DECODING USING BAYESIAN FILTERING

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BAYESIAN POPULATION DECODING OF MOTOR CORTICAL ACTIVITY USING A KALMAN FILTER

Wu et al. Neural Comput. 2006.

Introduction – Why Kalman Filtering?

- Incorporates information on the prior state of the system
  - Mitigates the negative effects of noise on model
  - Bayesian; estimates uncertainty
- Efficient and easy to update
  - Can (hopefully) be extended to an online setting
  - Requires minimal training data

Methods

- Prerecorded neural data
  - Extracellular recordings from 100 electrode array
  - Recorded from M1 in macaques
  - Two tasks
    - Pursuit tracking
    - Pinball
- Markov assumptions for Kalman filter:

$$p(\mathbf{x}_k|\mathbf{x}_{k-1}, \mathbf{x}_{k-2}, \ldots, \mathbf{x}_1) = p(\mathbf{x}_k|\mathbf{x}_{k-1})$$
$$p(\mathbf{z}_k|\mathbf{x}_k, \mathbf{z}_{k-1}) = p(\mathbf{z}_k|\mathbf{x}_k).$$

- Recursive equation for posterior:

$$p(\mathbf{x}_k|\mathbf{z}_k) = \kappa\, p(\mathbf{z}_k|\mathbf{x}_k) \int p(\mathbf{x}_k|\mathbf{x}_{k-1}) p(\mathbf{x}_{k-1}|\mathbf{z}_{k-1})\, d\mathbf{x}_{k-1},$$

Methods cont.

- Likelihood
  - Generative model for the activity of the population

$$\mathbf{z}_k = \mathbf{H}_k \mathbf{x}_k + \mathbf{q}_k,$$

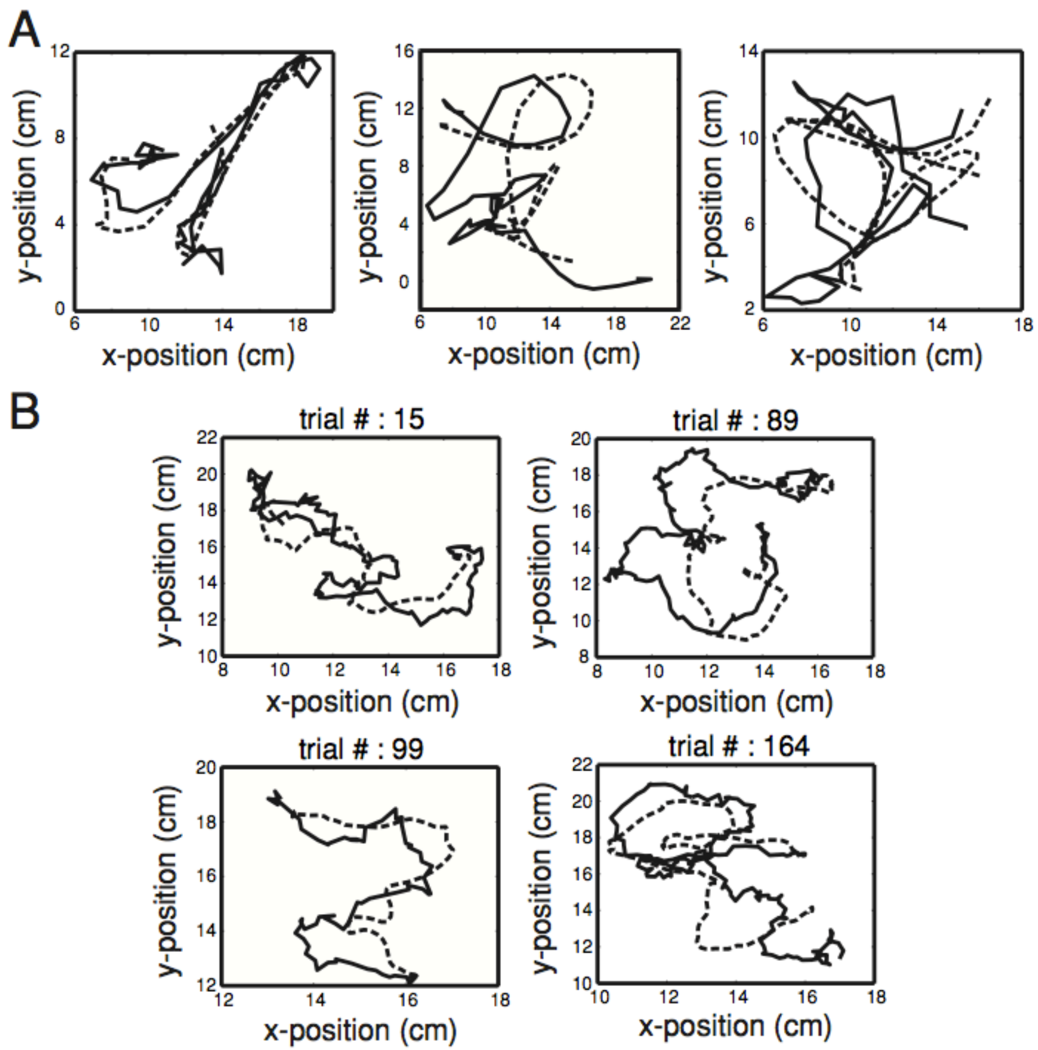
- Temporal Prior
  - Assumes the state evolves according to linear Gaussian model

$$\mathbf{x}_{k+1} = \mathbf{A}_k \mathbf{x}_k + \mathbf{w}_k,$$

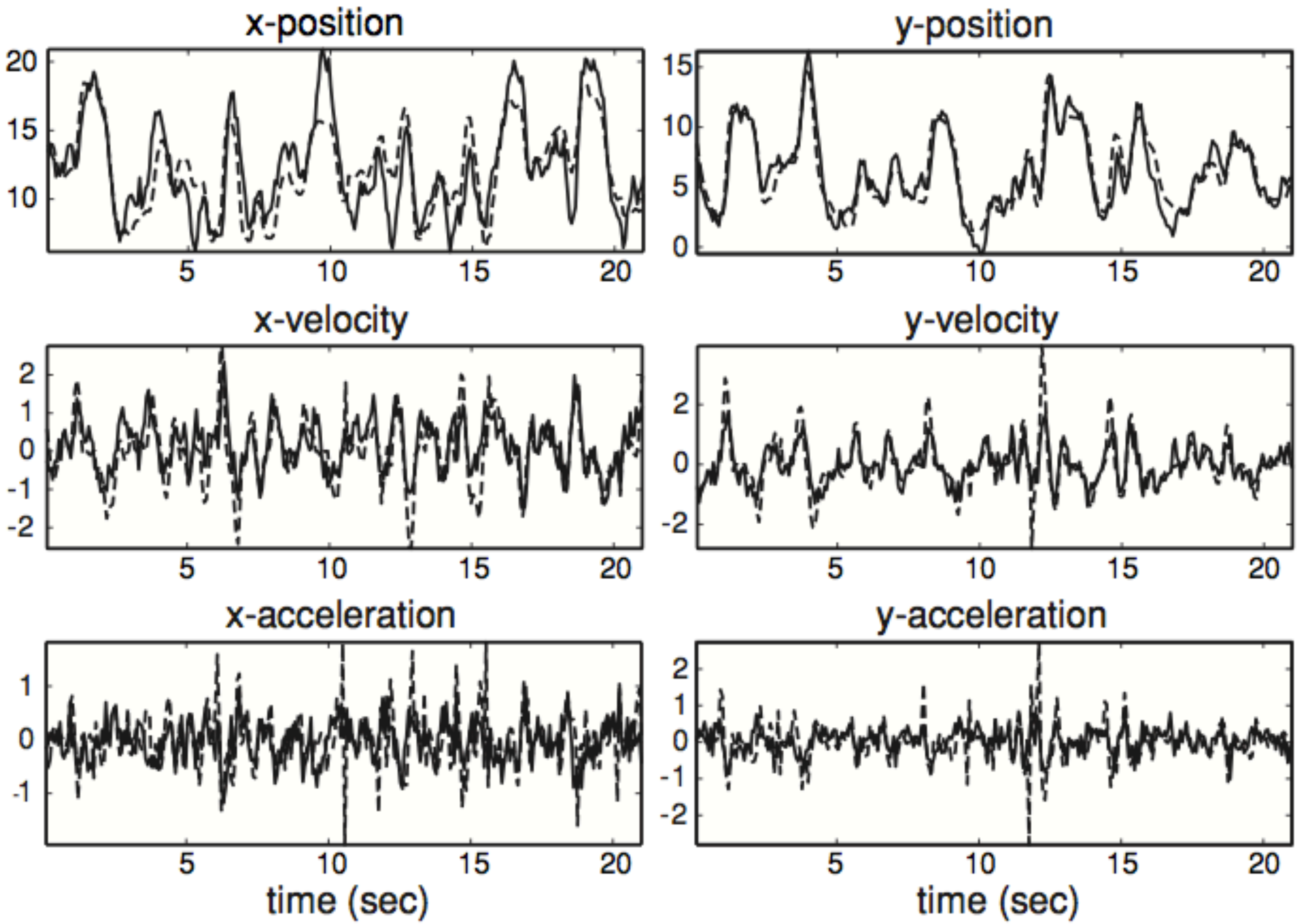
- Joint Probability Distribution (given Markov assumptions)

