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Dynamic neural field

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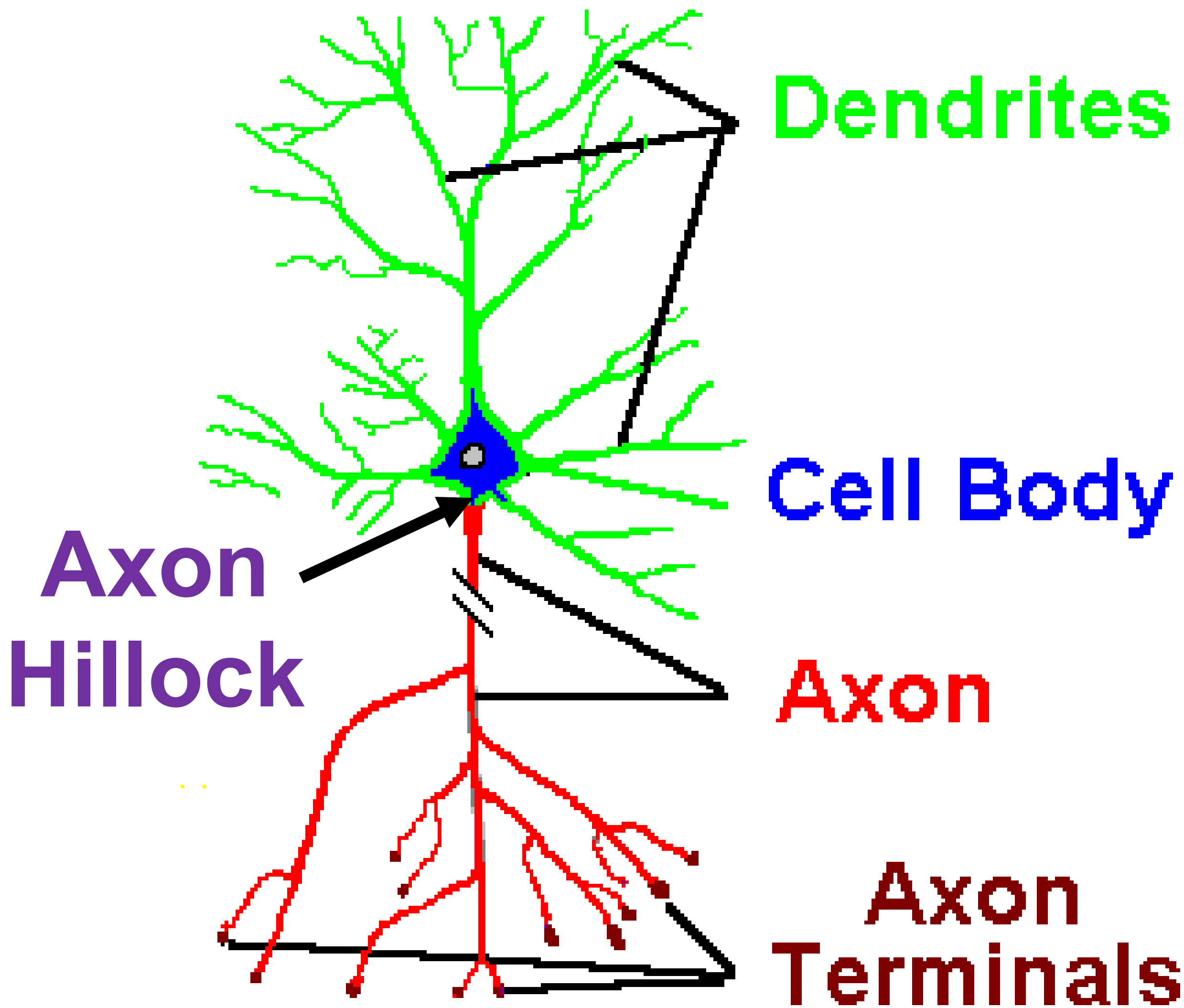
(based on material prepared by Dietmar Heinke)

Mind, **B**rain, and **M**odels

Overview

- **Dynamic neuron model**
- **Dynamic neural field theory**
- **Application**
  - **Model of visual search**
- **Source: Trappenberg p. 190-195**

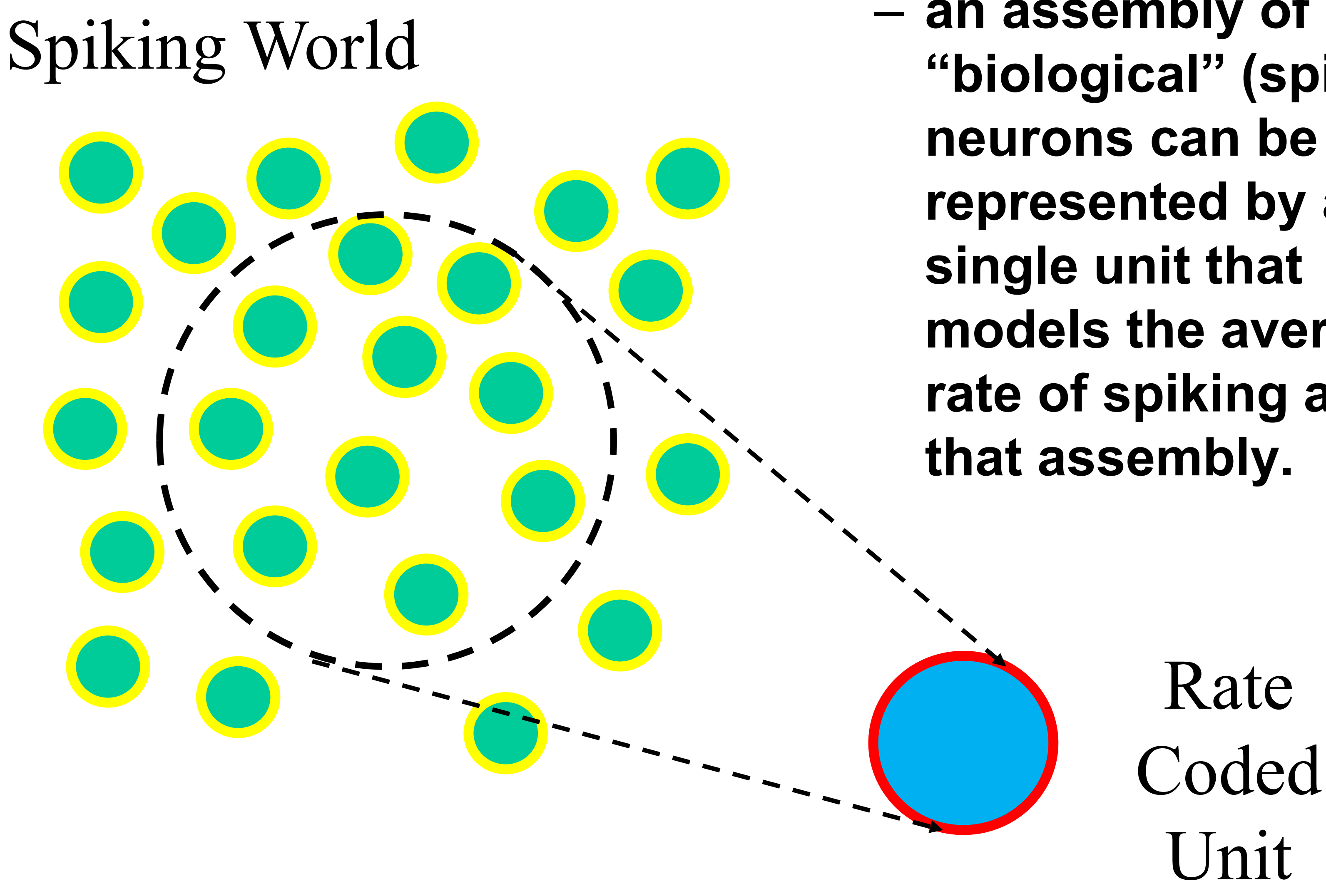
Everything begins with the neuron



Simplifications

- Spikes > Firing rate / population code
- Soma + Dendrites > summation
- Neurotransmitters > weights
- Internal (membrane) activation > weighted summation of incoming activation
- Axon Hillock > activation function
- Synapse: controls interaction

Rate Coding



- **Hypothesis,**
  - **an assembly of "biological" (spiking) neurons can be represented by a single unit that models the average rate of spiking across that assembly.**

Dynamics

- Greek: force
- Physics: the effect of forces on bodies, i.e. the change of body’s motion under the influence of forces.
- Opposite of “static”
- Psychodynamics

Static: Perceptron

- Activation function:

$$y_i = g(\sum_{j=1}^{N} w_{ij} \cdot x_j)$$

- w: weights
- y: output activation
- x: input
- g: activation function

Differential equation

- A differential equation is a mathematical equation for a function that relates the value of the function itself and its derivatives.

