Forearm Muscle Selection of EMG Controlled Robotic Limb

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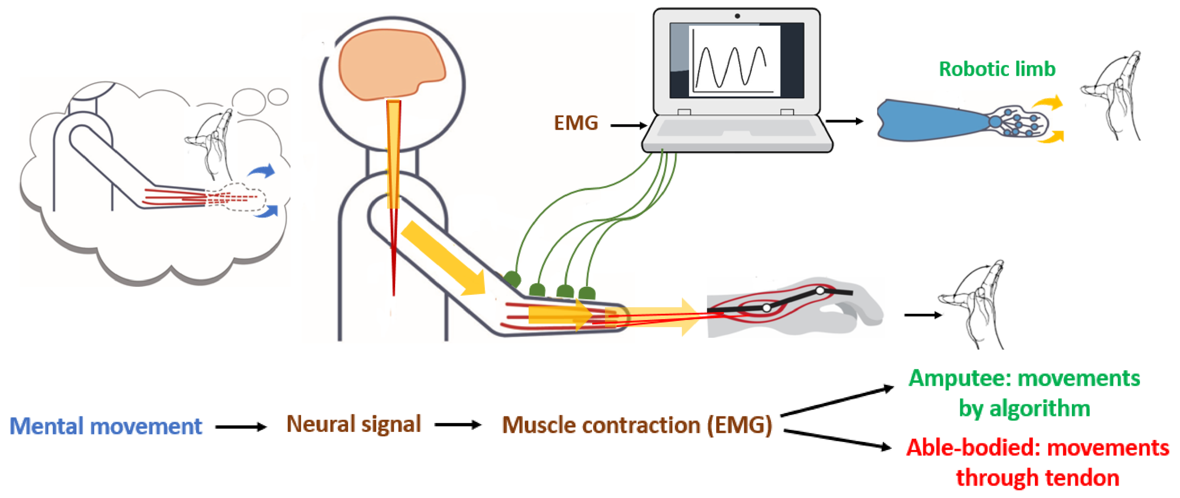
1. Kinematic movement

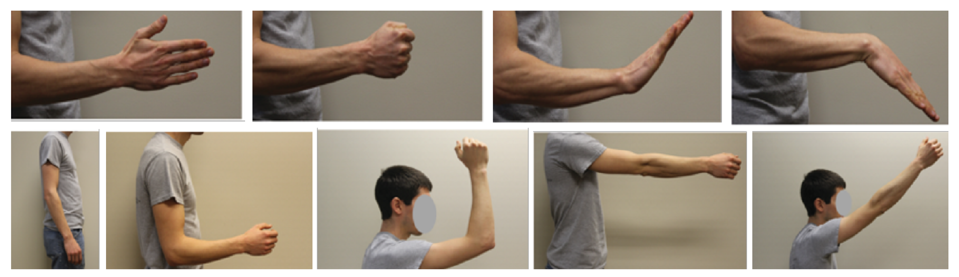
- **Objective** : Develop electromyography (EMG) controlled multi-functional robotic prosthetic limb for transradial amputee

