

Cybernetic Interfaces for the Restoration of Human Movement Through Functional Electrical Stimulation

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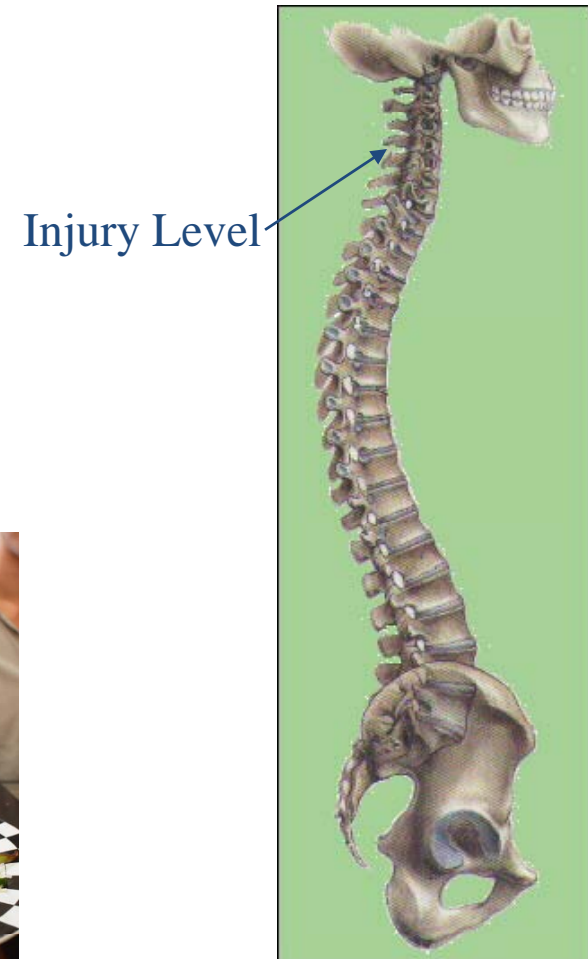


CASE WESTERN RESERVE
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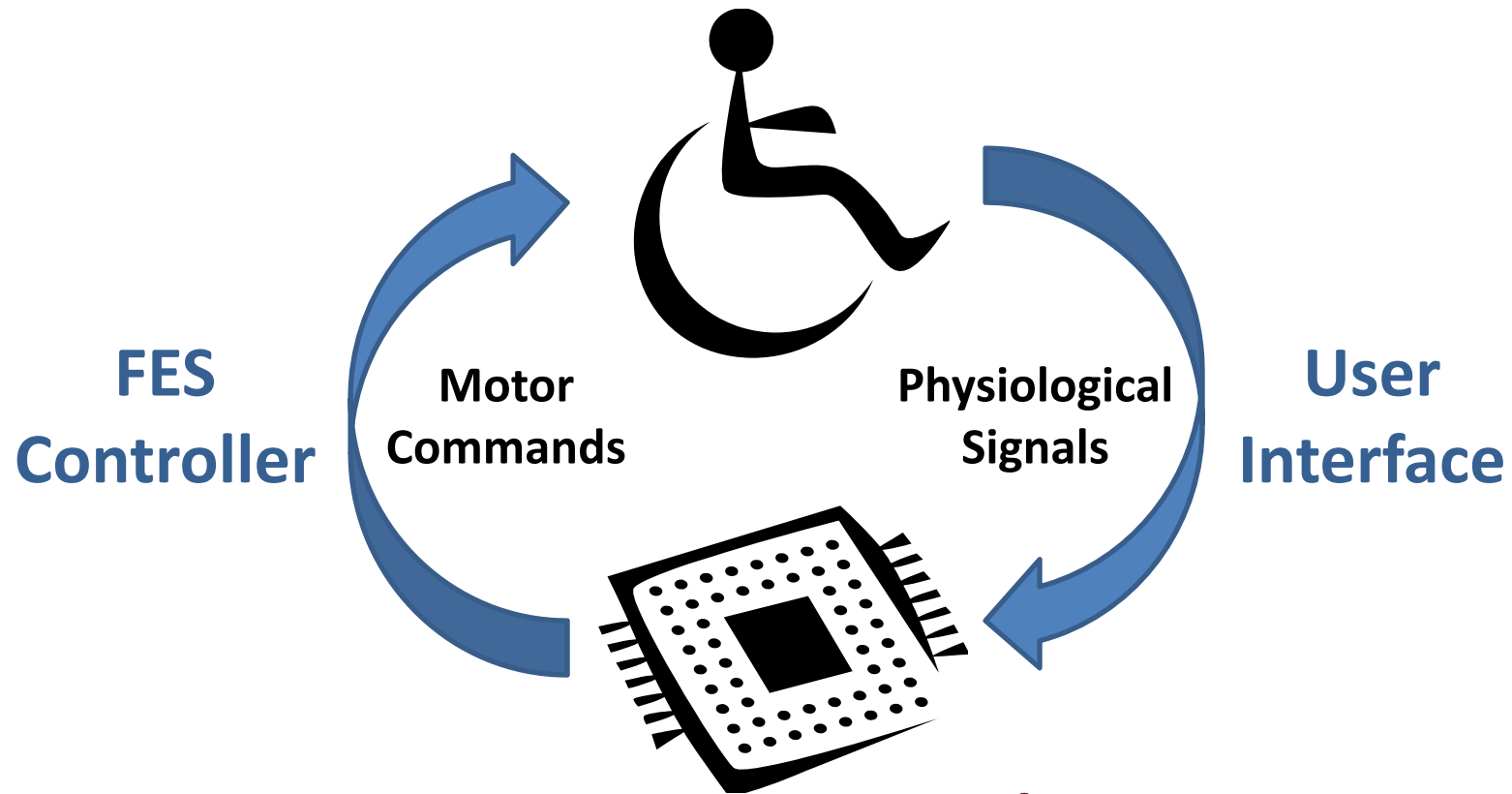


