# Deep Multi-State Dynamic Recurrent Neural Networks Operating on Wavelet Based Neural Features for Robust Brain Machine Interfaces

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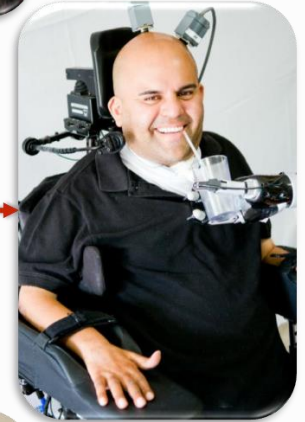**NeurIPS poster session: Dec. 8 – Dec 14**

2019

Symposia on VLSI Technology and Circuits
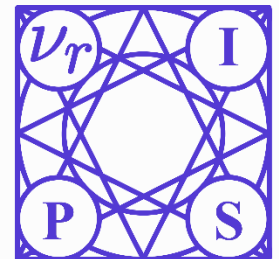
Applications of BMI

Controlling a prosthesis

Spelling

Controlling a Mechatronic Device
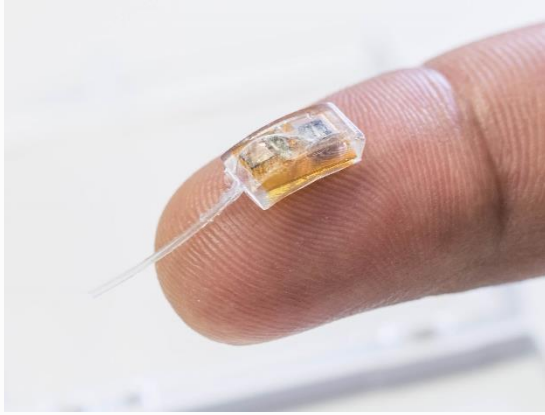
Brain Signal

Tiny Chip
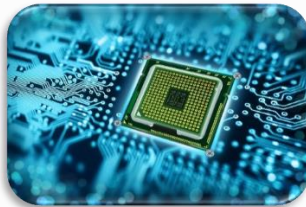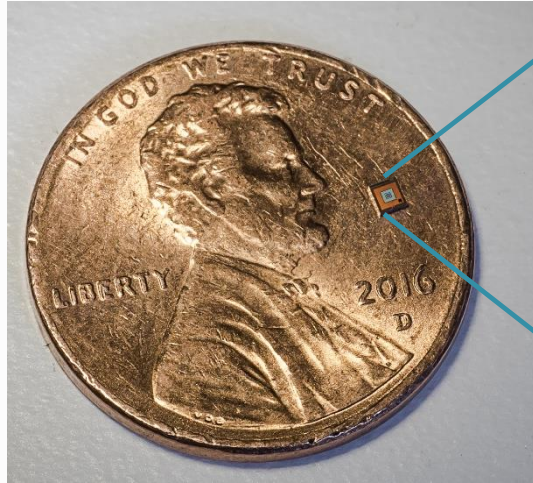
Virtual Reality

Gaming

A Sci-Fi Becomes Reality
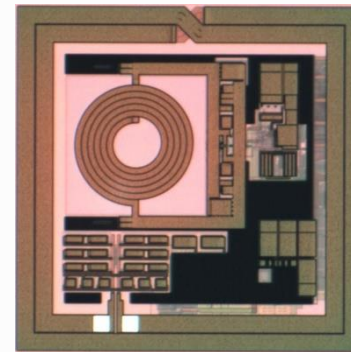
Implantable Wireless Medical Devices

