IST-2001-35271  Project SpikeFORCE: Real-time Spiking Networks for Robot Control

Project funded by the Future and Emerging Technologies arm of the IST Programme FET-Life-like Perception Systems (LPS) Proactive Initiative 2001 in Bionics
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http://www.spikeforce.org
Project Objectives

Produce a model of the cerebellum based on known physiology and latest analytical and computational results that can be implemented efficiently in software/hardware for running real-time robotic experiments.

Sony SDR-4X

Cerebellum helps provide smooth, coordinated body movement.
Real-time Spiking Network for Robot Control
Impacts:

- Advances in robot learning
  fine response modulation/anticipation with context
- Improve cerebellar neurophysiological knowledge
- Spiking representation
- Improve knowledge of action-perception loop
  cerebellum participation
- Real-time spiking hardware technology
- Potential use in human rehabilitation
The Cerebellum

The human central nervous system, Nieuwenhuys et al., 1988
Route to a spiking cerebellar model

Theory
- Analytical model

Physiology

Detailed Spiking Model

Simplified Spiking Model

Spiking Model Implementation
Figure 42-4 The cerebellar cortex is organized into three layers and contains five types of neurons. A vertical section of a single cerebellar folium, in both longitudinal and transverse planes, illustrates the general organization of the cerebellar cortex. The detail of a cerebellar glomerulus in the granular layer is also shown. A glomerulus is a clear space where the bulbous terminal of a mossy fiber makes synaptic contact with Golgi and granule cells.
Outline:

- Physiology
- Computer models
- Theoretical models
Modeling: from physiological complexity to simplified hardware implementation retaining the salient biophysical properties of neurons and synapses

Acute slice recordings
Patch-clamp / imaging

Hardware implementation
Granule cell

1) Repetitive firing
2) Inward rectification
3) Bursting
4) Resonance

Model

A

B

ADP

ADP

fAHP, sAHP

Gx 1.4 K-slow G x 4 Na-r

20 pA

200 ms

20 mV

62 mV

Spike freq. (Hz)

Stim. Freq. (Hz)

Gamma mV

20 mV

200 ms

20 mV

200 ms
Golgi cell

1) Autorhythmic firing
2) Subthreshold oscillations
3) Postinhibitory rebound
4) Post-burst pause
5) Inward rectification

$I_H 50\%$
Modeling neurotransmission dynamics by conductance-based models

Mossy fiber - granule cell neurotransmission
Mossy fibre – granule cell LTP

Diagram showing the interaction between mossy fibres and granule cells, highlighting the involvement of K-channels, Ca^2+ channels, cGMP, glutamate (glu), NMDA receptors (NMDA-R), PKC, NO synthase (NOS), and CN-C.
The presynaptic expression mechanism implies that neurotransmission dynamics are modified during LTP.

Control of spike initiation in the model by changing release probability:

\[ p = 0.1 \]
\[ p = 0.5 \]

The influence of dynamics changes caused by LTP are currently under testing in a detailed model network comprising 2000 Granule Cells.
Granular layer

Outline:

• Physiology
• Computer models
• Theoretical models
Granule cells perform a recoding of the mossy fibers inputs into a sparse representation using a biologically plausible ICA (Coenen et al., 2001; Eagleman et al., 2001), which permits optimal noise reduction by the Golgi cell & facilitates learning in the Purkinje and molecular layer of the cerebellum (simplifies credit assignment problem).
Experimental evidence: mossy fiber-granule cell synaptic weight changes:

- **Long-term potentiation (LTP)**
  - synaptic weight increase
  - EPSPs, presynaptic currents
- **Long-term depression (LTD)**
  - synaptic weight decrease
  - (D’Angelo, 1999; Maffei et al., 2002; etc.)

Changes in cell excitability
- intrinsic cell properties
  - (Armano et al., 2000)
Images as mossy fiber inputs to illustrate putative ‘statistical structure’

granule cell receptive field

one pixel = one mossy fiber input

granule cell weights adapt to become independent as much as possible using the mossy fibers statistical structure
Cerebellar inputs will contain noise:

original image

noisy mossy fibers inputs
Encoding by granule cells with Golgi cell inhibition
Encoding by granule cells: robust coding?

Other models:
- Random weights
- Decorrelating weights

Robust sparse coding:

Kettner et al., JNeurophys., 1997
Schweighofer et al., Neurosci., 2001
Chauvet, 1986; Jonker et al., 1998
Granule cells display facilitating and depressing synapses (D’Angelo, personal communication)

Constructing temporal basis function from experience (Bell & Sejnowski, 1995; Lewicki, 2002; Olshausen, 2002; van Hateren & Ruderman, 1998)

\[ s_j(t) = \sum_n \sum_i w_{ji}(n)x_i(t-n) \]
Outline:

• Physiology
• Theoretical models
Purkinje cell

High resolution fluorescence confocal image stacks (3D)
Inhibitory interneuron

High resolution fluorescence confocal image stacks (3D)

Reconstruction
Purkinje cell as a perceptron

Brunel *et al.*, submitted
Purkinje weight distributions & silent synapses

Perceptron weight distrib.

