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University of Liège
Montefiore Institute
Systems and Modeling Research Unit

BRAINS IN SILICON
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Spiking Neural Network Decoder for Brain-Machine Interfaces

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UGR MEETING IN NANCY

NOVEMBER 28TH 2011

BMIs:

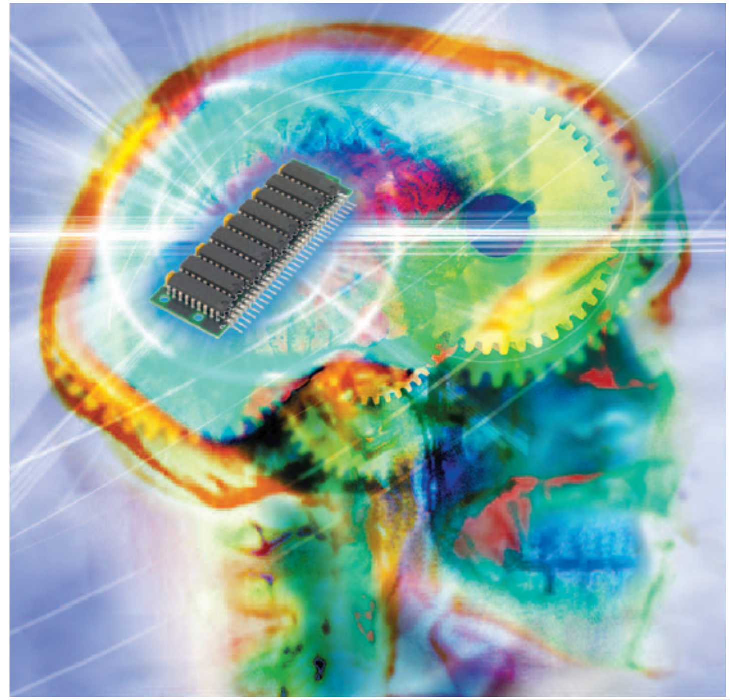
→Signal acquisition and conditioning

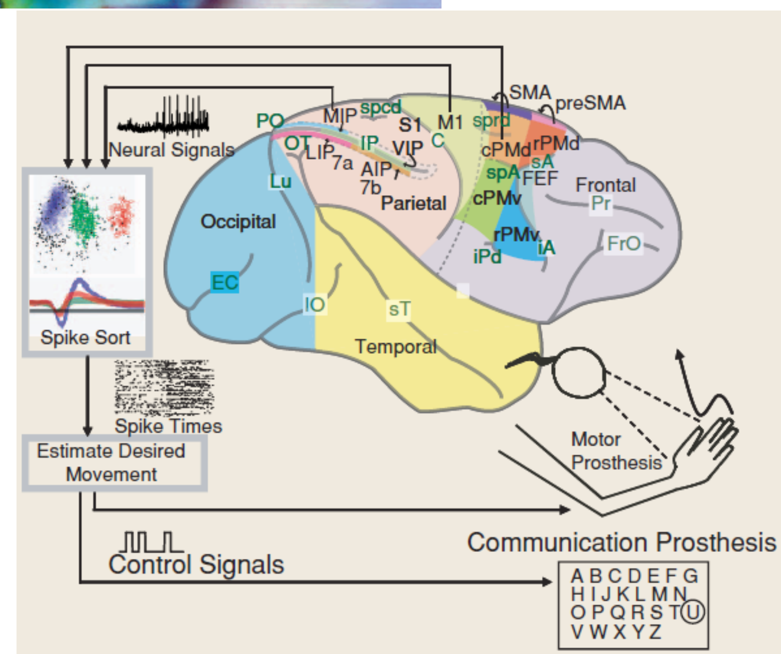
→Spike sorting

→Neural decoding

→Action:

- →Prosthetic limbs
- →Computer cursors





Key challenge:

→Temperature
→Power dissipation

Constraints	
Temperature	1°C
Power - 6x6mm^2 implant	10mW
2D Kalman-filter decoder	
3.6GHz Core Duo Intel processor	1.82mW
Neuromorphic chip	100 μW

Agenda

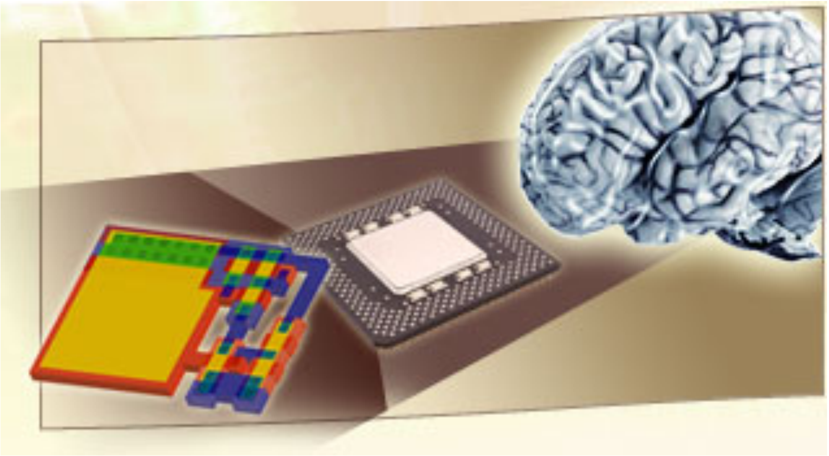
Agenda

1. The proposed alternative
2. Kalman filter decoder for BMI
3. Spiking neural network decoder with NEF
4. Implementations
5. Conclusions and future work