- Applications:
  - Physics
  - Engineering
  - economics

Dynamic neuron model

- Sluggishness of a neuron

- Differential equation:

$$\tau \cdot \frac{\mathrm{d}x(t)}{\mathrm{d}t} = -x(t) + I$$

$$y = f(x)$$

- I: input
- y: output activation
- x: internal (membrane) activation
- f: sigmoid function

Dynamic neuron model

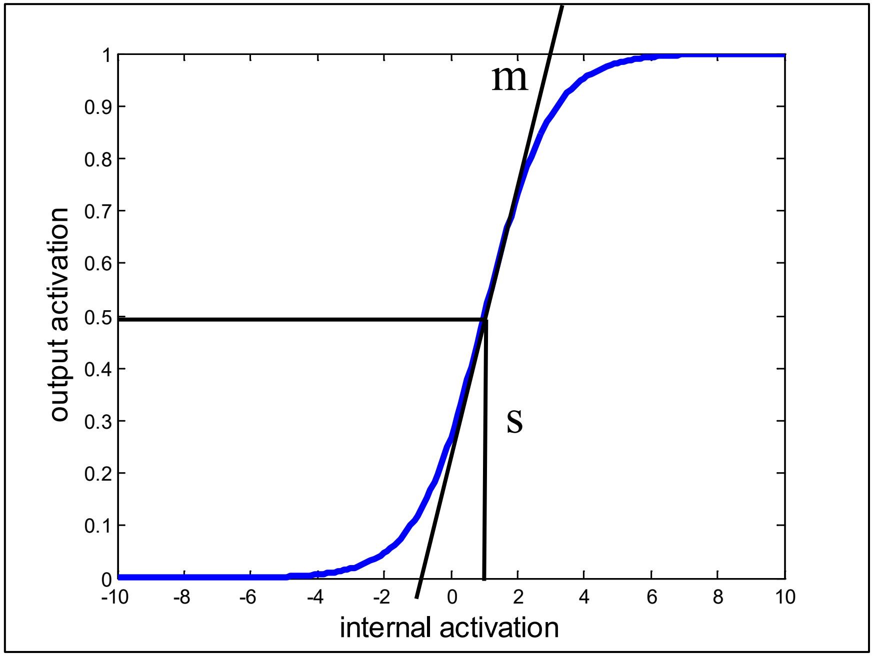
$$\tau \cdot \frac{\mathrm{d}x(t)}{\mathrm{d}t} = -x(t) + I$$

Rate of change = difference between current activation and input activation

Initial value:

$$x(0) = 0$$

Activation function: Sigmoid-function



$$y = f(x) = \frac{1}{1 + e^{-m \cdot (x - s)}}$$

Dynamic neural field theory

- Continuous spatial coordinates are called fields in physics
- Neural fields: N-dimensional layers
- Short-distance excitation (cooperation)
- Long-distance inhibition (competition)

Dynamic neural field theory

- Simplified Equations 7.6 – 7.14 (Trappenberg):

$$\tau \frac{dx(k,l)}{dt} = -x(k,l) + \sum_{ij} w(k-i, l-j) \cdot y(i,j) + I(k,l)$$

$$y(k,l) = f(x(k,l))$$

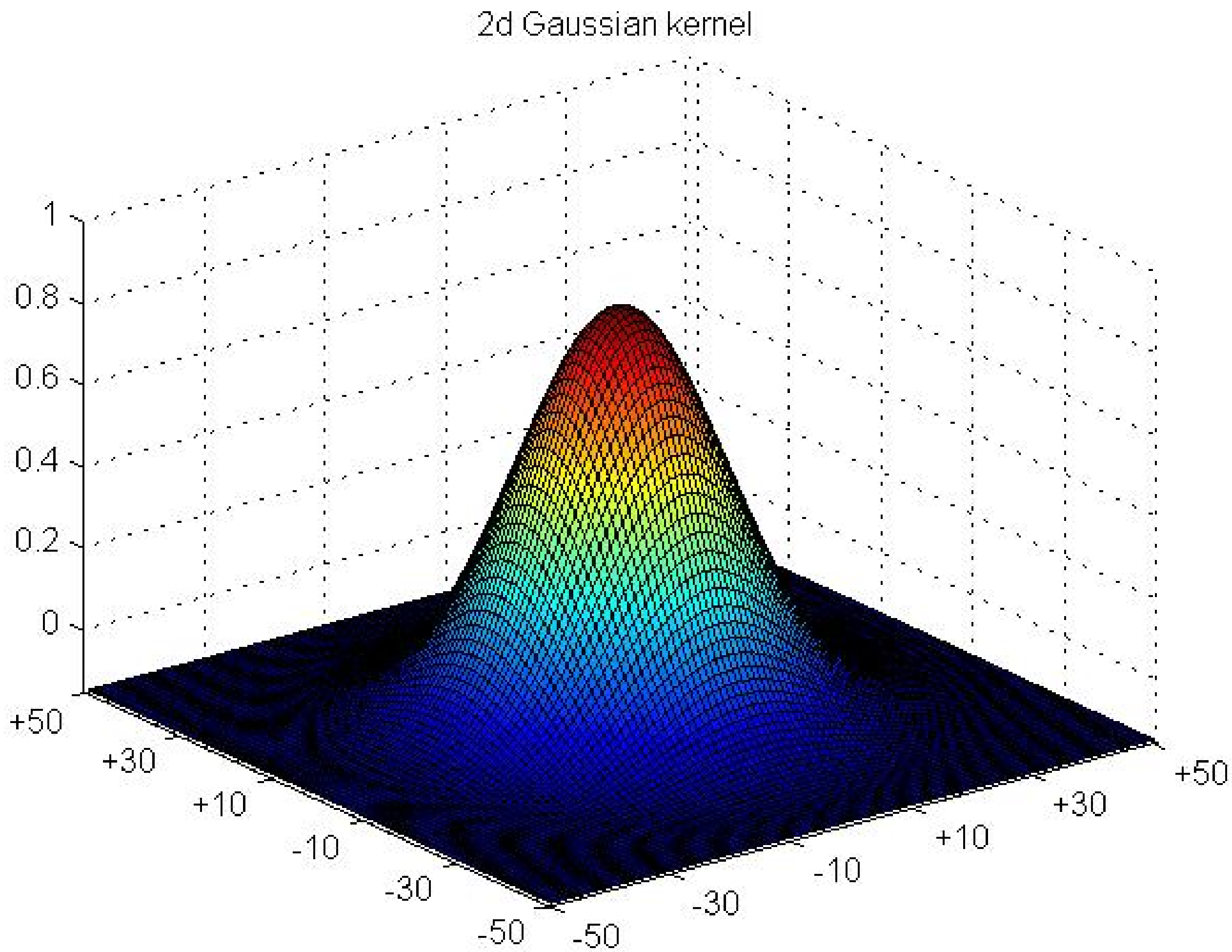
- w: interaction kernel
- I: external input
- y: output activation
- x: membrane activation
- f: sigmoid function

Kernel (2-d)

- C: strength of global inhibition
- σ: spread of excitation
- A: strength of excitation

$$w(i,j) = A \cdot e^{-\frac{i^2+j^2}{\sigma^2}} - C$$

Bell Shaped in 2-d

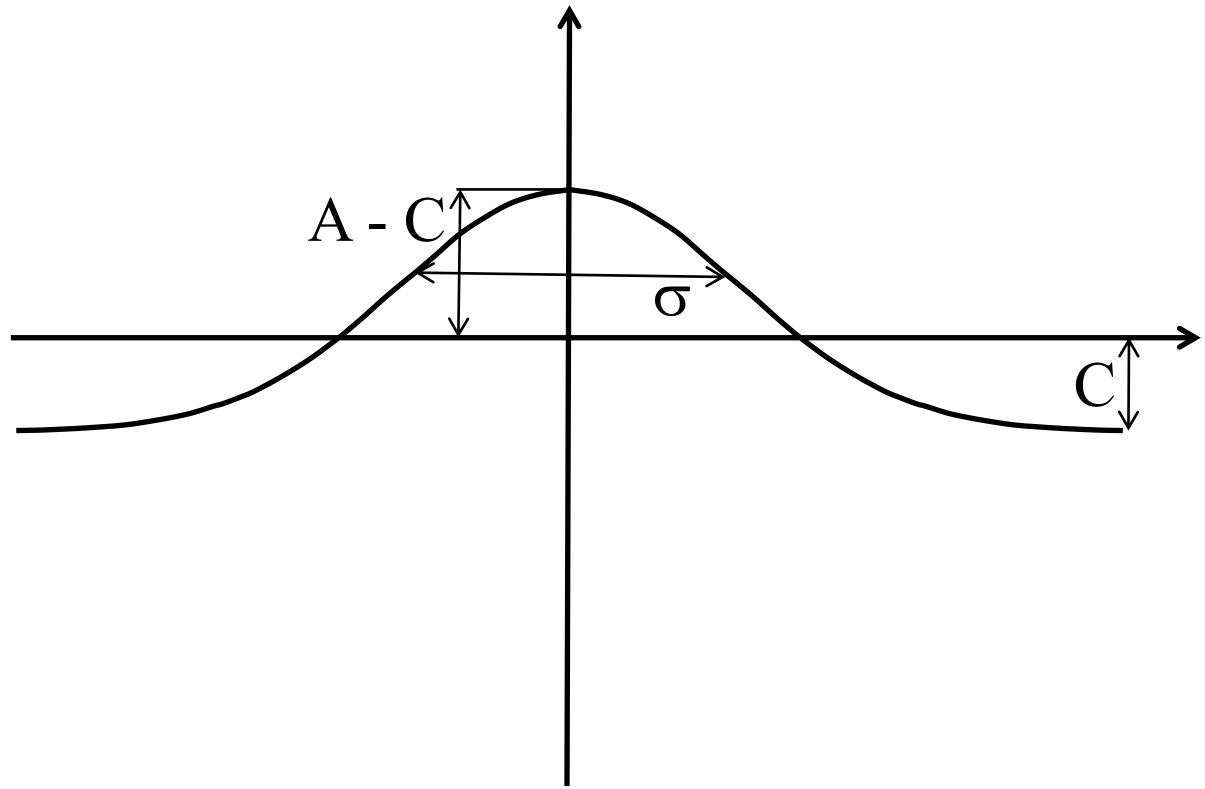


Kernel (1-d)