Experimental vs Theoretical

Capacity analysis: \( \sim 50000 \) patterns/Purkinje cell
Cerebellar Task Development

Outline:
- Task description
- Cerebellar simulation results
Task description: cerebellar plong player

Pong - 1972

Simulated sensory systems: visual, auditory, touch

Spiking cerebellar model

Computer, FPGA

Movement, motor actions

Computer
Task description: cerebellar pong player

One player
- racquet move with player

Two players
- racquet moves wrt player

Different configurations possible:
- ball dynamics (speed, spin, rebound effects)
- racquet dynamics
- racquet in 1D, 2D or 3D
- control strategies:
  tracking/pursuit
  colliding trajectory controller imitation
  etc.
Cerebellar pong player

Look for:

• Learning multiple tasks -> learning multiple games
  or one game with different dynamics
• Min interference  -> fast switching/modulation btw games
  with no need to relearn
• Flexible, possibly large sensorimotor context
• Cerebellar encoding: useful for high numbers of games/dynamics
to learn
Cerebellar pong player: smooth pursuer

Tennis spiking neural network simulator (Altiira Software)
Cerebellar pong player: cell responses during tracking before learning

Tennis spiking neural network simulator (Altjira Software)

Racquet position

Inferior olive neurons

Purkinje cells

Cerebellar nucleus neurons
Cerebellar pong player: cell responses during tracking after learning

**Tennis spiking neural network simulator** (Altjira Software)

- Racquet position
- Inferior olive neurons
- Purkinje cells
- Cerebellar nucleus neurons
Cerebellar pong player

Before learning

After
Task extension: mixing simulated with real

A robot playing videogames

Pong, 1972

simulated/real systems: visual, auditory, touch

Computer, FPGA

Spiking cerebellar model

Robot movement, action

Computer
Further extension: air-table hockey

Air-table hockey

real systems: visual, auditory, touch

Spiking cerebellar model

Computer, FPGA

Robot movement, action
Synapses as conductances (shunting or multiplicative synapses)

\[ V_x = V_x + (E_{exc} - V_x) \cdot \sum I_i^{exc} \cdot \omega_{ij}^{exc} + (V_x - E_{inh}) \cdot \sum I_i^{inh} \cdot \omega_{ij}^{inh} \]

Time-dependent synaptic characteristic: gradual injection of charge.

\[ F_{syn} = \frac{F_{syn} \cdot e^{-(t-t^{(f)})/\tau}}{\tau} \]

Analitical expression

16 values approach
Input connections

$W_1$

$W_2$

$W_i$

$W_n$

Input Spikes

$\sum$

$-V_{th}$

$V_{th}$

$\sum$

$IIR$ Filter

Firing threshold

Axon-Hillock

Gain term

Resting term
Experimental Results

- Weight values
- Membrane Potential
- Time steps
- Input Spikes
- Output Spikes
- $V_x$
- $T1$
- $T2$
## Preliminary Implementation (NRH approach)

Table 1. Implementation cost and computing time of different neural configurations.

<table>
<thead>
<tr>
<th>Inputs per Neuron</th>
<th>Functional Units</th>
<th>Total Num. of Neu.</th>
<th>Number of Slices</th>
<th>Max. Clock freq. (Mhz)</th>
<th>Computing time (ms)</th>
<th>Embedded Memory Blocks (EMB)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>2</td>
<td>4</td>
<td>1832 (9%)</td>
<td>23.3</td>
<td>0.0055</td>
<td>24 (15%)</td>
</tr>
<tr>
<td>2</td>
<td>2</td>
<td>1024</td>
<td>1966 (10%)</td>
<td>20.2</td>
<td>1.4</td>
<td>65 (60%)</td>
</tr>
<tr>
<td>8</td>
<td>4</td>
<td>8</td>
<td>5476 (28%)</td>
<td>20.9</td>
<td>0.0011</td>
<td>36 (22%)</td>
</tr>
<tr>
<td>8</td>
<td>4</td>
<td>1760</td>
<td>5595 (29%)</td>
<td>20.5</td>
<td>2.9</td>
<td>160 (100%)</td>
</tr>
<tr>
<td>8</td>
<td>8</td>
<td>16</td>
<td>12011 (62%)</td>
<td>18.7</td>
<td>0.0018</td>
<td>36 (22%)</td>
</tr>
<tr>
<td>8</td>
<td>8</td>
<td>1760</td>
<td>12010 (62%)</td>
<td>18.7</td>
<td>4.5</td>
<td>160 (100%)</td>
</tr>
</tbody>
</table>
Supporting Focus Group Software Framework

Outline:
• Network Model Interface (NMI)
Principal Investigators
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- Associate Prof. Eduardo Ros (Univ of Granada)
- Prof. Egidio D’Angelo (INFM, Pavia)
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- Edouard Dognin (SONY)
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