

## Modeling Neural Control of Physically Realistic Movement

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### Introduction

- Objective: neural control of artificial motor systems.
- Previous work has focused on kinematic control. This does not take into account physical constraints and may result in unnatural movement artifacts such as iitter.
- Possible solution is to use full biomechanical model of the system, but it is expensive and difficult to control with limited neural bandwidth.
- Our proposal: a computationally simple model with only a few parameters that are directly controlled by the decoded neural signal.

## The spring-based model



- Inspired by Hinton & Nair, 2005.
- Represent the hand as a **point mass** *m* located at the wrist.
- · Four virtual springs: one end attached to the hand, the other end slides without friction.
- · Control of the system is via dynamically modifying the spring **stiffness** coefficients  $k_A$ ,  $k_B$ ,  $k_C$  and  $k_D$ .
- Viscosity coefficient β controls damping.
- Impose stiffness constraints  $k_{A}+k_{B}=k_{C}+k_{D}=\kappa$  to maintain nonnegative coefficients.

# Methods: Direct decoding of system dynamics

- The controlling signal: firing rates of C units recorded from motor cortex
- Firing rates estimated in bins of fixed length.
- Let  $\widetilde{\mathbf{Z}}(t) = [\mathbf{Z}(t-l), \dots, \mathbf{Z}(t)]$  be the history of firing rates over *l* bins.
- We treat the movement decoding as a parametric regression problem:

$$\dot{\mathbf{E}}(t) \xrightarrow{f(\cdot;\theta)} \mathbf{K}(t) = \left[ k_{\mathrm{A}}(t), k_{\mathrm{B}}(t), k_{\mathrm{C}}(t), k_{\mathrm{D}}(t) \right]$$

- Training paradigm for the model:
- Observed data: firing rates  $\widetilde{\mathbf{Z}}_{i}(t)$  and hand positions  $\mathbf{x}_{i}(t)$ ;
- We estimate instantaneous velocities  $\hat{\mathbf{v}}(t)$  and accelerations  $\hat{\mathbf{a}}(t)$ .
- · From accelerations, we recover the stiffness coefficients, e.g.:

$$\hat{k}_{A} = \frac{m\hat{a}_{x}(t) + \hat{v}_{x}(t) + \kappa(L + x(t))}{2L}$$

- Given the coupled observed/estimated  $\widetilde{\mathbf{Z}}(t) \rightarrow k_{\star}(t), k_{c}(t)$ , fit the regression parameters for a chosen regression models.
- The complementary coefficients (B,D) recovered from stiffness constraint.
- Linear regression model: linear filter (LF)

$$k(t) = \mathbf{w}^T \widetilde{\mathbf{Z}}(t)$$
 where the weight vector **w** is learned from data.

Nonlinear regression model: Support Vector Machine (SVM)

$$k(t) = \sum_{i} \alpha_{i} h(\widetilde{\mathbf{Z}}(t), \widetilde{\mathbf{Z}}_{i})$$

- where h is a kernel function, and  $\alpha_i$  are learned from training data.
- Testing paradigm:
- $\hat{\mathbf{x}}(t)$  $\hat{\mathbf{a}}(t)$  $\hat{\mathbf{x}}(t+1)$  $\exists \hat{\mathbf{v}}(t)$

## **Methods: Data and Evaluation**

All analysis performed on an offline movement reconstruction tasks.

- •Monkey data: behaving animals, moving manipulandum to control cursor.
- 96-electrode arrays implanted in MI hand/arm area (see Shoham et al., 2005)
- CL: sequential tracking (piecewise linear movement, discrete target).
- LA: continuous pursuit (smooth target movement).
- Human data\*: paralyzed subject, instructed to attempt movement
- A single patient (brain stem stroke); see poster 256.10 for details.
- Pursuit tracking task (follow cursor manipulated by technician); see 256.11.

## Results

### Monkev data: m=400. β=200

	Session	MAE			CCx		CCv	
		SBM	Kinem	р	SBM	Kinem.	SBM	Kinem
Linear	CL (sequential)	0.29	0.27	<0.001	0.61	0.64	0.75	0.79
filter	LA (continuous)	0.09	0.09	>0.1	0.76	0.79	0.91	0.92
SVM	CL (sequential)	0.24	0.23	<0.001	0.78	0.79	0.84	0.86
	LA (continuous)	0.09	0.08	<0.001	0.80	0.81	0.92	0.94

Human data; *m*=1000, β=250

	Session	MAE			CCx		CCy	
		SBM	Kinem	р	SBM	Kinem.	SBM	Kinem
Linear	1	0.33	0.38	<0.001	0.56	0.47	0.41	0.32
filter	2	0.41	0.42	0.04	0.30	0.32	0.25	0.25
inter	3	0.57	0.55	>0.1	0.08	0.08	0.21	0.20
	1	0.28	0.29	0.07	0.66	0.62	0.50	0.46
SVM	2	0.30	0.30	>0.1	0.58	0.55	0.38	0.39
	3	0.31	0.32	<0.001	0.33	0.28	0.45	0.39



## Conclusions

• Direct decoding of the parameters of artificial spring-based models allows for movement reconstruction on par with kinematic decodina.

 Introduction of realistic physical constraints yields smoother decoded movement.

#### References

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 $\hat{\mathbf{K}}(t)$ • Observed firing rates  $\widetilde{\mathbf{Z}}(t)$  –