Predictive and Sparse Neural Fields in high dimensional dynamic environments

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Active perception in humans and robots

Perception → Active perception

sensorimotor loop

Stimuli
Perception
Cognition
Command

Active perception in humans and robots

Introduction

e.g. Active vision

camera

overt exploration

image

covert attention
Introduction

Quick psychological experiment

Giraffe

Dog

Stick figures (stimuli) from [Olman & Kersten, *Cognitive Science*, 2004]

EyeTracker (saccade $\approx$ information)
[Kietzmann et al., *PLOS One*, 2012]

MouseTracker (movement $\approx$ decision)
[Freeman et al., *Front Psychol*, 2011]
Dynamical decision-making involving prediction

- Various domains (motor control, categorization, stereotypes...)
- Various models (neural networks, classifiers, Bayesian, DNF)

[Catenacci et al., Neural Network, 2014]
[Quinton et al., IEEE Trans. on SMC, 2013]
**Competition**
(attention/decision)

- symmetric connections
- global → local (focus)
- inhibition

**Prediction**
(learning/planning)

- asymmetric connections
- local → global (trajectory)
- excitation

**Preprocessing**

- saliency maps (bio-insp.)
- feature points (artificial)

**Sensations**

- visual input (external)
- proprioception (internal)
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Focus on anticipation

Principles in living systems

Dynamical system

- Far from equilibrium
- Self maintaining
- Implicit anticipation

- Continuously adapt to the environment
  - Chaotic changes $\rightarrow$ react to adverse conditions
  - Rhythm/structure $\rightarrow$ synchronize by predicting changes
Focus on anticipation

Principles in living systems

- Continuously adapt to the environment
  - Chaotic changes → react to adverse conditions
  - Rhythm/structure → synchronize by predicting changes

Dynamical system
- Far from equilibrium
- Self-maintaining
- Implicit anticipation
Focus on anticipation

Principles in living systems

Dynamical system
- Far from equilibrium
- Self maintaining
- Implicit anticipation

- Acting in a dynamical environment
  - Perception complexity increases with possible actions
  - Need to take genetically unpredictable choices anytime
Focus on anticipation

Principles in living systems

- Acting in a dynamical environment
  - Perception complexity increases with possible actions
  - Need to take genetically unpredictable choices anytime

Dynamical system
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Focus on anticipation

Principles in living systems

Dynamical system
- Far from equilibrium
- Self maintaining
- Implicit anticipation
- Explicit anticipation

Immersed in a complex environment (because of one’s actions)
- Full of other complex dynamical systems striving for survival
- The environment itself becomes genetically unpredictable
Adapting during life rather than evolution

- Basic set of reflexes to survive with immediate actions
Adapting during life rather than evolution

- Basic set of reflexes to survive with immediate actions
- Learning to better anticipate and act accordingly
Why bothering with anticipation?

- **eliminate lag** from purely reactive behavior
- can be added up on top of reflexive behavior
- **normative value** of the prediction (epistemic contact)
- **filter out noise** and distractors from complex signals
- **coordination/planning** capabilities (in space and time)
- allows **abstracting** from sensorymotor signals
- concepts defined as **networks of potential interactions**
- easy to distribute and neurally plausible (population coding)

[Hawkins, *On Intelligence*, 2005]
[Bickhard, *JETAI*, 1998]
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Dynamical Neural Field (DNF) + dynamic stimuli

- **competition** (between distant stimuli)
- non-linear **convergence** toward a stimulus
- **noise/distracters** robustness

→ good **selection/tracking capabilities**

PNF (no predictor)

Standard equation and emergent properties

**DNF equation:**

\[ \tau \frac{\partial u(x,t)}{\partial t} = -u(x,t) + \int_{x' \in M} w(x,x') \sigma(u(x',t)) dx' + s(x,t) + h \]

\[ Ae \frac{|x-x'|^2}{a^2} - Be \frac{|x-x'|^2}{b^2} \]

