Dynamic Field Theory: Memory

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Recall from last lecture . . .

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

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

imperative signal = go signal

response

task set

time

RT
weak preshape in selection

in which specific (imperative) input dominates and drives detection instability

[Wilimzig, Schöner, 2006]
strong preshape in selection

supports categorical selection decisions

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

Timed movement initiation paradigm

Imperative stimulus

Imposed SR interval

Move on 4th to tone

[Ghez and colleagues, 1988 to 1990's]
Theoretical account for Henig et al.

Experimental results of Henig et al.

Distribution of Peak Forces

Number of trials

Amplitude value

Peak Force (N)

Minimal changes in the hand paths. 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.

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[Ghez et al 1997]
Neural evidence for preshape

Distribution of population activation = \sum_{neurons} tuning curve * current firing rate

[after Bastian, Riehle, Schöner, submitted]

DPA reflects prior information

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

[Figures A and B showing concentration over time with different information levels: complete information, 2 target information, 3 target information.]

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

Pre-shape and memory trace

how does pre-structuring of representations arise?

in some cases, from the perceptual layout, the environment…

but in other cases, from experience…. memory trace
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
(Working) memory instability

- Self-excited peak
- Sub-threshold attractor
- Self-sustained peak
Working memory as sustained peaks

- WM is marginally stable state: it is not asymptotically stable against drift within the low-dimensional space
- => empirically real.. ?
“space ship” task probing spatial working memory

[Schutte, Spencer, JEP: HPP 2009]
Conversely, of the "on" traces assumed to be generated by relatively low-level neural processes, many are not strong enough to build the traces SWM, stably align and realign egocentric and allocentric reference frames close to or aligned with midline (location 0), it would be either.

Suc.

For instance, if the working memory peak were positioned very close to or aligned with midline (location 0), it would be either.

However, when the target turns off, the target will attract the space (for evidence that symmetry axes are perceived as weak dynamite, note that this input to the model is.

\[ \text{Spencer, Schöner, 2006} \]
DFT account of repulsion: inhibitory interaction with peak representing landmark

[Simmering, Schutte, Spencer: Brain Research, 2007]
visual working memory

- has limited capacity
- based on the number of objects...
- about 4
- probed by change detection, free recall

[Luck, Vogel, 1997]
DFT account of WM capacity

- fundamentally caused by accumulation of inhibitory interaction across peaks
- => generic to DFT
WM capacity depends on interaction

- capacity increases across development
- consistent with “spatial precision hypothesis”… interaction becomes more excitatory/local over development

![Graph showing capacity estimates from the change detection task with children.](Simmering 2010)
Change detection

- the standard probe of working memory

Memory Array

(500 ms)

Delay

(1s)

Test Array

(until response)

Same/Different

[Johnson, et al. 2009]
DFT account for change detection

- separation between perceptual and memory function
3 layer model

sensory input

stimulus: memory item

perceptual field

while stimuli is present

after stimulus is off

inhibition field

memory field

AFTER STIMULUS IS OFF

SENSORY INPUT

STIMULUS MEMORY ITEM

WHILE STIMULI IS PRESENT

PERCEPTUAL FIELD

MEMORY FIELD

INHIBITION FIELD
\[ \tau \dot{u}(x, t) = -u(x, t) + h_u + S(x, t) + \int dx' c_{uu}(x - x') \sigma(u(x', t)) \\
- \int dx' c_{uv}(x - x') \sigma(v(x', t)) + \int dx' c_{uw}(x - x') \sigma(w(x', t)) \]
\[ \tau \dot{v}(x, t) = -v(x, t) + h_v \\
+ \int dx' c_{vu}(x - x') \sigma(u(x', t)) + \int dx' c_{vw}(x - x') \sigma(w(x', t)) \]
\[ \tau \dot{w}(x, t) = -w(x, t) + h_w + \int dx' c_{ww}(x - x') \sigma(w(x', t)) \\
- \int dx' c_{vw}(x - x') \sigma(v(x', t)) + \int dx' c_{wu}(x - x') \sigma(u(x', t)) \]
=> simulations
DFT account for change detection

=> account for how working memories arise from percepts, how percepts may detect change and update memories...
DFT account for change detection

- generate the categorical “answer” by two competing nodes
- based on the “hidden” go-signal in the task

[Johnson, et al. 2009]
DFT account for change detection

1) working memory is created

[Johnson, et al. 2009]
DFT account for change detection

2) change detection in “same” trial

[Johnson, et al. 2009]
DFT account for change detection

2) change detection in “different” trial

[Johnson, et al. 2009]
DFT account for change detection

- predict better change detection when items are metrically closer!
DFT account for change detection

- predict better change detection when items are metrically closer!

[Johnson, et al. 2009]
Multi-object tracking

Figure 5-5. Illustration of a typical Multiple Object Tracking experiment. A display of eight identical objects is shown (t=1) and a subset of 4 are briefly flashed to make them distinctive (t=2). Following this the objects stop flashing so the "target" set becomes indistinguishable from the other objects. All objects then move in a random fashion for about 10 seconds (t=3). Then the motion stops (t=4) and one of the objects is flashed. The observer's task is to say whether the flashed object was one of the objects that had been initially flashed.

In other experiments the observer has to indicate all the tracked objects by clicking on each one using a computer mouse.

If there had only been one object to track the answer would be relatively straightforward: Observers could simply track it with their eyes, or perhaps they could track the moving object using attention scanning (such error-driven tracking systems have been common since the development of feedback control theory and servo mechanisms). But how do observers do this task with 4 objects moving along independent random trajectories, interspersed among 4 other randomly moving identical "distractor" objects that must be ignored.

One possibility is that observers record and use the locations of each target object and visit them serially. After the initial recording of target locations they simply go to the location in the list that they have stored and look around for the nearest object, taking that to be the target they are tracking and updating its location code in the list using the following algorithm:

1. While the targets are visually distinct, scan attention to each target and encode its location on a list. Then, when targets begin to move;
2. For n=1 to 4; Check the n' th position in the list and retrieve the location Loc(n) listed there.
3. Scan attention to location Loc(n). Find the closest object to Loc(n).
4. Update the n' th position on the list with the actual location of the object found in #3. This becomes the new value of Loc(n).
5. Move attention to the location encoded in the next list position, Loc(n+1).
6. Repeat from #2 until elements stop moving.
7. Go to each Loc(n) in turn and report elements located there.

So long as attention moves fast enough from one object to another in relation to the speed of the objects themselves, and so long as targets are sufficiently far from nontargets to prevent frequent mistakes, such a strategy of serial attending and updating a list of locations could explain how observers could track multiple objects. In (Pylyshyn & Storm, 1988) however, we were able to show that the motion and dispersion parameters of our original experiments were such that tracking could not have been accomplished using such a serial strategy. The performance of the above algorithm when it is applied to the actual displays used in the Pylyshyn & Storm study results in the performance shown in Figure 5-6 below.
Multi-object tracking

[Spencer et al]
Multi-object tracking

[Spencer et al]
Combining working memory and the memory trace

in a case study that invokes all dynamic instabilities of DFT as well…
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)]
A location

B location

activation field

[Thelen, et al., BBS (2001)]

[Task input specific input preshape input]

[Thelen, et al., BBS (2001)]

[Task input specific input preshape input]

[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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old

young

Diagram showing activation fields and movement directions with interaction-based sustained activation and input-driven detection.
DFT of infant perseverative reaching

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

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

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

- In spontaneous errors, activation arises at B on an A trial.
- Which leads to correct reaching on B trial.
- Because reaches to B on A trials leave memory trace at B.

[Inoveva, 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
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