Challenge

Restoration of reaching following high-level spinal cord injury

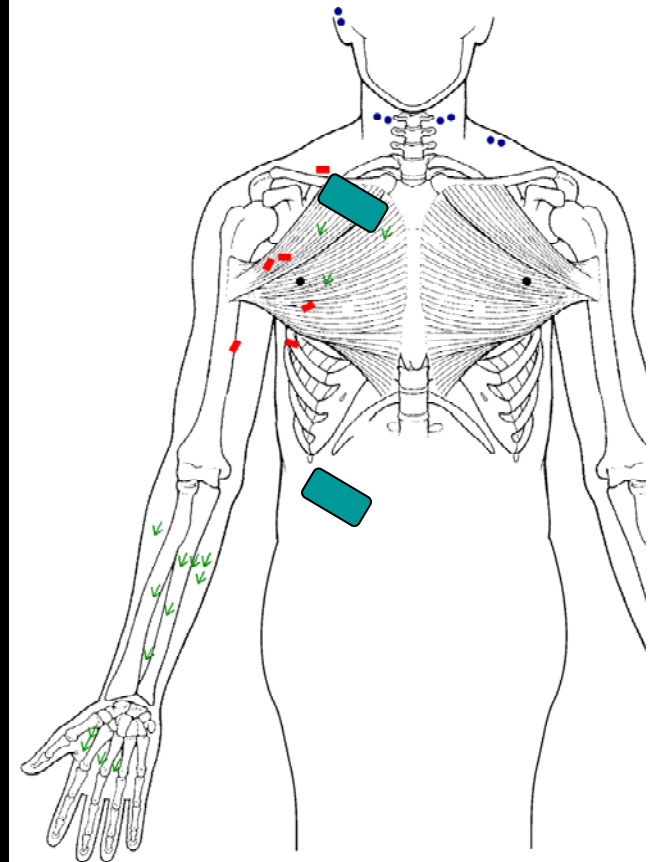
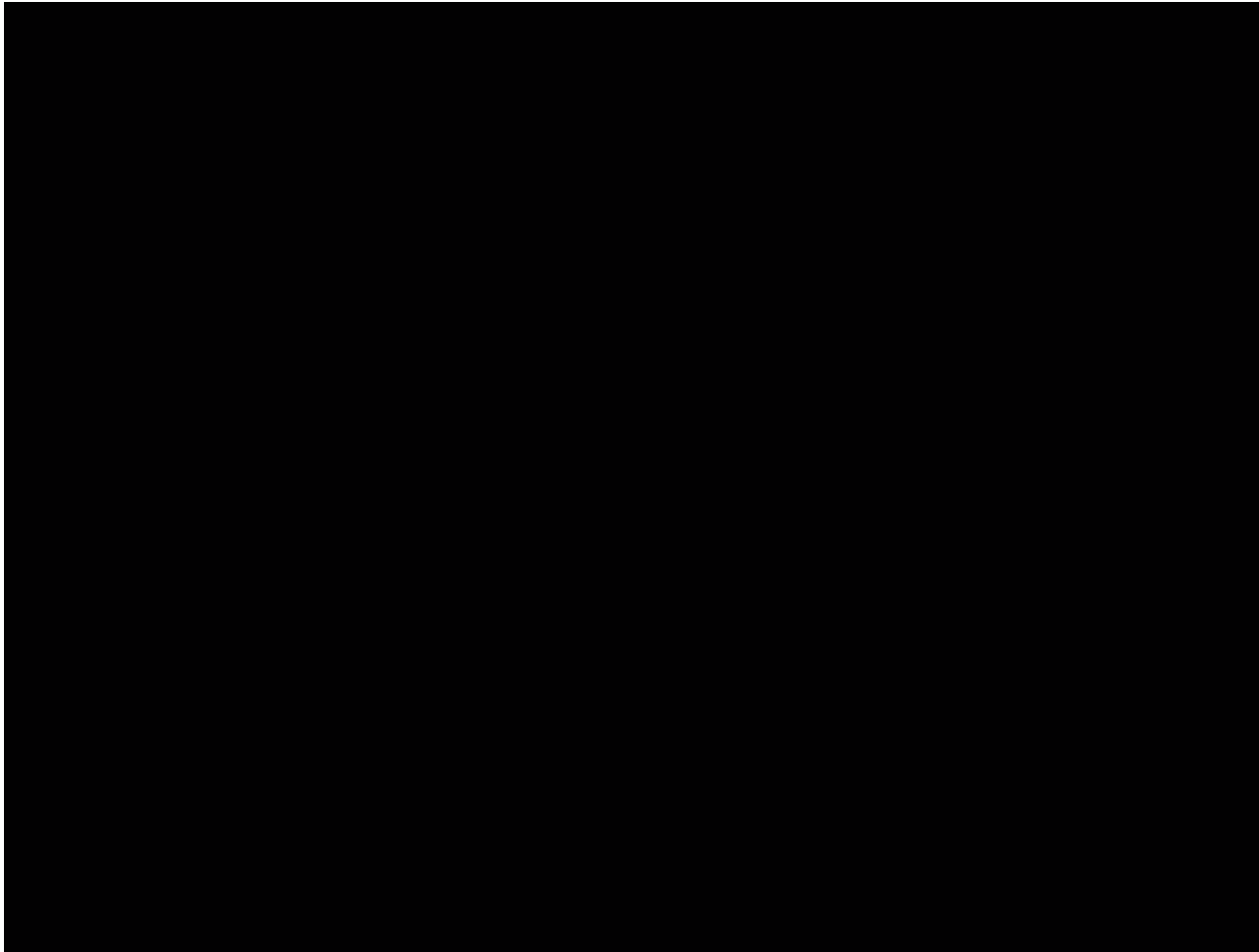


Cyber-Physical Challenges associated with Functional Electrical Stimulation (FES)