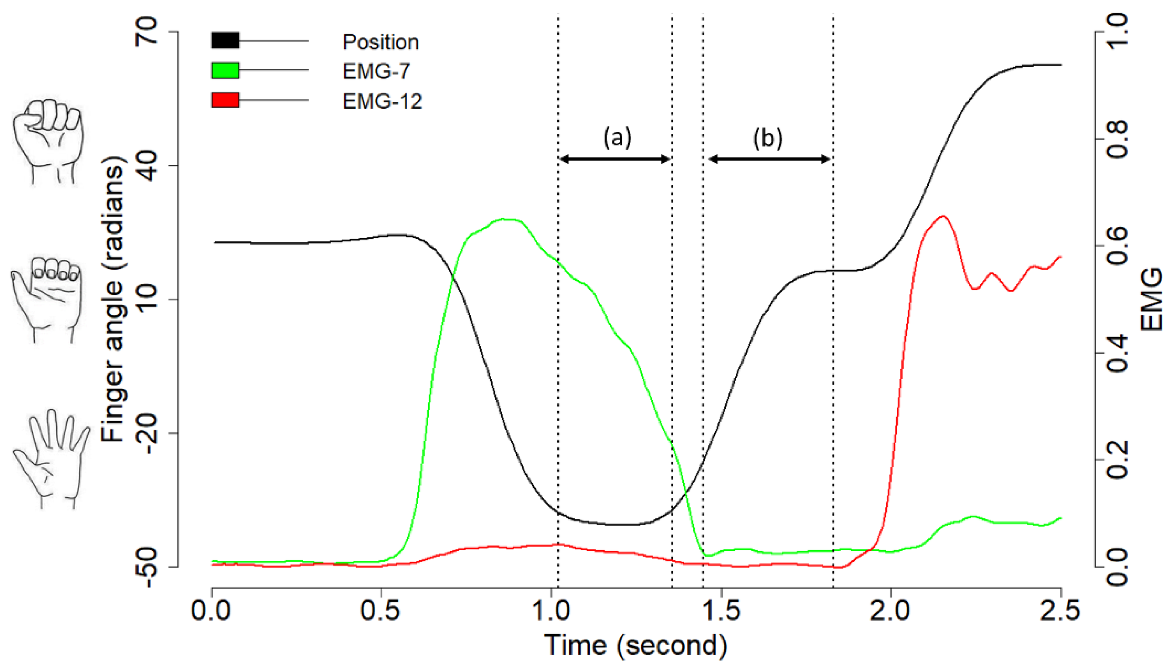


- **Specific objectives** : Link subset of EMG signals to specific finger/wrist movements & provide low-dimensional predictive model

2. Data & Challenges

- Finger & wrist flexion/extension at different postures with fixed & varying pattern by an able-bodied subject





- (a) Physical constraint : *signal but no movement*
  (b) Passive force : *no signal but movement*
- **State-of-the-art** prosthesis models do not respect known biomechanics and overfit data
- **Approach** : Biomechanically-motivated model using recent past of EMG to predict movement