$$p(\mathbf{X}_M, \mathbf{Z}_M) = \left[p(\mathbf{x}_1) \prod_{k=2}^{M} p(\mathbf{x}_k | \mathbf{x}_{k-1}) \right] \left[\prod_{k=1}^{M} p(\mathbf{z}_k | \mathbf{x}_k) \right].$$

Results – Reconstructed Trajectories (Fig. 3)



Results – System State Components (Fig. 4)



Results – Optimal Delay/Orders for Pinball Task (Tables 2/3)

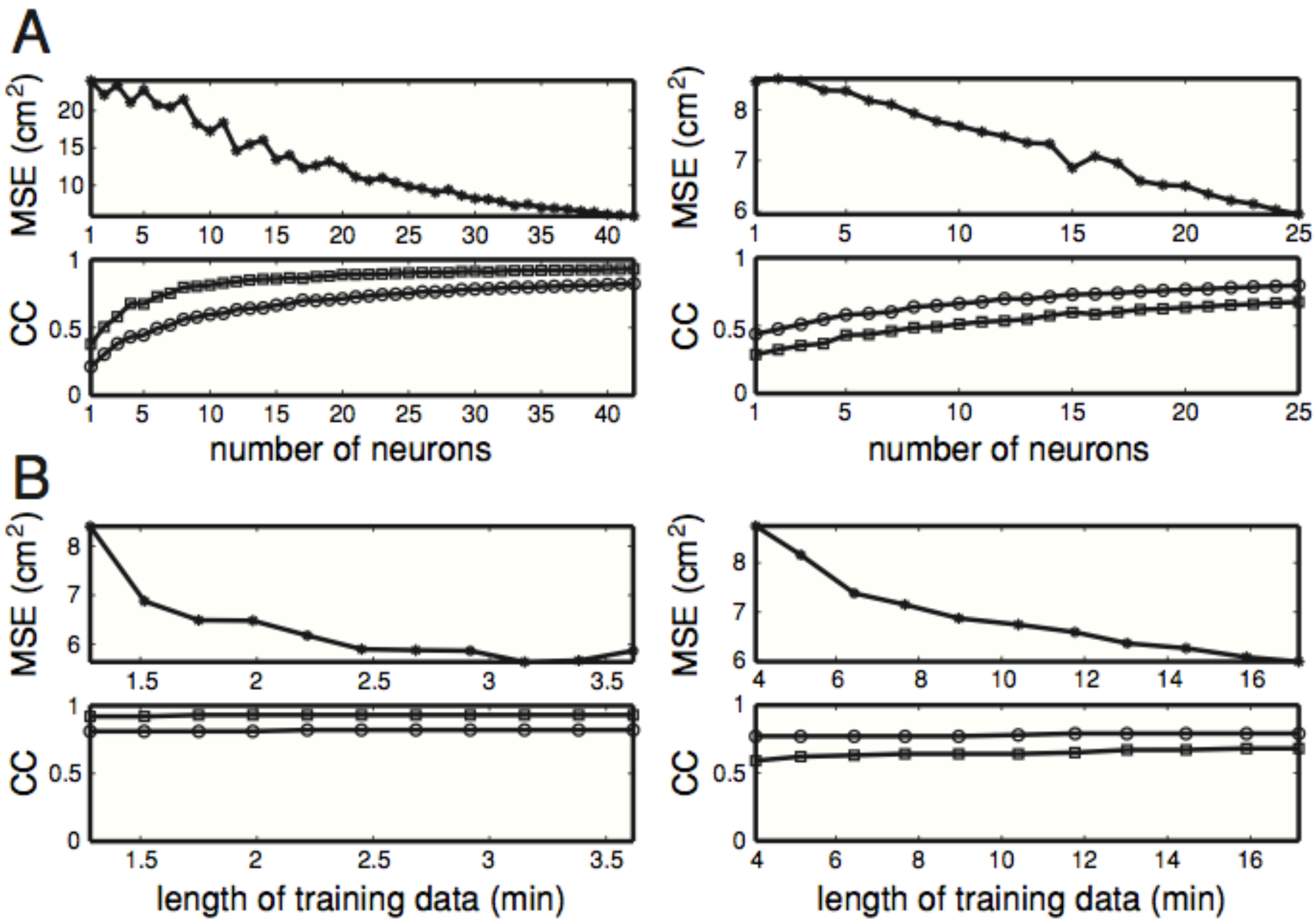
Method	$CC\ (x, y)$	MSE (cm^2)
Kalman (0 ms lag)	(0.78, 0.91)	7.01
Kalman (70 ms lag)	(0.80, 0.93)	6.25
Kalman (140 ms lag)	(0.82, 0.93)	5.87
Kalman (210 ms lag)	(0.81, 0.89)	6.80
Kalman (280 ms lag)	(0.76, 0.82)	8.81
Kalman (nonuniform, init 1)	(0.84, 0.93)	4.75
Kalman (nonuniform, init 2)	(0.84, 0.93)	4.77

Number of Orders	$CC\ (x, y)$	MSE (cm^2)	$\alpha + \beta$
0	(0.72, 0.87)	7.72	−80834
1	(0.82, 0.91)	6.31	−84049
2	**(0.82, 0.93)**	**5.87**	**−84411**
3	**(0.82, 0.93)**	**5.72**	**−84458**
4	(0.82, 0.93)	5.61	−84307
5	(0.82, 0.93)	5.60	−84081

Results – Optimal Delay for Pursuit Task (Table 4)

