Cooperation and Competition in VLSI Networks of Spiking Neurons

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Neural computation → neurotechnologies

Binzegger et al. 2004
Cooperative-Competitive Networks (CCNs)

1977 Arbib and Amari

Competition and Cooperation in Neural Nets

Excitatory units compete through the activation of the inhibitory unit. Eventually the unit which receives the maximum input stimulus wins and remains in the excited state, while all other units stay in the quiescent state: WINNER-TAKE-ALL (WTA).

Self-excitation maintains the winning unit in the excited state even if another input stimulus becomes bigger than one to the winning unit (unless the difference is very large): HYSTERESIS.
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Dynamic Neural Fields:
The neural network is described as a continuous medium rather than a set of discrete neurons. A differential equation describes the activation of the neural tissue at different positions in the continuous network.
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Modeling Feature Selectivity in Local Cortical Circuits

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- Each neuron is selective to a particular range of orientations and it fires maximally when a particular value of orientation is present in the input stimulus (preferred orientation).
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- Each neuron is selective to a particular range of orientations and it fires maximally when a particular value of orientation is present in the input stimulus (preferred orientation).
- Cooperative interactions are strongest in magnitude for neurons that have identical preferred orientation and get weaker as the difference between preferred orientation increases.
Rich linear and non-linear set of behaviors

- **linear**
  - linear analog gain (above threshold)
  - locus invariance
  - non-linear gain control (by common mode input)

- **non-linear**
  - non-linear selection (soft winner-take-all)
  - signal restoration (invariance)
  - multi-stability
Digital selection and analogue amplification coexist in a cortex-inspired silicon circuit

VLSI Spiking Cooperative-Competitive Networks

- DeYong et al. 1992 *The Design, Fabrication, and Test of a New VLSI Hybrid Analog-Digital Neural Processing Element*
  - all-to-all inhibitory connections
  - 4 neurons
- Hylander et al. 1993 *VLSI implementation of Pulse Coded Winner Take All Networks*
  - global inhibition
  - 3 neurons
- Indiveri et al. 2001 *A Competitive Network of Spiking VLSI Neurons*
  - global inhibition and first neighbors lateral excitation
  - 32 neurons
VLSI Spiking Cooperative-Competitive Networks

- Oster and Liu 2004 *A Winner-take-all Spiking Network with Spiking Inputs*
  - all-to-all inhibitory connections and self excitation
  - 64 neurons

- Chicca et al. 2004 *An Event Based VLSI Network of Integrate-and-Fire Neurons*
  - global inhibition, first and second neighbors lateral excitation
  - 31 neurons

- Abrahamsen et al. 2004 *A Time Domain Winner-Take-All Network of Integrate-and-Fire Neurons*
  - global reset
  - 3 WTA: $2 \times 48$ neurons + $1 \times 4$ neurons
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The IFRON Chip

| Technology: | AMS 0.8µm |
| Size:       | 1.1 × 1.9 mm² |
| Neurons:    | 32 |
| AER Synapses: | 16 × 32 |
| Local Synapses: | 6 × 31 |

The IFRON Chip – Network architecture

The IFRON Chip – Network architecture

A Spike–Based neuromorphic VLSI System

Experimental Results

Input Stimulus

Neuron address

Time (s)

Mean $f$ (Hz)

AER OUTPUT

AER INPUT

AER INPUT

AER OUTPUT
Experimental Results

Feedforward Network

![Diagram of AER Input and Output with Neuron Addresses and Time (s) on the x-axis, Mean f (Hz) on the y-axis.](Diagram.png)
Experimental Results

Feedback Network

Time (s)
Neuron address
Mean $f$ (Hz)

AER OUTPUT

AER INPUT

AER INPUT

AER OUTPUT

uni | eth | zürich
Experimental Results

![Graph showing mean frequency vs neuron address for feedforward and feedback networks. The graph has two peaks, with one peak for the feedforward network and another for the feedback network. The x-axis represents neuron address, and the y-axis represents mean frequency (Hz).]
Experimental Results

The graph shows the mean frequency (Hz) as a function of neuron address for two networks: Feedforward Network (green) and Feedback Network (blue). The peaks indicate areas where the activity is concentrated, with the Feedforward Network showing a broad peak around neuron addresses 10-15 and the Feedback Network having multiple peaks at addresses 15, 25, and 30. The graph provides insights into the activity patterns of these networks.
Experimental Results

![Graph showing mean frequency (Hz) vs neuron address for Feedforward and Feedback Networks.]

- **Mean Frequency (Hz)**
- **Neuron address**
- **Feedforward Network**
- **Feedback Network**
Digital versus neural systems
An Emergent Model of Orientation Selectivity in Cat Visual Cortical Simple Cells

Feedforward

Inhibitory

Recurrent

Cortex

LGN

a)

b)

c)
CCNs Applied to Orientation Selectivity

1995 Somers et al.
An Emergent Model of Orientation Selectivity in Cat Visual Cortical Simple Cells

Figure 2. Response of a cell selective for 0° stimuli. a, Simulated intracellular trace from one cell in the model network in response to flashed dark bars oriented at 0°, 22.5°, 45°, and 90°. Horizontal bars on time axis indicate 500 msec stimulus presentation. b and c, Thalamic (b) and cortical (c) input fields of this cell. ON (white) and OFF (black) thalamic subfields exhibited only a mild orientation bias for 0° stimuli. Cortical excitatory (triangles) and inhibitory (circles) inputs arose most densely from cells within the 0° column. Cortical connection probabilities fell off with distance, and no connections were permitted beyond the 60° column. Inhibitory distribution was broader than the excitatory distribution.

Sharp orientation selectivity was observed across a broad range of stimulus contrasts. Mean HW tuning (n = 105) for 5%, 15%, and 100% contrast stimuli were 18.3° ± 0.6° SD, 17.4° ± 0.7° SD, and 17.7° ± 0.6° SD, respectively. As stimulus contrast increased from 5% to 100% average peak responses of excitatory neurons increased by 122% [22.1 ± 4.8 sp/s (±SD) vs 49.1 ± 17.1 sp/s]. This contrast invariance of orientation tuning in the model replicates experimental findings (Sclar and Freeman, 1982). Figure 3 displays orientation response curves at three different contrasts for an example cell.

The mechanisms underlying orientation tuning of the model were investigated by measuring the postsynaptic potentials (PSPs) contributed by different synaptic input sources. Both excitatory and inhibitory PSPs were strongest at the preferred orientation (see Fig. 4a,b). Notably, stimulus-evoked IPSPs (in excess of spontaneous levels) were, on average, 8.3 times as strong for the preferred orientation as for the orthogonal or cross-orientation (90°) stimulus. These PSP tuning properties of the model are consistent with intracellular reports of weak cross-orientation IPSPs and strong iso-orientation IPSPs (Ferster, 1986; Douglas et al., 1991a).

In the model, the EPSP tuning resulted from a combination of broadly tuned thalamocortical input and sharply tuned corticocortical excitation. Broad tuning of thalamocortical input resulted from the low length-to-width ratios of the (regions of thalamic convergence onto) cortical subfields (see Fig. 2). Sharp tuning of cortical EPSPs reflected input from well-tuned cortical excitatory cells with similar orientation preferences. Cortical inhibitory inputs were also drawn most heavily from within the preferred orientation column (see Fig. 2b) and these cells were also well tuned. Cortical inhibitory inputs were drawn...
CCNs Applied to Orientation Selectivity

1995 Somers et al.
An Emergent Model of Orientation Selectivity in Cat Visual Cortical Simple Cells

![Graph showing mean tuning and mean response for different network configurations: Feedforward, Inhib 1, Inhib 2, and Full Network. The y-axis represents mean HW tuning (degree), and the x-axis represents different network configurations. The graph illustrates how different network configurations impact mean tuning and mean response.]
Orientation Selectivity Experiment
Orientation Selectivity Experiment
Least-squares Fit of the Tuning Curves

![Graph showing tuning curves with fit and data markers]

<table>
<thead>
<tr>
<th>Parameter</th>
<th>FF</th>
<th>FB</th>
</tr>
</thead>
<tbody>
<tr>
<td>A (Hz)</td>
<td>16</td>
<td>30</td>
</tr>
<tr>
<td>HWHH (°)</td>
<td>30</td>
<td>23</td>
</tr>
<tr>
<td>R–square (%)</td>
<td>98.7</td>
<td>99.3</td>
</tr>
</tbody>
</table>
Least–squares Fit of the Tuning Curves

![Graph showing tuning curves for FF and FB, with data points and fitted lines for Mean Frequency and Amplitude FB, and HWHH FB and HWHH FF.](image)
CCN Summary

- Spiking CCNs exhibit rich linear and non-linear set of behaviors (e.g. selective amplification, noise suppression, feature selectivity) in the mean rate domain.
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- Possibility to use the time domain as additional dimension to perform computation.
CCN Summary

- Spiking CCNs exhibit rich linear and non-linear set of behaviors (e.g. selective amplification, noise suppression, feature selectivity) in the mean rate domain.
- VLSI spiking CCNs are robust to noise and perform computation in real-time.
- Possibility to use the time domain as additional dimension to perform computation.
- General computational module that can be used for sensory input filtering, learning enhancement, relational networks.
Constrains Satisfaction and Relational Networks using CCNs
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Simple relations for computation

\[ X + Y = a \]

\[ X + Y < b \]

\[ Y = f(X) \]
Simple relations for computation

$X + Y = a$

$X + Y < b$

$Y = f(X)$
Simple relations for computation
The IFSLWTA chip

<table>
<thead>
<tr>
<th>Technology:</th>
<th>AMS 0.35µm</th>
</tr>
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<tbody>
<tr>
<td>Total area:</td>
<td>3.94mm × 2.54mm</td>
</tr>
<tr>
<td>Core area:</td>
<td>2.6mm × 1.9mm</td>
</tr>
<tr>
<td>Neurons:</td>
<td>128 (124 exc. + 4 inh.)</td>
</tr>
<tr>
<td>Synapses:</td>
<td>32 × 128</td>
</tr>
<tr>
<td>Dendritic tree multiplexer:</td>
<td>32x128</td>
</tr>
</tbody>
</table>
Address Event Representation (AER) used to implement constraints between CCNs

(b) VLSI CCN

(c) Coupled CCNs
Shifted Inverse Identity Relation $X + Y = a$
Blobby Connectivity Implements Analog Input to Discrete Output Relation
A 2D Spiking Cooperative-Competitive Network - Motivations

- Implement several relations on a single chip.
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- Implement several relations on a single chip.
- 2D feature selectivity.
A 2D Spiking Cooperative-Competitive Network - Motivations

- Implement several relations on a single chip.
- 2D feature selectivity.
- Explore different connectivity patterns between the excitatory and the inhibitory populations.
2D Network - Cooperation
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Single cell components

1 I&F neuron
1 self-excitatory synapse
1 local excitatory integrator
10 nMOS for local excitatory weights
2 nMOS + 1 pMOS for membrane voltage output
2 AER excitatory synapses
1 AER inhibitory synapse
2D System - Cooperation and Competition

Excitatory Neurons

Inhibitory Pool

Excitatory to Inhibitory Connections

Inhibitory to Excitatory Connections
The 2DIFWTA chip

<table>
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<tr>
<td>Technology</td>
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<tr>
<td>Area</td>
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<tr>
<td>Neurons</td>
<td>2048 (32 × 64)</td>
</tr>
<tr>
<td>AER Synapses</td>
<td>2048 × 3</td>
</tr>
<tr>
<td>Local Synapses</td>
<td>2048 × 11</td>
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</table>
Conclusions and Outlook

- **VLSI spiking cooperative competitive networks (CCNs)**
  - We can implement VLSI spiking CCNs.
  - In the mean rate domain, VLSI spiking CCNs perform as well as models.
  - Time domain can be exploited.

- Relational networks can be built as combinations of CCNs.
  - The hardware to build simple relational networks is already available.
  - Preliminary results are promising.

- 2D VLSI spiking CCN chip
  - 2D feature selectivity
  - Arbitrary connectivity between excitatory and inhibitory populations
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Acknowledgments

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Thank you ... ... for your attention.
Cooperative-Competitive Networks (CCNs)

1969 Kilmer, McCulloch and Blum
Model of the role of the vertebrates’ reticular formation of the brainstem in deciding the overall mode of behavior (e.g. sleeping, fighting, fleeing or feeding).

1975 Dev
Model of the use of stereopsis to recognize depth in space.

1976 Didday
Model of how the frog’s tectum decides the snapping position.