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

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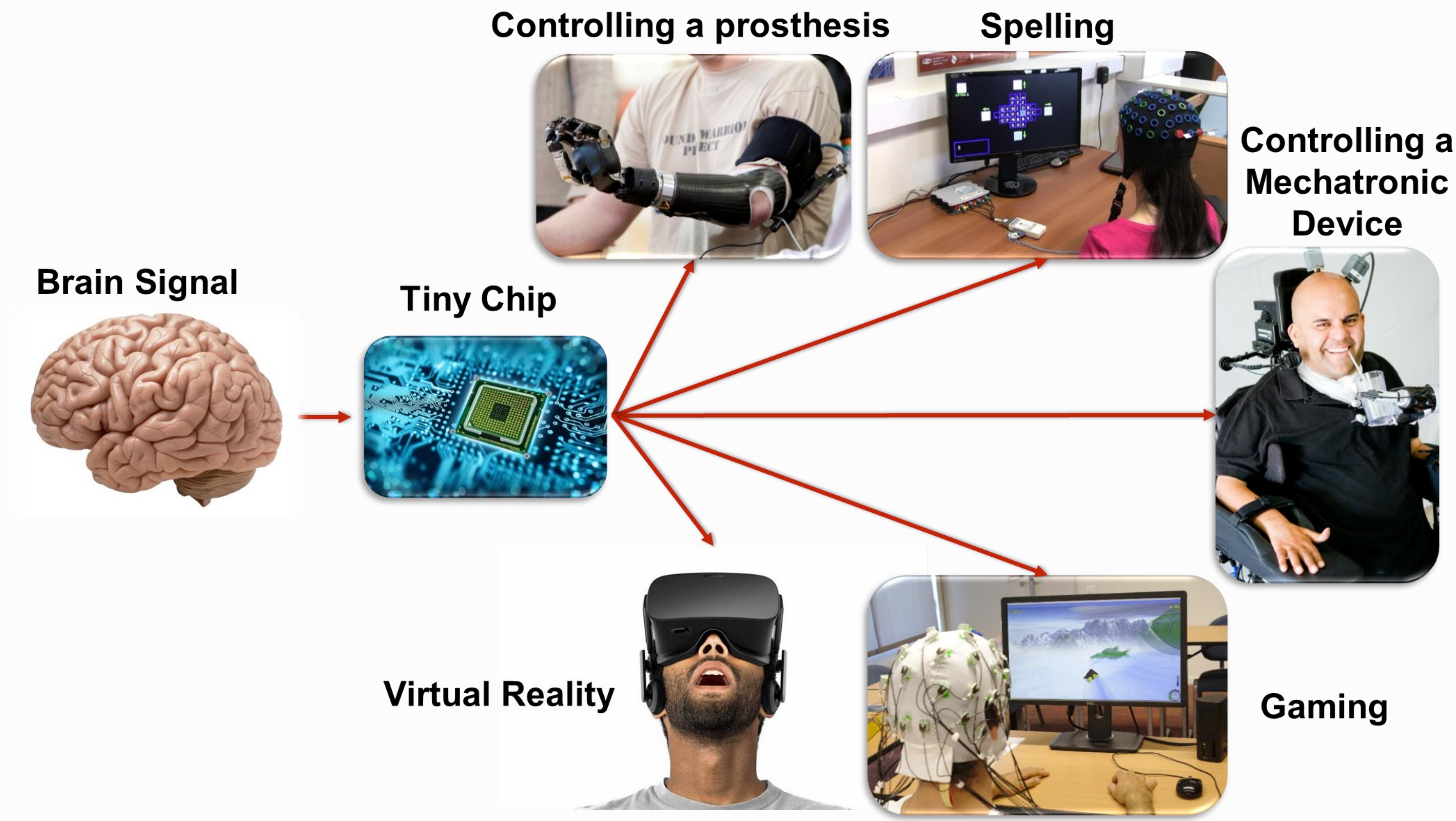
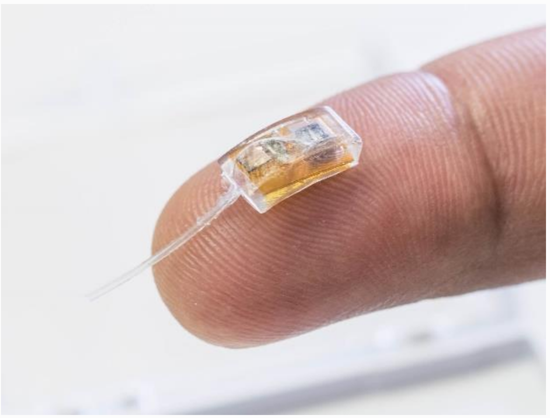
Applications of BMI