	Position		Position, Velocity		Pos, Vel, Accel	
Lag	CC (x, y)	MSE (cm^2)	CC (x, y)	MSE (cm^2)	CC (x, y)	MSE (cm^2)
0 ms	(0.43,0.39)	7.64	(0.79,0.68)	6.16	(0.78,0.65)	6.22
50 ms	(0.46,0.40)	7.56	(0.79,0.68)	6.08	(0.78,0.66)	6.17
100 ms	(0.49,0.40)	7.46	(0.79,0.68)	6.08	(0.79,0.65)	6.17
150 ms	(0.51,0.41)	7.38	**(0.79,0.68)**	**5.99**	(0.79,0.64)	6.15
200 ms	(0.53,0.41)	7.34	(0.79,0.67)	5.96	(0.78,0.64)	6.18
250 ms	(0.54,0.40)	7.33	(0.78,0.67)	6.02	(0.78,0.64)	6.16
Nonuniform	(0,53,0.41)	7.14	(0.79,0.68)	6.00	(0.79,0.65)	6.19

Results – Performance vs Number of Neurons and Training Data Length (Figure 6)



Results – Comparison to Other Methods (Table 6)

	$CC\ (x, y)$	MSE (cm^2)
Pinball task		
Method	$CC\ (x, y)$	MSE (cm^2)
Population vector	(0.26, 0.21)	75.0
Linear filter ($N = 14$)	(0.79, 0.93)	6.48
Kalman $\Delta t = 140$ ms, nonuniform lag	**(0.84, 0.93)**	**4.55**
Pursuit Tracking task		
Method		
Population vector	(0.57, 0.43)	13.2
Linear filter ($N = 30$)	(0.73, 0.67)	4.74
Kalman $\Delta t = 300$ ms, 150 ms **uniform lag**	**(0.81, 0.70)**	**4.66**

Conclusions

- More accurate than other models
  - Population vectors
  - Linear filters
- More efficient than linear filtering
- Less susceptible to overfitting than linear filtering
- Estimates full kinetic state vector

DECODING COMPLETE REACH AND GRASP ACTIONS FROM LOCAL PRIMARY MOTOR CORTEX POPULATIONS

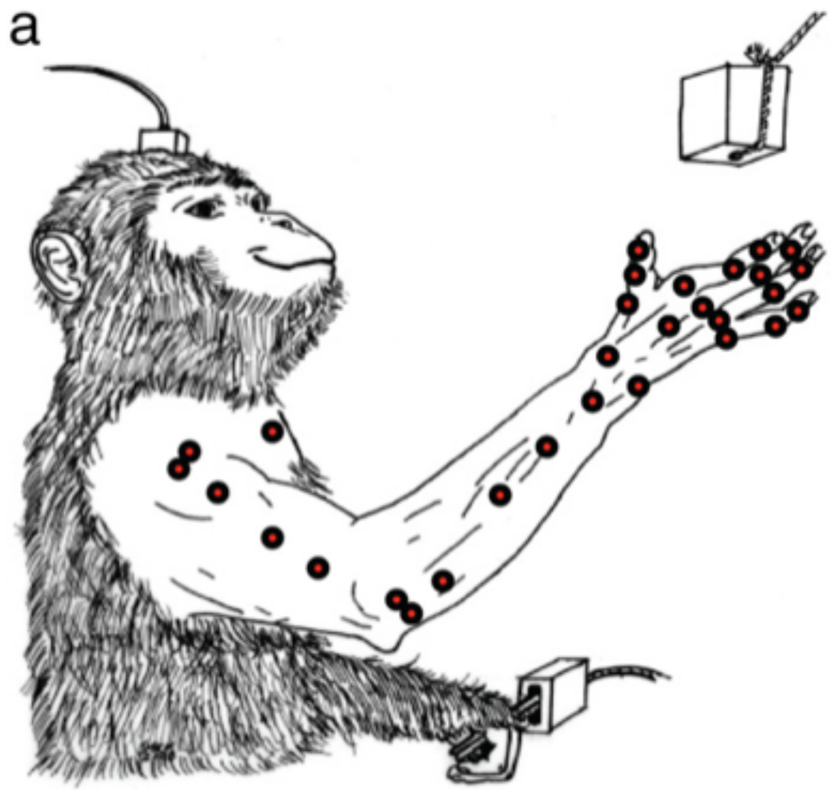
Vargas-Irwin et al. J Neurosci. 2010.

Introduction – Motivation

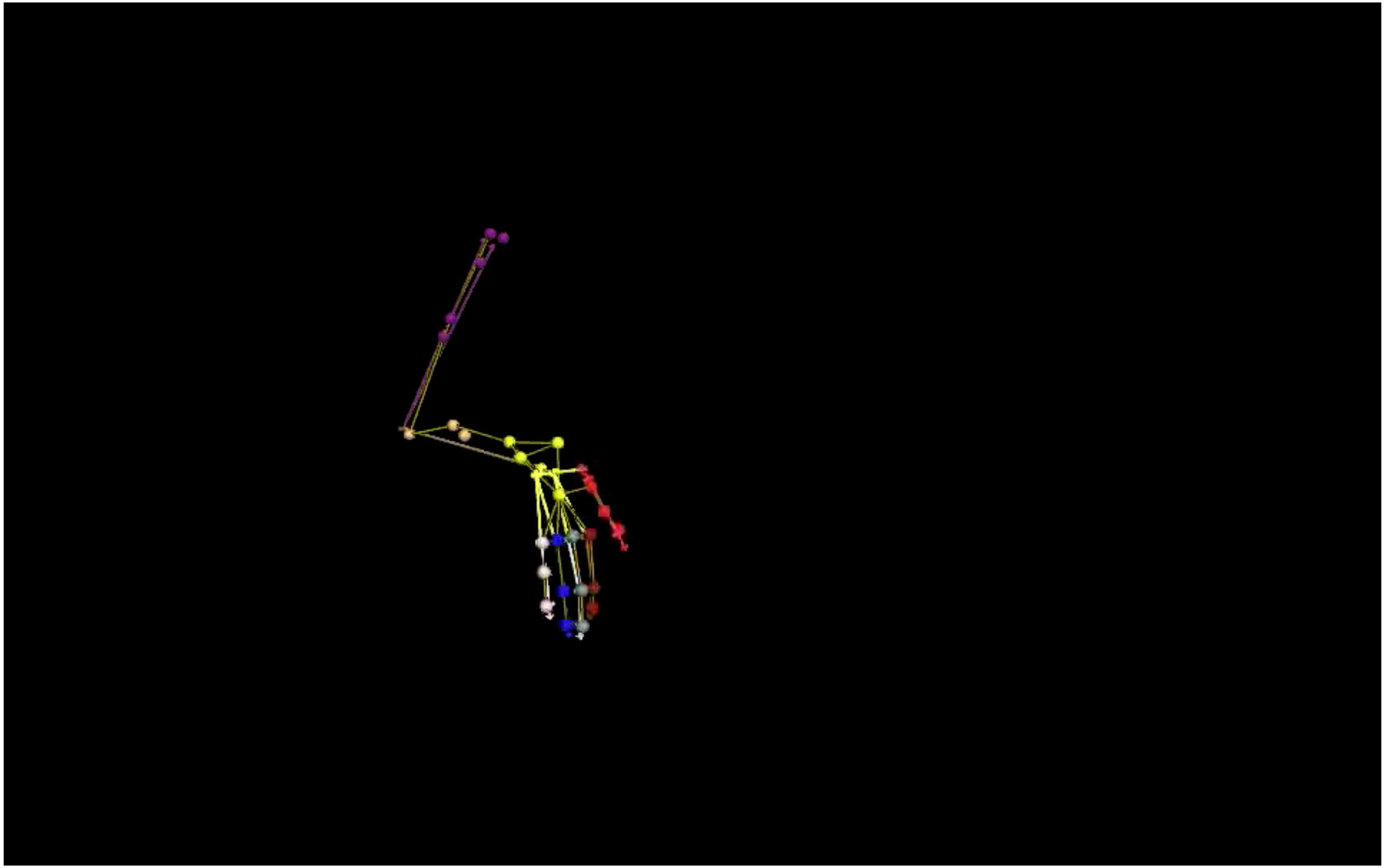
- To determine how M1 encodes naturalistic multijoint movements
- To improve upon studies that restrict movement to limited space/dimensions

Methods – Experimental (Fig. 1A)

- Recorded from M1 upper limb area in macaque
- Used a 96 electrode extracellular array
- Recorded motion using infrared capture of 29 reflective markers
    - 25 total degrees of freedom



Methods – Experimental cont.