CNFT_Weights

1. Selection
2. Interpolation
3. Focusing
4. A-B

Ae - B
Oscillations when tracking a moving input
focus, assume the stimulus does not move, relax, focus... repeat
DNF extension:
\[
\tau \frac{\partial u(x,t)}{\partial t} = -u(x,t) + \int_{x' \in M} w(x,x') \sigma(u(x',t)) \, dx' + i(x,t) + h
\]

\[Ae \frac{|x-x'|^2}{a^2} - Be \frac{|x-x'|^2}{b^2}\]
**Possible ways of introducing predictions**

- **Asymmetric kernels** (e.g. ACNFT [Cerda, 2010])
  - merge kernels for different predictions?
  - different kernel at each point?
  - keep DNF properties?
- **Bias the field activity**
  - (similar problems)
- **Bias the stimulation**
  - bottom-up + top-down projections

---

**DNF extension:**

\[
\tau \frac{\partial u(x,t)}{\partial t} = -u(x,t) + \int_{x' \in M} w(x,x') \sigma(u(x',t)) dx' + i(x,t) + h
\]

\[
\alpha p(x,t) + (1-\alpha)s(x,t)
\]

**Spatiotemporal constraints \rightarrow extension**
PNF (1 predictor)

1) Compute prediction ($p$)
   - transform of $u^t$
   - expected activity $u^{t+dt}$

2) Update the CNFT ($u^{t+dt}$)
   - competition term
   - integration scheme
   - biased convergence
PNF (1 predictor)

How to evaluate performance?

Environment...
- inputs to the model
- representative dynamics
  → input scenario(s)

Tracking performance...
- hypothesis: 1 bubble
- compute center of mass
- compute error/inputs
  → expected properties

CNFT model
  → only access raw data

stimuli
stimuli
stimuli
cnft parameters
+ predictors
noise
distracters
input
input
input
focus
focus
focus
error
error
error
Evaluation scenarios

Specific scenarios to test the predictive capabilities

- C: 2 moving stimuli
  - slight dissymmetry
  - slow alternation

- D: 1 moving stimulus
  - distracters at t=1

- E: 1 moving stimulus
  - noise at t=0

- F: 1 moving stimulus
  - distracter on trajectory

- G: 1 moving stimulus
  - full occlusion
Results

PNF (1 predictor)

Mean tracking error as a function of the Gaussian noise standard deviation.

- Alternation between targets
- Distractor on trajectory
- Occlusion
- Mean tracking error as a function of the Gaussian noise standard deviation
PNF (1 predictor)

Linear predictor:

\[ p(x,t) = u(x - v dt, t) \]

\[ p(x,t) = u(x - \gamma(v) dt, t) \]

- Sensation from the CNFT
- Action on the CNFT

\[ \int w(x) \sigma(u(x,t)) \]

\[ \left(1 - \frac{dt}{\tau}\right) u(x,t) \]

stimulation

\[ \frac{(1-\alpha)dt}{\tau} s(x,t) \]

prediction

\[ \gamma(v) dt \]
Results

Qualitative results

- reproduces the DNF properties and add new properties
- lower error with correct predictor (hopefully)
- fallback on the standard version with bad predictor
- how to deal with an arbitrary trajectory?
Pattern discrimination

Extending the equation (again)

**DNF extension:**

\[
\tau \frac{\partial u(x,t)}{\partial t} = -u(x,t) + \int_{x' \in M} w(x,x') \sigma(u(x',t)) dx' + i(x,t) + h
\]

\[
\alpha p(x,t) + (1-\alpha) s(x,t)
\]

\[
\sum w_k(t) p_k(x,t)
\]

\[
\sum w_k(t)
\]

[Quinton & Girau, CNS, 2012]

---

**Generalization**

\[ A \cdot e \left( -\frac{|x-x'|^2}{a^2} - Be \frac{|x-x'|^2}{b^2} \right) \]

**Differentiation**

\[ M \cdot x \]

---

**CNFT_Weights**

\[ > a \]

\[ < b \]

\[ A-B \]
Pattern discrimination

Computation steps

1) Confidence update ($w_k$)
   - match prediction
   - to stimulation
   - error committed

2) Compute predictions ($p_k$)
   - transform of $u^t$
   - merge in a single field
   - expected activity $u^{t+dt}$

3) Update the CNFT ($u^{t+dt}$)
   - competition term
   - integration scheme
   - biased convergence
Qualitative results