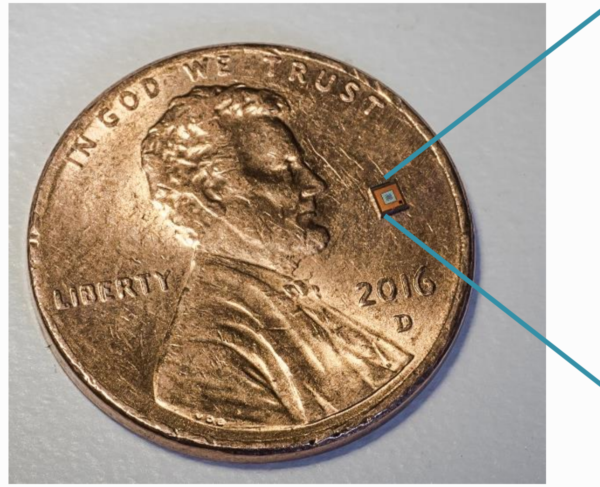


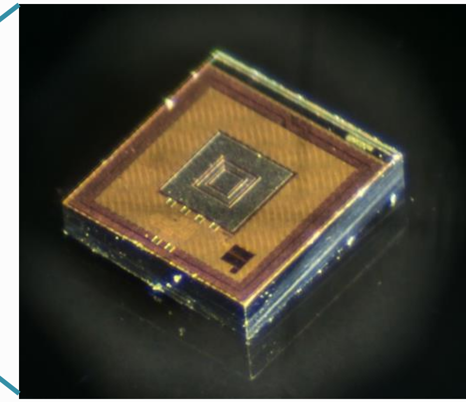
A Sci-Fi Becomes Reality

Implantable Wireless Medical Devices



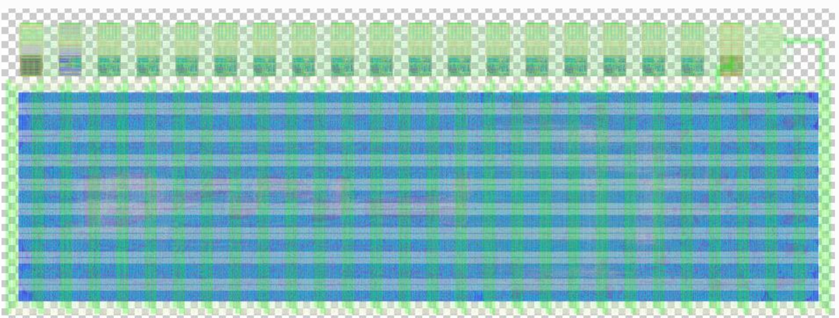
Intra-Ocular Pressure Sensor



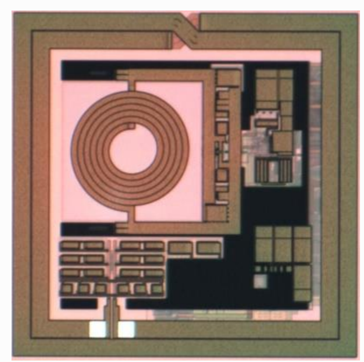


Injectable Glucose Sensor

External Reader