Intra-Ocular Pressure Sensor

Injectable Glucose Sensor
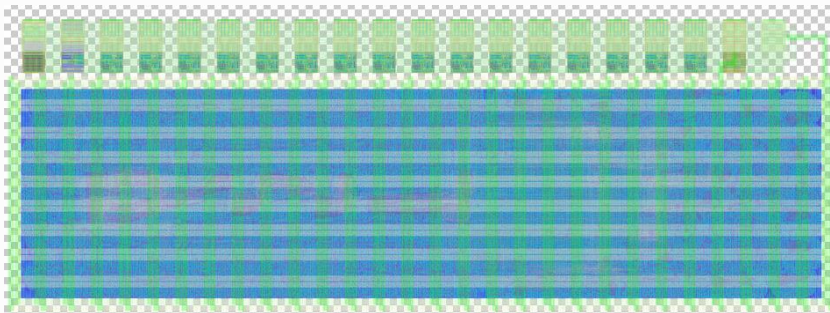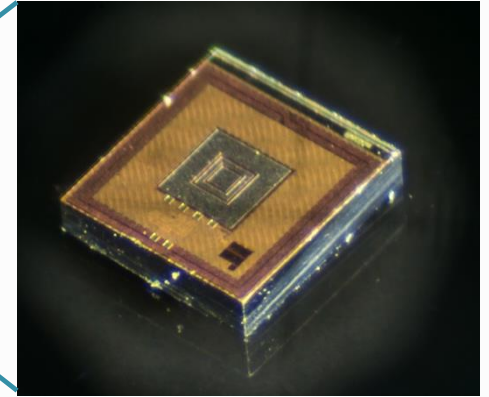
External Reader

1mm x 0.5mm classifier CMOS chip for seizure prediction

ATOMS, Smart Pill

33rd Conference on Neural Information Processing Systems (NeurIPS 2019), Vancouver, Canada
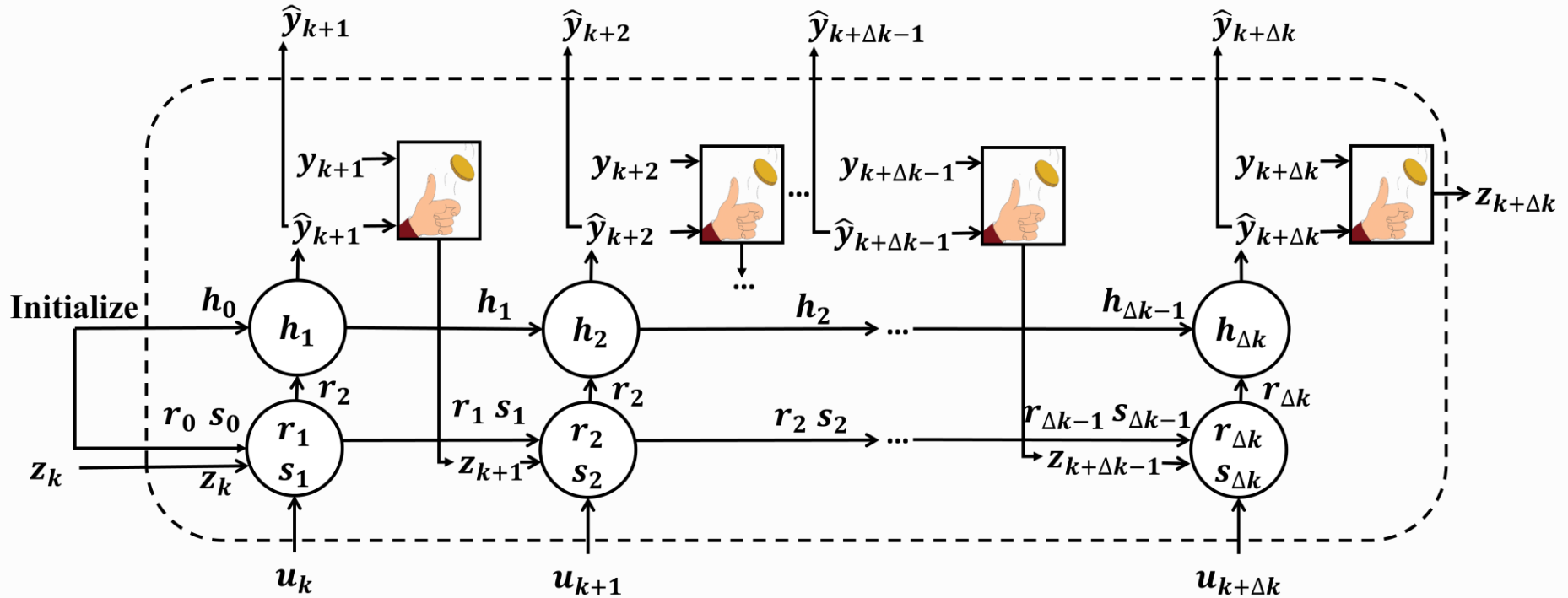
Goals