Methods – Model

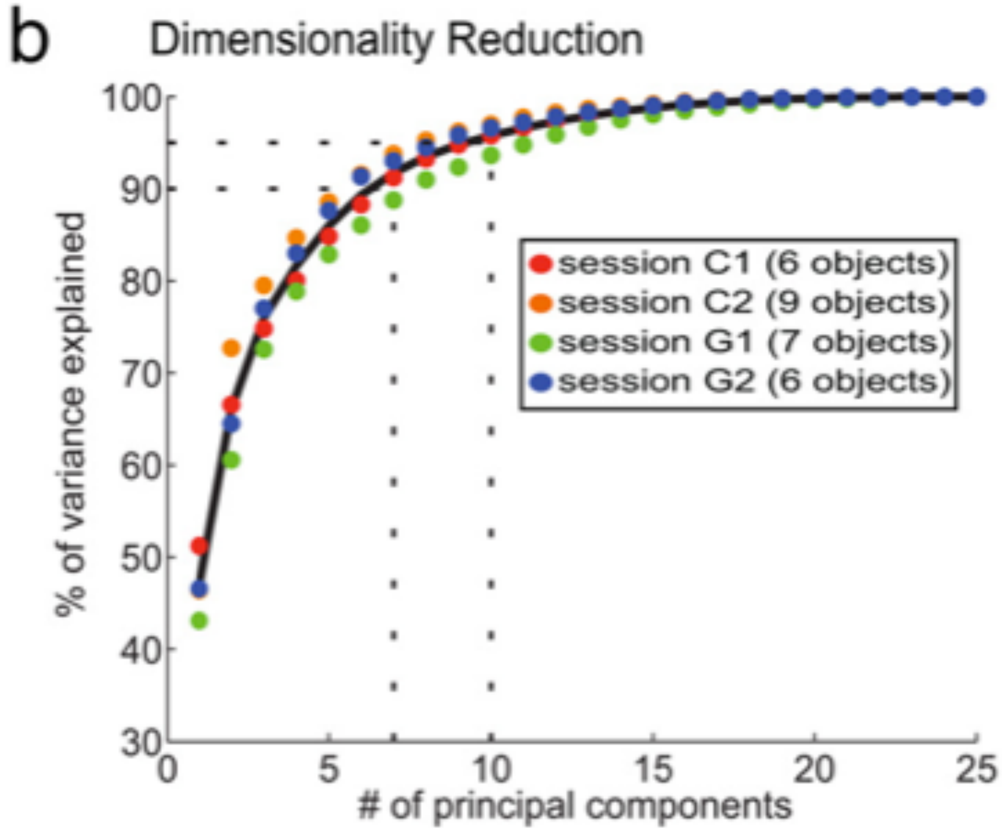
- Linear state space model for zeroth order kinematics
- Offline training
  - 60% of data for training
  - 20% for validation
  - 20% for testing
- Determined firing rate 100 ms overlapping time bins
- Recursive formulation for hidden state update rule:

$$\mathbf{x}_k = F\,\mathbf{x}_{k-1} + L\,\mathbf{u}_k + \mathbf{w}_k,$$

- Output:

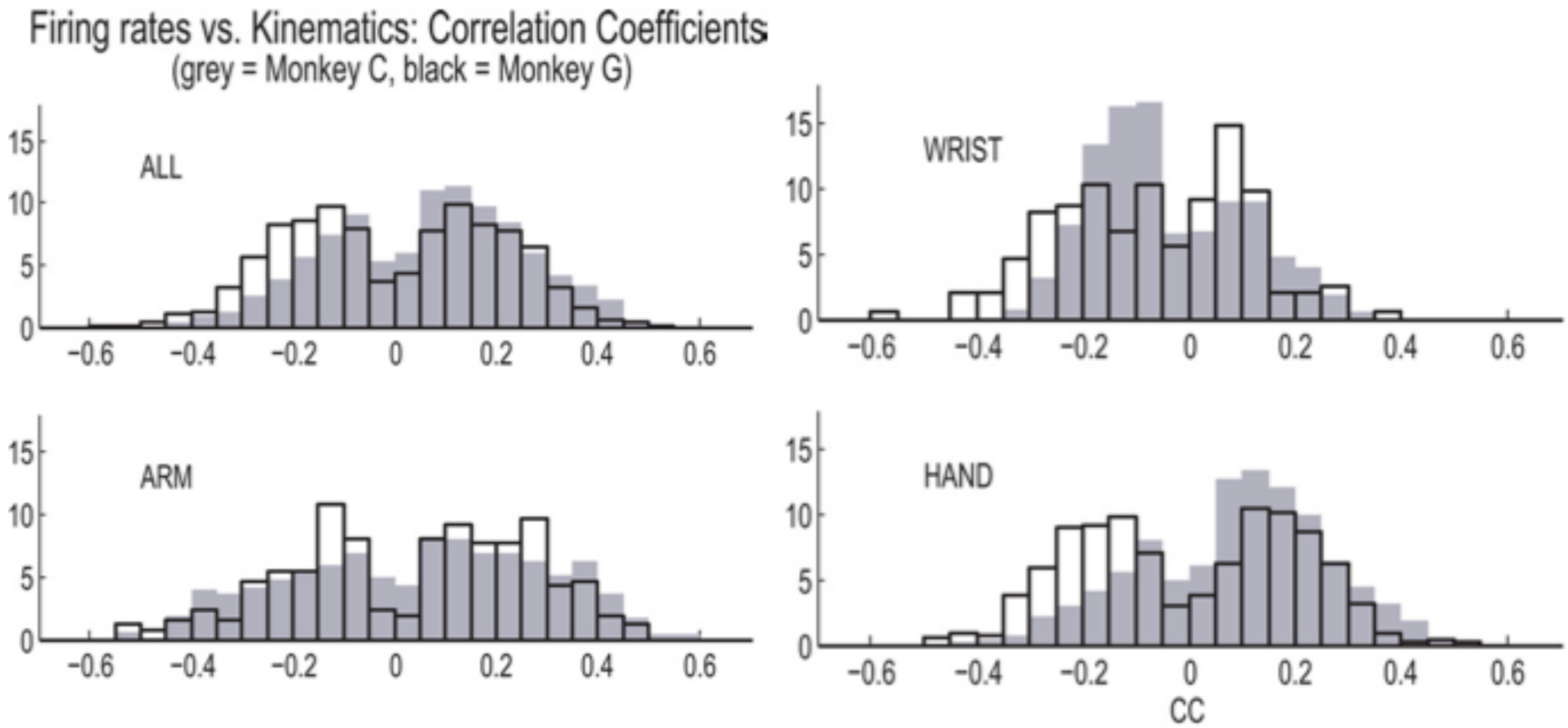
$$z_k = C\,\mathbf{x}_k + \mathbf{v}_k.$$