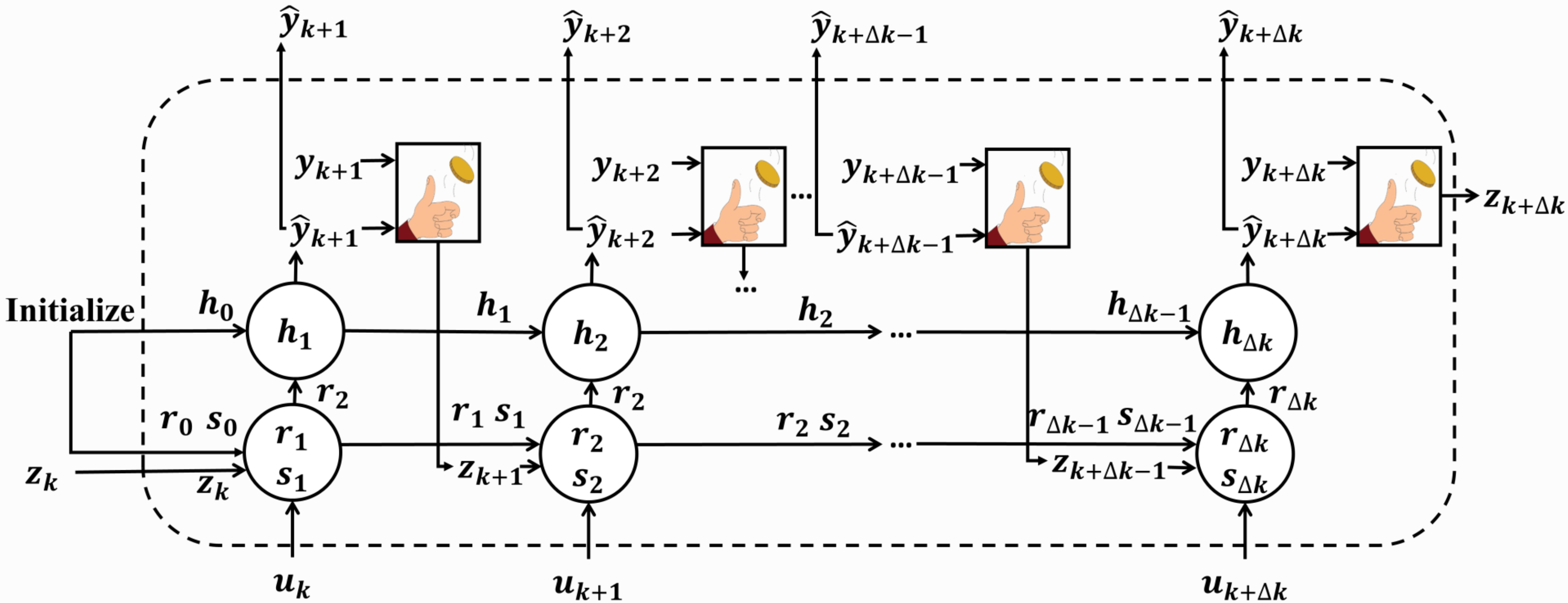
1mm x 0.5mm classifier CMOS chip for seizure prediction



ATOMS, Smart Pill

Goals	Challenges
• Minimize Treatment Cost	• Achieving High Speed Design
• Low Power/Area Chip	• Non-Stationarity of Neural Data
• Robustness	• Noise
• High Performance	• Limited Data