- reproduces the results obtained with a single predictor
- fast selection of adequate predictors
- interpolation in time and space + multi-scale support (hyperacuity)
Visual attention (overt and covert)

- Overt exploration
- Covert attention

Combining overt and covert predictions

PNF (overt + covert)

Implementation for tracking

- Stimuli rapidly crossing the field of view
- Eye movement prediction
- Stimulus movement prediction

Stimulus movement prediction and focus in the output

Overall view (stimulus and retinal view)

Stimulus (input) and Focus (output)

Error graph
Eye movement
- **saccade** (lag)
- **smooth pursuit**

Overshoot?
- centered stimuli
- excit/inhib pred.

→ compensation

**Computation steps**

1. **Eye predictor**
   - $p_m$

2. **Predictors**
   - $p_0$, $p_1$, $p_2$

3. **Focus**
   - $u^t$, $u^{t+dt}$

4. **Eye movement**
   - $m^{t+dt}$

**PNF (overt + covert)**

**Predictors**

- $p_0$
- $p_1$
- $p_2$

**Focus**

- $u^t$
- $u^{t+dt}$

**Eye movement**

- $m^{t+dt}$

**Competition**

- $c$

**Stimulation**

- $s$

**Pan-tilt camera**

**Visual environment**

**JC Quinton - Predictive and Sparse Neural Fields**
Conclusion

- **DNF as robust competition mechanism** (to noise, distracters, occlusions)
- **PNF** reproduces the original behavior, but also allows **active perception**
- **simple extension** of the original DNF (inner/outer interactions)
- compatible with **learning** methods (e.g. sensorimotor contingencies)
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Dynamic Neural Fields (DNF)

- **mesoscopic** distributed model (tissue level, cortical sheet)
- **over a topological manifold** (1D / 2D continuous space)
- spatiotemporal **evolution of variables** (e.g. mean-field potential)
- described by **(local) equations** (same at all points)
Parameters and equation for the potential...

\[ \tau \frac{\partial u(x,t)}{\partial t} = -u(x,t) + \int_{x' \in M} w(x,x') \sigma(u(x',t)) dx' + s(x,t) + h \]

- 1D-3D manifold → fixed dimensionality
- matrix computations → fixed resolution
- convolution → polynomial complexity

Many implementations...
- rate coding [Rougier & Vitay, Neur. Net., 2006]
- spikes [Chevallier & Tarroux, ESANN, 2008]
  [Vasquez, Quinton & Girau, IJCNN, 2011]

Similar constraints...
- 1D-3D manifold → fixed dimensionality
- matrix computations → fixed resolution
- convolution → polynomial complexity
Dealing with **high dimensional data** (and the **curse of dimensionality**)!

- **Brute force**
  - Higher order matrix convolution: complexity $O(n^{2d})$
  - Numerical linear algebra (SVD, FFT...): $O(nd+1)$
  - Fast hardware implementation (GPU, FPGA): connectivity pb

- **Reduce dimensionality**
  - Machine learning techniques (SVD, PCA...): meaningfulness ?
  - Self-organizing maps (e.g. projection in 2D): shearing, distortions
  - Combination (e.g. detectors/descriptors): hard tuning
Visual saliency

designed to be salient

[Itti & Koch, *PAMI*, 1998]

Architectures and improvements

[Fix et al., *Cognitive Computation*, 2010]
Dealing with high dimensional data (and the curse of dimensionality!)

- Brute force
  - Higher order matrix convolution  \( \text{complexity } O(n^{2d}) \)
  - Numerical linear algebra (SVD, FFT...)  \( \text{SVD } \rightarrow O(nd+1) \)
  - Fast hardware implementation (GPU, FPGA)  \( \text{connectivity pb} \)

- Reduce dimensionality
  - Machine learning techniques (SVD, PCA...)  \( \text{meaningfulness ?} \)
  - Self-organizing maps (e.g. projection in 2D)  \( \text{shearing, distortions} \)
  - Combination (e.g. detectors/descriptors)  \( \text{hard tuning} \)

- Couple low dimensional maps
  - Sharing dimensions (i.e. linear projections)  \( \text{binding pb} \)
  - Other projections  \( \text{lattice + constraints ?} \)

- Other approximations of the continuum
  - Spiking neurons  \( \text{update potential} \)
  - Mixtures (GMM, RBF...)  \( \text{robustness ?} \)
From simple observations

- dynamics converges toward a set of peaks
- peaks often have spatial and temporal continuity
- peaks are stereotyped (shape depending on the kernel)
Why a “sparse” implementation?