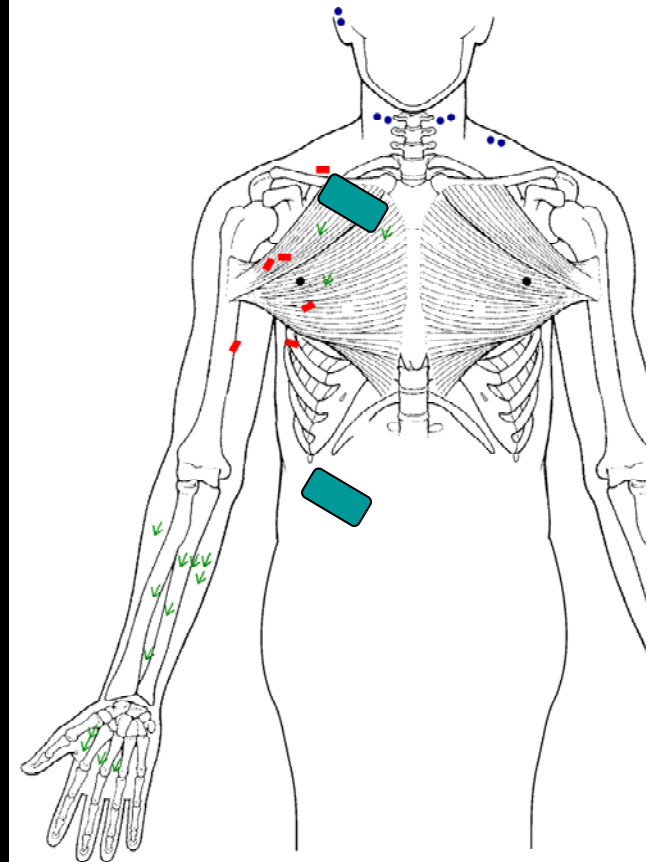
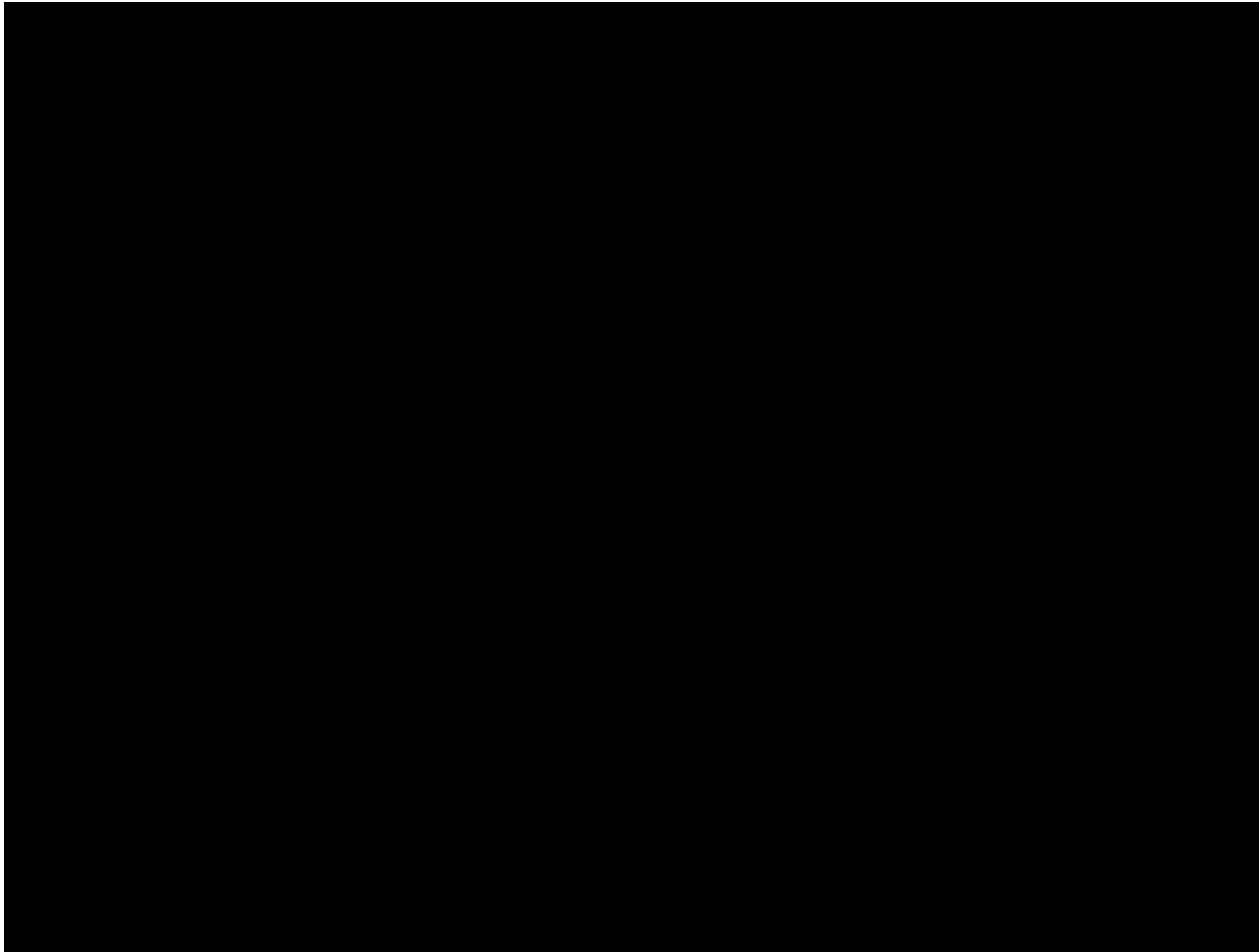


- **Nonlinear & non-stationary**
- **'Natural' and effortless**
- **Fault tolerant**

