]
Experimental results of Henig et al

Distribution of Peak Forces

Peak Force (N)

short SR interval

medium SR interval

long SR interval
theoretical account for Henig et al.

Experimental results of Henig et al.

[Amplitude value vs. Number of trials]

- Zero SR interval
- Short SR interval
- Medium SR interval
- Long SR interval

[Distribution of Peak Forces]

- Short SR interval
- Medium SR interval
- Long SR interval

[Peak Force (N)]

[125 75 25]

Table 1 shows the means and standard errors of curvature and linearity indices (see Materials and methods) across subjects (n = 5) for predictable targets and for each time interval for unpredictable targets. Small increases in curvature of 1°–2° and reductions in linearity occur among movements initiated between 80 and 200 ms after target presentation. However, all values are well within the range of normal values for linearity in reaching movements (e.g. Atkeson and Hollerbach 1985; Georgopoulos 1988a, b; Georgopoulos and Massey 1988; Gordon et al. 1994b). Moreover, as can be noted among the hand paths illustrated in Fig. 5, change in direction associated with curvature did not appreciably reduce the directional error at the end point. Similarly, the improvement in accuracy was not achieved through variations in movement time. Those data will, however, be considered in greater detail below when the systematic effects of target separation on movement time are described (see Fig. 10).

Threshold target separation for discrete directional specification

Figure 7 shows the distributions of initial movement directions in one subject at five target separations and smoothed for clarity. Data from the same three successive S-R time interval bins used in earlier figures are shown in different line types. For the 30° degree target separation, at S-R intervals \( \leq 80 \text{ ms} \) (dotted line and histogram to show effect of smoothing) initial directions are distributed unimodally around the midpoint of the range. In the top plot, the actual histogram for responses with S-R intervals \( \leq 80 \text{ ms} \) is displayed to demonstrate the relationship of the fitted line to the actual distribution. On the right side of each plot, the actual target locations are displayed for reference.

\[ \text{Fig. 7: Experiment 2. Distributions of movement directions at the time of peak acceleration in one subject for five target separations. In each plot, distributions were fitted with a smooth line using a cosine function (Chambers et al. 1983). The arrows on the x-axis point to the required direction for each target separation. In the top plot, the actual histogram for responses with S-R intervals } \leq 80 \text{ ms is displayed to demonstrate the relationship of the fitted line to the actual distribution. On the right side of each plot, the actual target locations are displayed for reference. } \]

\[ \text{[Ghez et al 1997]} \]
probability in timed movement initiation

short SR interval: observe preshape

long SR interval: observe stimulus-defined movement plan

Ghez et al, 1997
Conclusion

- DFT concept of selection decisions supported by ample behavioral signatures
- multiple contributions to specification
  - task set/preshape
  - imperative signal /go signal
- metrics of task layout matters
- time course of decision making can be understood …