Deep Multi-state DRNN Architecture

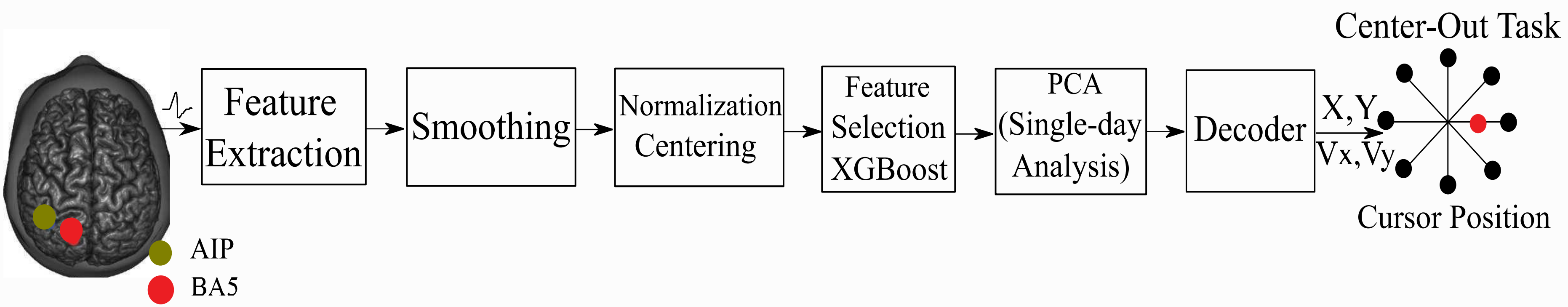


$$
\begin{cases}
s_k = W_{ss} s_{k-1} + W_{sr} r_{k-1} + W_{si} u_k + W_{sf} z_k + b_s \\
r_k = \tanh(s_k) \\
h_k^{(1)} = \tanh\left(W_{h^{(1)}h^{(1)}} h_{k-1}^{(1)} + W_{h^{(1)}r} r_k + b_{h^{(1)}}\right) \\
h_k^{(i)} = \tanh\left(W_{h^{(i)}h^{(i)}} h_{k-1}^{(i)} + W_{h^{(i)}h^{(i-1)}} h_k^{(i-1)} +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

Architecture of BMI System

- 32 year-old tetraplegic (C5-C6) human
- FDA- and IRB-approved
- Sampling Rate: 30 KHz
- Utah electrode arrays

192 Channels



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

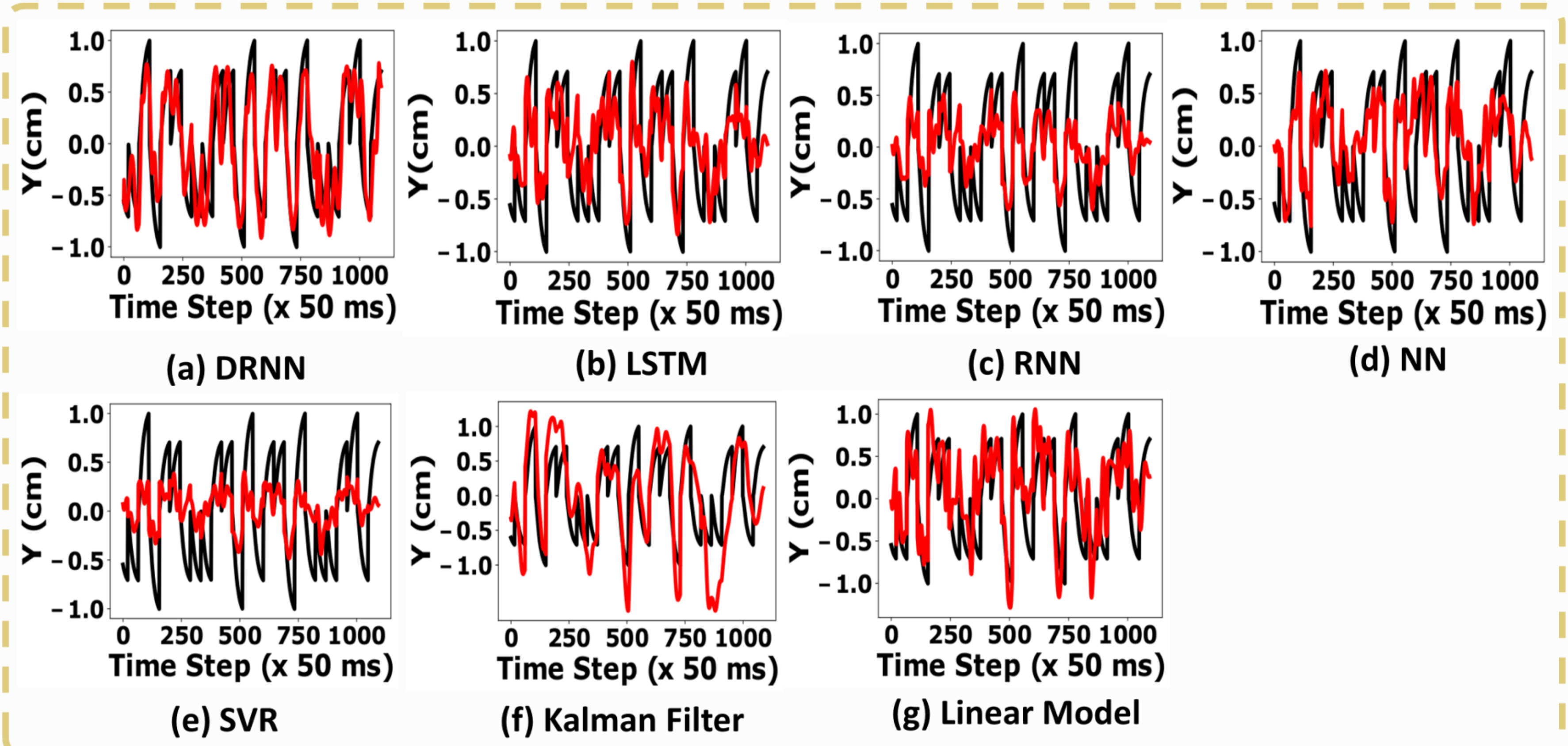
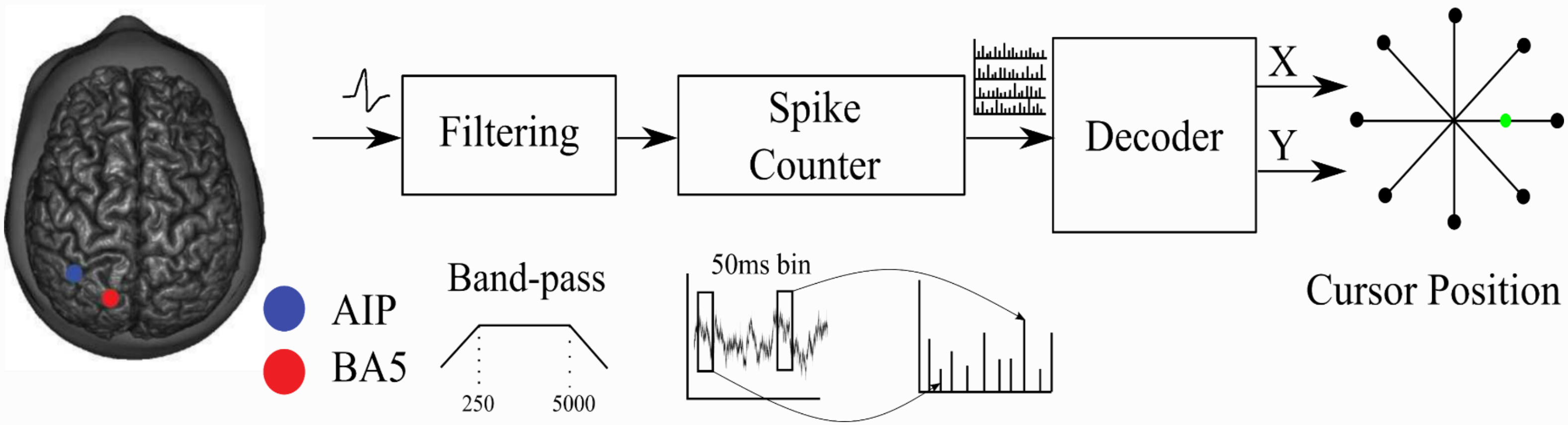