Results – Dimensionality (Fig. 3B)

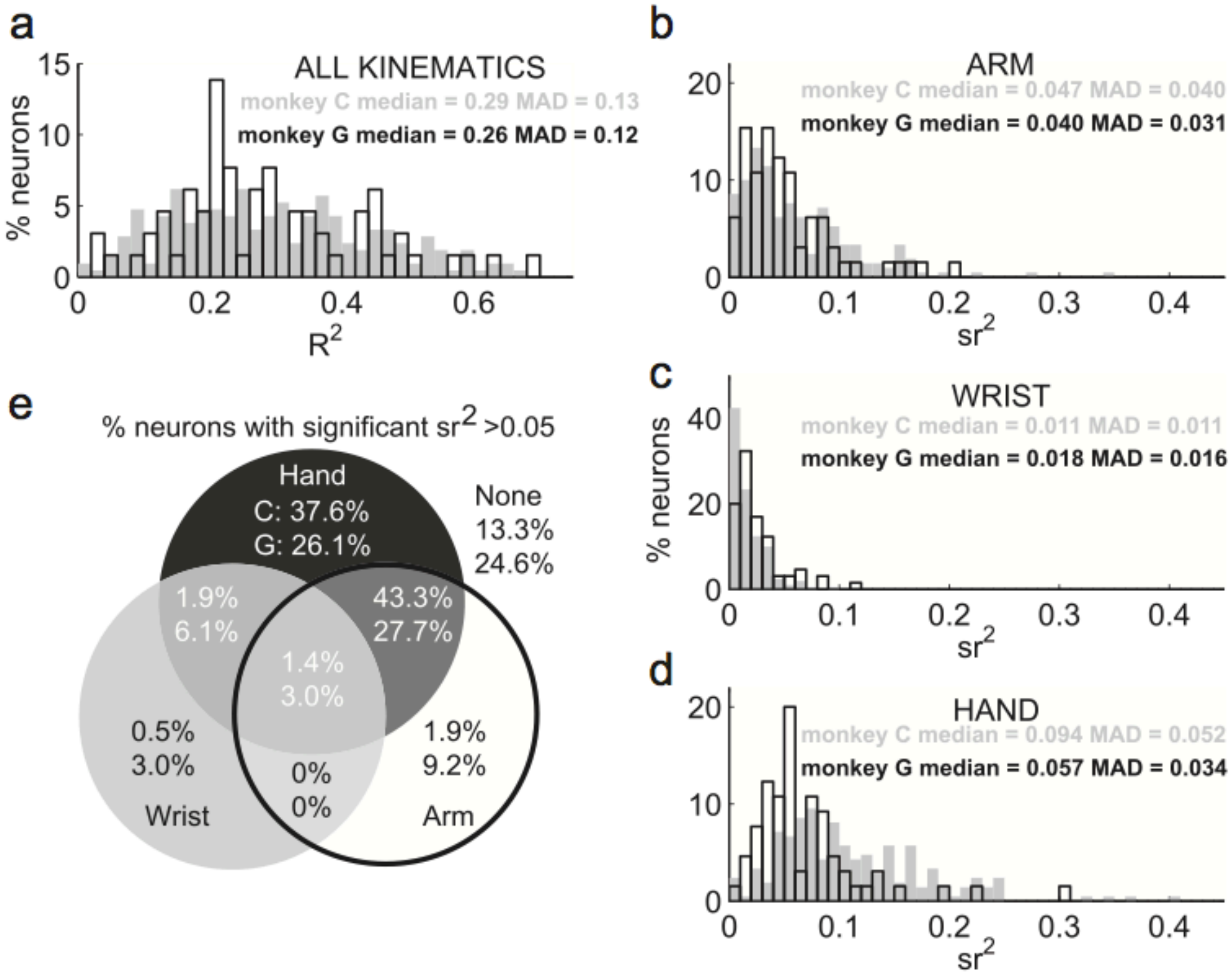


- 10 principal components were sufficient to account for 95% of the variance
  - → 10 dimensional control signal

Results – Firing Rate/Joint Angle Correlation (Fig. 3C)



Results – Neural Correlation for Sets of Kinematic Parameters (Fig. 4)

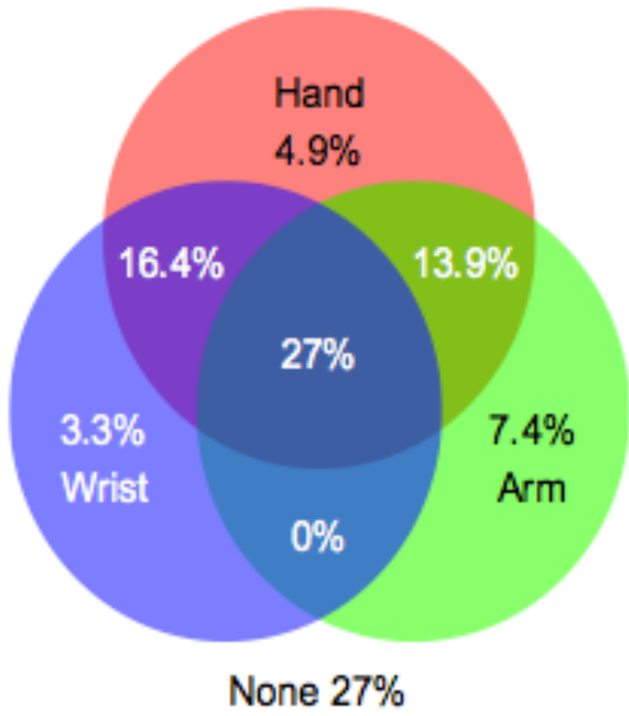


Results – Semipartial Correlation for Model Neurons (Supplemental Table 2/Fig. 5)

