Developing the Next-Generation Neural-Machine Interfaces for Neurorehabilitation Applications by Utilizing Sensor Arrays and Spatial Features

Justin Phan, Undergraduate Electrical/Computer Engineering, justinphan96@gmail.com

Advisor: Xiaorong Zhang, xrzhang@sfsu.edu

Intelligent **C**omputing and **E**mbedded Systems (**ICE**) Lab, School of Engineering, San Francisco State University

Background

- ❖ Neural-machine interfaces (NMI) utilize neural activity to control external devices
- ❖ A person's thoughts or conscious actions generate electrical activity in their CNS and can be analyzed to recognize the person's intentions
- ❖ A NMI uses PR algorithms on electrical activity to predict intentions and enable intuitive control of external applications

Objectives

Improve the recognition accuracies in the next generation of NMI that utilize electrode sensor arrays to collect richer EMG data.

- ❖ Utilize computationally-efficient **spatial features (Adjacent features)** in EMG PR algorithms

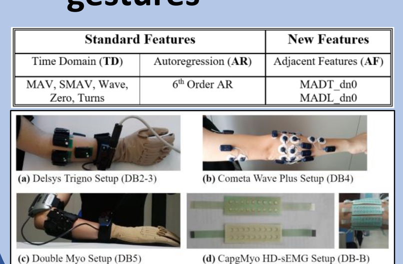
Methodology

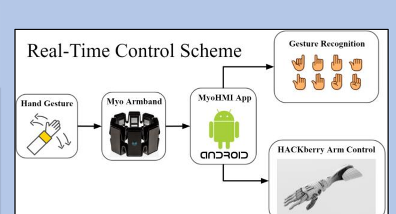
Offline Analysis

- Database Analysis
  - Ninapro (DB2-5)
  - CapgMyo (DB-B)
- An **LDA** PR algorithm was trained to recognize **8 hand gestures**

Real-Time Analysis

- Evaluate robustness and delay in real-time application
  - Myo Armband
  - MyoHMI mobile Android App
  - HACKberry Arm





EMG Pattern Recognition (PR)

Input Devices

- **Delsys Trigno** (DB2, DB3) – 2000 Hz sampling frequency
- **Cometa Wireless sEMG** (DB4) – 2000 Hz sampling frequency
- **Myo Armband** (DB5) – 200 Hz sampling frequency

Feature Extraction

Time Domain (TD) Features
Robust characteristics of EMG signals

- **MAV** – Mean Absolute Value
- **RMS** – Root Mean Square
- **W** – Wavelength
- **Z** – Zero Crossings
- **T** – Sign Slope Turns

Auto Regression (AR) Features
Characteristics that capture high frequency components in EMG signals, but involves deriving a computationally costly time series model

- **AR(6th)** – Coefficients for a 6th order autoregression model

Adjacent Features (AF)
Spatial characteristics that map the patterns of activity in motor unit action potentials (MUAPs)

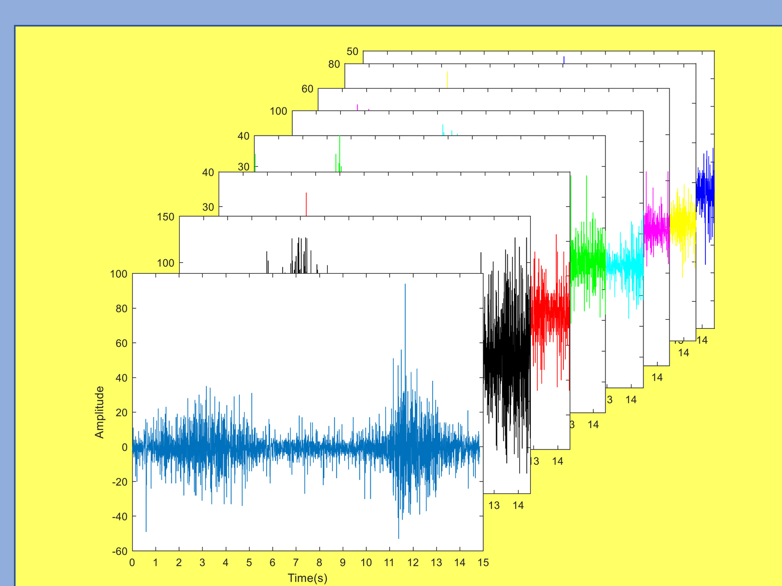
- **MADT_dn0** – Mean absolute difference of two windows of data from two adjacent electrodes in the transverse direction

Scaled Time Domain (TD) Features – Normalization of the intensity-based features

- **SMAV/SRMS** – Scaled MAV/RMS calculated by dividing the MAV/RMS of each channel by the average MAV/RMS across all channels

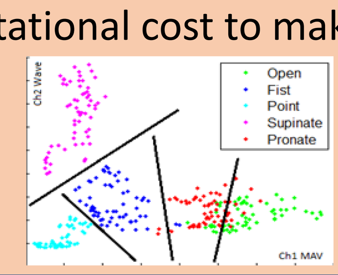
Features were extracted from 200ms windows of raw data , extracted every 100ms