Fig.1. Regression of different algorithms on test data from the same day 2018-04-23: true target motion (black) and reconstruction (red)

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

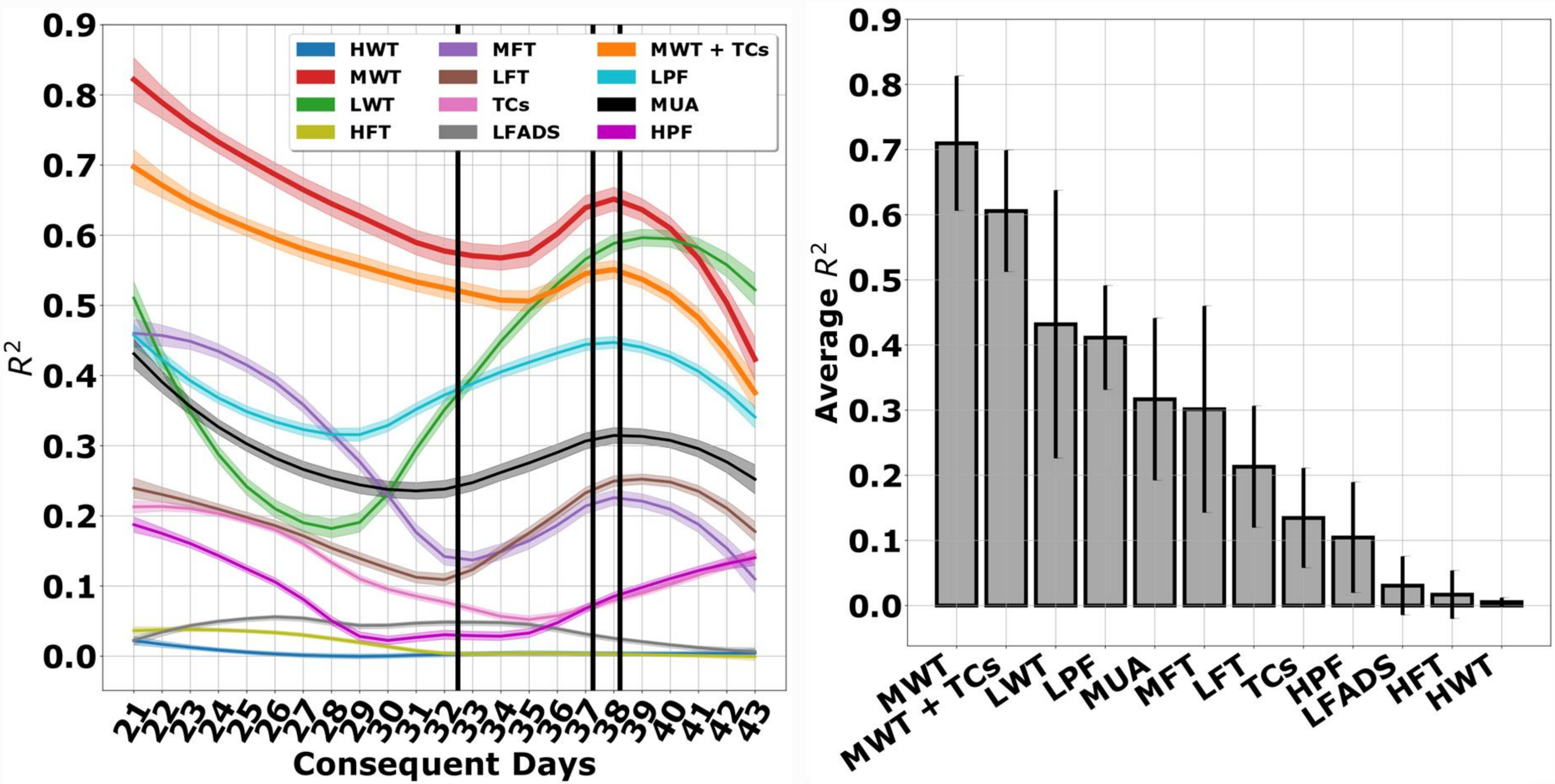


Fig.2. The DRNN operating on different features.