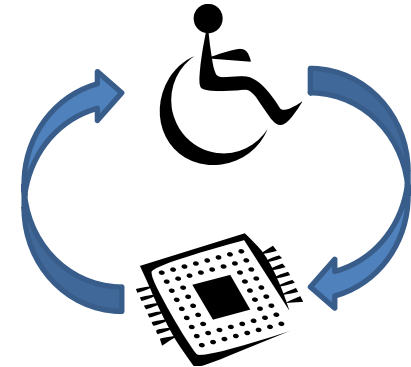
Current State of the art in FES



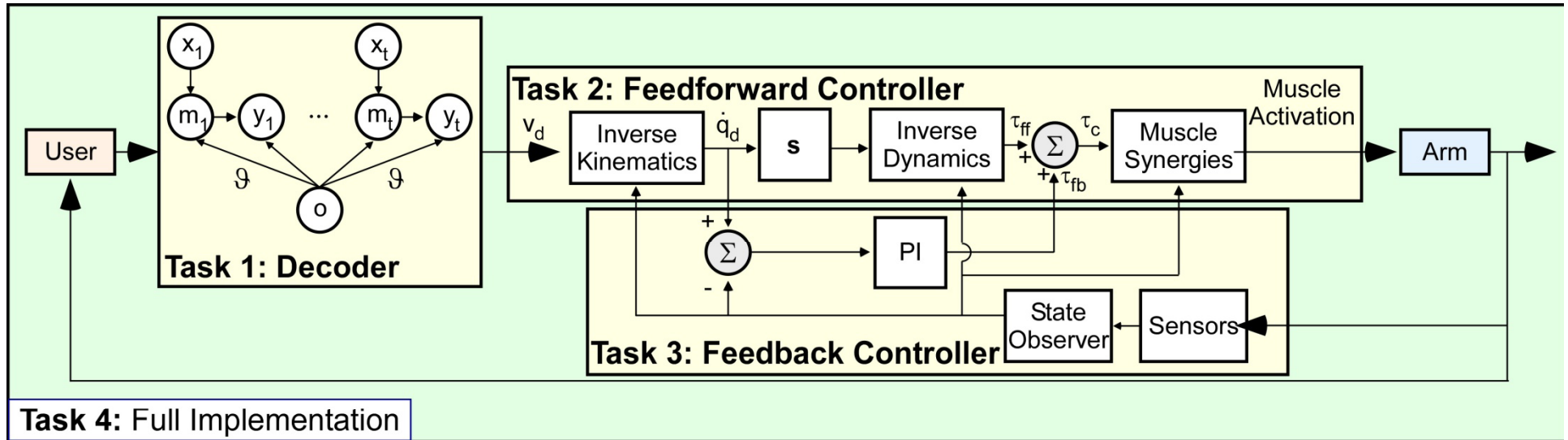
Current State of the art in FES



Research Overview

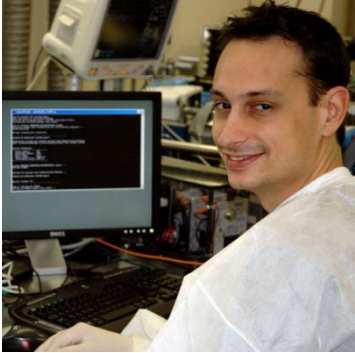


- Noisy measurements from many sensors
- Probabilistic outputs



- High model uncertainties
- Non-stationary
- Noisy sensors
- Robust control

Performance of brain-controlled FES during grasping



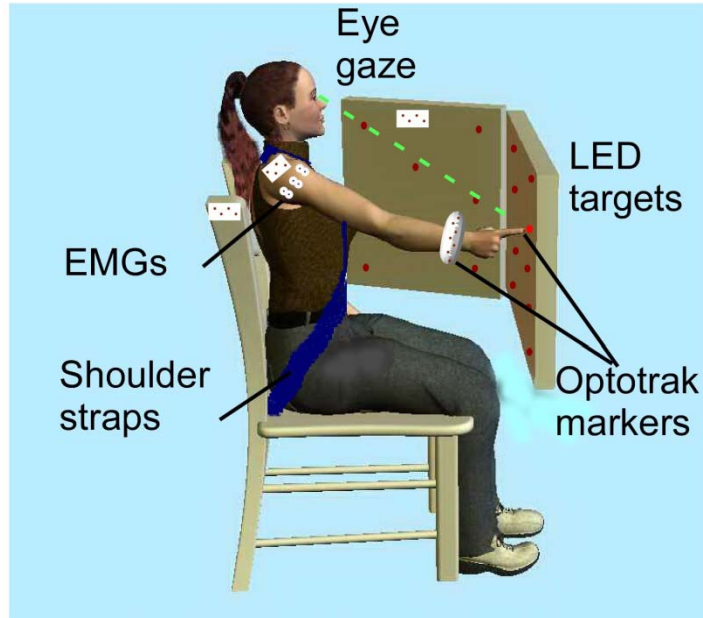
Christian Ethier,
Lee Miller



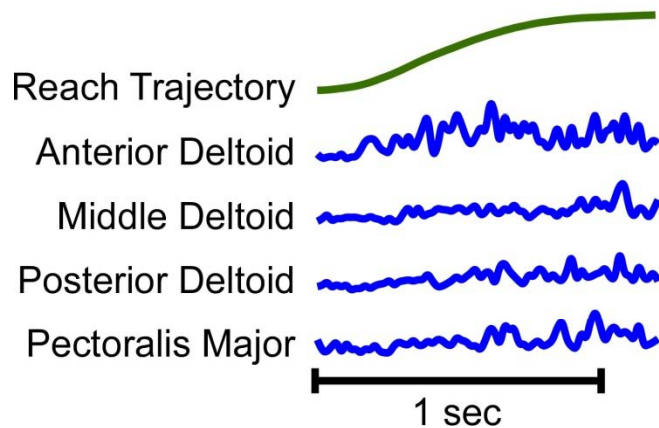
Decoder Design Objectives

- “Natural” control
- Incorporate information from multiple sources
 - Continuous physiological signals
 - Discrete information related to probable targets
- Able to replicate characteristics of natural reaching
 - Arbitrary target locations
 - Arbitrary speeds

Experimental Setup

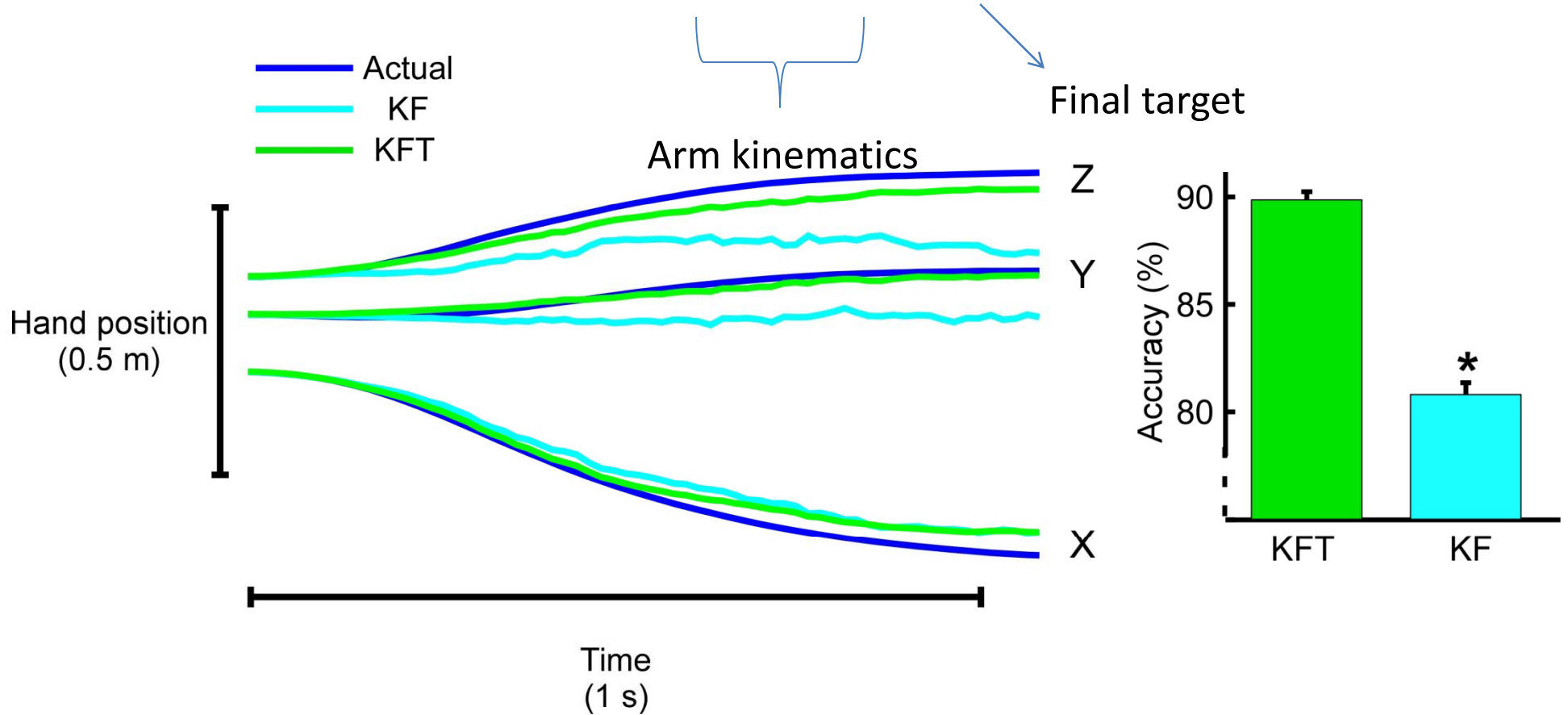


- Protocol
 - Slow, normal and fast reaches
 - 16 targets
 - ~450 trials per subject
- Outputs
 - Endpoint and joint kinematics
- Inputs
 - Electromyograms
 - Gaze direction



Kalman Filter with Target (KFT)

$$\mathbf{X}_t = [x_t, \dot{x}_t, \ddot{x}_t, xT]$$

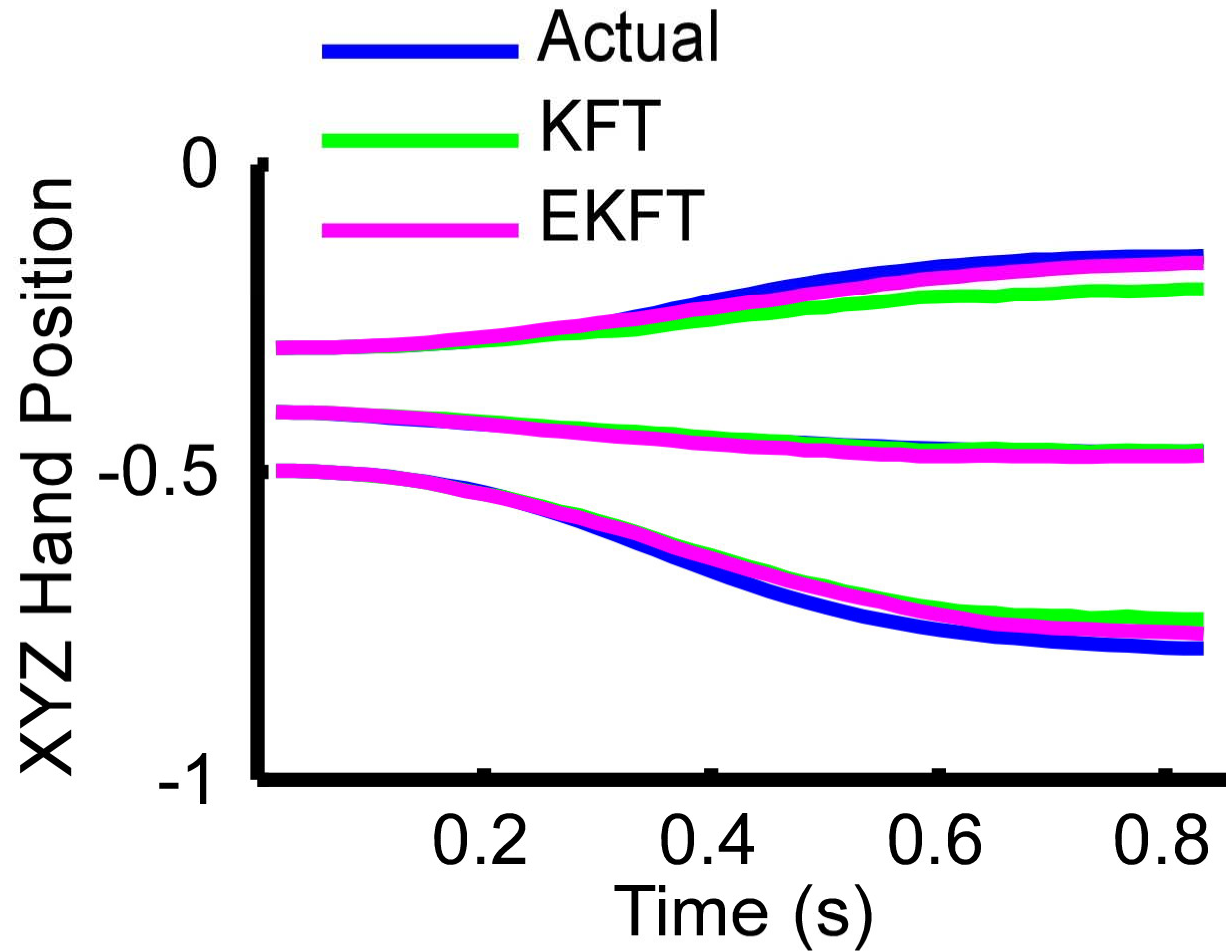


Time-warping

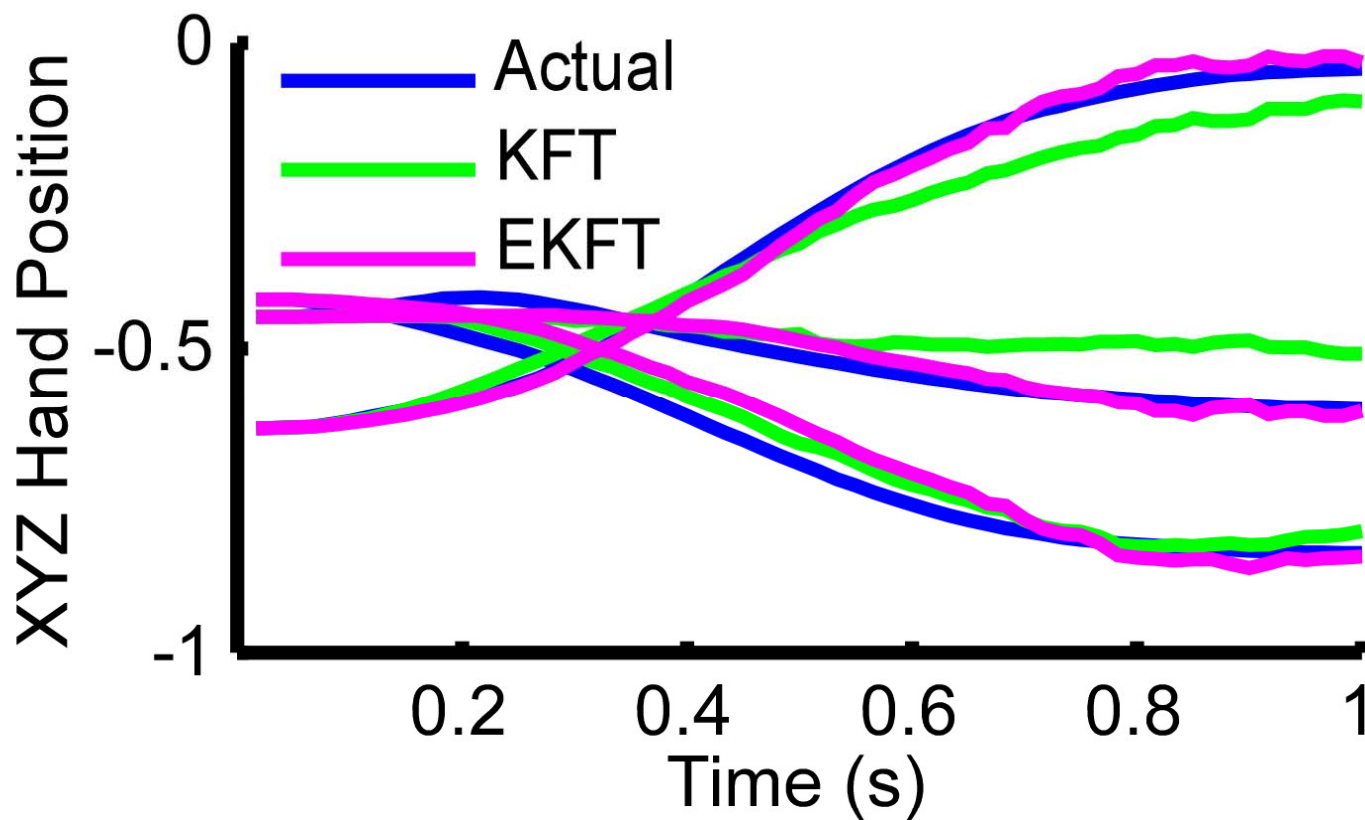
$$\mathbf{x}_t = [\mathbf{x}_t \dot{\mathbf{x}}_t \ddot{\mathbf{x}}_t \mathbf{x}T_t \chi S_t]^T = [\mathbf{x}_t \dot{\mathbf{x}}_t \ddot{\mathbf{x}}_t \mathbf{x}T_t \log(S_t)]^T$$

$$\mathbf{x}_t = \begin{pmatrix} \mathbf{x}_t \\ \dot{\mathbf{x}}_t \\ \ddot{\mathbf{x}}_t \\ \mathbf{x}T_t \\ \chi S_t \end{pmatrix} = \begin{pmatrix} I_p & \Delta t \times I_p & 0_{p \times p} & 0_{p \times p} & 0_{p \times 1} \\ 0_{p \times p} & I_p & \Delta t \times I_p & 0_{p \times p} & 0_{p \times 1} \\ S_{t-1}^2 \alpha_P & S_{t-1} \alpha_V & \alpha_A & S_{t-1}^2 \alpha_T & 0_{p \times 1} \\ 0_{g \times p} & 0_{g \times p} & 0_{g \times p} & I_g & 0_{g \times 1} \\ 0_{1 \times p} & 0_{1 \times p} & 0_{1 \times p} & 0_{1 \times p} & 1 \end{pmatrix} \begin{pmatrix} \mathbf{x}_{t-1} \\ \dot{\mathbf{x}}_{t-1} \\ \ddot{\mathbf{x}}_{t-1} \\ \mathbf{x}T_{t-1} \\ \chi S_{t-1} \end{pmatrix} + \mathbf{w}_t$$

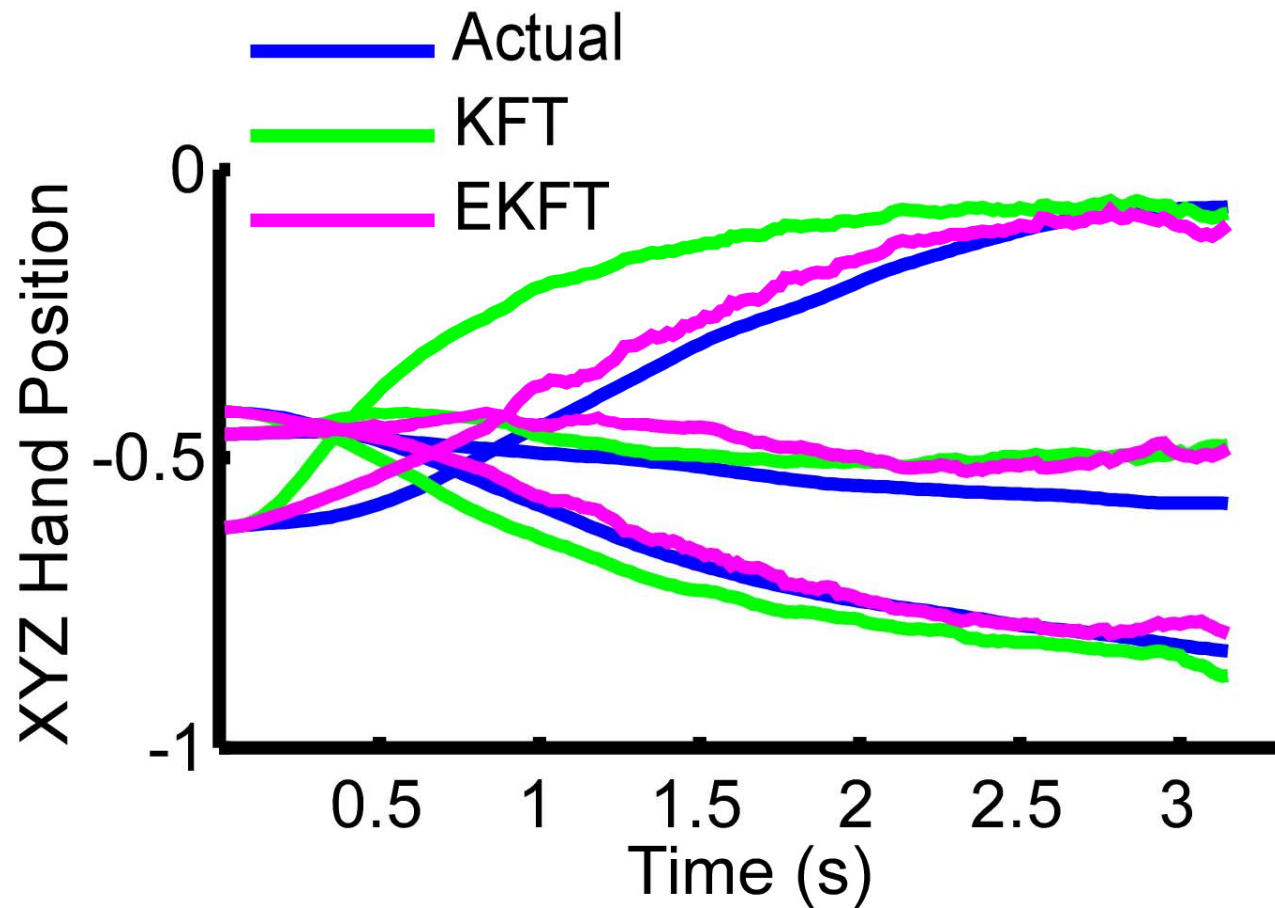
Sample predictions – normal reach



Sample predictions – fast reach



Sample predictions – slow reach



Probabilistic mixtures



1



2



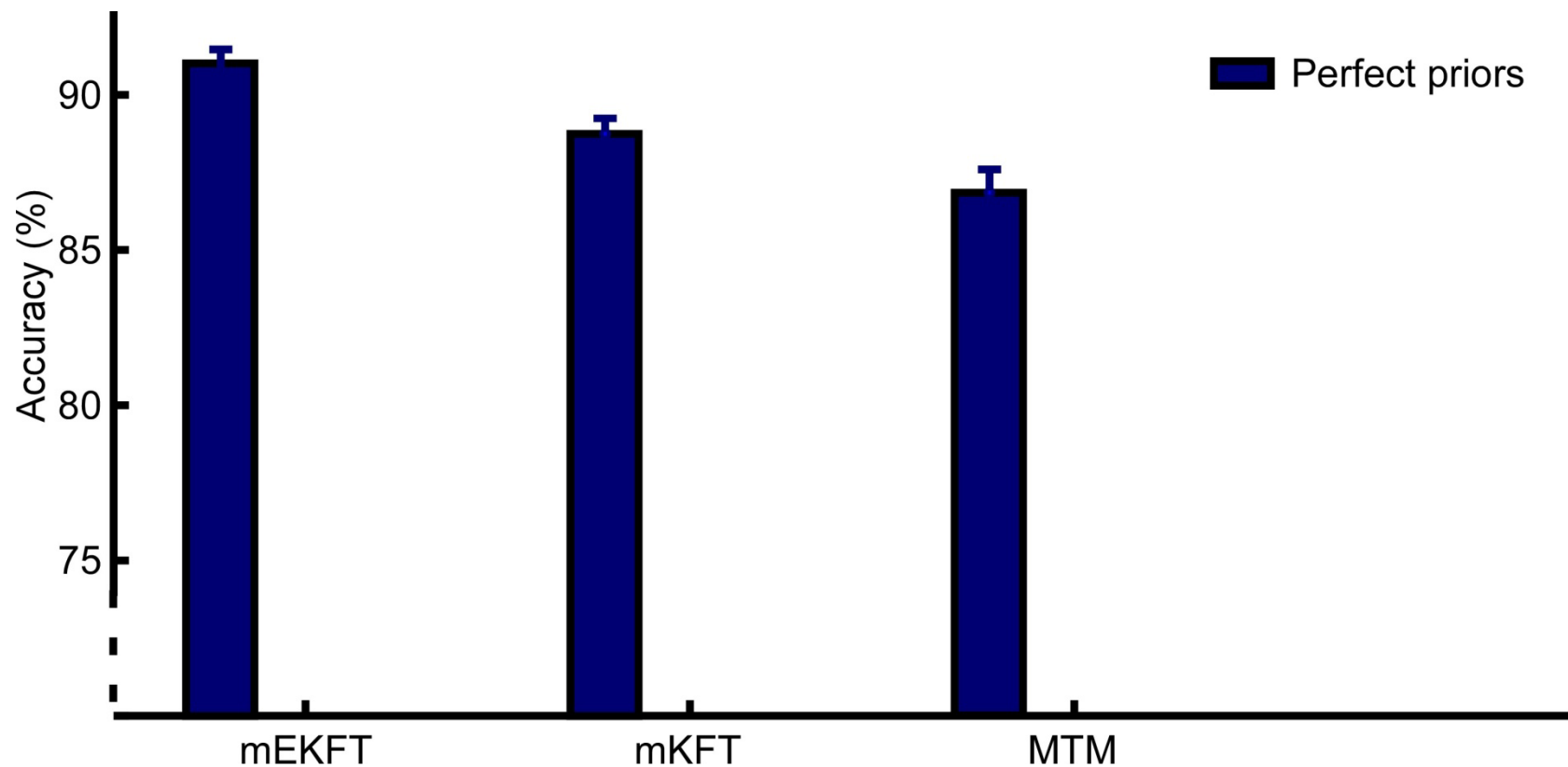
3

Yarbus, A. L. (1967)

Mixtures of targets and generalization

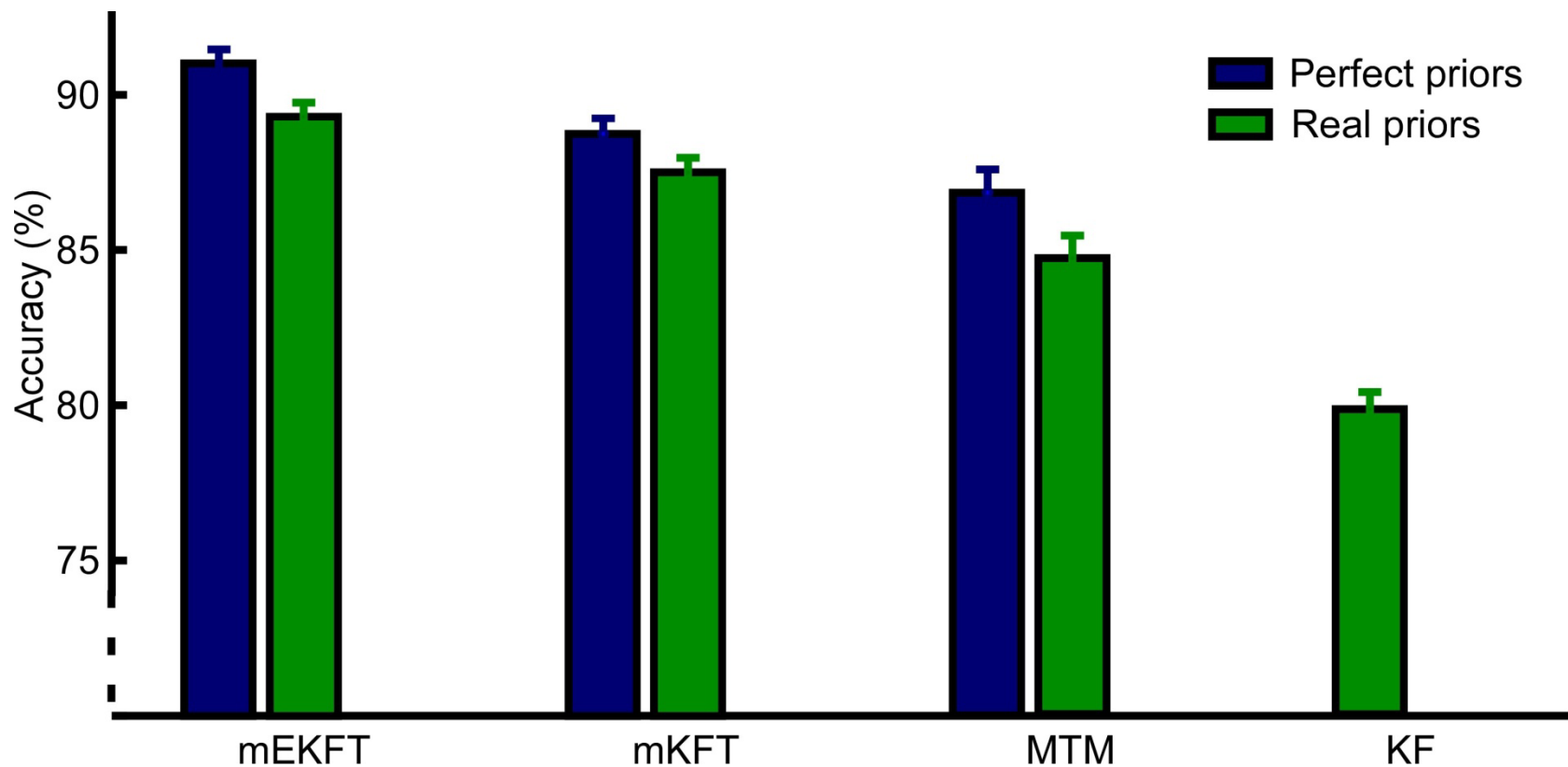
$$P(\mathbf{x}_t | \mathbf{y}_{1..t}) = \sum_{T=T_1}^{TN} P(\mathbf{x}_t | \mathbf{y}_{1..t}, \mathbf{x}_{T_t}) P(\mathbf{x}_{T_t} | \mathbf{y}_{1..t})$$