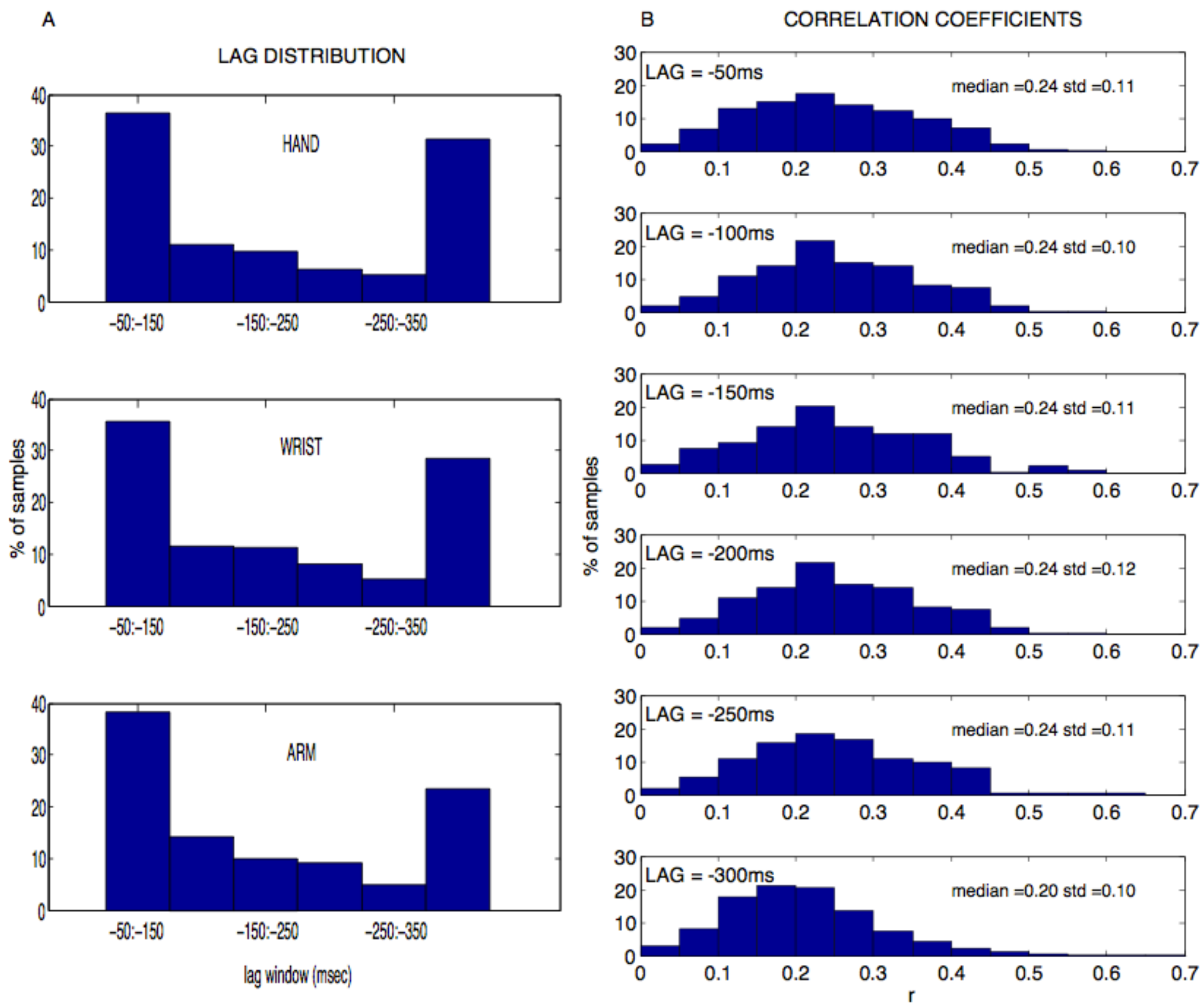
a

	C1	C2	G1	G2
TOTAL	89 / 122 (73%)	78 / 88 (89%)	35 / 35 (100%)	30 / 30 (100%)
ARM	59 / 89 (66%)	38 / 78 (49%)	35 / 35 (100%)	30 / 30 (100%)
WRIST	57 / 89 (64%)	55 / 78 (70%)	35 / 35 (100%)	30 / 30 (100%)
HAND	76 / 89 (85%)	74 / 78 (95%)	35 / 35 (100%)	30 / 30 (100%)

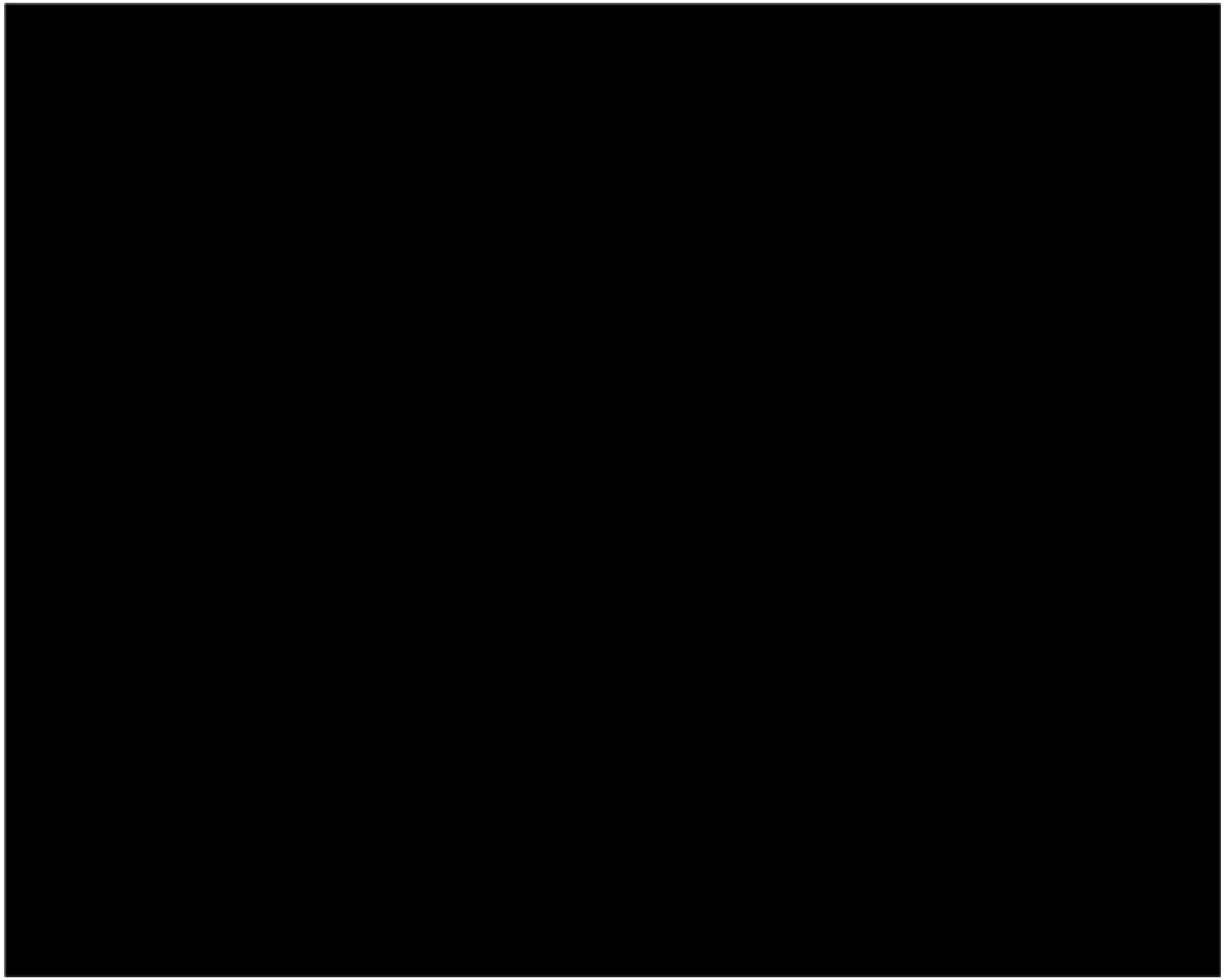
b



Results – Lag Distribution (Supplemental Fig. 3)