Multi-Day Performance of the Decoders

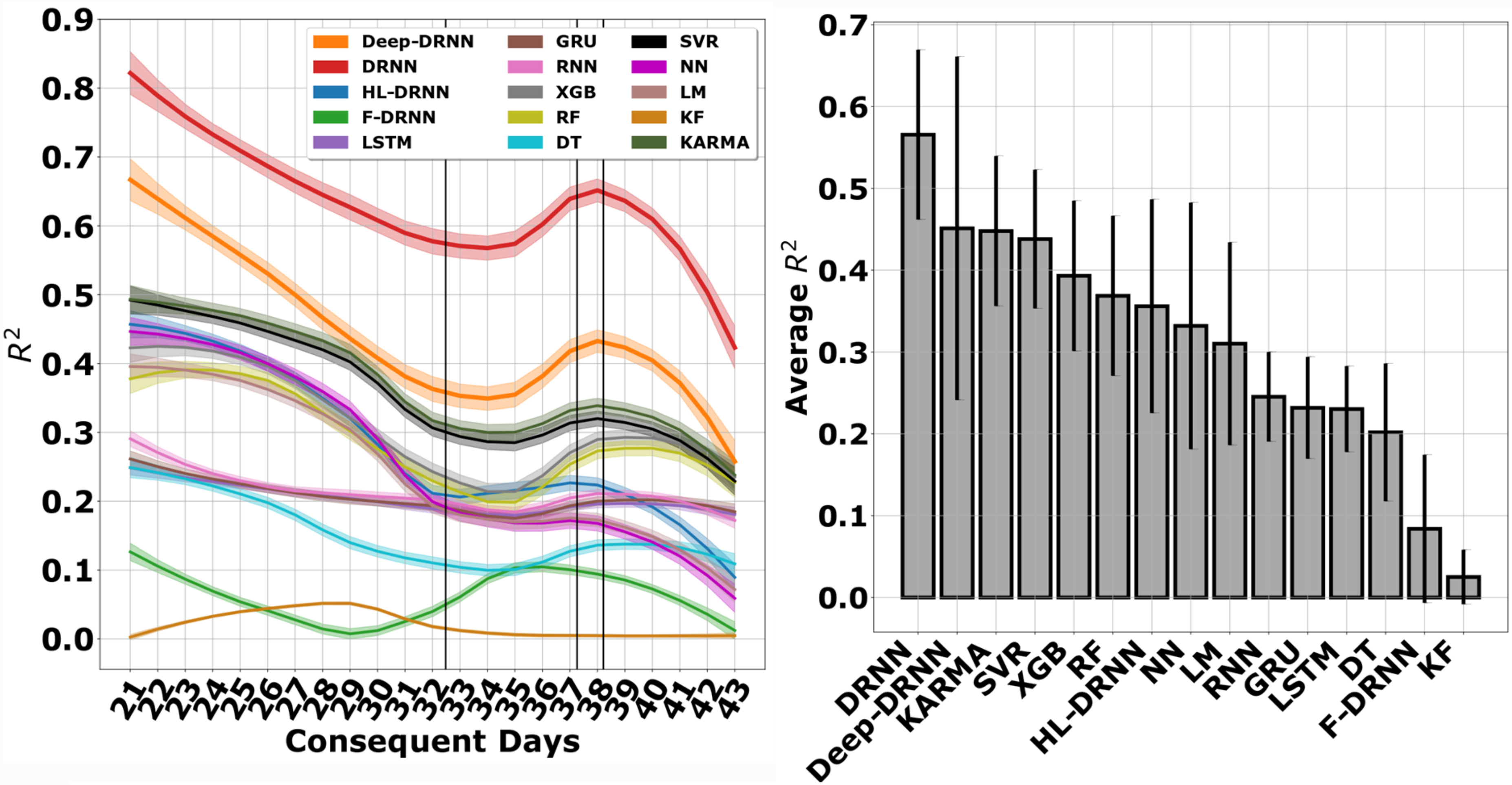


Fig.3. Multi-day performance of the decoders.