Yu, 2007



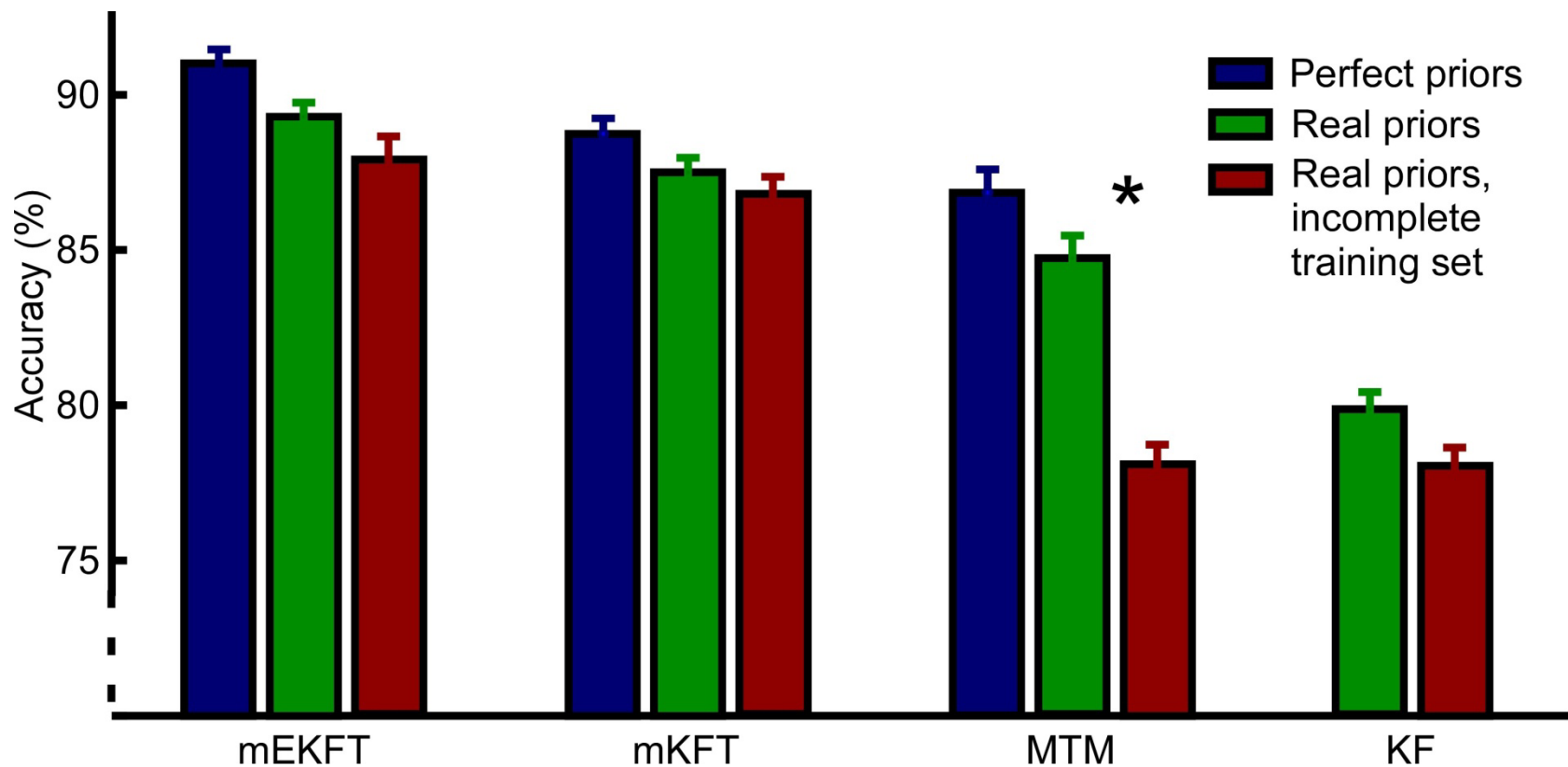
Mixtures of targets and generalization

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Mixtures of targets and generalization

$$P(\mathbf{x}_t | \mathbf{y}_{1...t}) = \sum_{T=T_1}^{TN} P(\mathbf{x}_t | \mathbf{y}_{1...t}, \mathbf{x}_{T_t}) P(\mathbf{x}_{T_t} | \mathbf{y}_{1...t})$$



Summary

- CPS Challenges
 - Human in the loop
 - Data fusion
 - Robust control
- Development of a continuous user interface
 - Multiple continuous and discrete noisy sources
 - Arbitrary target locations
 - Arbitrary reach velocities
- Coming soon
 - Evaluation with direct intracortical recordings
 - Controller development

Broader Impacts



- Laboratory outreach program
- Middle school CPS curriculum



Rehabilitation Institute of Chicago

Time-warping improved accuracy