Results – Reconstruction Accuracy



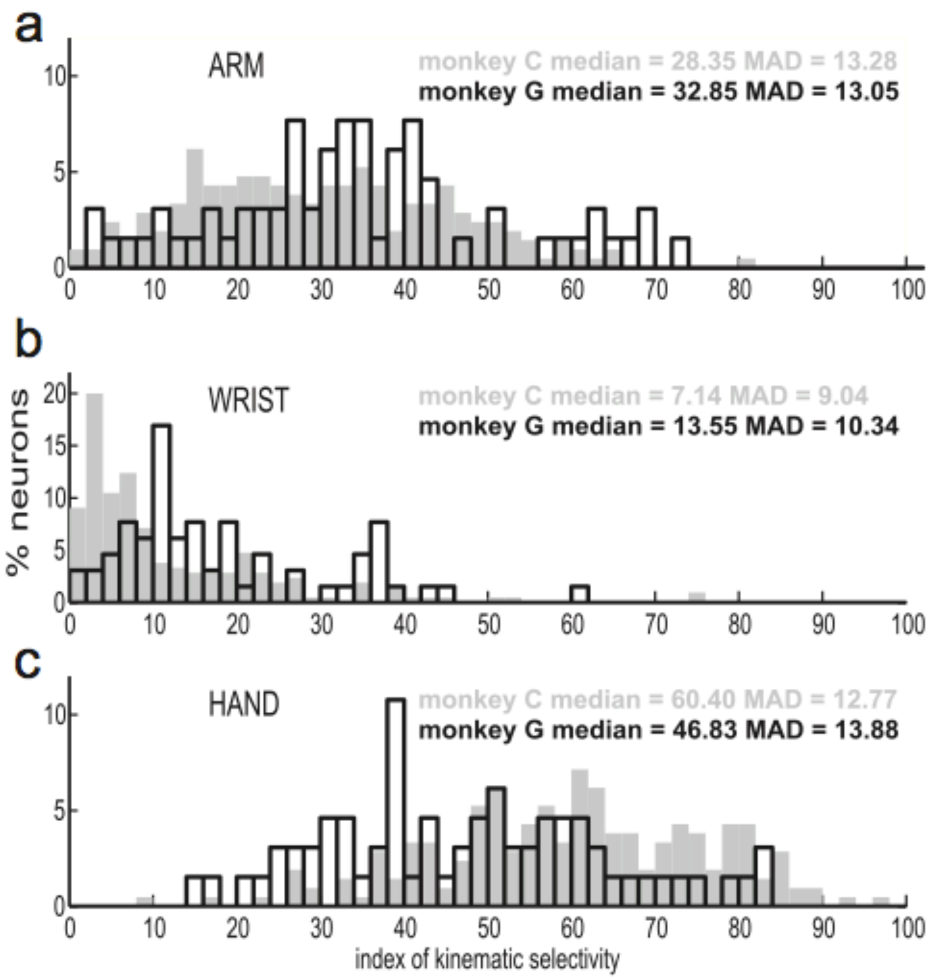
Results – Comparison to Previous Studies (Supplemental Table 3)

Study	Decoding method	X position	Y position	Z Position	other
(Wang et al., 2010)	Population vector (indirect optimal linear estimator)	0.91*	0.86*	0.83*	0.69* (wrist pr/su)
(Wu et al., 2004)	Switching Kalman filter	0.84	0.93		
(Hatsopoulos et al., 2004)	Linear filter	0.68	0.70		
(Carmena et al., 2003)	Linear filter	~ 0.85 (avg. x + y)	~ 0.85 (avg. x + y)		~ 0.91 (grip force)
Results from this study	State-space decoder	0.7440	0.7198	0.7948	0.72 (wrist pr/su) 0.73 (grip aperture)

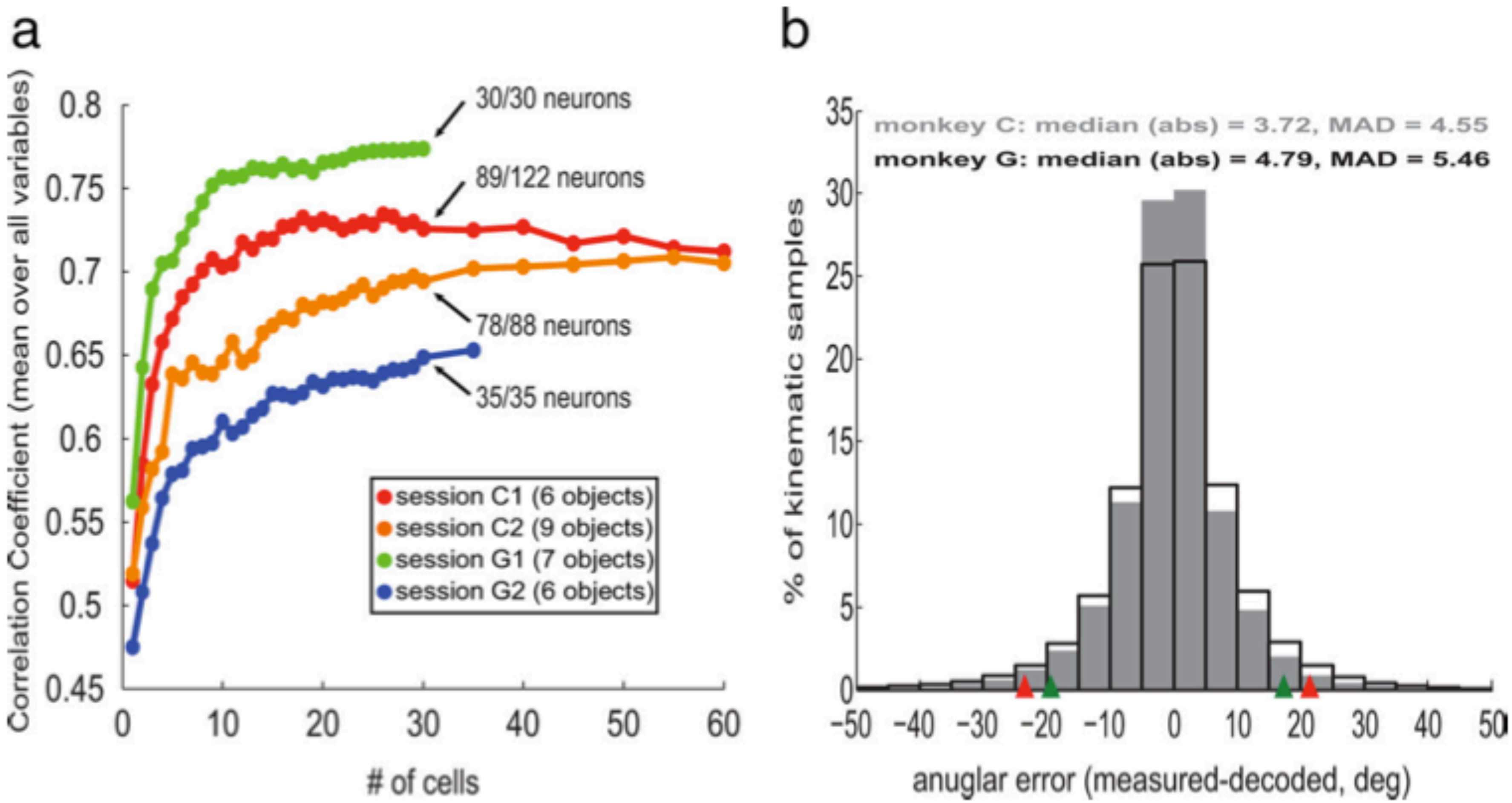
Results – Index of Kinematic Selectivity (Fig. 6)

Index of Kinematic Selectivity (Arm):