- Minimize Treatment Cost

- Low Power/Area Chip

- Robustness

- High Performance

Challenges

- Achieving High Speed Design

- Non-Stationarity of Neural Data

- Noise

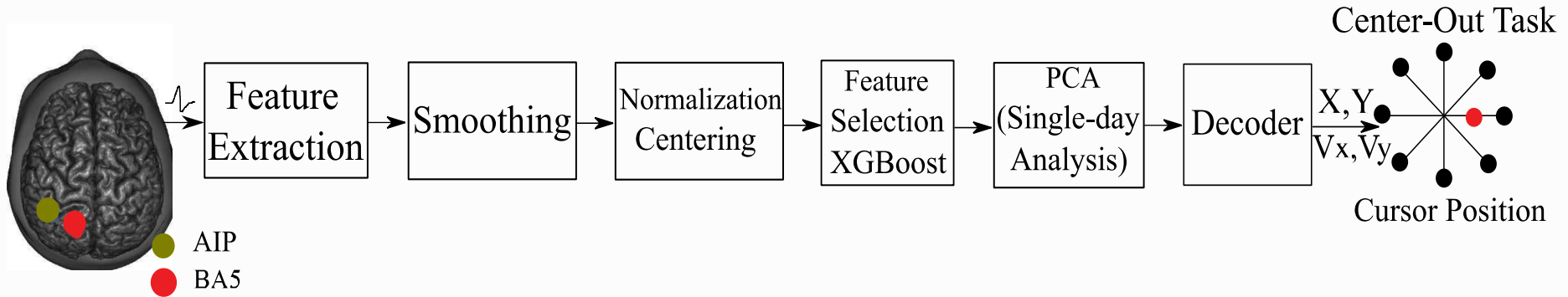- Limited Data

Deep Multi-state DRNN Architecture

$$\begin{cases} s_k = W_{ss}s_{k-1} + W_{sr}r_{k-1} + W_{si}u_k + W_{sf}z_k + b_s \\ r_k = \tanh(s_k) \\ h_k^{(1)} = \tanh\left(W_{h^{(1)}h^{(1)}}h_{k-1}^{(1)} + W_{h^{(1)}r}r_k + b_{h^{(1)}}\right) \\ h_k^{(i)} = \tanh\left(W_{h^{(i)}h^{(i)}}h_{k-1}^{(i)} + W_{h^{(i)}h^{(i-1)}}h_k^{(i-1)} + b_{h^{(i)}}\right) \\ \hat{y}_k = W_{yh^{(l)}}h_k^{(l)} + b_y \\ \hat{y}_k = tanh(\hat{y}_k) \quad |\hat{y}_k| > 1 \\ z_k \leftarrow \hat{y}_k \text{ or } y_k \text{ (Scheduled Sampling)} \end{cases}$$

Architecture of BMI System

- **32 year-old tetraplegic (C5-C6) human**
- **FDA- and IRB-approved**

- **Sampling Rate: 30 KHz**
- **Utah electrode arrays**

192 Channels

Feature Extraction → Smoothing → Normalization Centering → Feature Selection XGBoost → PCA (Single-day Analysis) → Decoder → X,Y Vx,Vy

Center-Out Task

Cursor Position

AIP
BA5

AIP: Anterior Intraparietal
BA5: Broadman's Area 5

Features	Frequency Range
HWT, HFT, HPF	**> 3.75KHz**
TCs, LFADS	**250Hz − 5KHz**
MWT, MFT, MUA	**234Hz − 3.75KHz**
LWT, LFT, LPF	**< 234HZ**