Multi-Day Performance of the Decoders

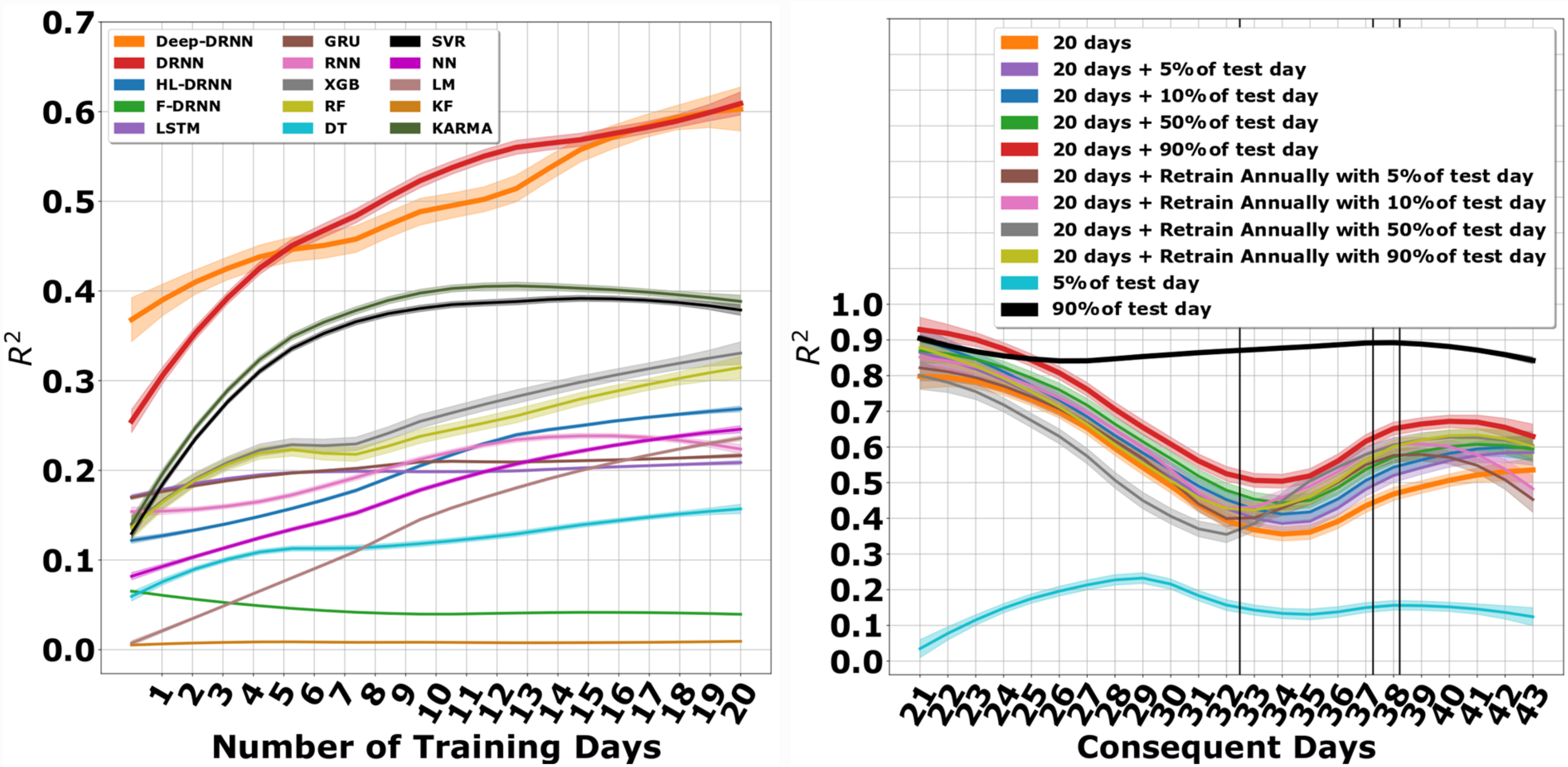
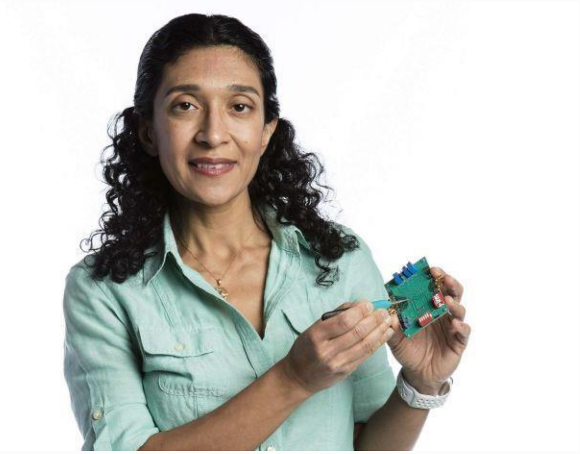


Fig.4. (Left) Effect of number of training days on the performance of the decoders. (Right) The DRNN operating in different training scenarios.

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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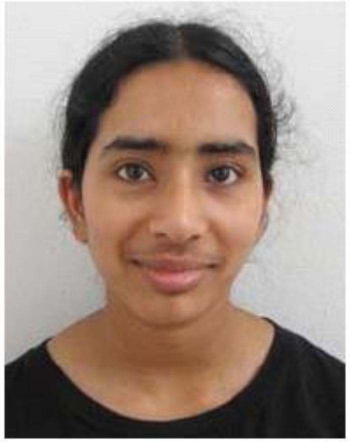

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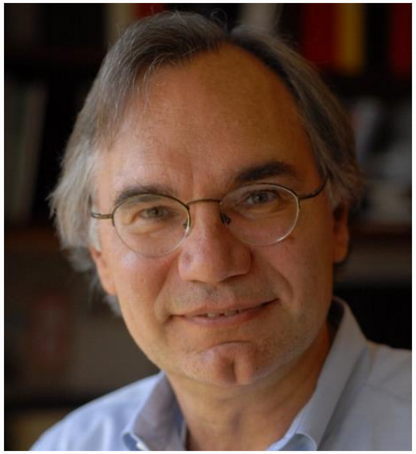

Richard Andersen

Luke Bashford

Thank you!

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

- **Codes:**
  https://github.com/BenyaminHaghi/DRNN-NeurIPS2019
- Poster: