Neuromorphic Computation for Autonomous Mobility in Natural Environments

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Autonomy for the Real World
Bats as a Model

photos: D. Nill
Complexity of Bat Habitats
Components of Peripheral Dynamics

- reorientation
- non-rigid deformation
- nonlinear transform

Gao & Müller
(2011)

Yin & Müller
Proc. Natl. Acad. Sci. USA
(under revision)

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Softrobotic Reproductions

Schneider & Möhres, Z. Vergl. Physiol. (1960)  

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Performance Gain Example: Direction Finding


Natural Stimulus Ensemble

- 4 different field sites
- 220,000+ uncorrelated echoes
Real-World Task: Finding Passageways in Foliage

- Foliage size: 1.5 x 1 x 0.8 m (LxHxW)
- Gap widths: 10, 20, 30 cm
- Distances: 0.6 – 1.4 m
- Number of echoes: 12,000
Real-World Task: Finding Passageways in Foliage
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Real-World Task: Finding Passageways

- Energy gap: 10 cm x 30 cm
- Distance: 1.4 m
Real-World Task: Finding Passageways

ConvNet

energy

gap: 10 × 30 cm
distance: 1.4 m
Real-World Task: Finding Passageways


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1. time variance encodes sensory information
   $\rightarrow$ timing matters
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2. short time scales (1 - 50 ms) → computation based on a few spike times
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3. fast (<100 ms) closed-loop control → hardware implementation
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   \[\rightarrow\] computation based on a few spike times

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   \[\rightarrow\] hardware implementation

4. pilot data …
Neuromorphic Signal Representations

- Stimulus - Echoes from environment
  - Basilar Membrane Model
    - Gammatone
    - Gammachirp
    - DRNL
  - Inner Hair Cells Model
  - Auditory Nerve Spiking Model
    - Leaky IAF
    - SRM Kernel
  - Controller

Graphs illustrating time and channel data.
Linear Models: Symmetric vs. Asymmetric

Gammatone
Gammachirp
Simple Complex
Amplitude (dB) Amplitude (dB)
Frequency [kHz]
DRNL

Gammatone
Gammachirp

Amplitude (dB) Amplitude (dB)
Frequency [kHz]
Dual-Resonance Nonlinear (DRNL) Model

Simple
- Gammatone
  - Linear gain
  - Cascade of 2 1st-order GTF
  - Cascade of 4 2nd-order Butterworth LPF

Nonlinear path
- Cascade of 3 1st-order GTF
- Broken sticky nonlinearity
- Cascade of 3 1st-order GTF
- Cascade of 3 2nd-order Butterworth LPF

Input
Output

Complex
DRNL

Input signal level 80 dB
Amplitude (dB)

Input signal level 20 dB
Amplitude (dB)

Frequency [kHz]
Spike Response Models

- **Leaky Integrate-And-Fire:**
  - simple integration
  - static threshold
  - 3 parameters

- **Response Kernels:**
  - after-potential computation
  - reduced responsiveness after spike
  - dynamic threshold
  - 6 parameters
Optimization of Model Parameters

- optimization over entire parameter space
- objective: static/dynamic difference in coding capacity
- information-theoretic analysis (entropy)
Information-Theoretic Analysis: Direct Entropy Method

\[ H(w) = - \sum P(w_i) \cdot \log_2 P(w_i) \]
Peripheral Dynamics & Primary Signal Representation

Gammatone
Gammachirp
DRNL

Dynamic
Static
Difference

Entropy Difference

Frequency [kHz]

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Peripheral Dynamics & Neural Coding Capacity

LIAF spike model
Peripheral Dynamics & Neural Coding Capacity

Entropy difference [Dynamic - Static]

- Gammatone
- Gammachirp
- DRNL

Effect of basilar membrane model

Effect of spike model

Response kernel spike model

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autonomy in complex natural environment is possible
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hypothesised key components:
autonomy in complex natural environment is possible

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autonomy in complex natural environment is possible
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  2. primary signal representation
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hypothesetical key components:

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2. primary signal representation
3. neuromorphic signal representation & computing

future work:

- useful information
- better neuromorphic computing (paradigms & hardware)
- adaptive control
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pilot data: coding capacity depends integration of peripheral dynamics, primary representation, & neural model
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Acknowledgments

ONR "MURI: Bioinspired Adaptive Sonar for Classification and Guidance in Complex Environments"

NAVSEA/NEEC "Bioinspired Broadband Sonar"

NSF "Novel Dynamic Paradigms for Wave-based Sensing"

IBM Faculty Award
### Information-Theoretic Analysis: CDM Entropy Method

#### Entropy Calculation - Centered Dirichlet Method

<table>
<thead>
<tr>
<th>N bins</th>
<th>K = 2(^N) words</th>
</tr>
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<tbody>
<tr>
<td>0 0 0 0 1</td>
<td>0 0 1 1 1 0 1 0</td>
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<tr>
<td>0 0 0 1 0</td>
<td>0 1 1 0 0 1 1 0</td>
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<td>1 1 0 1 0 0 1 1</td>
</tr>
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<td>0 1 0 0 0</td>
<td>1 0 0 0 1 1 1 1</td>
</tr>
</tbody>
</table>

Prior \(\pi|\alpha, p \sim \text{Dir}(\alpha, \alpha, \alpha, \alpha, \alpha)\)

Words

| 0 0 0 0 0 0 |
| 0 1 0 1 0 1 |
| 0 0 0 0 0 0 |
| 0 0 0 0 0 1 |

Histogram

Posterior \(\pi|\alpha, p \sim \text{Dir}(3\alpha, 2\alpha, 1\alpha, \alpha, \alpha)\)