The proposed alternative

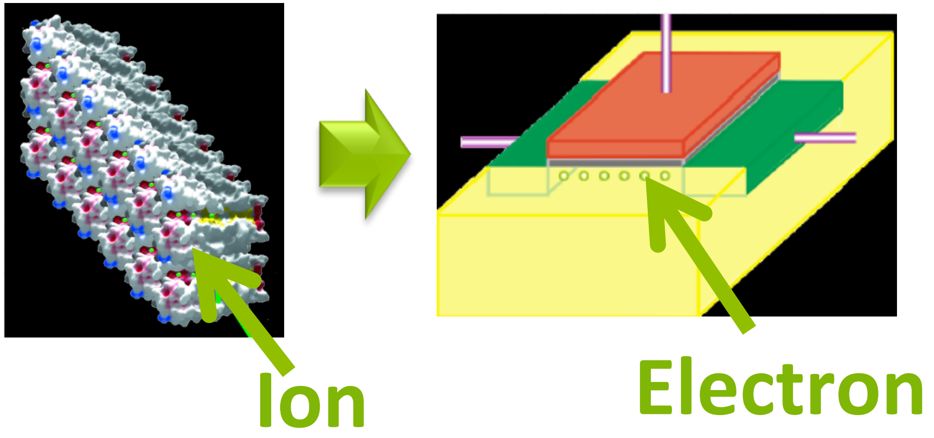
Solution:

→Ultra-low-power neuromorphic approach



→*Morphes* neural systems into silicon chips

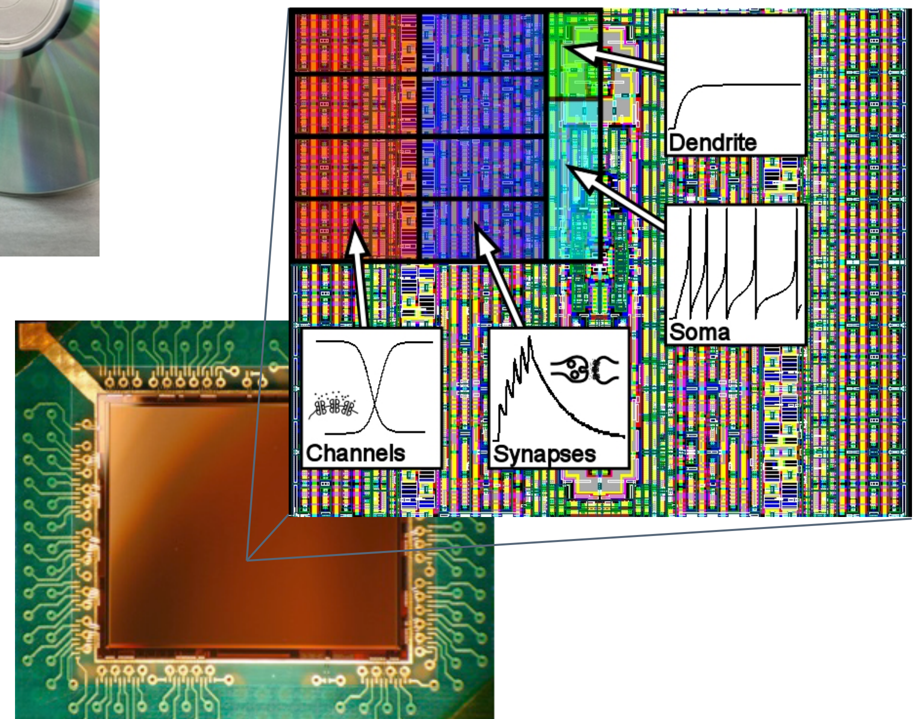
→Transistors analog to ion channels



Neurogrid:

→1M neurons
→6B synapses

65 536 neurons
23M transistors
160 mm^2
0.18 um CMOS



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Kalman filter decoder for BMI

Estimate of the current system state using:

→Model dynamics
→Noisy measurements

State update:

$$\mathbf{x}_t = \mathbf{A}\mathbf{x}_{t-1} + \mathbf{w}_t \quad \text{where} \quad \mathbf{w}_t \sim N(0,\mathbf{W})$$

$$\mathbf{y}_t = \mathbf{C}\mathbf{x}_t + \mathbf{q}_t \quad \text{where} \quad \mathbf{q}_t \sim N(0,\mathbf{Q})$$

Steady-state assumption:

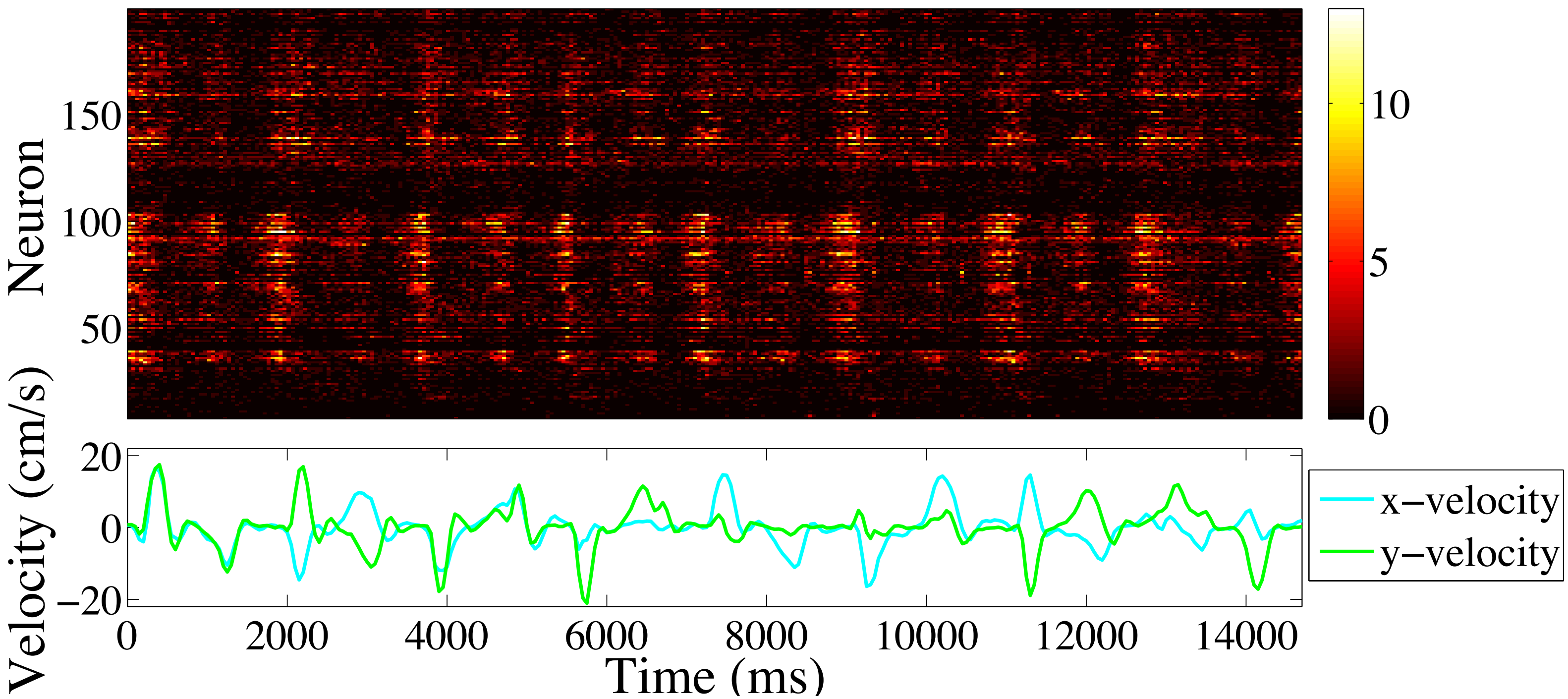
$$\mathbf{x}_t = (\mathbf{I} - \mathbf{K}\mathbf{C})\mathbf{A}\mathbf{x}_{t|t-1} + \mathbf{K}\mathbf{y}_t = \mathbf{M}_x^{\mathrm{DT}}\mathbf{x}_{t|t-1} + \mathbf{M}_y^{\mathrm{DT}}\mathbf{y}_t$$

with $\mathbf{K} = (\mathbf{I} + \mathbf{W}\mathbf{C}\mathbf{Q}^{-1}\mathbf{C})^{-1}\mathbf{W}\mathbf{C}^T\mathbf{Q}^{-1}$

Neural applications:

→System state: $\mathbf{x}_t = \left[vel_t^{\mathrm{x}}, vel_t^{\mathrm{y}}, 1 \right]$
→Measurements: $\mathbf{y}_t$ neural spike rate of the recorded neurons

Fitting the model parameters:



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Spiking neural network decoder with NEF

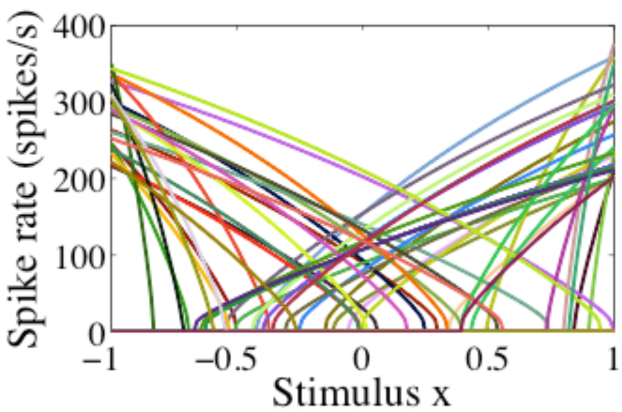
Neural Engineering Framework:

→A formal methodology for mapping control-theory algorithms onto spiking neural networks

1. Representation **2. Transformation** **3. Dynamics**

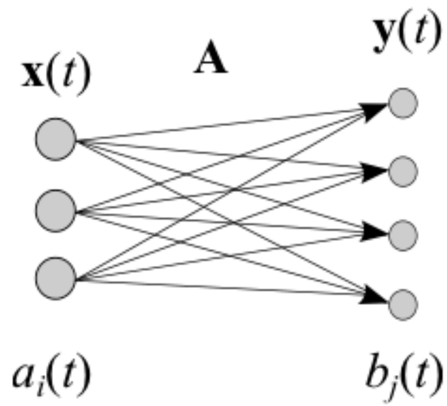
$$\mathbf{x} \rightarrow a_i(\mathbf{x}) \rightarrow \hat{\mathbf{x}} = \sum_i a_i(\mathbf{x})\phi_i^{\mathbf{x}}$$

$$a_i(\mathbf{x}) = G\left(\alpha_i \left\langle \tilde{\phi}_i^{\mathbf{x}} \cdot \mathbf{x} \right\rangle + J_i^{bias}\right)$$



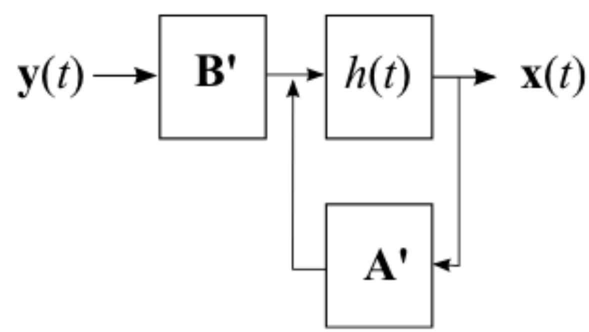
$$\mathbf{y} = \mathbf{A}\mathbf{x} \rightarrow b_j(\mathbf{A}\hat{\mathbf{x}})$$

$$\mathbf{A}\hat{\mathbf{x}} = \sum_i a_i(\mathbf{x})\mathbf{A}\phi_i^{\mathbf{x}}$$

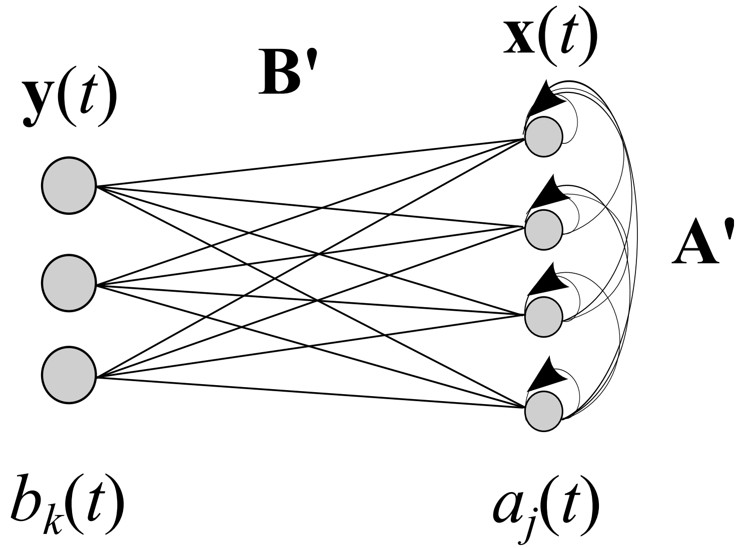


$$\dot{\mathbf{x}} = \mathbf{A}\mathbf{x} \rightarrow \mathbf{x} = h * \mathbf{A}'\mathbf{x}$$

$$\mathbf{A}' = \tau\mathbf{A} + \mathbf{I}$$



Kalman filter:



j^{th} neuron's firing rate:

$$a_j\left(\mathbf{x}(t)\right) = G\left[\alpha_j \left\langle \tilde{\phi}_j^{\mathbf{x}} \cdot \mathbf{x}(t) \right\rangle + J_j^{bias}\right]$$

$$= G\left[\alpha_j \left\langle \tilde{\phi}_j^{\mathbf{x}} \cdot h(t) * \left(\mathbf{A}'\mathbf{x}(t) + \mathbf{B}'\mathbf{y}(t)\right) \right\rangle + J_j^{bias}\right]$$

$$= G\left[\alpha_j \left\langle \tilde{\phi}_j^{\mathbf{x}} \cdot h(t) * \left(\mathbf{A}' \sum_i a_i\left(t\right) \phi_i^{\mathbf{x}} + \mathbf{B}' \sum_k b_k\left(t\right) \phi_k^{\mathbf{y}}\right) \right\rangle + J_j^{bias}\right]$$

$$a_j\left(\mathbf{x}(t)\right) = G\left[h(t) * \left(\sum_i \omega_{ji} a_i\left(t\right) + \sum_k \omega_{jk} b_k\left(t\right)\right) + J_j^{bias}\right]$$

with $\omega_{ji} = \alpha_j \left\langle \tilde{\phi}_j^{\mathbf{x}} \; \mathbf{A}' \phi_i^{\mathbf{x}} \right\rangle$ and $\omega_{jk} = \alpha_j \left\langle \tilde{\phi}_j^{\mathbf{x}} \; \mathbf{B}' \phi_k^{\mathbf{y}} \right\rangle$

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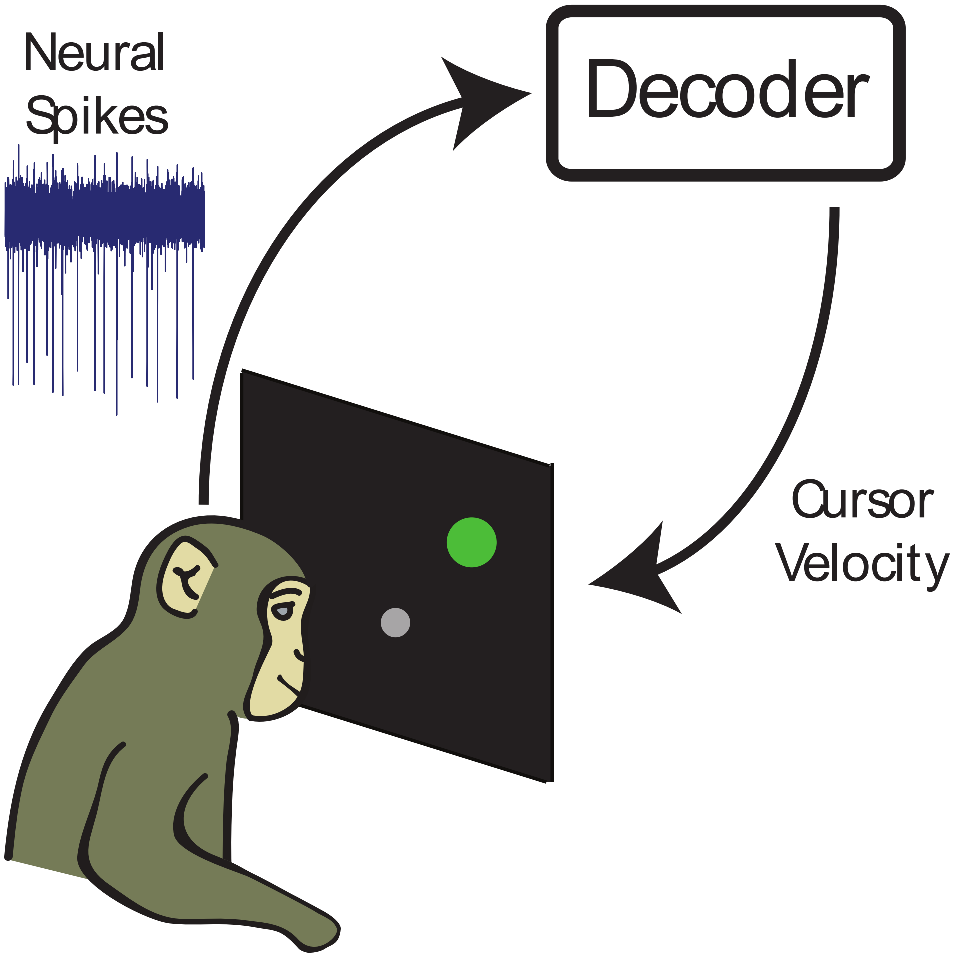
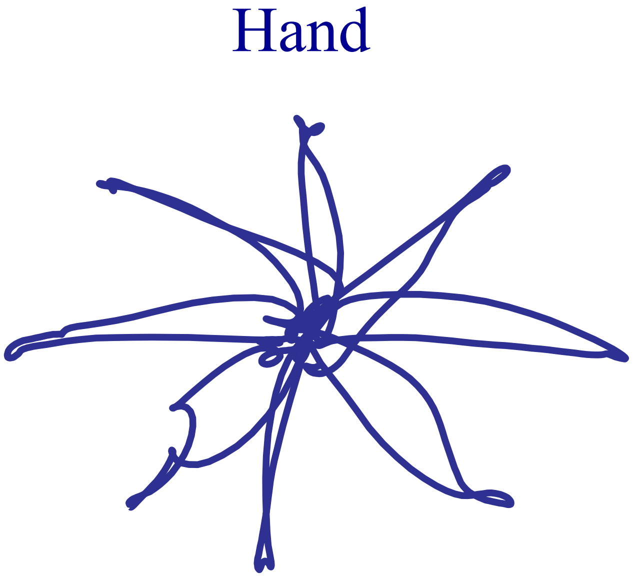
Implementations