From simple observations

- dynamics converges toward a set of peaks
- peaks often have spatial and temporal continuity
- peaks are stereotyped (shape depending on the kernel)
- architectures with might be many interconnected maps
- learning method that requires dense mapping (no regression)

(only true when the goal is to select/track)
Model peaks of activity as point-like elements

- **center coordinates** (2D+), **width** and **intensity** (arbitrary distribution)
- input as a **set of points** (use receptive fields and filters)

→ exclusively manipulate point-like elements

\[ g_1 = x_1, y_1, \ldots, w_1, i_1 \]

\[ g_2 \]
Sparse CNFT

Computation steps

1) Competition step
- between centers only
- mainly inhibition (-)
- need to account for \( s_i^t \)

2) Integration step
- all in one sparse map
- excitatory & inhibitory
- growing number of elts

3) Merging step
- merge close elements
- eliminate weak ones
- convergence
Activity in hyperspaces (i.e. lower dimensional fields)
- **binding** through attention → prediction / planning or multiple hypotheses?
- **ridges** with matrix (DNF) → **sparse vectors** with arbitrary distributions (SNF²)

Sparse vectors
- \([h_1] [h_2] [x_1,y_1] [x_2,y_2]\)
- \([x_1,y_1,h_1] [x_2,y_2,h_2]\)

Similarity measure
- \([x_1,y_1,h_1] → [x_2,y_2,h_2]\)
- \([[x_1-x_2,y_1-y_2,h_1,h_1] \approx |x_1-x_2,y_1-y_2]\)
- \([x_1,y_1,h_1] → [x_2,y_2]\)
- \([[x_1-x_2,y_1-y_2] \approx |x_1-x_2,y_1-y_2]\)
- \([h1] → [x1,x2]\)
- \([[x_1-x_2,y_1-y_2] \approx 0]})
Conclusion

Qualitative results

- **low computational cost** (even with non parallel hardware)
- **update time** depending on the number of elements (quadratic)
- another approximation of the **continuous neural dynamics**
- reproduces the **properties** of the standard version
- produces **synthetic values** for easy interfacing with artificial systems
- able to simulate **multi-dimensional** DNF in a single field
- **sparsity** in space and in dimensions (abstract adaptive topology)
- yet, if too few components → **reduced robustness**
- except for performance, functionally/theoretically **useful?**

---

Iteration time (in µs) for the various versions implemented and tested

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<th>Scenario</th>
<th>Discrete version</th>
<th>Discrete (SVD)</th>
<th>Sparse version</th>
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<tr>
<td>A (alternation)</td>
<td>321131</td>
<td>37537</td>
<td>596</td>
</tr>
<tr>
<td>B (distracters)</td>
<td>321084</td>
<td>37724</td>
<td>953</td>
</tr>
<tr>
<td>C (noise)</td>
<td>321003</td>
<td>37491</td>
<td>632</td>
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Model

Swallowing (autonomy, goal constraints)

[Quinton, 2008]

h (neurohormone)

p_b (throat pos.)

c_g (contraction)

e_g (throat water)

p_b (mouth pos.)

c_b (contraction)

Motor situation

Goal

Context → Consequence

Sensory situation

Command

Δt

v_1 > 0

v_2 > 0

v_3

h → 6

e_b → 9

e_g → 0

p_b → 9

p_g → 8

c_b ← 6

c_g ← 2

[Quinton, 2008]
**Introduction**

**Anticipatory mechanisms and DNF**

**Prediction**
(learning/planning)

- asymmetric connections
- local → global (trajectory)
- excitation

**Competition**
(attention/decision)

- symmetric connections
- global → local (focus)
- inhibition

**Preprocessing**

- saliency maps (bio-insp.)
- feature points (artificial)

**Sensations**

- visual input (external)
- proprioception (internal)