Sequential processing in DFT

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Sequences

- All actions in real life consist of sequences of movements, perceptual acts, inferences.
  - Often fixed by the logic of action.
  - Often highly automated: routines.

- But also flexible:
  - Serial order: arbitrary sequences.
Challenge in DFT

- behaviors/representations are stable states
- in sequence: need to switch out of one behavior to the next. How to do that?
- answer: induce an instability
search for objects of a given color in order

1 blue

2 red

green

vehicle

target 1

target 2

obstacles

target 3
The problem of sequential processing

- each step in the sequence is a visual search, which takes a variable (here: unpredictable) amount of time

- so stabilize the goal of the visual search until the search is successful

- only then switch to the next element of the sequence
Implementation as an imitation task

- learn a serially ordered sequence from a single demonstration
- perform a serially ordered sequence with new timing

yellow-red-green-blue-red

yellow-red-green-blue-red

[Sandamirskaya, Schöner: Neural Networks 23:1163 (2010)]
Neural dynamics of sequence generation

represent the target color by a stable peak that resists attractors
red a distractor

red a target

[Sandamirskaya, Schöner: Neural Networks 23:1163 (2010)]
When the sought color is found, switch to the next color by releasing the previous state from stability...through an instability.
“Condition of Satisfaction” (CoS)

excites the corresponding memory node, which, in its turn, provides an excitatory input to the ordinal node which is to be activated next. The active ordinal node also projects onto a single intention field defined over the dimension of color. Which color each node activates is learned, or memorized, in the training phase through a fast Hebbian learning mechanism. The intention field is reciprocally coupled with a two-dimensional space-color field, in which the spatial dimension samples the horizontal axis of the camera image. The space-color field receives ridge-input localized along the color dimension, but not along space, from the intention field. It also receives a two-dimensional space-color input from the visual array. Where visual input overlaps with the ridge, a peak is formed, the spatial projection of which specifies the visual angle under which an object of the color being sought is located. The space-color field projects along the spatial dimension onto the dynamics of heading direction, creating an attractor that steers the robot to the detected object. As that object is approached, its image grows in the robot’s visual array. The condition-of-satisfaction field (top-right on Fig. 8) is pre-activated by input from the intention field and is pushed through the detection instability when the object of the color being sought looms sufficiently large. This brings about the transition to the next step in the sequence as described in Section 3.3.

Before an object that matches the current intention has been found, no peak exists in the space-color field. The heading direction does not receive input at that time from the space-color field and the vehicle’s navigation dynamics is dominated by obstacle avoidance, which is implemented using a standard dynamic method (Bicho, Mallet, & Schöner, 2000). This results in the roaming behavior that helps the robot search for objects of the appropriate color. During teaching, the visual input from the object shown to the robot is boosted enough to induce a peak in the space-color field. This peak projects activation backwards onto the intention field, where a peak is induced at the location that the object of the desired color is located on the camera image.

[Sandamirskaya, Schöner, 2010]
Camera image

Color histogram of the column

Color-space DF
Perception for navigation

Perception for CoS

Camera image

Color-space DF

Input strength

Activation

Color

Input strength

Activation

Color

0 20 40 60 80 100 120 140 160 180

0

0.2

0.4

0.6

0.8

1

1.2

1.4

1.6

1.8

2

x, hue values

P

CoS

(x,t)

x, hue values

CoS DF

Color-space DF

Intention DF

Activation

Color

Camera image
ordinal stack

condition of satisfaction (CoS)

intentional state

2D feature-space field
Generalization

A framework for behavioral organization based on intention
node and a dynamic neural field (DNF) (see satisfaction (CoS)
consist of two parts, an
that are organized are
flexibly organize timed behaviors.

...Manoid robot in a grasping task [19], is extended to

C. Behavioral organization
perceptual items, and memory items. Are the units of representation for motor parameters,
localized peaks of activation. Within DFT, such peaks
or mid-range inhibition, promoting the formation of

Kernel
The type of interaction is governed by the interaction
su
input
at feature location

In Eq. 5, Grossberg [17] and was analyzed by Amari [18]

following dynamic equation, which can be traced back to

pattern evolves in continuous time

Feature dimensions (e.g., color or space). The activation
represent neural activity patterns over continuous, metric

motor streams of the robot and the higher level cognitive
architectures based on discrete behaviors.

B. Dynamic Field Theory
DFT, which we now briefly review.

To summarize, a single timed movement consists of

three separate behaviors: the postural, movement, and
remaining distance.

Movement to be executed, and

starting to move and the movement has to suppress the

behaviors must be activated and deactivated in the correct

update behavior. In order to function properly, these be-

haviors...
A DFT cognitive architecture for sequence generation

- every action is represented by an "intentional" node
- an an "intentional field" that represents the specific action (parameter value) that is to be enacted

[Sandamirskaya, Zibner, Schneegans, Schöner: New Ideas in Psychology (2013)]
A DFT cognitive architecture for sequence generation

- The intention pre-activates a “condition of satisfaction” field with the predicted sensory information.
- The CoS field goes through a detection instability as sensory input matches the prediction.

Figure 2. Elementary behavior (EB) in Dynamic Field Theory.

[Sandamirskaya, Zibner, Schneegans, Schöner: New Ideas in Psychology (2013)]
A DFT cognitive architecture for sequence generation

This detection instability in CoS triggers the sequential transition by inhibiting the intention

[Sandamirskaya, Zibner, Schneegans, Schöner: New Ideas in Psychology (2013)]
active transient of the CoS

set intention: blue => red

detection CoS:
blue => green
back to the DFT model

- the DFT model we have so far clearly is an instance of the positional model
- in which a positional context (ordinal node) is associated with the contents of an item
- the generic mechanism makes this link more explicitly as a neural (synaptic) association
[Sandamirskaya, Schöner: Neural Networks 23:1163 (2010)]
Ordinal nodes

Action field

CoS field

motor system

action perception

environment

CoS perception

positional

stability

[Sandamirskaya, Schöner: Neural Networks 23:1163 (2010)]
mechanism for transition

Matching perceptual input
Learning first item ("green")

Camera image

Ordinal nodes

Intention DF

CoS DF

Transition

Learning second item ("yellow")
Autonomous sequence generation

- discrete events in time are autonomously generated
- when the world matches the intention: condition of satisfaction

[Sandamirskaya, Schöner: Neural Networks 23:1163 (2010)]
Generalization
Sensorimotor DFs

environment

Mem.

Ord.

CoS

i.

c.

i.

c.

i.

c.
Sensorimotor DFs

environment

chaining
The multi-dimensional DFT model

Ordinal nodes

Action field: color

Action field: arm

Action field: gripper

CoS field: color

CoS field: arm

CoS field: gripper

Robot

color perception

find color

set arm pose

get current arm pose

get current gripper pose

set gripper pose

[Sandamirskaya, 2011]
hierarchy

[Level 0]

\[ \text{EB}_{11} \rightarrow \text{EB}_{12} \rightarrow \ldots \rightarrow \text{EB}_{1n} \]

[Level 1]

\[ \text{EB}_{11} \rightarrow \text{EB}_{12} \rightarrow \text{EB}_{13} \rightarrow \text{EB}_{14} \rightarrow \text{EB}_{1m} \]

\[ \text{EB}_{15} \rightarrow \text{EB}_{16} \rightarrow \text{EB}_{17} \rightarrow \text{EB}_{18} \]

\[ \vdots \]

[Level \( p \)]

\[ \text{EB}_{p1} \rightarrow \text{EB}_{p2} \rightarrow \text{EB}_{p3} \rightarrow \text{EB}_{p4} \rightarrow \text{EB}_{pq} \]

\[ \text{EB}_{p5} \rightarrow \text{EB}_{p6} \rightarrow \text{EB}_{p7} \rightarrow \text{EB}_{p8} \]

[Duran, Sandamirskaya, 2014]
Neural Dynamic Architectures

that we reviewed earlier... all use the CoS mechanism
A neural dynamics resolves spatial language about visual scenes.

Fig. 2. Overview of the architecture, showing the activation state when answering the question "What is to the right of the green object?" on the scene in Fig. 1. On the right, dynamic fields are shown as color-coded activation patterns (blue for lowest, red for highest activation). On the left, dynamic nodes are denoted as circles with activation levels indicated by fill color opacity. The three-dimensional perceptual field is shown as slices through the activation pattern for the colors orange and green. Excitatory synaptic connections are denoted by arrows, inhibitory connections by lines ending in circles. Arrows marked with stars are patterned connections that encode concepts.

2 Methods

The DFT architecture shown in Fig. 2 can be viewed as one integrated dynamical system, that combines coupled dynamics fields (DFs) supporting perception with coupled dynamic nodes that instantiate concepts and organize sequential processing.

2.1 Dynamic fields and dynamic nodes

DFs can be thought of as a temporally and spatially continuous form of neural networks. Activation fields, $u(x,t)$, over a continuous feature dimension $x$ (e.g., hue or spatial position) evolve over time $t$ according to

$$\tau \dot{u}(x,t) = -u(x,t) + h + S(x,t) + \int f(u(x',t))w(x-x')dx',$$

where $\tau$ is a time constant, $h < 0$ is a resting level, and $S(x,t)$ is external input. Lateral interactions in the field are homogeneous and can be described as a

[Richter, Lins et al. ICANN 2014]
into the reference and target field and enable these fields to track moving objects even if spatial attention is currently focused elsewhere.

3.2. Attention

The core of the attentional system consists of two three-dimensional attention fields. They are defined over the same dimensions as the two perception fields, but their activation remains below threshold unless additional input arrives from a feature attention field or a spatial attention field.

Fig. 2. Architecture with activation snapshots while it is generating a phrase about a video. Fields are shown as color-coded activation patterns; for three-dimensional fields, two-dimensional slices are shown. Node activation is denoted in opacity-coded circles. Spatial templates are illustrated as color-coded weight patterns (bottom left). Excitatory synaptic connections are denoted by lines with arrowheads, inhibitory connections by lines ending in circles. Transformations to and from polar coordinates are marked with a “T.” Steerable neural mappings are denoted as diamonds.
Conclusions

- I reviewed the mechanism of transitions between stable (intentional) state by the condition of satisfaction and its underlying dynamical mechanism of active transient generation.

- This is a critical element that enables DFT to account for complex sequential behaviors and autonomous cognitive processes.

- This key mechanism sets apart DFT architectures from almost all other neural processing accounts.