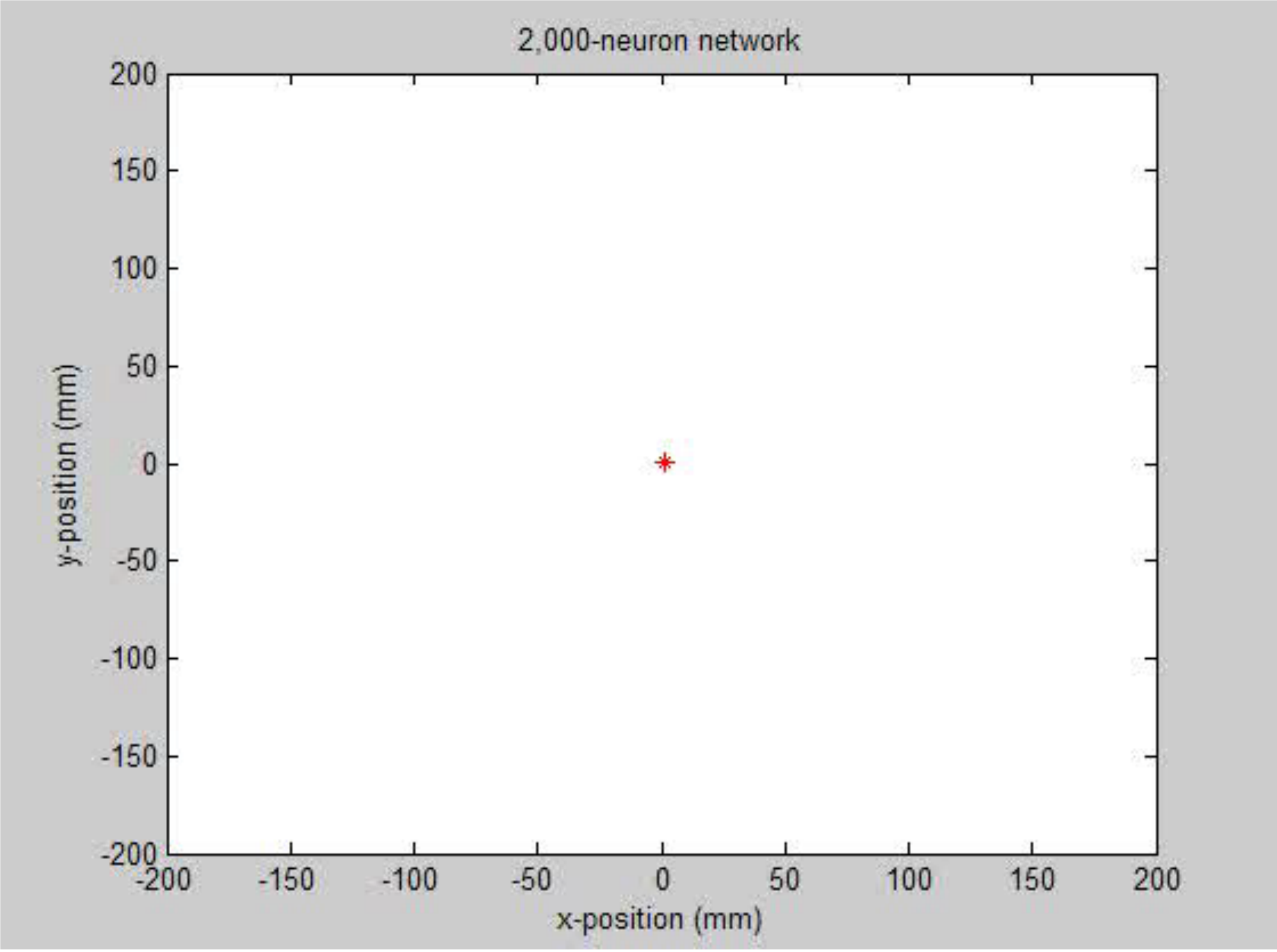
Experimental setup:





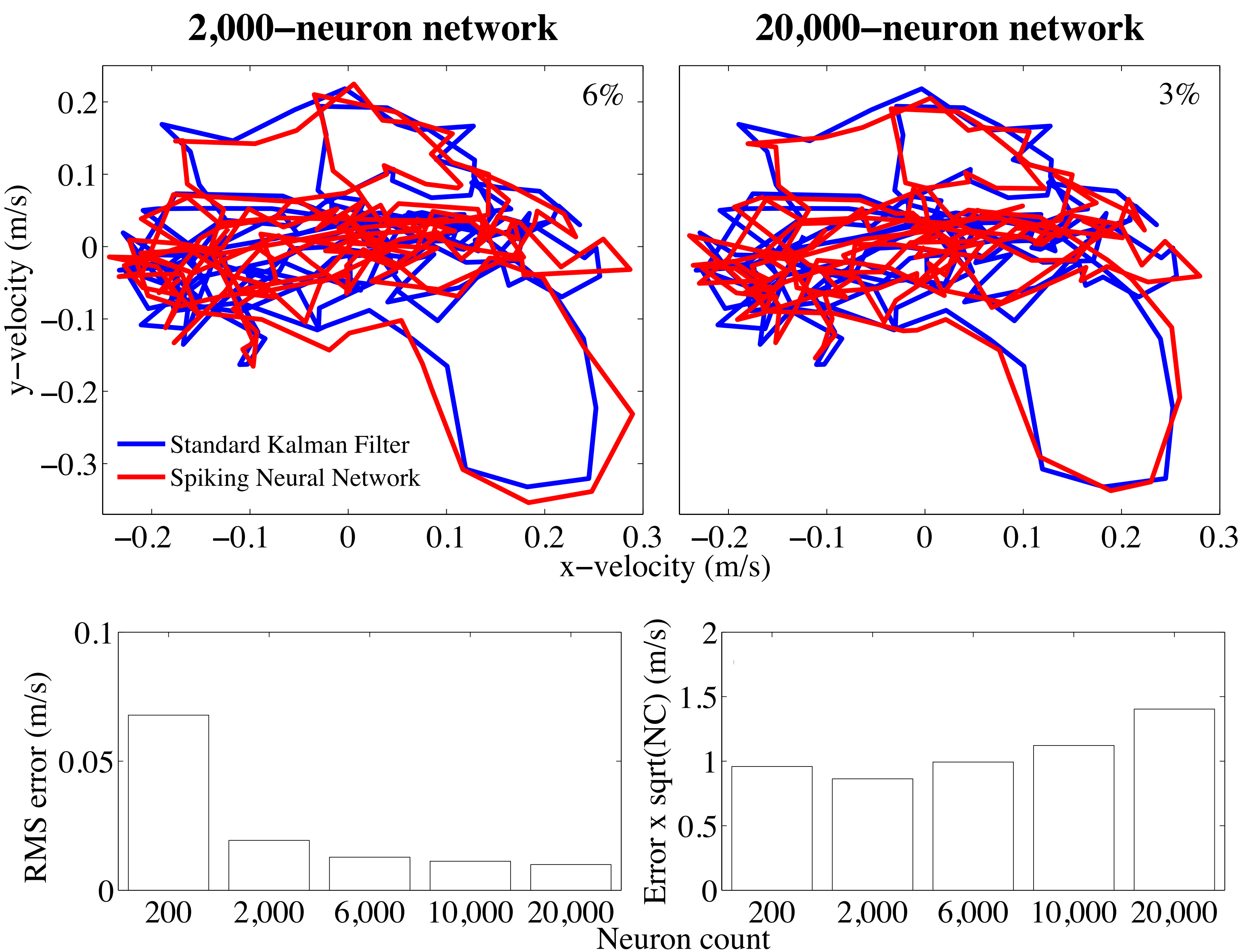
Trials: 0018 - 0033

Open-loop:



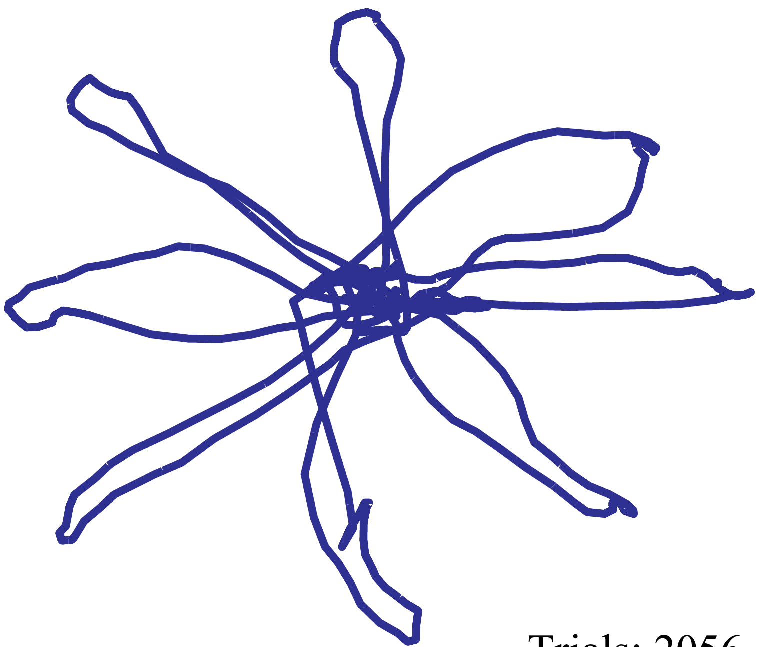
2,000-neuron network
200
150
100
50
0
-50
-100
-150
-200
y-position (mm)
-200
-150
-100
-50
0
50
100
150
200
x-position (mm)

Open-loop:


2,000–neuron network
20,000–neuron network
6%
3%
y–velocity (m/s)
x–velocity (m/s)
0.2
0.1
0
–0.1
–0.2
–0.3
0.3
Standard Kalman Filter
Spiking Neural Network
RMS error (m/s)
0.1
0.05
Error x sqrt(NC) (m/s)
2
1.5
1
0.5
200
2,000
6,000
10,000
20,000
Neuron count

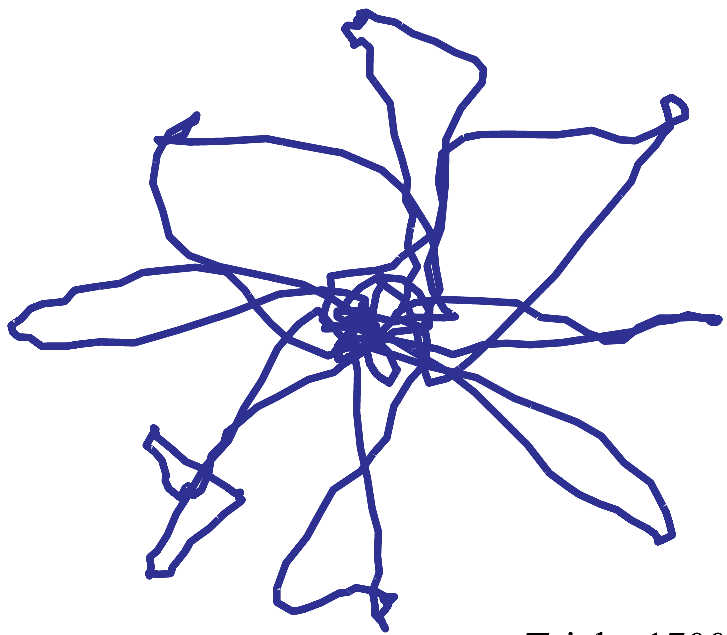
Closed-loop:

BMI: standard Kalman



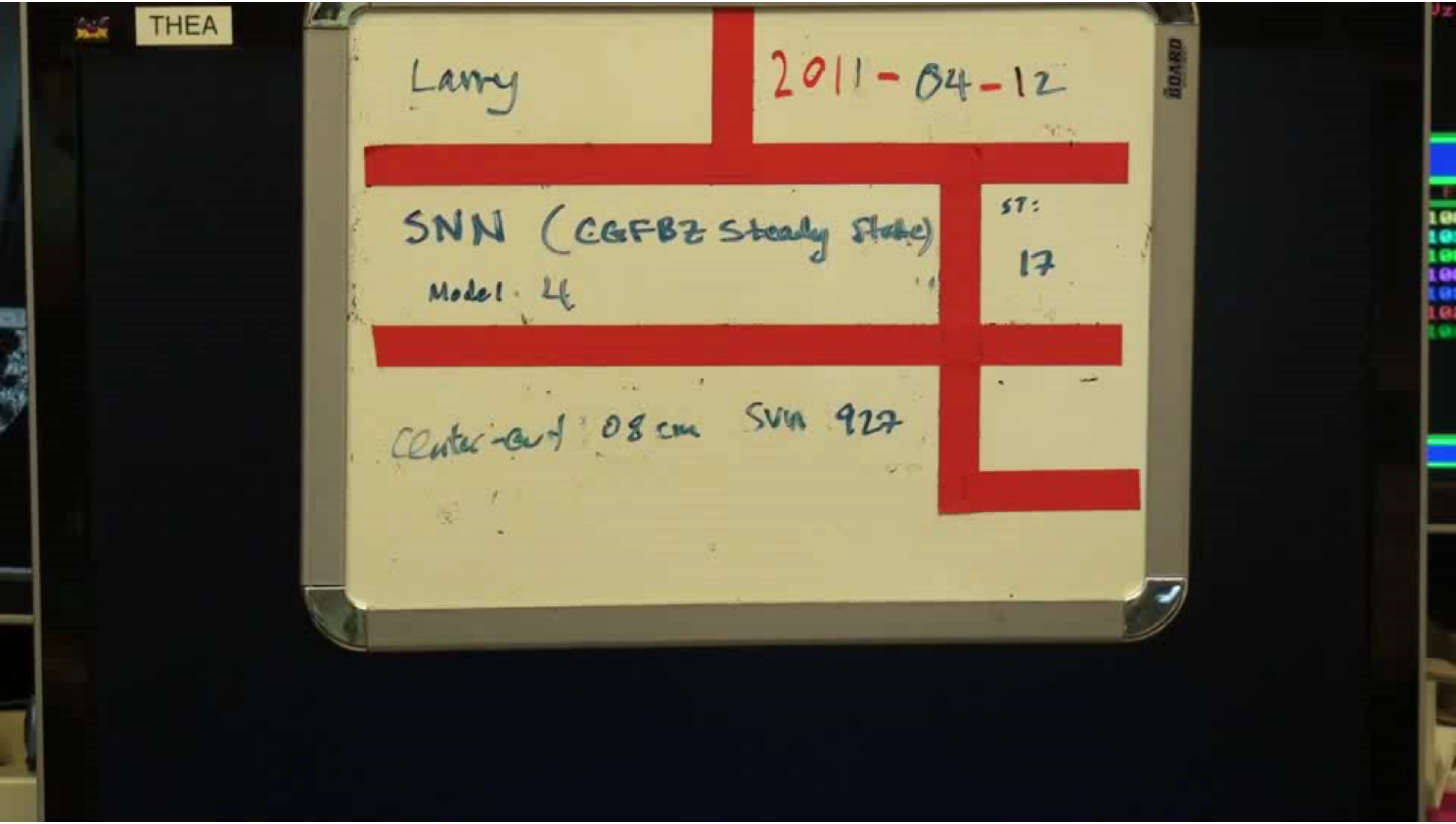
Trials: 2056- 2071

BMI: Siking neural network

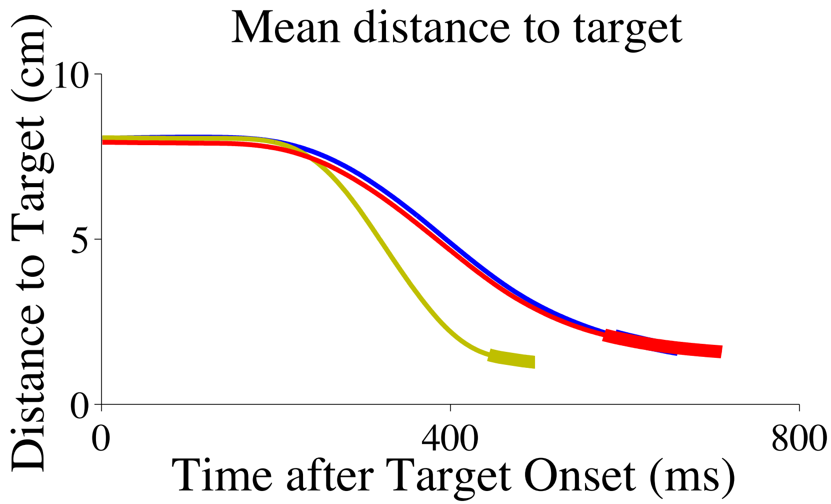


Trials: 1700 - 1715

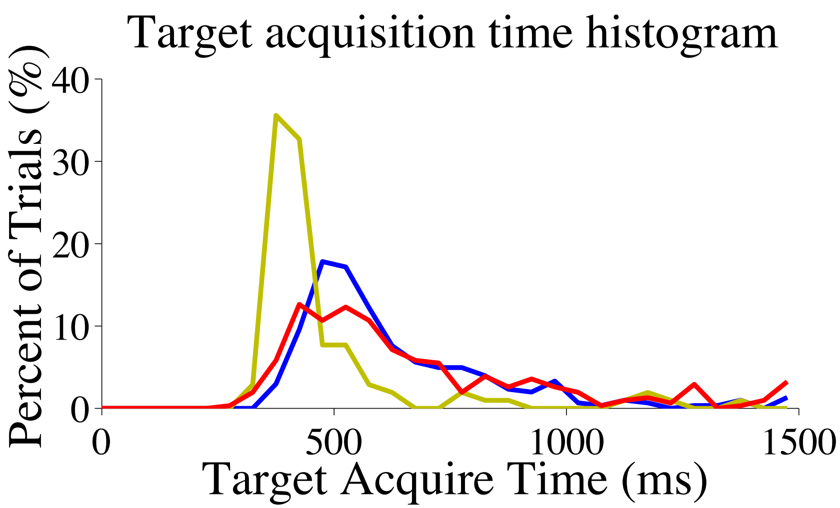
Closed-loop:


THEA
Larry
2011-04-12
SNN (CGFBZ Steady State)
Model 4
ST:
17
Center-out 08 cm
Svn 927

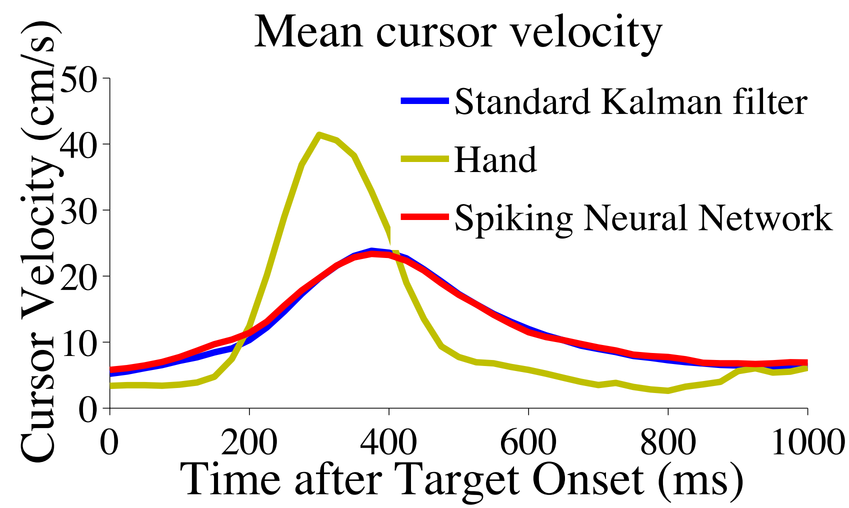
Closed-loop:



Mean distance to target
Distance to Target (cm)
10
5
0
0
400
800
Time after Target Onset (ms)



Target acquisition time histogram
Percent of Trials (%)
40
30
20
10
0
0
500
1000
1500
Target Acquire Time (ms)



Mean cursor velocity
Cursor Velocity (cm/s)
50
40
30
20
10
0
0
200
400
600
800
1000
Time after Target Onset (ms)
Standard Kalman filter
Hand
Spiking Neural Network

Conclusions and future work

SNN decoder

→Virtually identical to standard Kalman filter
→99% success rates

Next step

→Mapping with Neurogrid

- →Columnar organization
- → Topographically assigned preferred directions vectors

→Novel signal processing techniques

Reference:

→Kalman-filter based decoder

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→Neurogrid

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→Neural Engineering Framework

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→Present work

1. J.Dethier, V.Gilja, P.Nuyujukian, S.A.Elassaad, K.V.Shenoy, and K.Boahen *IEEE EMBS Conf. on Neural Engineering*, Cancun, Mexico, 2011, pp 396–399.
2. J.Dethier, P.Nuyujukian, C.Eliasmith, T.Stewart, S.A.Elassaad, K.V.Shenoy, and K.Boahen, *NIPS*, Granada, Spain, 2011, to come.

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Thank you for your attention