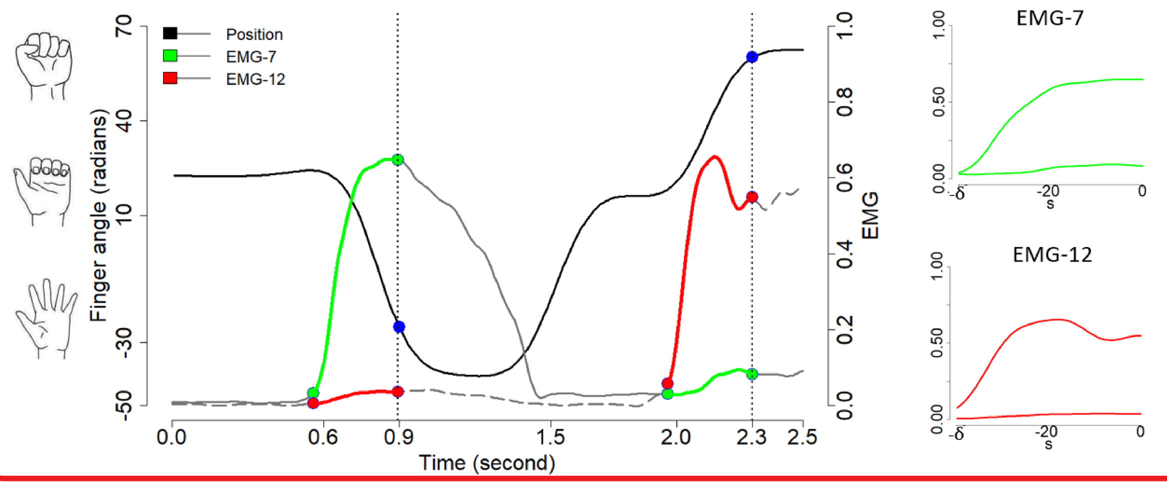
References

[1] Jan Gertheiss, Arnab Maity, and Ana-Maria Staicu. Variable selection in generalized functional linear models. *Stat*, 2, 2013.
[2] Yi Yang and Hui Zou. A fast unified algorithm for solving group-lasso penalize learning problems. *Statistics and Computing*, 25:1129–1141, 2015.
[3] Yingying Fan, Gareth M James, Peter Radchenko, et al. Functional additive regression. *The Annals of Statistics*, 43:2296–2325, 2015.
[4] Jing Lei, Max G'Sell, Alessandro Rinaldo, Ryan J. Tibshirani, and Larry Wasserman. Distribution-free predictive inference for regression. *Journal of the American Statistical Association*, 0:0–0, 2017.
[5] Jasdeep Pannu and Nedret Billor. Robust group-lasso for functional regression model. *Communications in Statistics-Simulation and Computation*, 46:3356–3374, 2017.
[6] David R Roberts, Volker Bahn, Simone Ciuti, Boyce, et al. Cross-validation strategies for data with temporal, spatial, hierarchical, or phylogenetic structure. *Ecography*, 2017.

3. Data Structure

Data : $[z_i, y_i, \{X_{k,i}(s_r), r=1,\dots,\delta\}_{k=1}^{K}]_{i=1}^{N}$

- z_i is finger/wrist position at instance i, $z_i \in \mathcal{Z}$
- y_i is corresponding velocity
- $X_{k,i}(s_r)$ is kth EMG signal recorded at s_r, $s_r \in \mathcal{S} = [-\delta, 0]$ & represents the recent past time window with length $\delta + 1$



4. Modeling framework

We consider functional linear model

$$E[y_i|X_{1,i},\dots,X_{K,i}] = \alpha + \sum_{k=1}^{K}\int_{-\delta}^{0} X_{k,i}(s)\gamma_k(s,z_i)ds$$

- α is an overall intercept
- $\gamma_k(\cdot,\cdot)$ is a smooth coefficient defined on $\mathcal{S}\times\mathcal{Z}$ & quantifies effect of kth EMG on mean velocity y_i through covariate z_i
- Minimize **SSE** $= \sum_i \left(y_i - E[y_i|X_{1,i},\dots,X_{K,i}]\right)^2$
- $\mathcal{K} \subseteq \{1,\cdots,K\}$ denotes true nonzero index set
- $\mathcal{B} = \{\gamma_k(\cdot,\cdot) \neq 0; k \in \mathcal{K}\}$ denotes true effects

5. Selection of variables & Post-Selection Inference

- **S**equential **A**daptive **F**unctional **E**mpirical selection by group LASSO (**SAFE-gLASSO**)
- **First stage.** Select EMG signals as *"all-in-all-out"* manner by solving adaptive penalized criterion

$$\widehat{\gamma} = \underset{\gamma}{\text{argmin}}\left\{\textbf{SSE} + \sum_{k=1}^{K}\lambda\left(\mathbf{f_k}||\gamma_k||^2 + \phi_1\mathbf{g_k}||\gamma''_{k,s}||^2 + \phi_2\mathbf{h_k}||\gamma''_{k,z}||^2\right)^{1/2}\right\}$$

