Dynamic Field Theory: Selection Decisions

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Recall from last lecture ...

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

[bistable]

[after Kopecz, Schöner: Biol Cybern 73:49 (95)]
reaction time (RT) paradigm

imperative signal = go signal

response

task set

time

RT
metric effect

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

[from Schöner, Kopecz, Erlhagen, 1997]
weak preshape in selection

- specific (imperative) input dominates and drives detection instability

[Wilimzig, Schöner, 2006]
same metrics, different probability

[from Erlhagen, Schöner: Psych. Rev. 2002]
[from McDowell, Jeka, Schöner, Hatfield, 2002]
this supports categorical behavior

when preshape dominates

[Wilimzig, Schöner, 2006]
interaction metrics-probability

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

Wilimzig, Schöner, 2006
Behavioral evidence for the graded and continuous evolution of decision time

imposed SR interval

imperative stimulus

timed movement initiation paradigm

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

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

Peak Force (N)
theoretical account for Henig et al.

Experimental results of Henig et al.

Amplitude value

Number of trials

Distribution of Peak Forces

Peak Force (N)

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 $\leq 80$ ms (dotted line and histogram to show effect of smoothing) initial directions are distributed unimodally around the midpoint of the range. 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 $\leq 80$ 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
rare  frequent

short SR interval:
observe preshape

long SR interval:
observe stimulus-defined movement plan

Ghez et al, 1997
Neural evidence for preshape

Distribution of population activation = \( \sum \) tuning curve * current firing rate

[after Bastian, Riehle, Schöner, submitted]
DPA reflects prior information

[Bastian, Schöner, Riehle 2003]
DPA reflects prior information

[Bastian, Schöner, Riehle 2003]
preshape correlates with RT

[Bastian, Schöner, Riehle 2003]
inhomogeneities from simplest from the memory trace

~ habit formation (?) William James: habit formation as the simplest form of learning

habituation: the memory trace for inhibition
mathematics of the memory trace

\[ \tau \dot{u}(x, t) = -u(x, t) + h + S(x, t) + u_{\text{mem}}(x, t) \]
\[ + \int dx' \ w(x - x') \ \sigma(u(x')) \]
\[ \tau_{\text{mem}} \dot{u}_{\text{mem}}(x, t) = -u_{\text{mem}}(x, t) \]
\[ + \int dx' \ w_{\text{mem}}(x - x') \sigma(u(x', t)) \]

- memory trace only evolves while activation is excited
- potentially different growth and decay rates
memory trace reflects history of decisions formation
Memory instability

- **Dimensions:**
  - **Input:** 0
  - **Output:** h

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

[Schutte, Spencer, JEP:HPP 2009]
Central to the DFT account of geometric biases is how the
perceptual field (PF) of the target is assumed to be generated by relatively low-level neural pro-
terceptual field (PF). This lower activation is due to the strong inhibition around
memory field during the delay. Figure 3c shows a time slice of the
assumed to be generated by relatively low-level neural pro-
terceptual field (PF).

The SWM memory peaks are not always dominated by inhibition as in Figure
3b. In Figure 3c, repulsion from mid-line affects the behavior significantly.

[Spencer, Schöner, 2006]
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.
Piaget’s A not B paradigm: “out-of-sight -- out of mind”
Toyless variant of A not B task

[Smith, Thelen et al.: Psychological Review (1999)]
Toyless variant of A not B task reveals that A not B is essentially a decision task!

[Smith, Thelen et al.: Psychological Review (1999)]
[Thelen, et al., BBS (2001)]

[Dineva, Schöner, Dev. Science 2007]
Instabilities

- detection: forming and initiating a movement goal
- selection: making sensori-motor decisions
- (learning: memory trace)
- boost-driven detection: initiating the action
- memory instability: old infants sustain during the delay, young infants do not
Instabilities

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DFT of infant perseverative reaching

[Dinveva, Schöner, Dev. Science 2007]
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DFT of infant perseverative reaching

- In spontaneous errors, activation arises at B on an A trial
- Which leads to correct reaching on B trial

[Dinveva, Schöner, Dev. Science 2007]
that is because reaches to B on A trials leave memory trace at B

[Dinveva, Schöner, Dev. Science 2007]
DFT is a neural process model

- that makes the decisions in each individual trial, by amplifying small differences into a macroscopic stable state

- and that’s how decisions leave traces, have consequences

[Wilimzig, Schöner, 2006]
Decisions have consequences

- A spontaneous error doubles probability to make the spontaneous error again

Figure 7. Estimates from experiment (solid lines) and DFT simulations (broken lines) of the rate of spontaneous errors across A-trials (black lines). The grey lines show the conditional probability that a reach again goes to B on a given A-trial given that the first spontaneous reach to B has just occurred on the previous trial.

Figure 8. Estimates from infant experiments (solid line) and DFT simulations (broken line) for the probability to make exactly n spontaneous errors as a function of n. According to this hypothesis, the overall rate of spontaneous errors reflects the distribution of the side bias across babies and is, therefore, constant across A-trials. This hypothesis predicts that the conditional probability of repeating a spontaneous error after a previous error should be high (close to one in the limit case of completely deterministic decisions). In fact, this limit case predicts that babies with a bias to B should repeat spontaneous errors across the entire A-trials phase of the paradigm. This prediction is tested in Figure 8 showing the probability that an infant/simulation makes exactly n spontaneous errors as a function of n (Equation (3)). The deterministic account predicts that this probability should have a U-shape: Some infants should systematically make no spontaneous errors, while the biased babies should make a large number of spontaneous errors. Intermediate numbers of spontaneous errors should not be frequent, as these reflect stochastic decision making. The data clearly refute this hypothesis. The monotonic decrease of the probability of n spontaneous errors with the number n is consistent with a stochastic contribution to sensorimotor decision making.

[Dineva, Schöner: Connection Science 2018]
Conclusions

- Action, perception, and embodied cognition takes place in continuous spaces. Peaks = units of representation are attractors of the neural dynamics.
- Neural fields link neural representations to these continua.
- Stable activation peaks are the units of neural representation.
- Peaks arise and disappear through instabilities through which elementary cognitive functions (e.g. detection, selection, memory) emerge.
The conceptual framework of DFT

DST/DFT

DFT models for experiment: account for experimental results

Laboratory experiment neural behavioral

Robotic demonstrations of DST/DFT models

robotic demonstrations of experimental results

DST/DFT approaches to technical autonomous robotics

DST/DFT human factors models

Naturalistic experiment