Single-day Analysis with Mid-Wavelet Feature

(a) DRNN (b) LSTM (c) RNN (d) NN

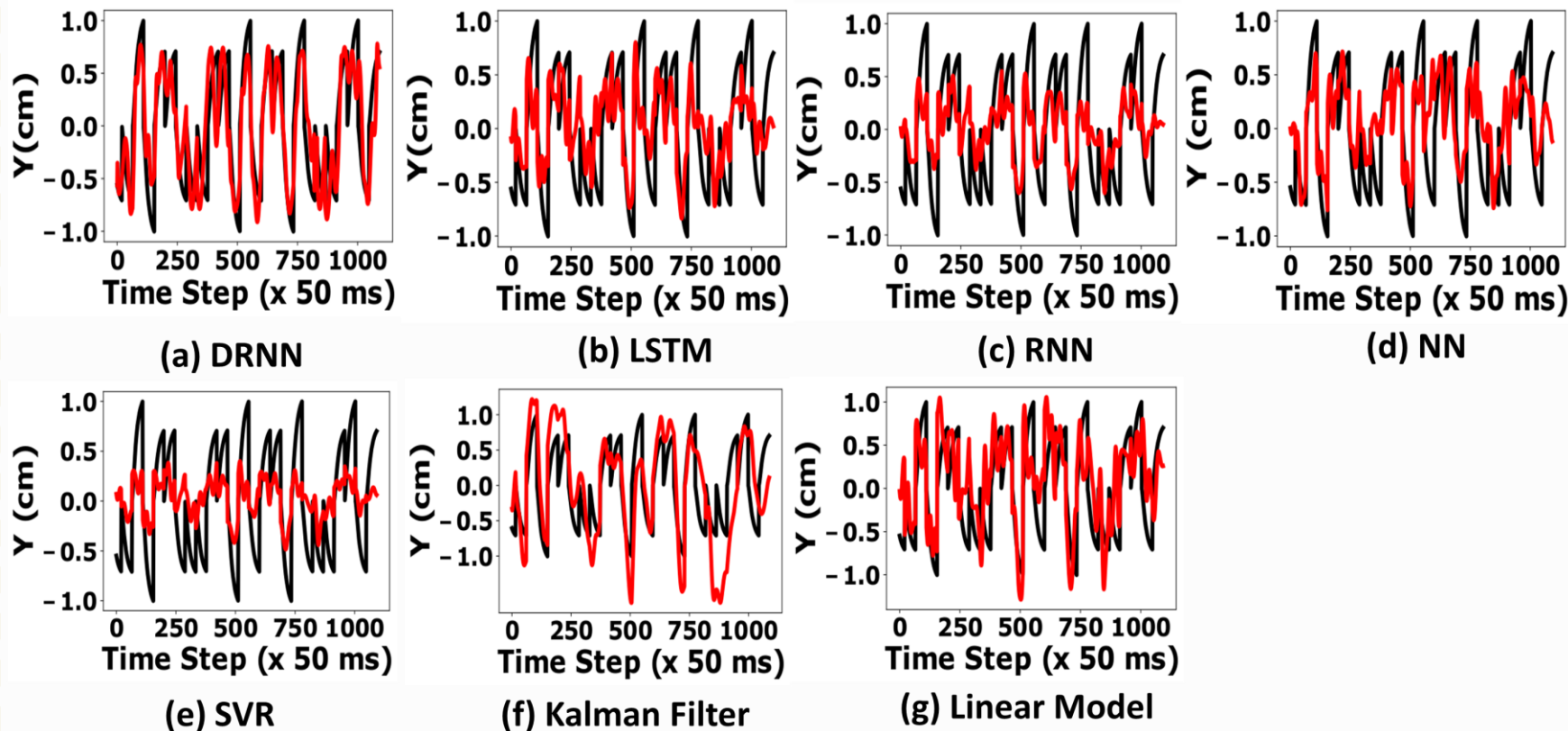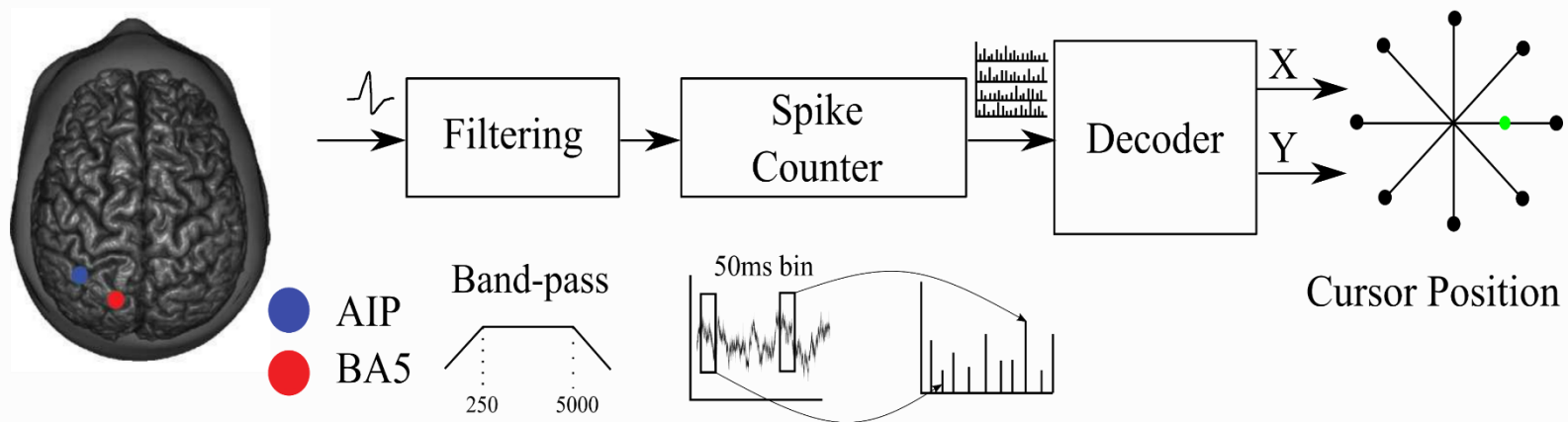(e) SVR (f) Kalman Filter (g) Linear Model

Fig.1. Regression of different algorithms on test data from the same day 2018-04-23: true target motion (black) and reconstruction (red)

System architecture

- Decoding kinematics from Anterior intraparietal sulcus (**AIP**) and Brodmann's Area 5 (BA5)
- Open loop phase of Center-Out reaching task
- 53 trials each 3 minutes long
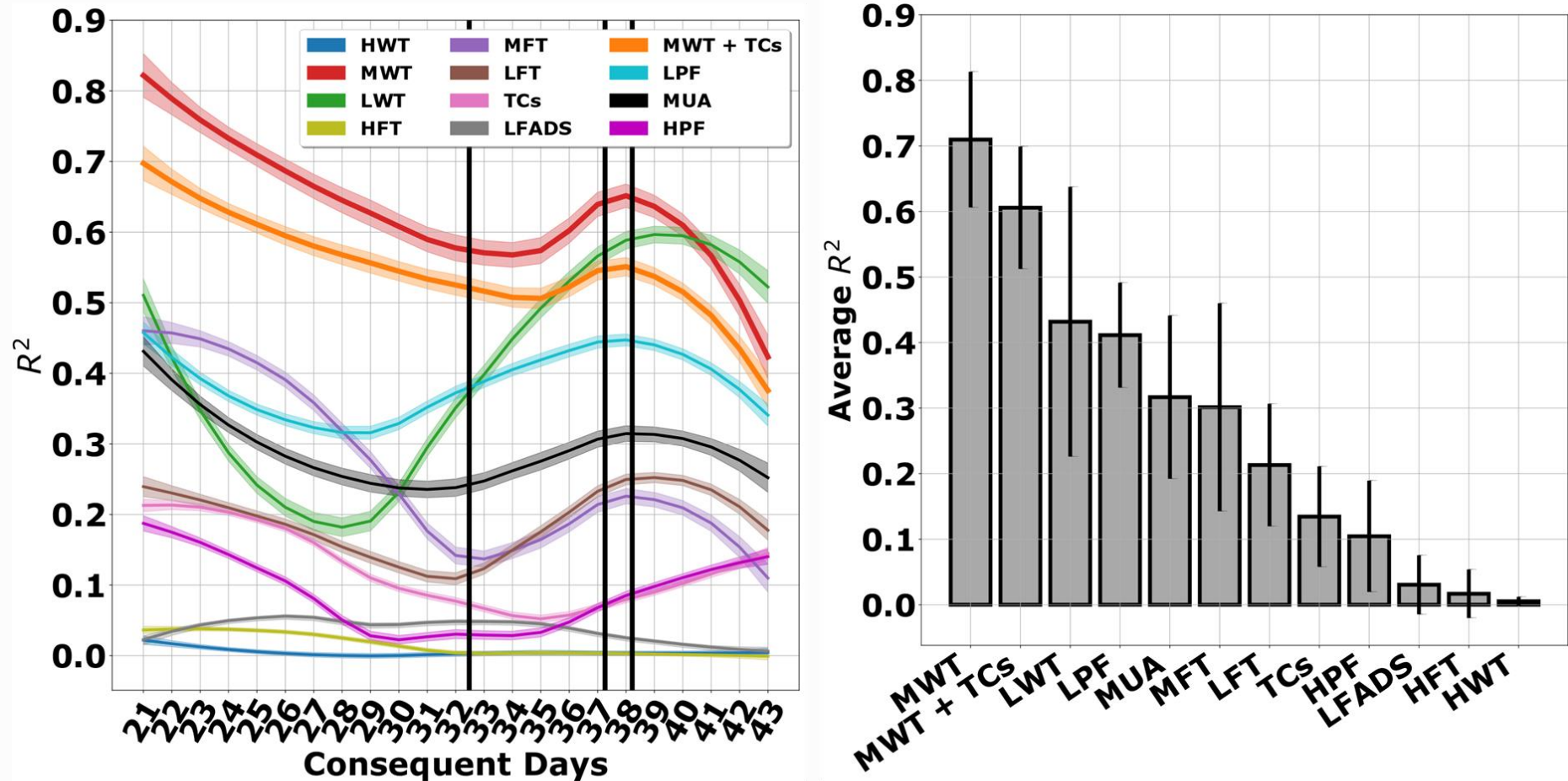- Five such sessions

Multi-Day Performance of the Decoders

Fig.2. The DRNN operating on different features.

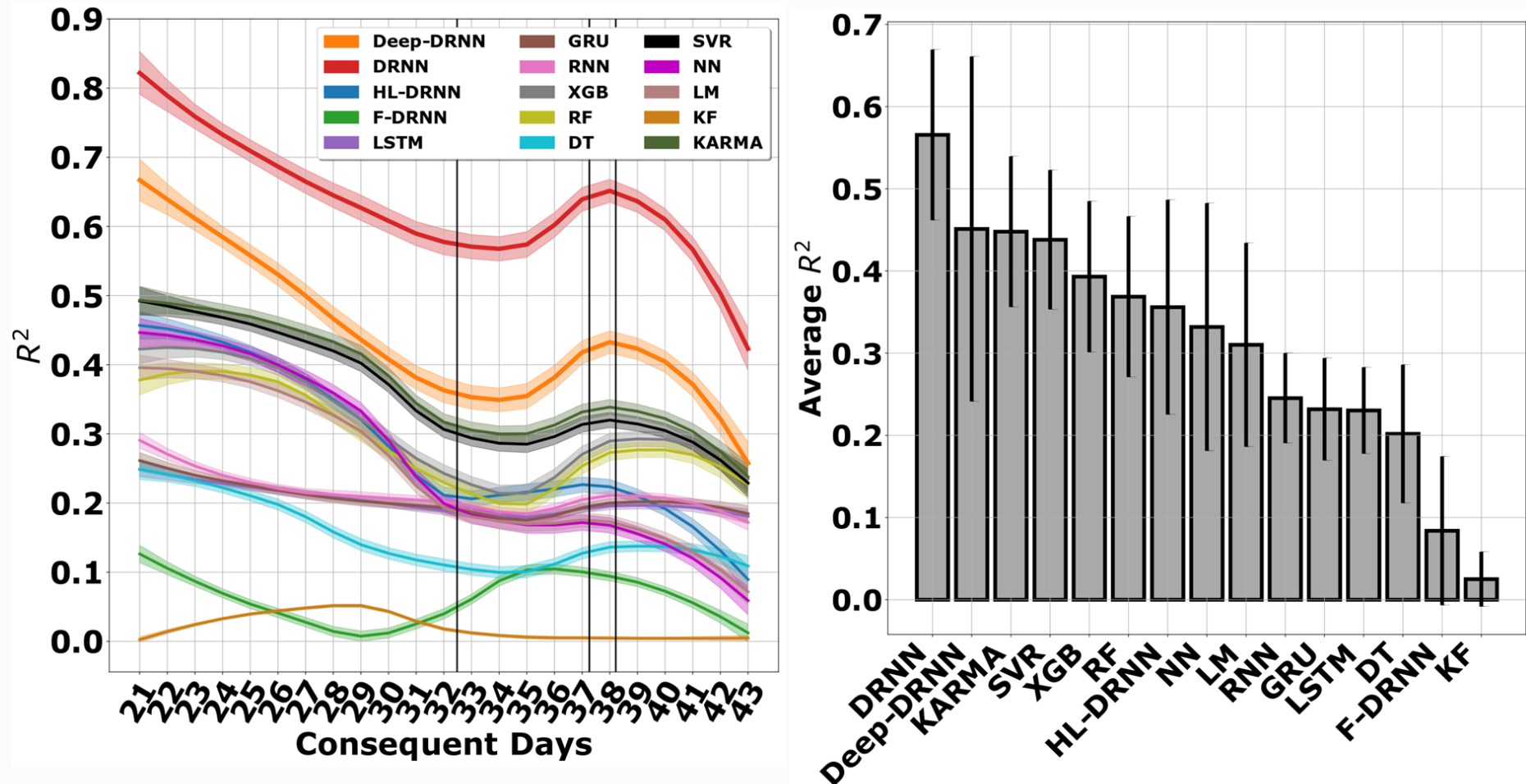# Multi-Day Performance of the Decoders

Fig.3. Multi-day performance of the decoders.
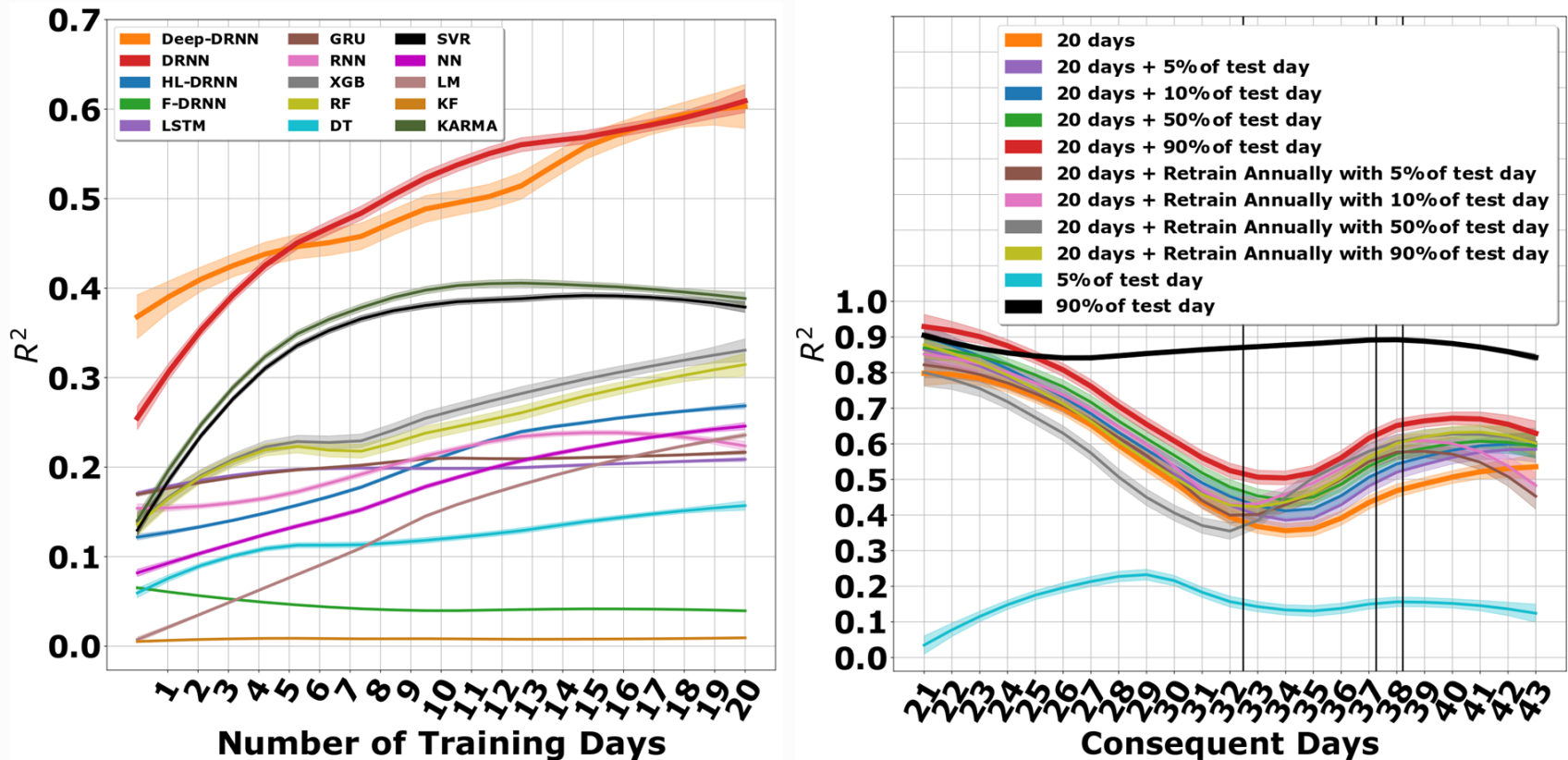
Multi-Day Performance of the Decoders

Fig.4. (Left) Effect of number of training days on the performance of the decoders. (Right) The DRNN operating in different training scenarios.

Summary

- Neural networks for BMI: promising

- Hardware requirements of NN: challenges toward implantable devices

- Algorithms that can translate to energy-efficient hardware

- Need to deal with significant variations and non-stationary conditions
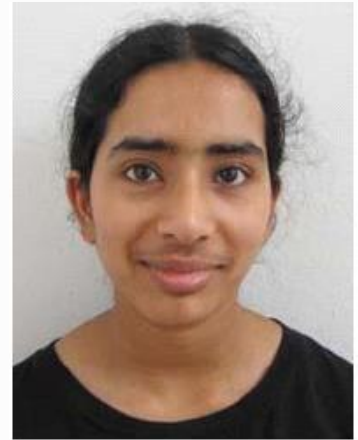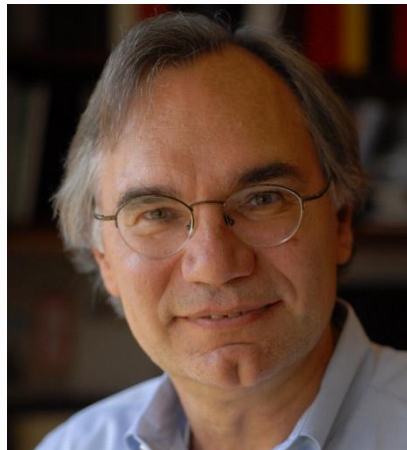
Team Members
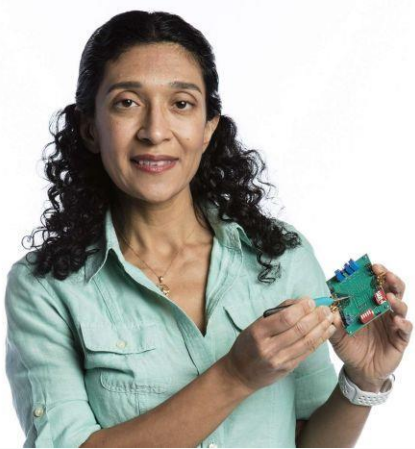
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Luke Bashford

Thank you!

- **Paper:**

  https://www.biorxiv.org/content/biorxiv/early/2019/08/30/710327.full.pdf

- **Codes, Poster, and Slides:**

  https://github.com/BenyaminHaghi/DRNN-NeurIPS2019