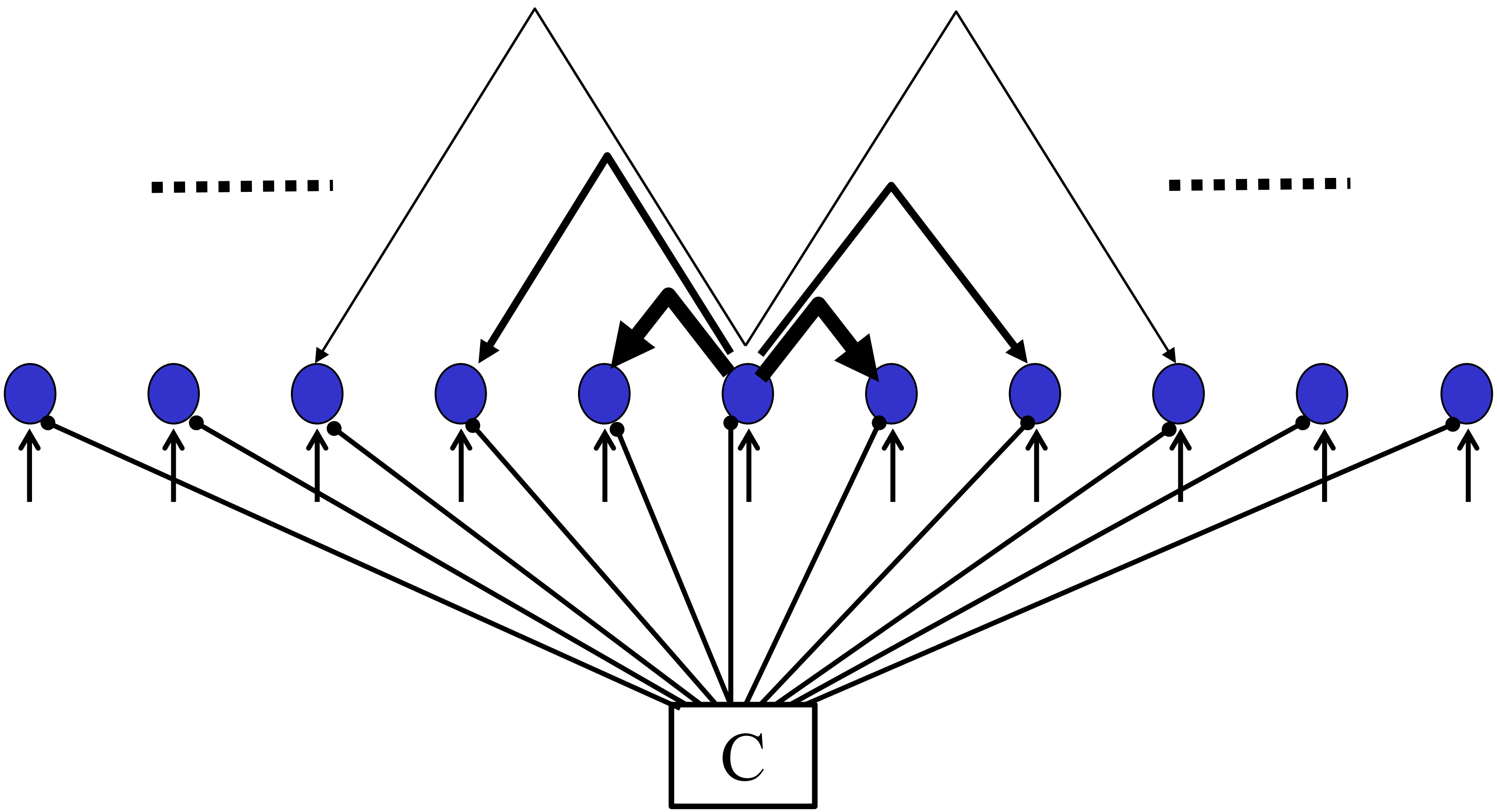
$$w(i) = A \,.\, e^{-\frac{i^2}{\sigma^2}} - C$$

- C: strength of global inhibition
- σ: spread of excitation
- A: strength of excitation

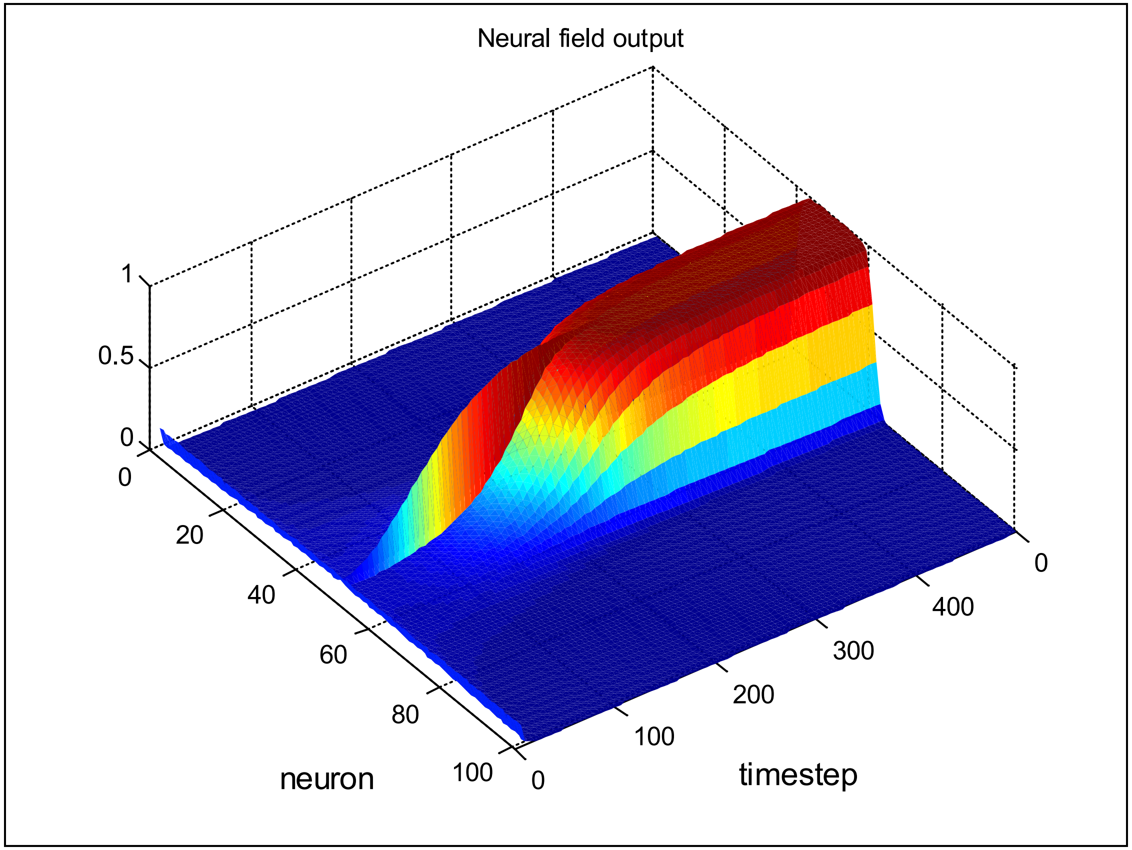
Kernel (1-d)



Dynamic neural field



Result



Neural field output
1
0.5
0
0
20
40
60
80
100
neuron
0
100
200
300
400
0
timestep

Asymptotic states

- Growing activity
- Decaying
- Memory activity

“Right” level of abstraction

- local computations
- (layered) network of neurons
- dynamic interactions
- non-linearity
- rate code

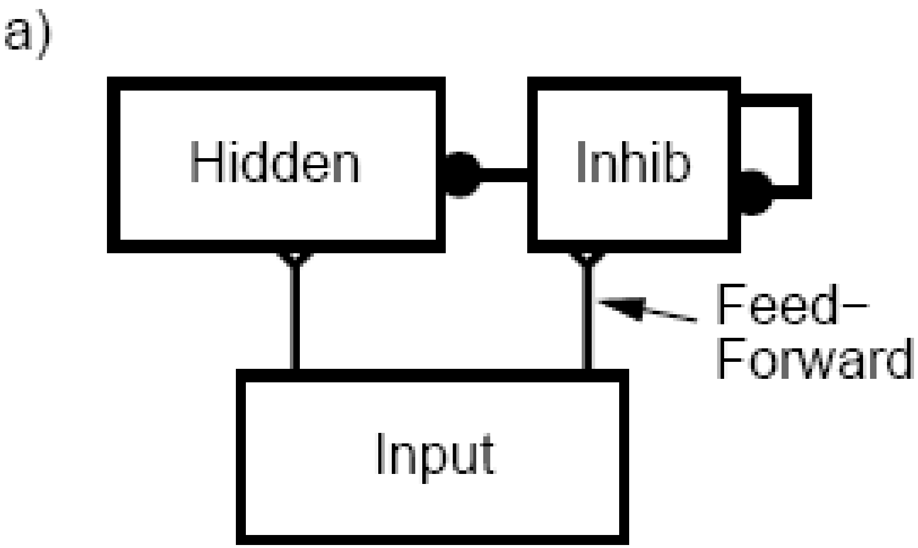
Reactive Inhibition

Reasons for inhibition

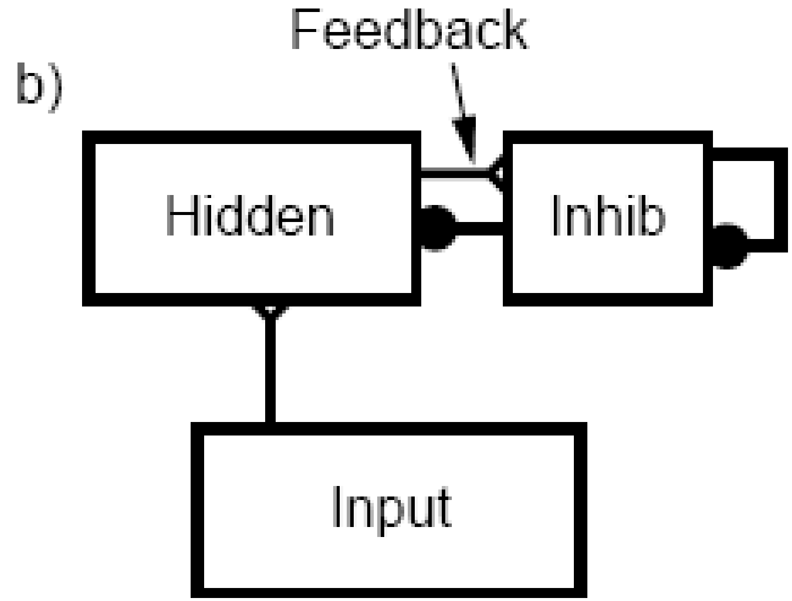
1. In field, C does not adapt to "temperature" of field;
2. Reactive inhibition:
   a. **Controls activity** (bidirectional excitation).
   b. **Competition** → selection.
   c. Supports **sparse** distributed representations (consistent with single cell recordings).
   d. Has localized "regulatory" effect – supporting **set-point** behaviour
   e. Different to **classic Artificial Neural Network** handling of inhibition.

What does sparse mean?

Types of Inhibition



Anticipates excitation



Reacts to excitation

Why is inhibition needed, over and above the leak?

Analogy – air conditioning system and, in general, control theory.

What "problem" can arise from Reacts example?

VISUAL COGNITION, 2006, 13 (4), 401–480

Psychology Press
Taylor & Francis Group

A neural network model of inhibitory processes in subliminal priming

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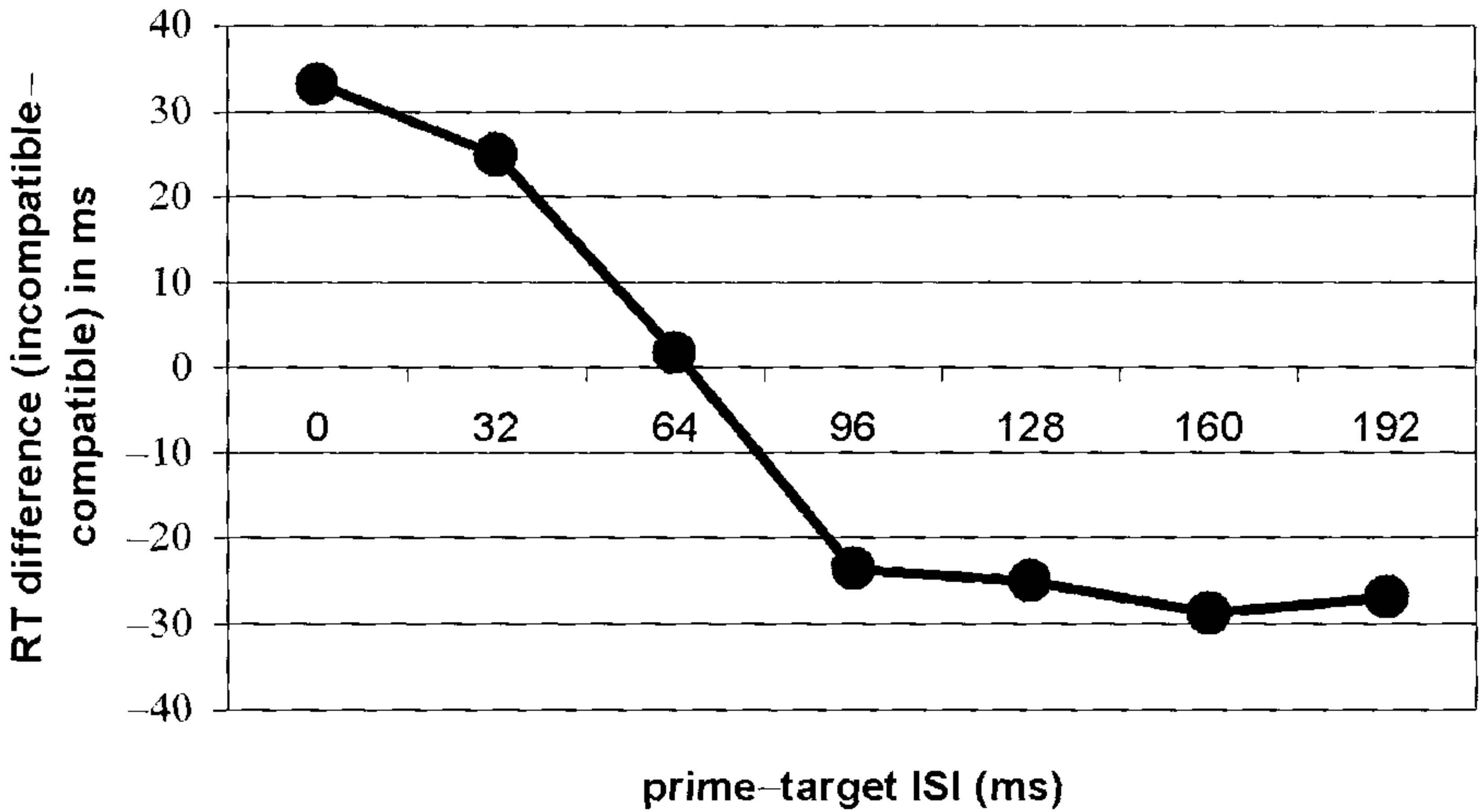
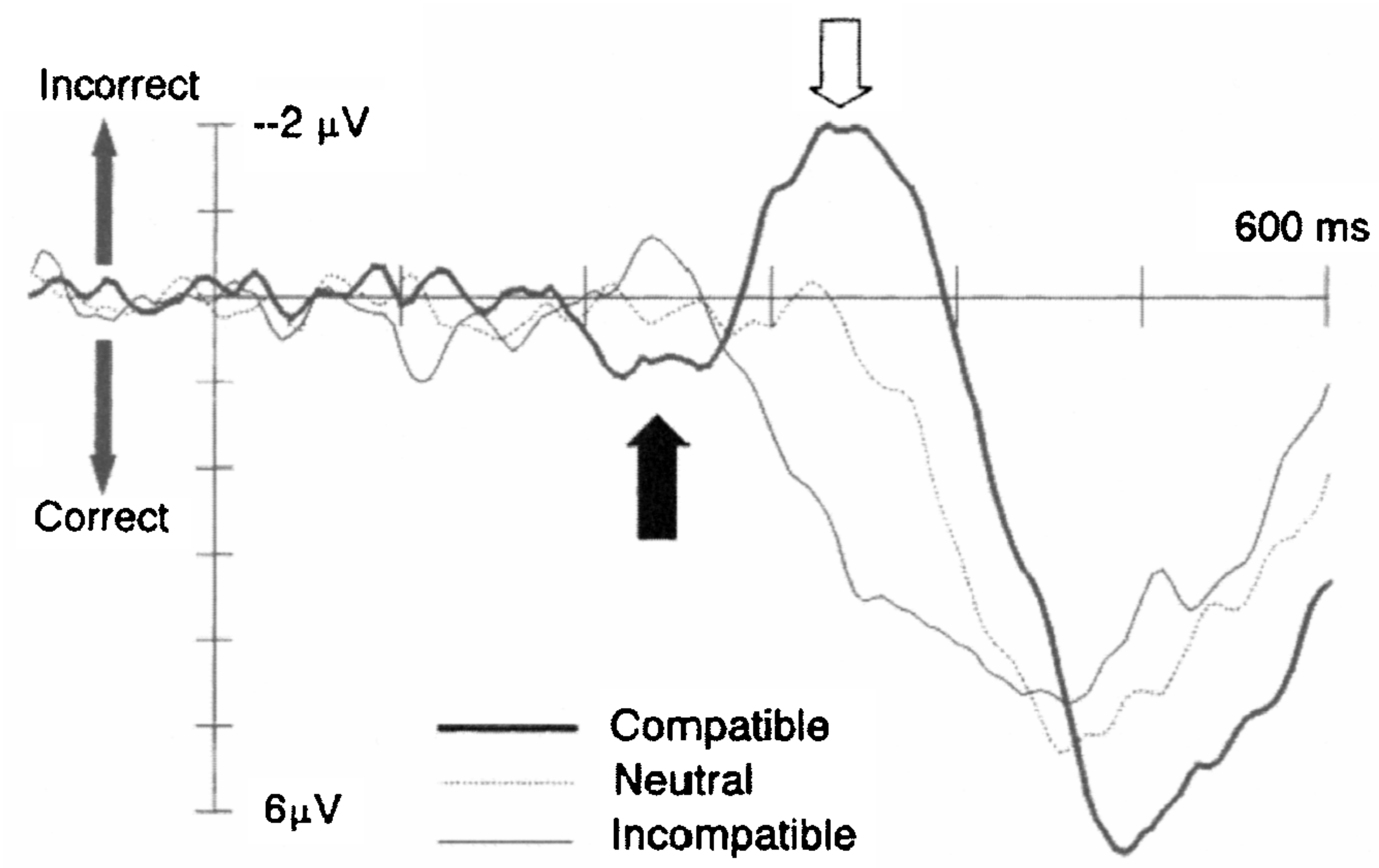
Negative Compatibility Effect

- Experiment:
  - prime stimulus << or >>, followed by mask; followed by target, << or >>; followed by speeded response;
  - mask makes prime “subliminal”.

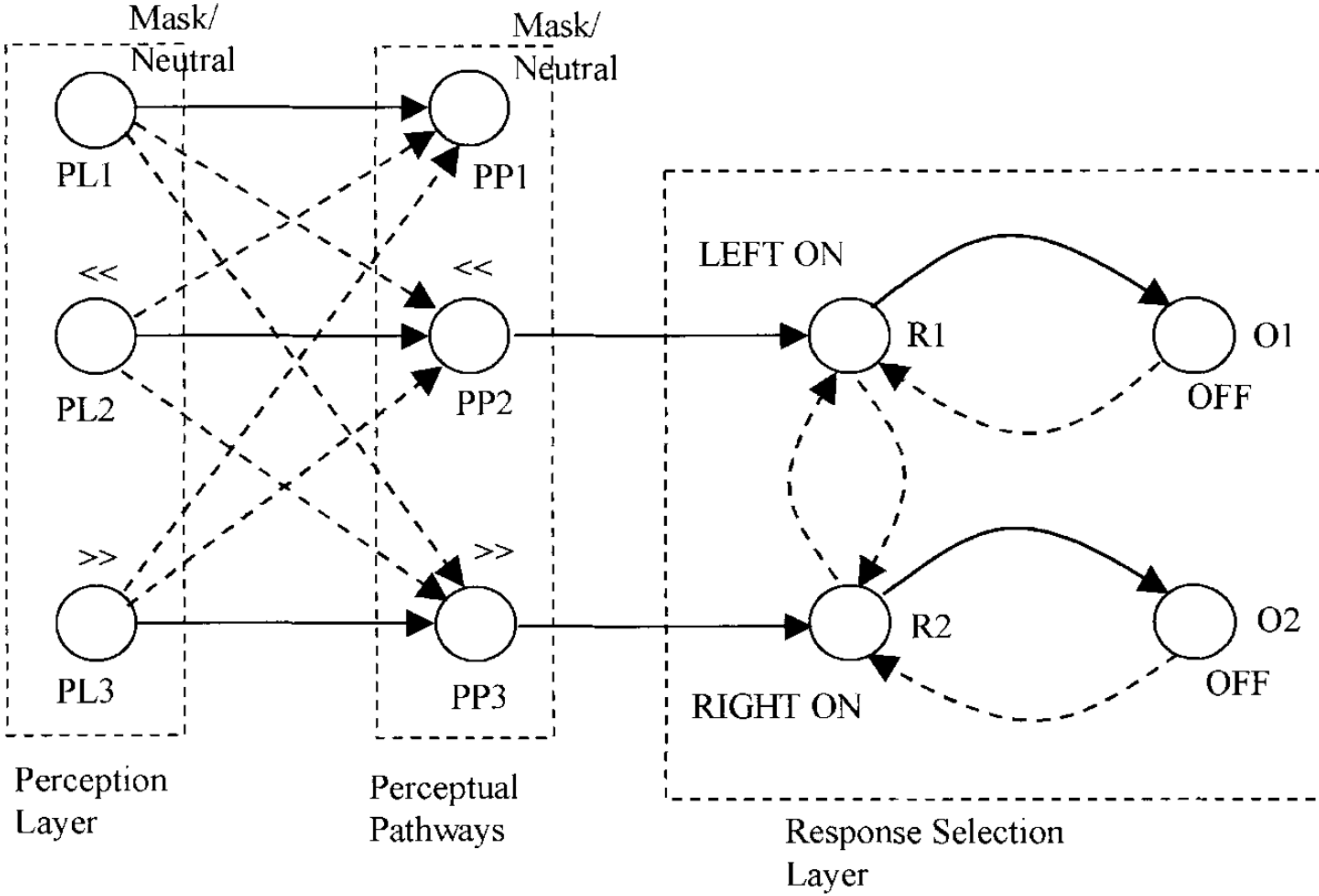
Behavioural finding



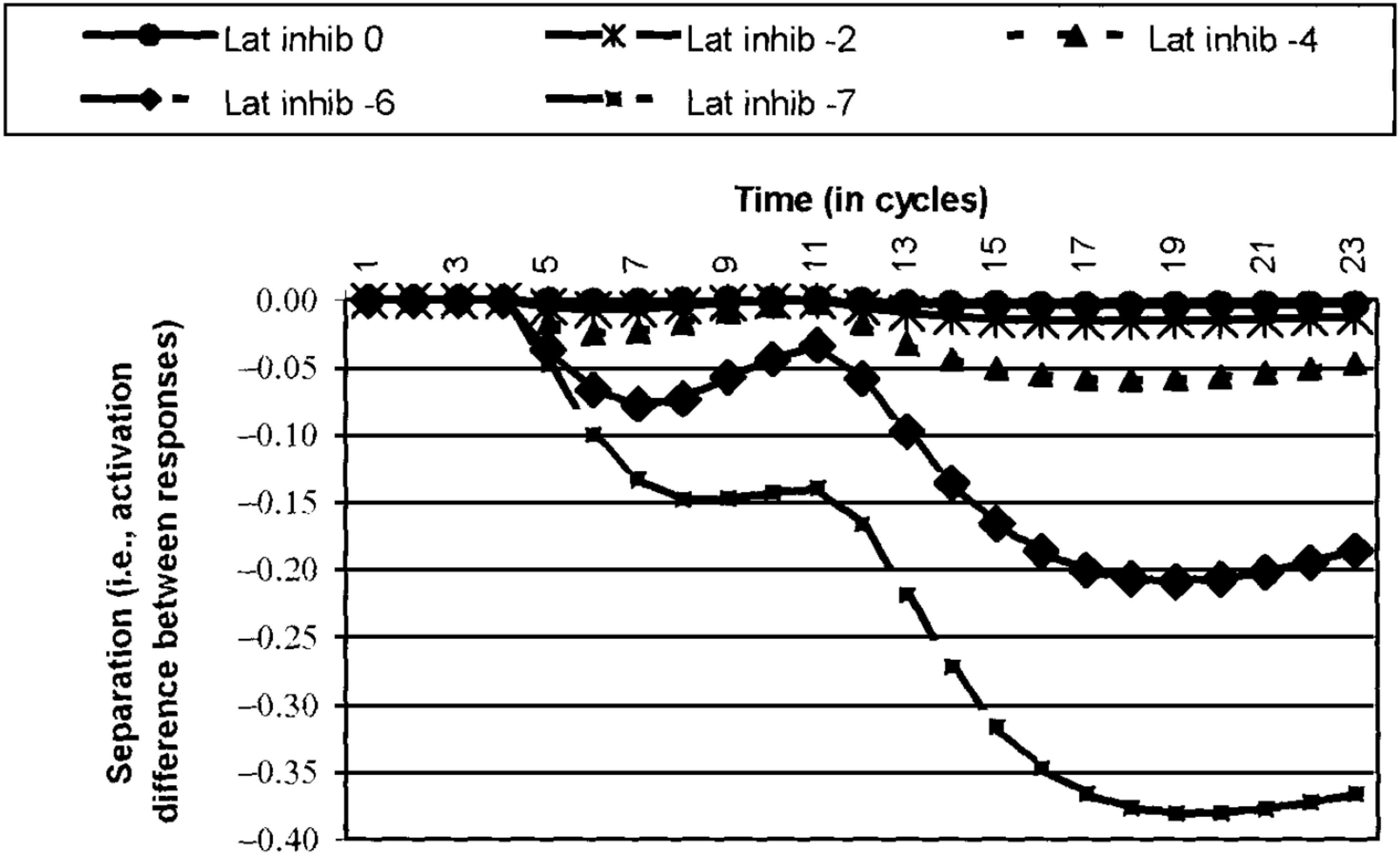
Lateralized Readiness Potential



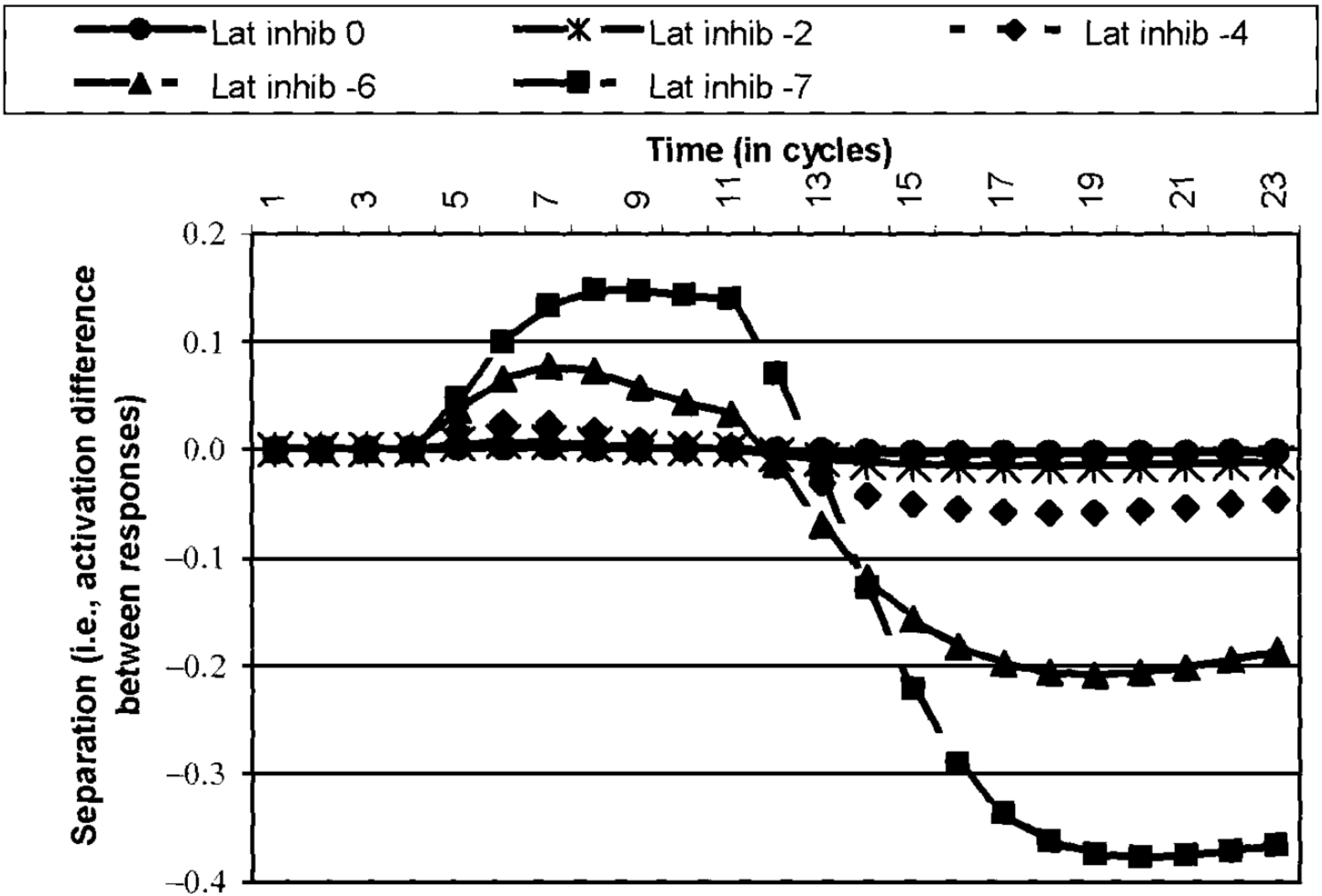
The Model


Mask/
Neutral
Mask/
Neutral
PL1
PP1
<<
<<
PL2
PP2
>>
>>
PL3
PP3
LEFT ON
R1
O1
OFF
R2
O2
OFF
RIGHT ON
Perception
Layer
Perceptual
Pathways
Response Selection
Layer

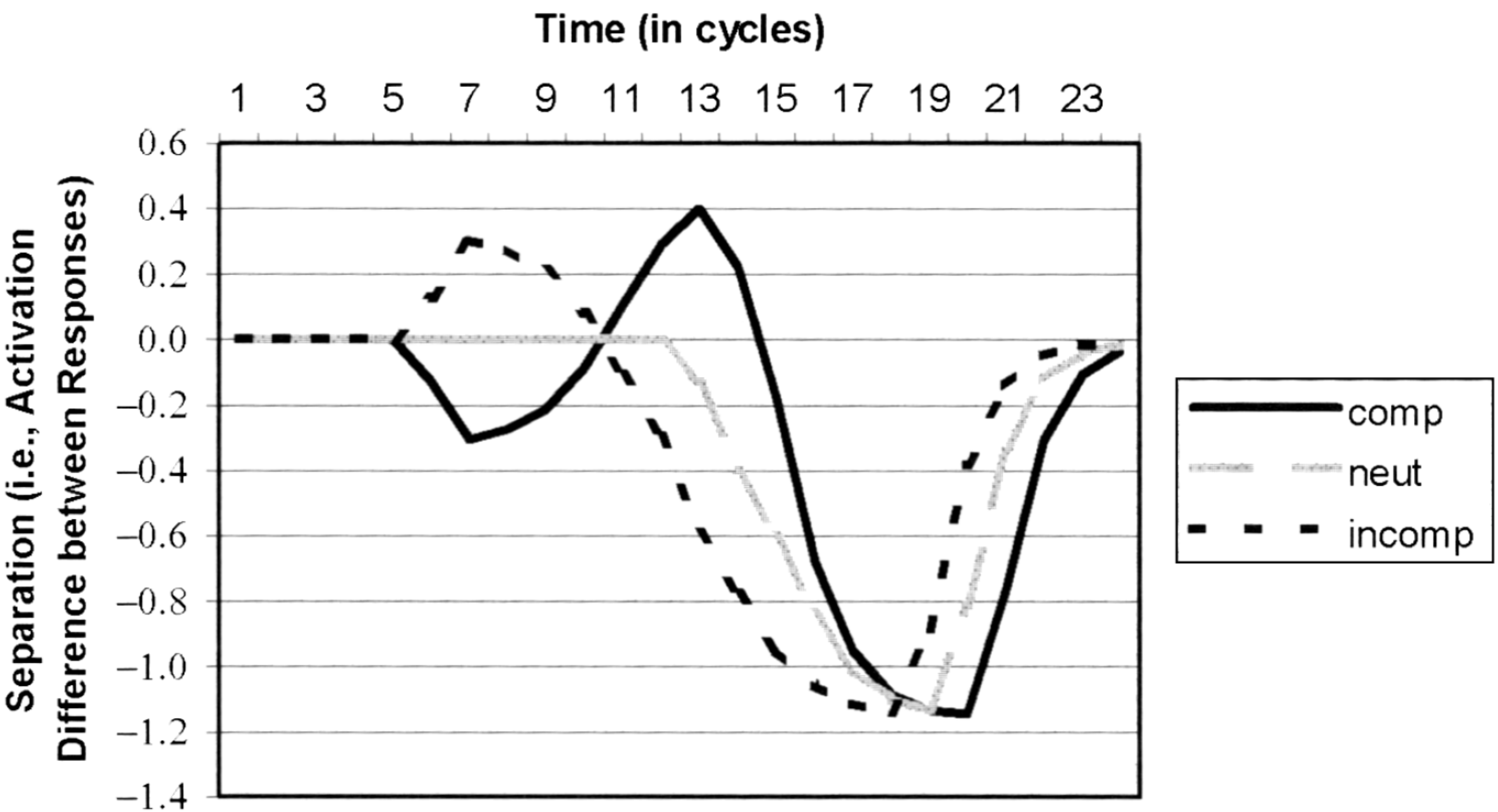
No Opponent Process, compatible



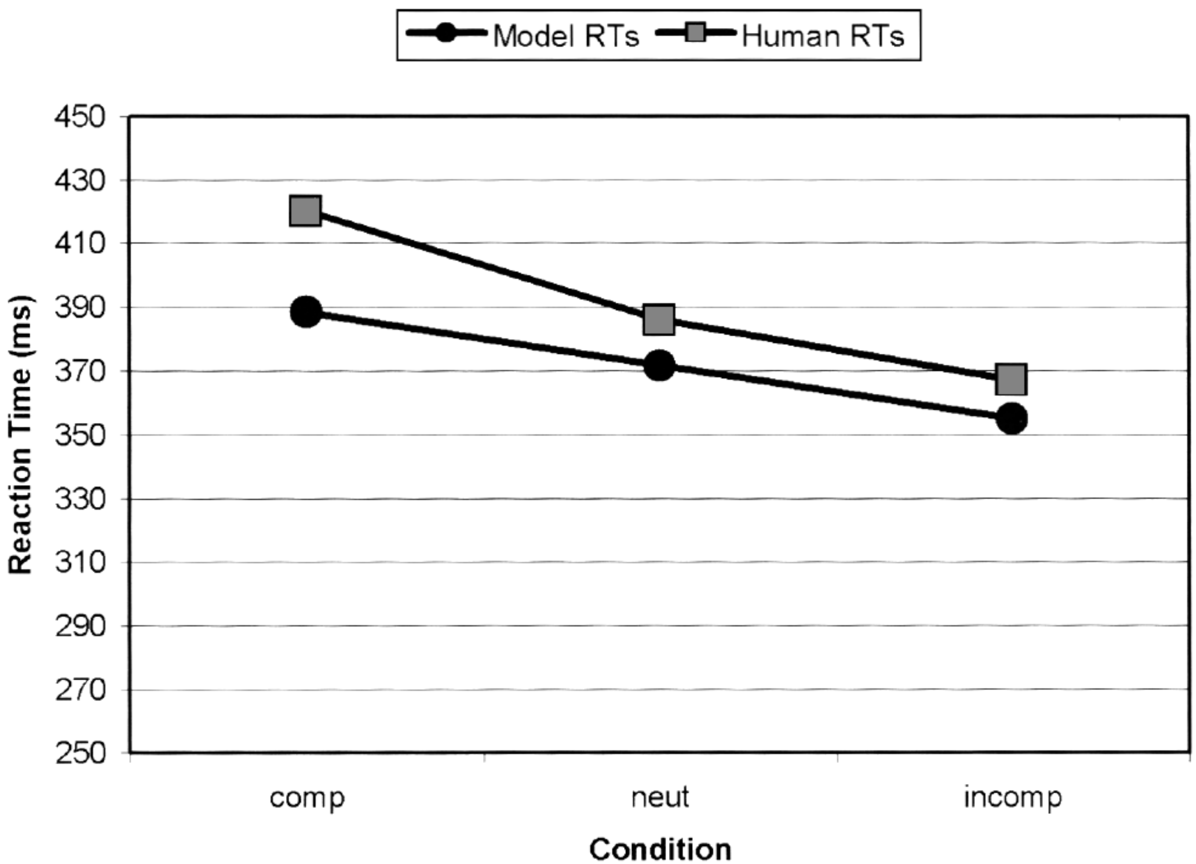
No Opponent Process, incompatible



Full Model, with Opponent Process (Masked, ISI 100ms)



Reaction Times from Model, with Opponent Process (Masked, ISI 100ms)



Prediction: Response Systems Oscillate

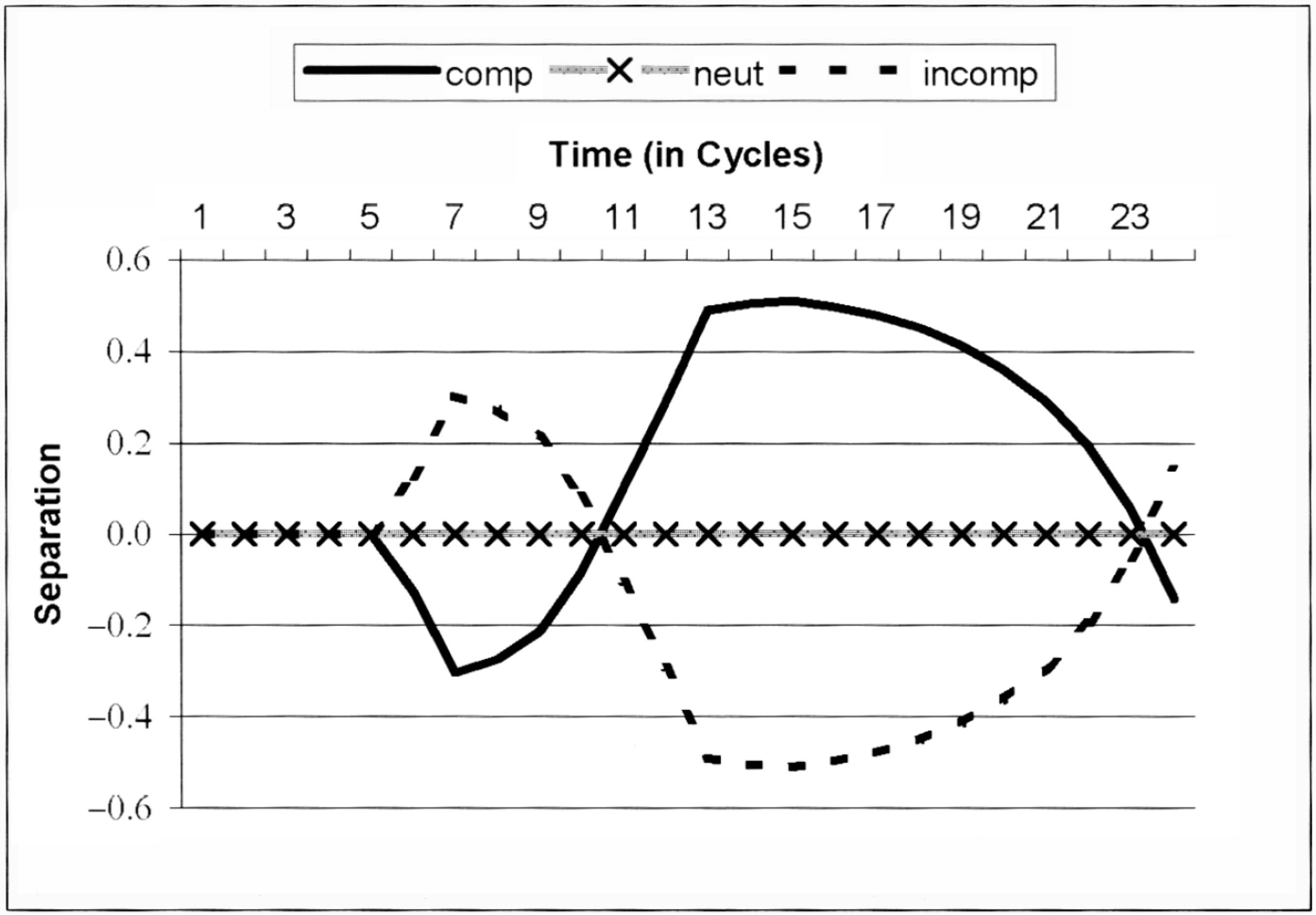


Figure 33. Separation profiles across conditions in the forced choice condition, in which a 16.666 ms prime is followed by a 100 ms mask and no target is presented.

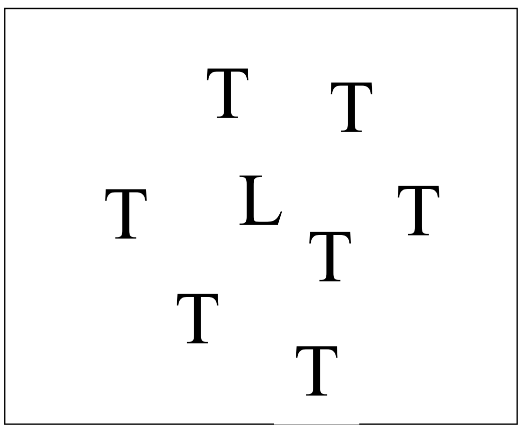
Visual Search

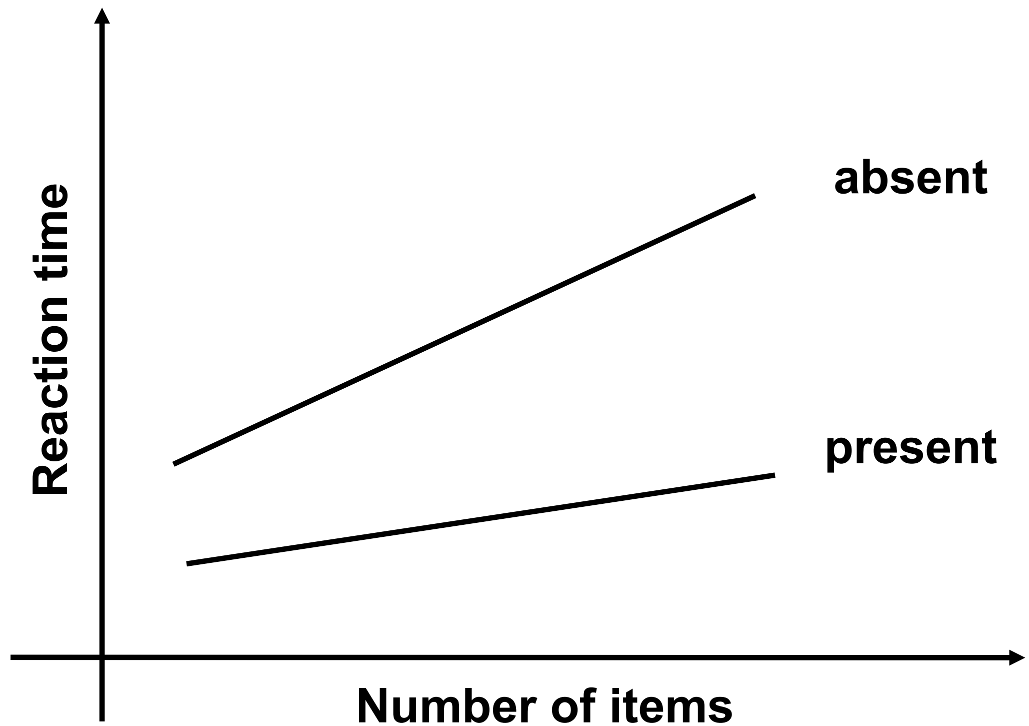
Theories

- Saliency map
- Serial search
- Parallel search

Visual Search

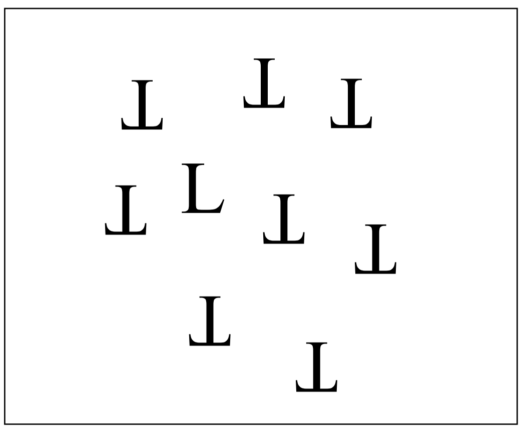
- **Is there a L?**

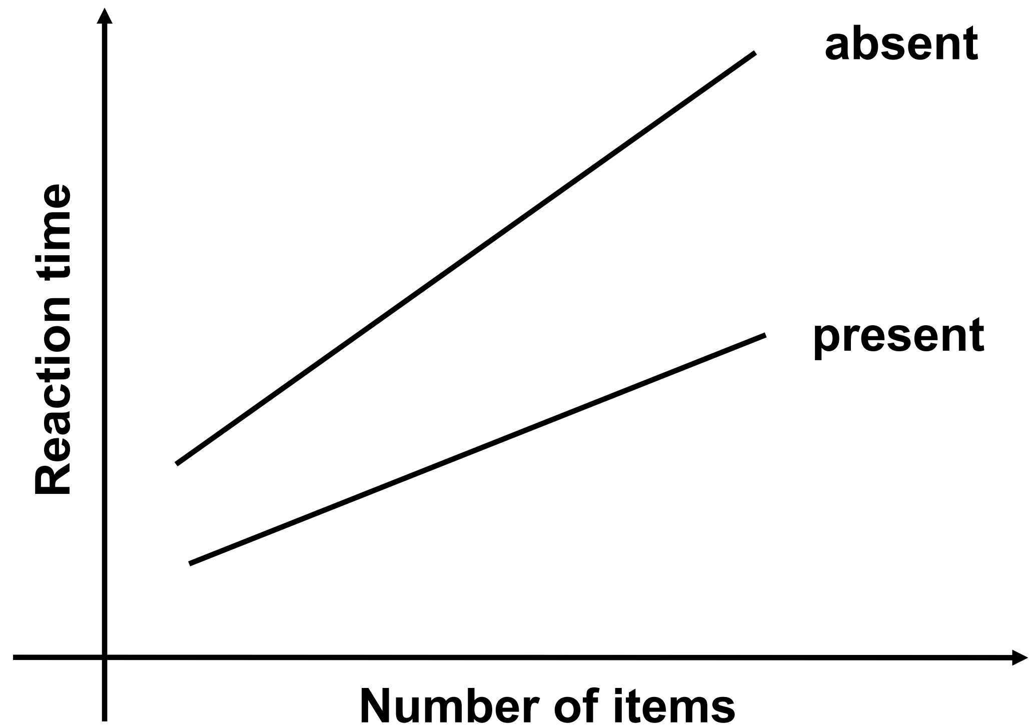




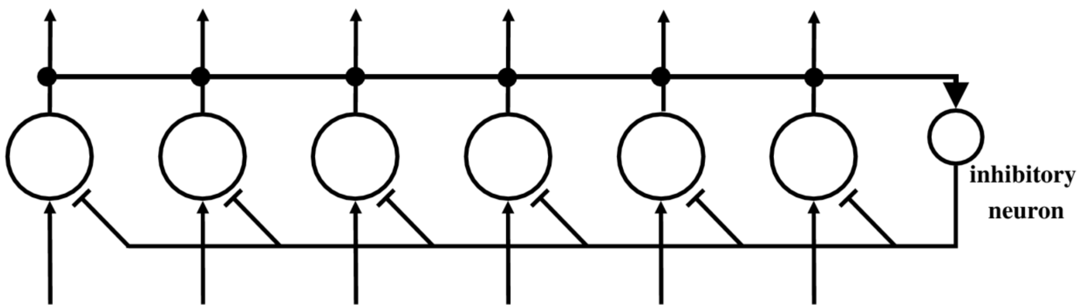
Visual Search

- **Is there a L?**



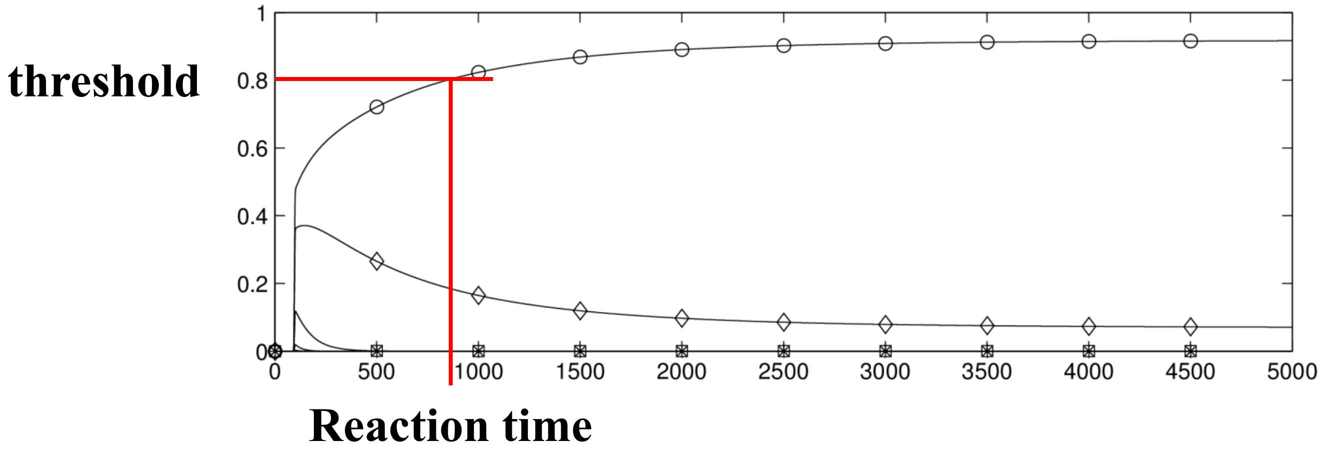


Winner take all model of visual search



Saliency map:	1	0.6	0.6	0.6	0	0	easy search	(item num. = 4)
	1	0.6	0.6	0	0	0		(item num. = 3)
	1	0.9	0.9	0.9	0	0	difficult search	(item num. = 4)
	1	0.9	0.9	0	0	0		(item num. = 3)

Reaction times



- **decreases with contrast (Emergent behaviour)**

- **increases with “number of items”**