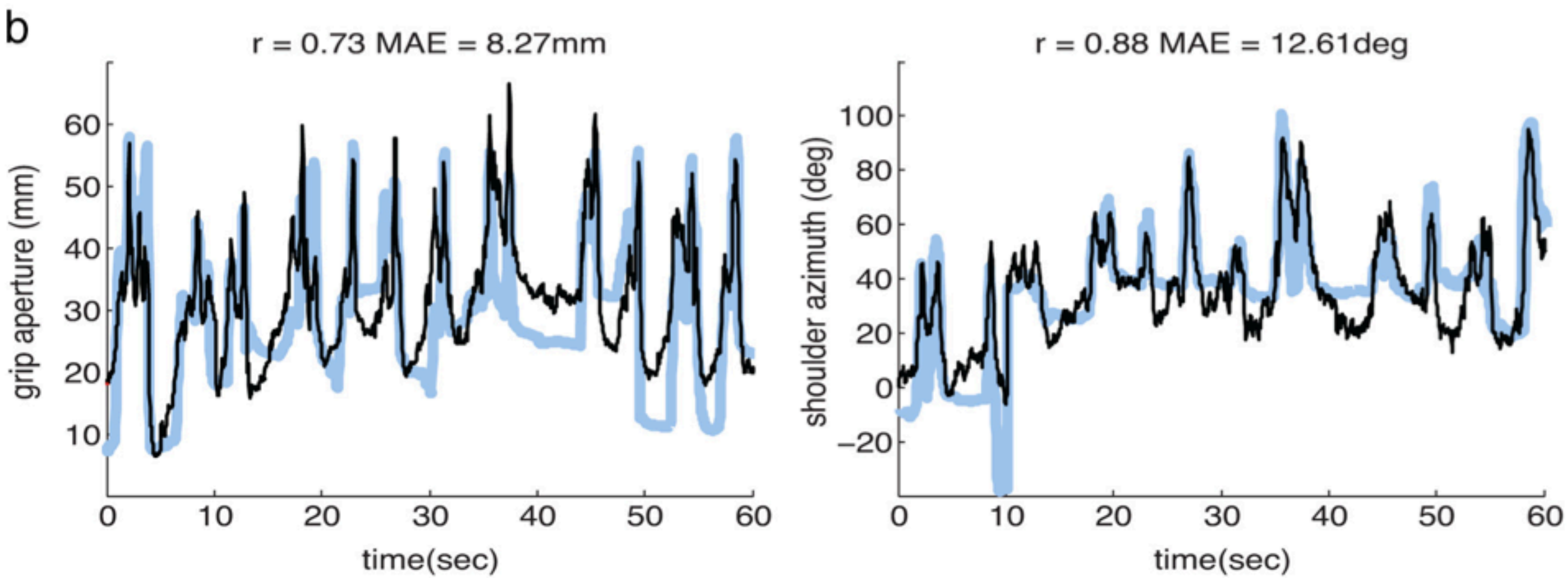
$$\frac{sr^2_{\mathrm{Arm}}}{sr^2_{\mathrm{Arm}} + sr^2_{\mathrm{Wrist}} + sr^2_{\mathrm{Hand}}}$$



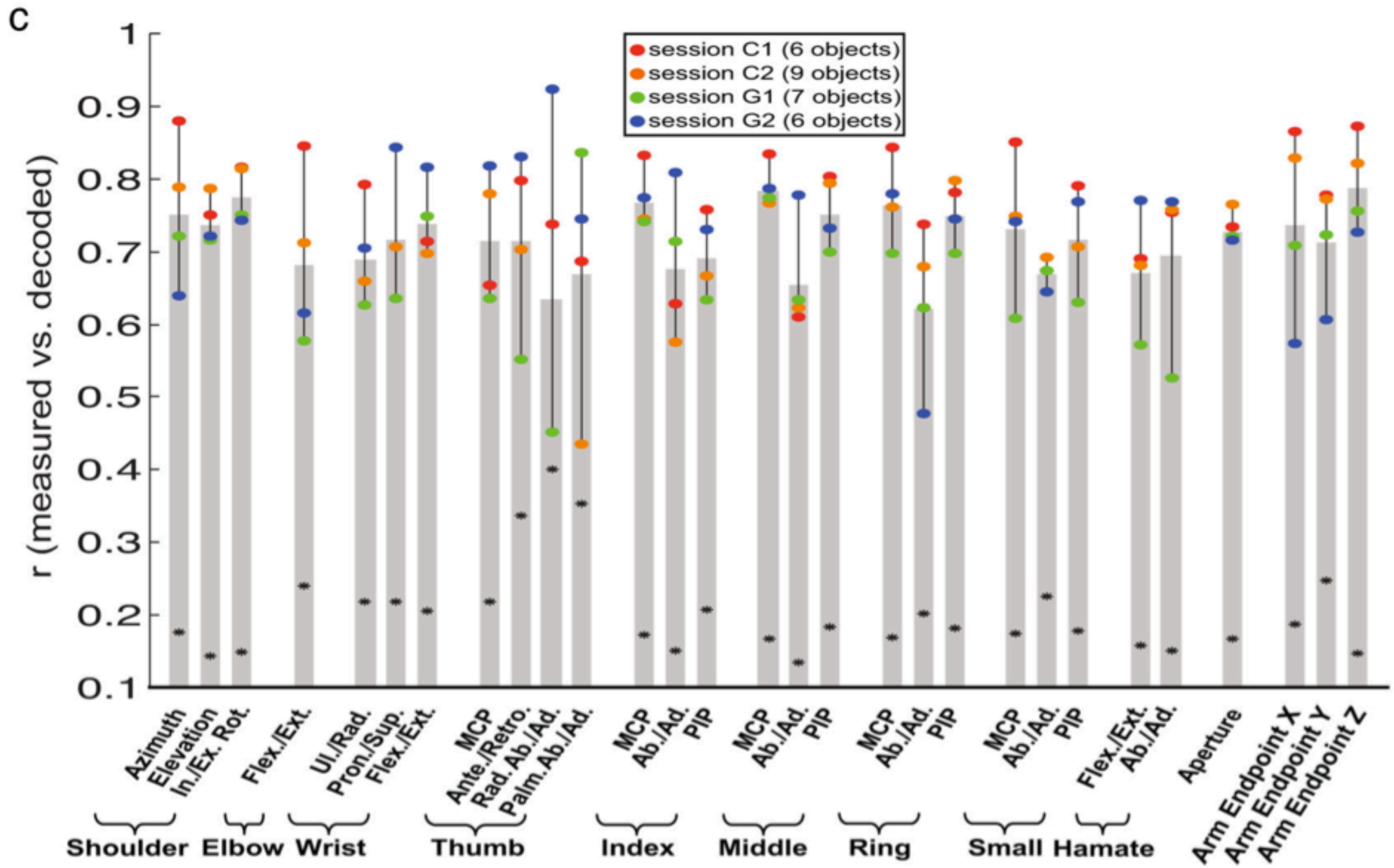
Results – Correlation and Error Distributions (Fig. 8)



Results – Measured and Decoded Kinematic Variables (Fig. 9B)



Results – Correlation Coefficients for Decoded Kinematic Variables (Fig. 9C)



Conclusion

- Achieved a decoding accuracy for each DoF similar to previous methods
- Accurate with relatively small number of neurons
  - Neuron selection does not appear to be crucial
- Individual neurons in the M1 arm/hand area represent unrelated and weakly correlated kinematic parameters

Limitations

- M1 might not encode kinematic parameters directly
  - Might encode muscle information instead
- Did not explore the ability to reconstruct individual finger motion
- Did not include sensory feedback in model
- Might not be easy to extend the model to desired movement of paralyzed individuals
- Each DoF state is evolved independently of the other DoFs