Multi-Channel EMG Data



Machine Learning & Pattern Recognition

- **Linear Discriminant Analysis (LDA)** – Reduces dimensionality of feature matrix while minimizing loss to class discriminatory information
  - Projects data onto a lower dimensional space to avoid overfitting
  - Low computational cost to make predictions



External Applications

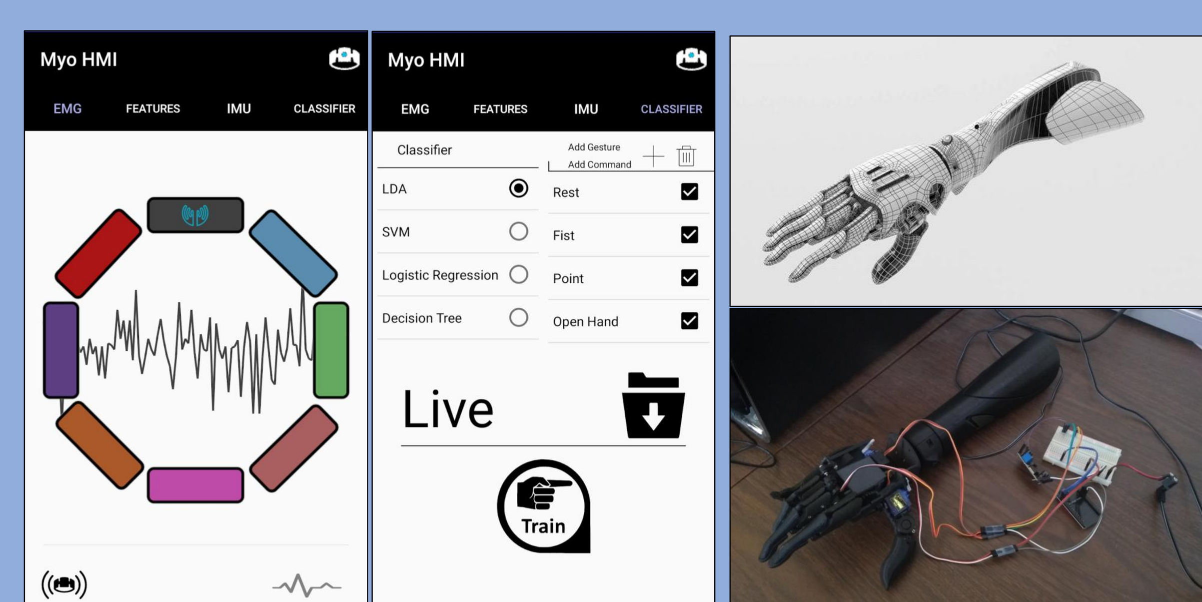
Results

Offline Analysis

Recognition Accuracies (8 Hand Gestures)		Ninapro DB2 (2000 Hz)	Ninapro DB5 (200 Hz)	CapgMyo DB-B (1000 Hz)
Feature Types	Features	8 electrodes	8 electrodes	128 electrodes
Time Domain (TD)	MAV	80.22%	75.39%	99.17%
	SMAV	83.57%	74.77%	99.35%
	RMS	79.49%	75.16%	99.08%
	SRMS	82.43%	75.08%	99.27%
	MAV, W, Z, T	85.65%	72.89%	99.23%
	SMAV, W, Z, T	88.09%	77.19%	99.40%
Autoregression (AR)	MAV, 6th Order AR	89.38%	69.55%	96.20%
	SMAV, 6th Order AR	**90.48%**	70.83%	97.09%
Adjacent Features (AF)	MADT_dn0	64.96%	50.73%	99.40%
	MADT_dn1	73.43%	49.66%	**99.42%**
	SMAV, MADT_dn0	87.00%	79.77%	99.32%
	SMAV, MADT_dn1	87.90%	77.40%	99.35%
Mixed Features	MAV, SMAV, W, Z, T, MADT_dn0	89.62%	**79.78%**	99.08%

- ❑ At higher sampling frequencies, **AR feature sets** achieved higher recognition accuracies
- ❑ At lower sampling frequencies, **AF feature sets** performed best
  - Combining AF and scaled intensity (SMAV) achieved higher performance
- ❑ A mixed feature set consisting of **TD and AF features** achieved robust recognition accuracies within 1% of the highest performing feature sets across all tests performed

Real-Time Analysis



Real-Time MyoHMI Interface				
Decision Length	1	2	**5**	10
Average Delay (ms)	109.75 ± 30.34	324.76 ± 44.66	**642.61 ± 50.50**	1202.78 ± 86.44

- ❑ A Myo Armband collected EMG data from a user's forearm muscles, while performing 8 hand gestures
- ❑ A MyoHMI Android App collected that EMG data and extracted the selected mixed feature set from EMG data
- ❑ An LDA algorithm was trained to recognize hand gestures based on unique patterns in the mixed feature set
- ❑ Predictions on the user's current hand gesture were used to control a 3D-printed robotic arm

Conclusion

- ✓ Developed feature sets that **utilize spatial features** for EMG pattern recognition with **high performance in sensor arrays**
- ✓ Developed a **working prototype to implement PR strategies** through the use of a low cost, portable, and flexible neural-machine interface

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