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 jitter.

• 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 \( k_B, k_C, k_D \) and \( k_0 \).
- Viscosity coefficient \( \beta \) controls damping.
- Impose stiffness constraints \( k_A \) to maintain non-negative 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 \( \tilde{Z}(t) = [Z(t-1), \ldots, Z(t)] \) be the history of firing rates over \( i \) bins.

• We treat the movement decoding as a parametric regression problem:
  \[\tilde{Z}(t) = K(t) = [k_A(t), k_B(t), k_C(t), k_D(t)]\]

Training paradigm for the model:

• Observed data: firing rates \( \tilde{Z}(t) \) and hand positions \( x(t) \).

• From accelerations, we recover the stiffness coefficients, e.g.:
  \[k_A = \frac{m\tilde{a}_x(t) + \tilde{v}_x(t) + \kappa(L + x(t))}{2L}\]

• Given the coupled observed/estimated \( \tilde{Z}(t) \rightarrow k_A(t), k_C(t), k_D(t) \), fit the regression parameters for a chosen regression models.

• The complementary coefficients \((B, D)\) recovered from stiffness constraint.

• Linear regression model: linear filter (LF)
  \[k(t) = w^T\tilde{Z}(t)\]
  where the weight vector \( w \) is learned from data.

• Nonlinear regression model: Support Vector Machine (SVM)
  \[k(t) = \sum_i \alpha_i h(\tilde{Z}(t), \bar{Z}_i)\]
  where \( h \) is a kernel function, and \( \alpha_i \) are learned from training data.

Testing paradigm:

• Observed firing rates \( \tilde{Z}(t) \rightarrow \tilde{K}(t) \rightarrow \tilde{a}(t), \tilde{v}(t), \tilde{s}(t) \rightarrow \tilde{s}(t+1)\)

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).

• **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

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<thead>
<tr>
<th>Session</th>
<th>MAE</th>
<th>( \beta )</th>
<th>( \rho )</th>
<th>CC</th>
<th>CC</th>
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<tbody>
<tr>
<td>Linear filter</td>
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<td></td>
</tr>
<tr>
<td>CL (sequential)</td>
<td>0.26</td>
<td>0.27</td>
<td>&lt;0.005</td>
<td>0.61</td>
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<td>LA (continuous)</td>
<td>0.06</td>
<td>0.09</td>
<td>&gt;0.1</td>
<td>0.76</td>
<td>0.79</td>
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<td>SVM</td>
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<tr>
<td>CL (sequential)</td>
<td>0.24</td>
<td>0.23</td>
<td>0.78</td>
<td>0.79</td>
<td>0.84</td>
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<tr>
<td>LA (continuous)</td>
<td>0.09</td>
<td>0.08</td>
<td>&lt;0.005</td>
<td>0.80</td>
<td>0.81</td>
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<tr>
<td>CL (sequential)</td>
<td>0.33</td>
<td>0.38</td>
<td>&lt;0.005</td>
<td>0.56</td>
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<tr>
<td>LA (continuous)</td>
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<td>0.42</td>
<td>0.04</td>
<td>0.30</td>
<td>0.32</td>
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<tr>
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Conclusions

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Training paradigm for the model:

• Observed data: firing rates \( \tilde{Z}(t) \) and hand positions \( x(t) \).

• We estimate instantaneous velocities \( \tilde{v}(t) \) and accelerations \( \tilde{a}(t) \).

• From accelerations, we recover the stiffness coefficients, e.g.:
  \[k_A = \frac{m\tilde{a}_x(t) + \tilde{v}_x(t) + \kappa(L + x(t))}{2L}\]

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References


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