  - λ controls sparseness as $\lambda\to\infty$ then $\gamma_k \to 0$ & $\phi = \{\phi_1,\phi_2\}$ control smoothness of fit
  - $||\gamma_k||^2$, $||\gamma''_{k,s}||^2$, & $||\gamma''_{k,z}||^2$ measure overall magnitude & size of curvatures
  - Weights $\mathbf{f_k} = 1/||\widetilde{\gamma}_{\mathbf{k,0}}||^d$, $\mathbf{g_k} = 1/||\widetilde{\gamma}''_{\mathbf{k,s,0}}||^d$, $\mathbf{h_k} = 1/||\widetilde{\gamma}''_{\mathbf{k,z,0}}||^d$, $d \geq 0$ based on initial estimates $\widetilde{\gamma}_{\mathbf{k,0}}$
  - Reparametrize & solve using group LASSO approach by *groupwise-majorization-descent* algorithm [2]
  - Obtain $\mathcal{K}^{(1)}_{\widetilde{\lambda},\widetilde{\phi}}$ & estimate $\mathcal{B}^{(1)}_{\widetilde{\lambda},\widetilde{\phi}}$ for optimal $\widetilde{\lambda}$ & $\widetilde{\phi}$ chosen by block CV [6]
- **Second stage.** Select EMG signals from reduced subset $\mathcal{K}^{(1)}_{\widetilde{\lambda},\widetilde{\phi}}$ with re-weighted penalized criterion
  - Calculate new weights based on estimates of first stage $\mathcal{B}^{(1)}_{\widetilde{\lambda},\widetilde{\phi}}$
  - Solve criterion as before, obtain $\mathcal{K}^{(2)}_{\widehat{\lambda},\widehat{\phi}}$, & estimate $\mathcal{B}^{(2)}_{\widehat{\lambda},\widehat{\phi}}$ for new optimal $\widehat{\lambda}$ & $\widehat{\phi}$ chosen by block CV
- **Post-selection prediction.** With $\mathcal{K}^{(2)}_{\widehat{\lambda},\widehat{\phi}}$, refit the model with smooth penalty to reduce prediction bias

$$\widehat{\gamma} = \underset{\gamma}{\text{argmin}}\left\{\textbf{SSE}_{\mathcal{K}^{(2)}_{\widehat{\lambda},\widehat{\phi}}} + \sum_{k\in\mathcal{K}^{(2)}_{\widehat{\lambda},\widehat{\phi}}}\left(\phi_1||\gamma''_{k,s}||^2 + \phi_2||\gamma''_{k,z}||^2\right)^{1/2}\right\}$$

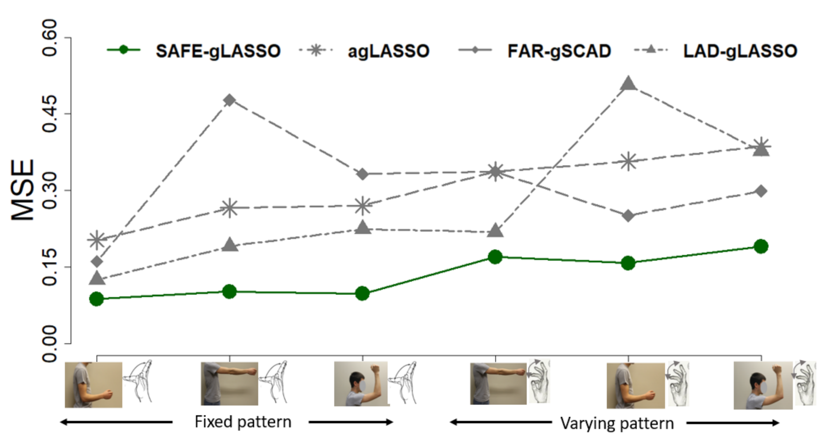
  - Prediction intervals based on *"data splitting"* adjusting for event of variable selection by [4]

6. Application Results for Finger movements

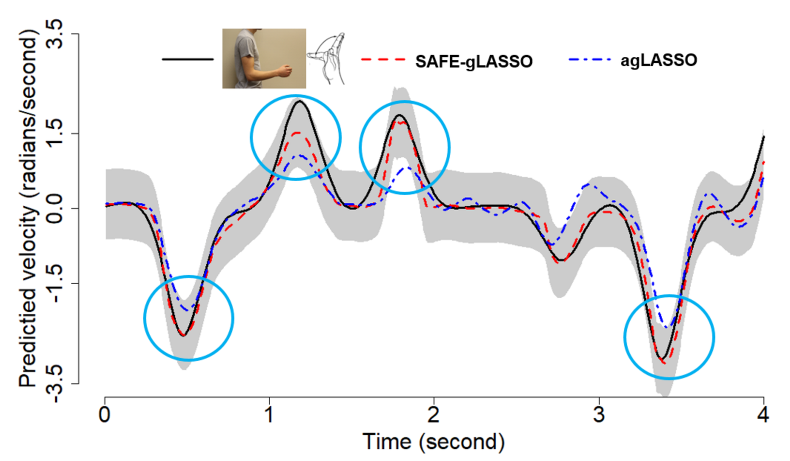
Methods	Fixed pattern			Varying pattern		
SAFE-gLASSO	2 (0)	2 (0)	2 (0)	2 (0)	2 (0)	2 (1)
agLASSO	2 (0)	2 (0)	2 (0)	2 (0)	1 (0)	1 (0)
LAD-gLASSO	3 (5)	3 (3)	3 (5)	2 (3)	3 (2)	3 (1)
FAR-gSCAD	3 (0)	3 (0)	3 (0)	2 (0)	3 (0)	3 (0)

number of true & false (parenthesis) positives

- Compare to [1], [3], & [5]
- **High** true & **low** false positives
- Excludes similar muscles
- Selects **important** muscles across **postures** & **patterns**

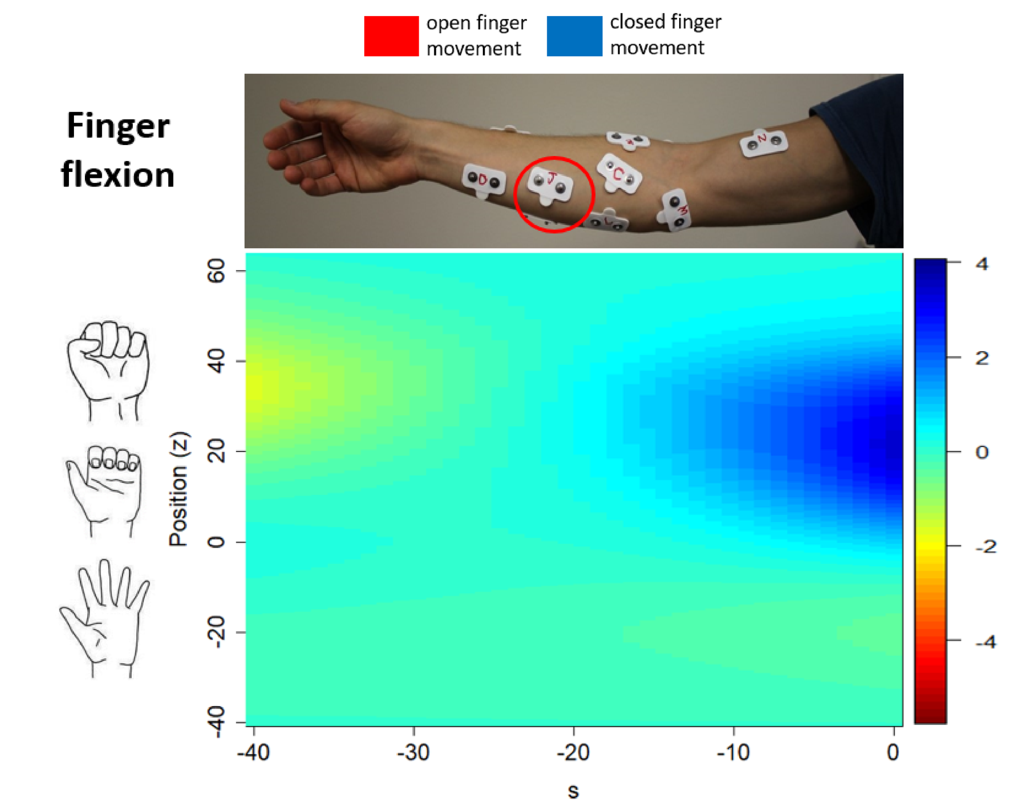


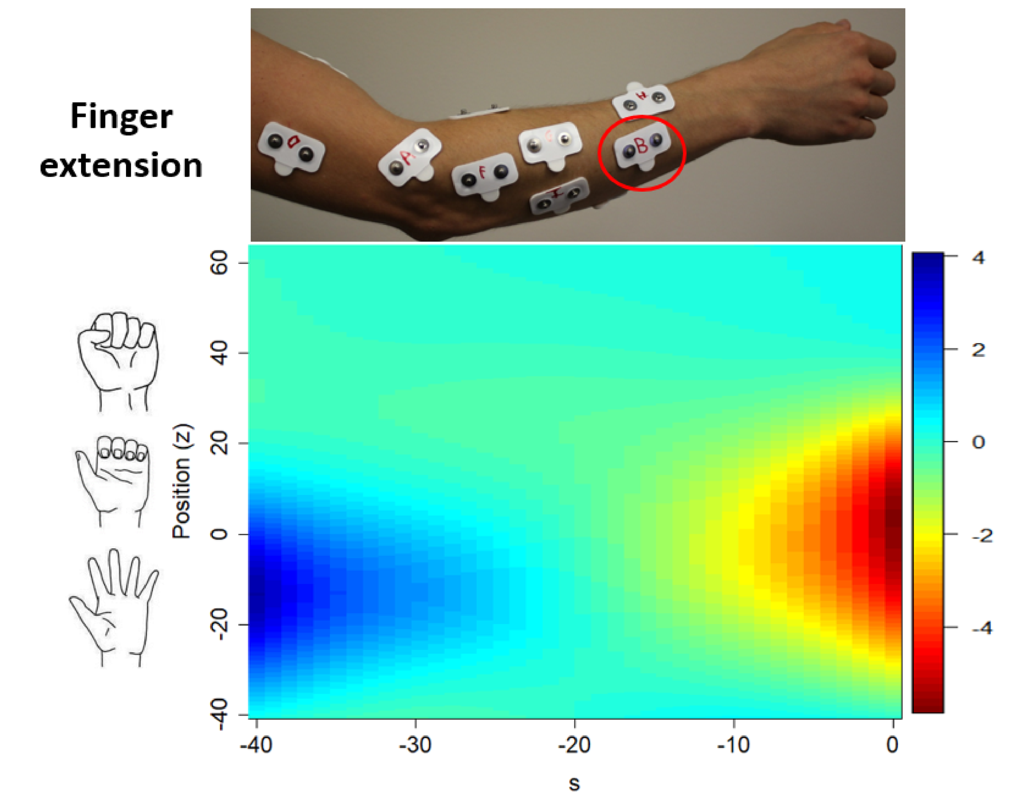
- **Consistently** fits data better yielding **low prediction error**



- Competitor [1] suffers from lack of **position-varying** effect

7. Muscle Mechanism





- **Concurrent** activation of top (bottom) muscle yields flexion (extension) but for some positions
- **Historical** relationship explains **passive forces**
- Similar interpretation follows for muscles associated with wrist flexion & extension

8. Final Remarks

- **Simulation** study shows excellent performance under **various model assumptions**
- Two-stage selection approach applicable to models in [1], [3], & [5]
- Create **parsimonious**, highly **predictive**, & **intuitive** prosthesis controller for amputees
- **Less calibration** and **training** needed unlike **state-of-the-art** prosthesis
- Implement model in **real-time prosthesis**

- Develop and evaluate model for **individual-specific** robotic limb