SAN FRANCISCO STATE UNIVERSITY

Toward Improving the Life of Amputees by Integrating Neural-Machine Interface with Machine Learning Technology

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Biomedical **I**maging & **D**ata
Analysis **L**ab

Motivation

- Over *1.6 million* amputees in the US, over *32 million* worldwide
- Most commercial prosthetic arms require the user to switch the control mode manually

Image from:
http://www.sfchronicle.com/business/article/Teen-helps-test-design-3-D-printed-prosthetic-6871543.php#photo-9501708

Motivation

- Can we control a prosthetic limb as if it is the user's own limb?

Picture from: http://www.runleiarun.com/choppedoffhands/sw5.html

- **Luke Skywalker's prosthetic arm in Star Wars: The Empire Strikes Back (1980)**

Our Project

- To develop **prosthetic arms** that perform like **natural arms** by integrating **neural-machine interface** and **machine learning** technology

Research Team:

Dr. Xiaorong Zhang

School of Engineering

ICE Lab

Dr. Kazunori Okada

Department of Computer Science

BIDAL

Supported by:

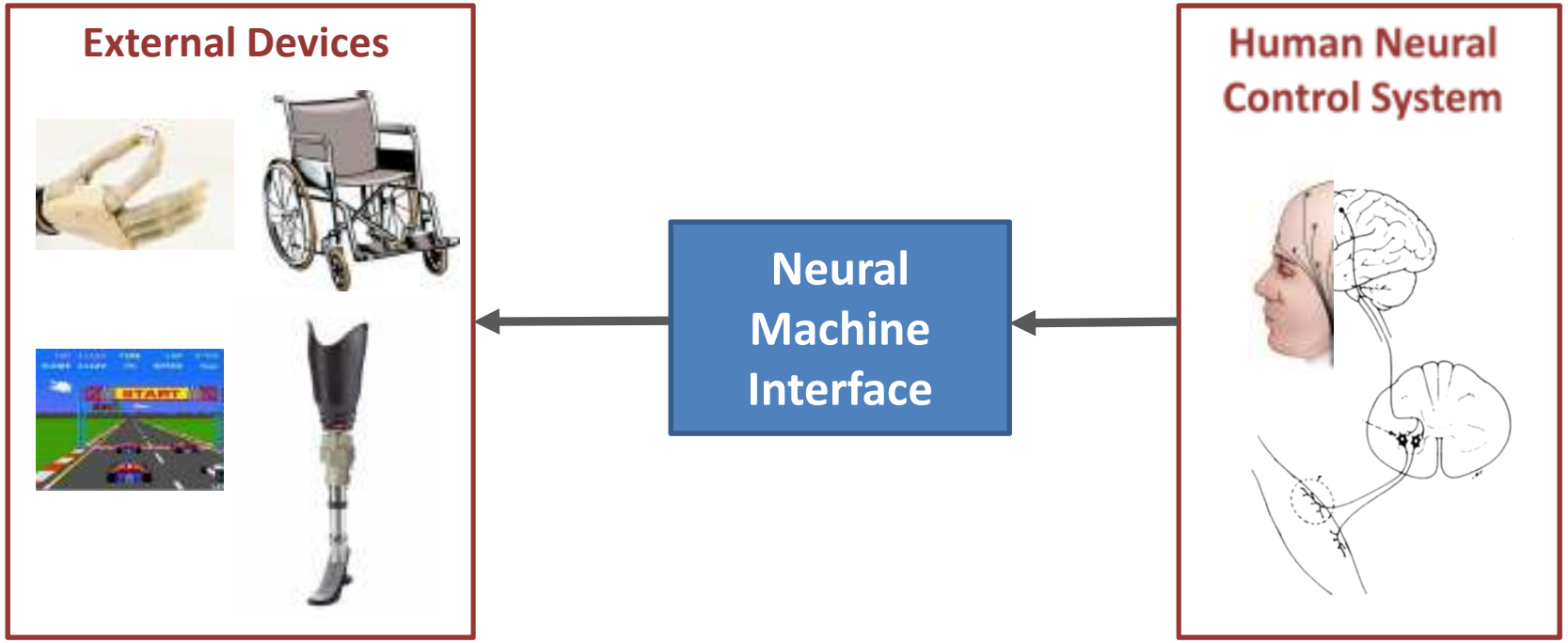
Ken Fong Translational Research Fund

CCLS

What is Neural-Machine Interface?

Neural-Machine Interface (NMI)

- NMI utilizes neural activities to control machines.



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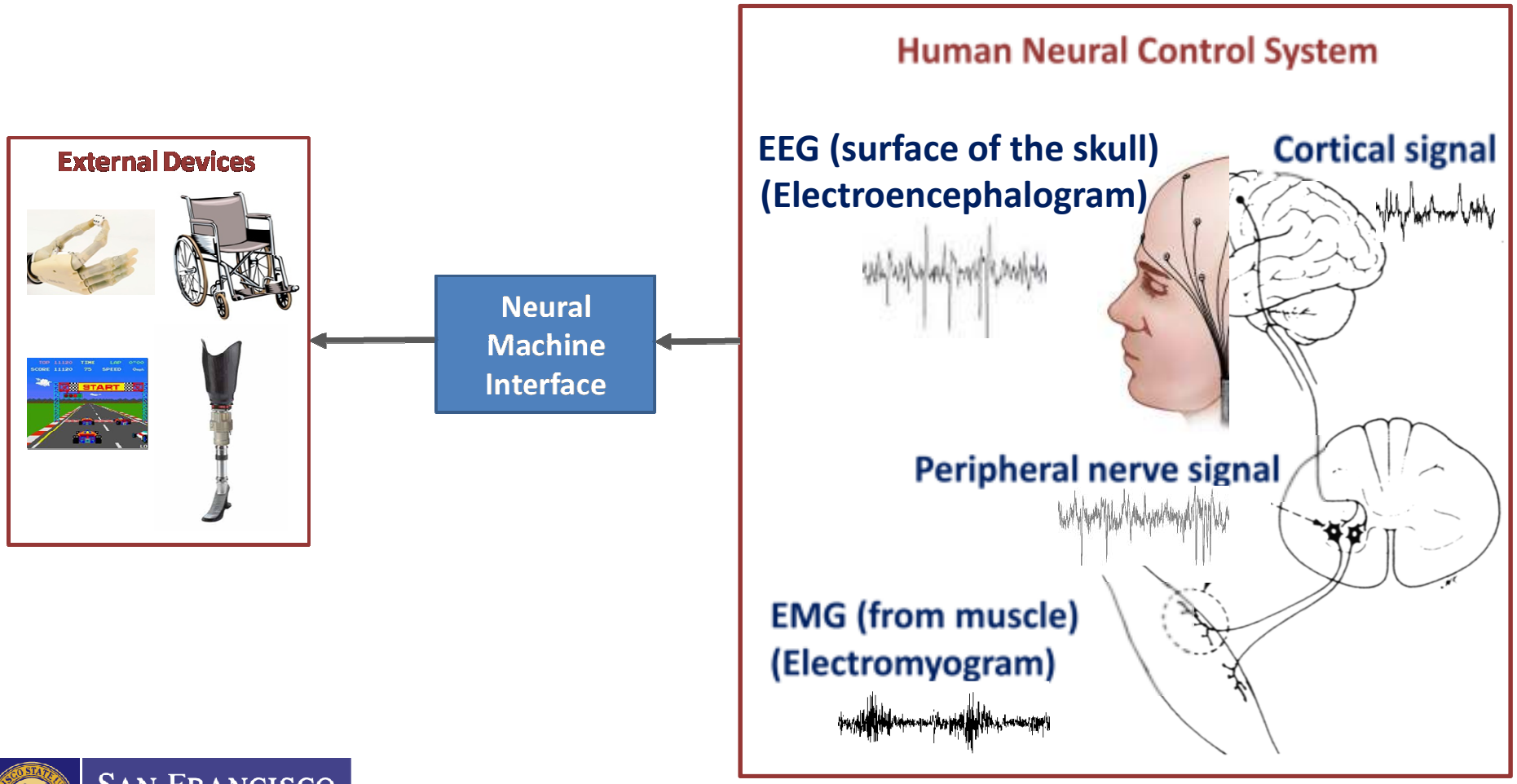

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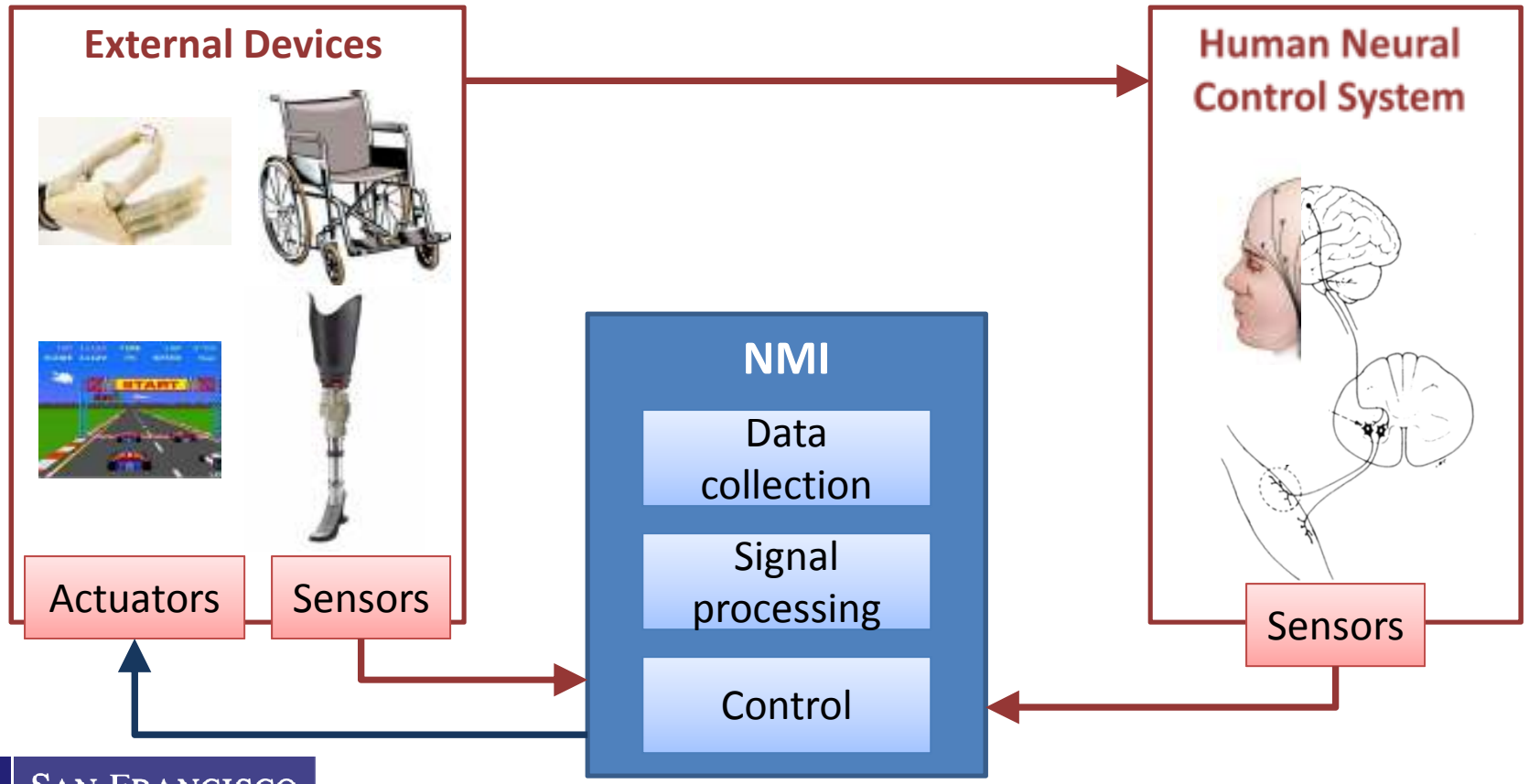
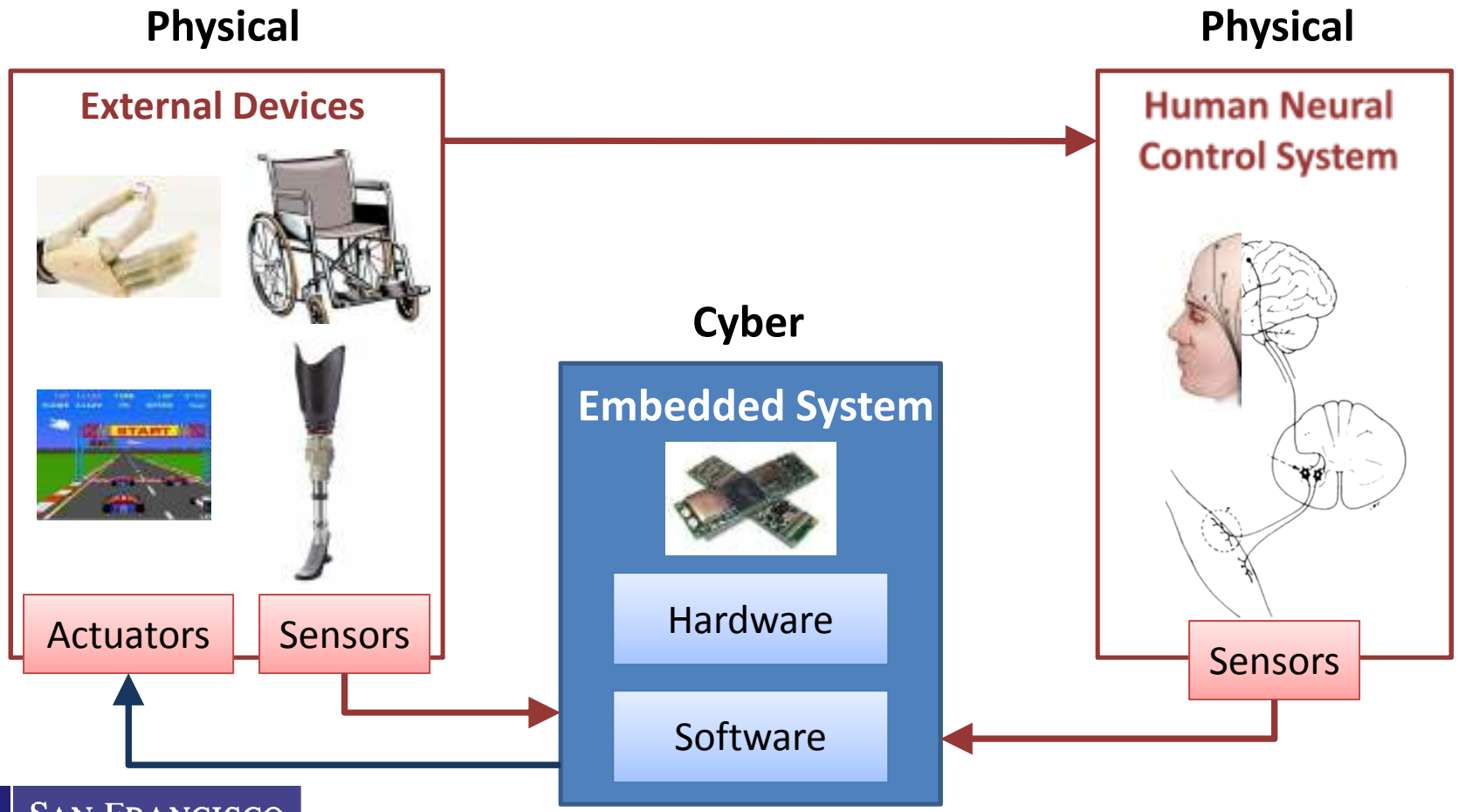


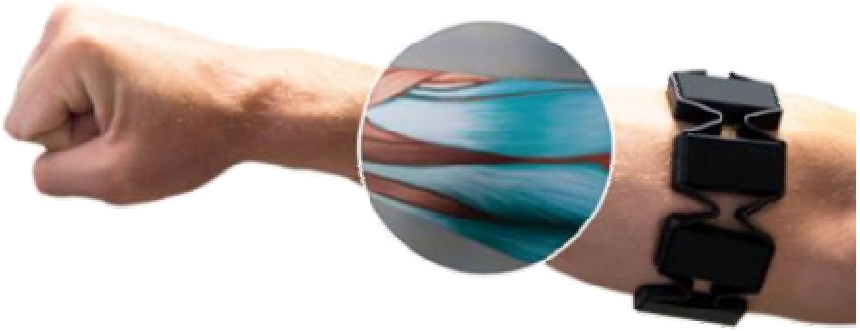
Neural-Machine Interface (NMI)

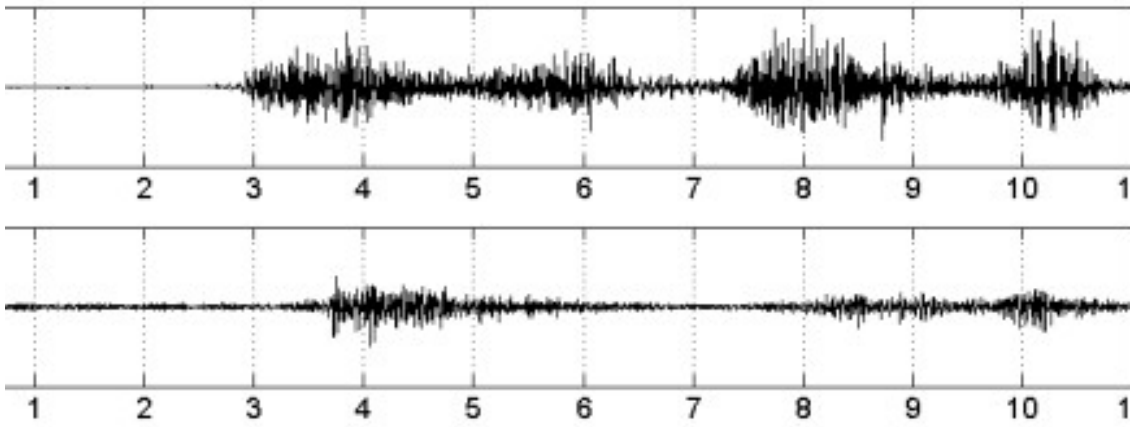
- NMI utilizes neural activities to control machines.
- NMI is a biomedical **cyber-physical system** (CPS).



Neural-Machine Interface (NMI)

- **EMG (Electromyogram) signals**
  - Effective bioelectric signals for expressing movement intent

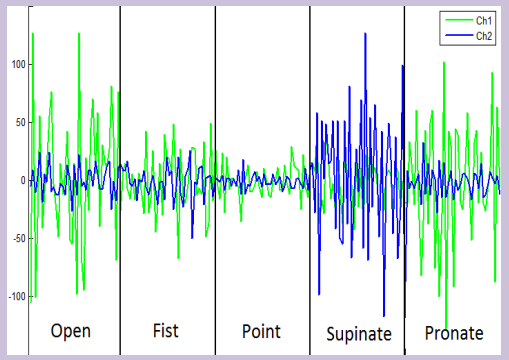




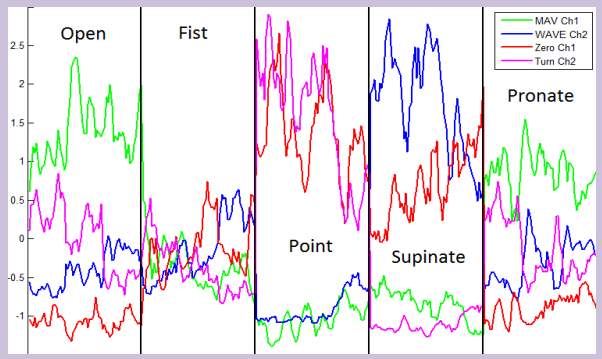
Picture from: http://www.readcube.com/articles/10.1186/

NMI

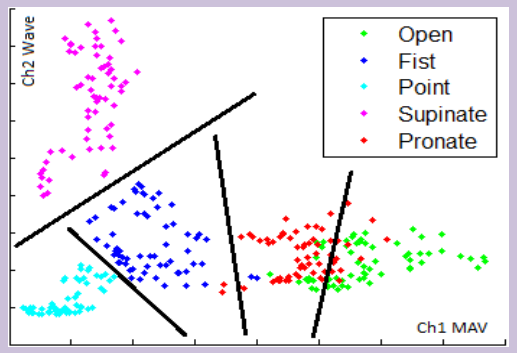
Data Collection



Feature Extraction



Machine Learning & Pattern Recognition

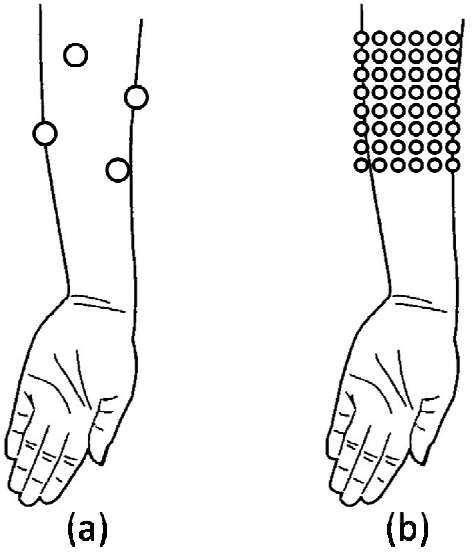


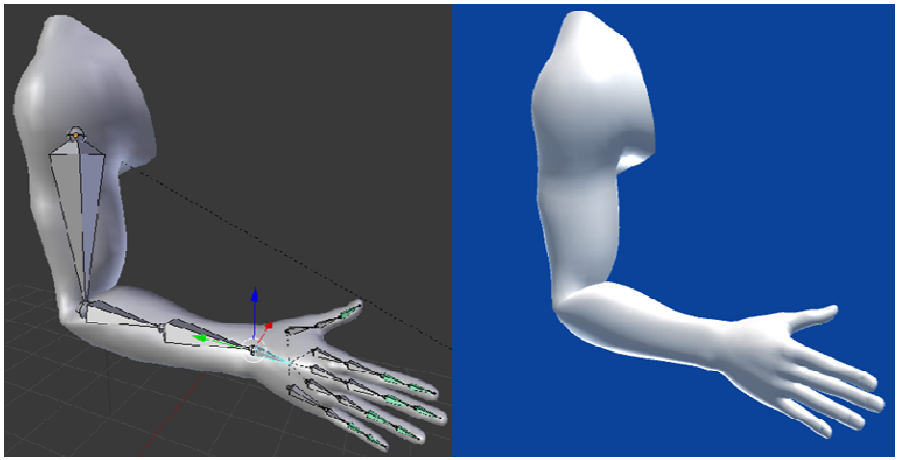
Challenges

- **Challenges in recognizing user intent from EMG signals**
  - Limited signal sources
  - Natural limb movement are continuous and dynamic
- **Challenges in HW/SW integration on embedded system**
  - Real-Time
  - Memory efficient
  - Reliable
  - Robust
  - Energy efficient

Innovations

- Grid Sensing
- Feature Selection
- Machine Learning
- 3D Printing
- Virtual Reality
- Embedded System Design





ICE Lab

Intelligent Computing & Embedded Systems Laboratory

ICE Lab Members:

Ian Donovan (MS in EECS)
Kartik Bholla (MS in EECS)
Sergey Dusheyko (MS in EECS)
Chayasri Akkiraju (MS in EECS)
Kevin Valenzuela (BS in CompE)
Alejandro Ortiz (BS in CompE)
Ian Hanna (BS in ME)
Kyle Edward Goodridge (BS in EE)
Christian Gomez (BS in EE)
Jose Rivera (BS in ME)
Kashetu Junior Momodu (BS in EE)
Alex David (BS in ME/CompE)
Chloe Zirbel (BS in CompE)
Peter Wald (Undergrad in Biology (CCSF))
Robert Shi (Senior at Lowell High)

Publications:

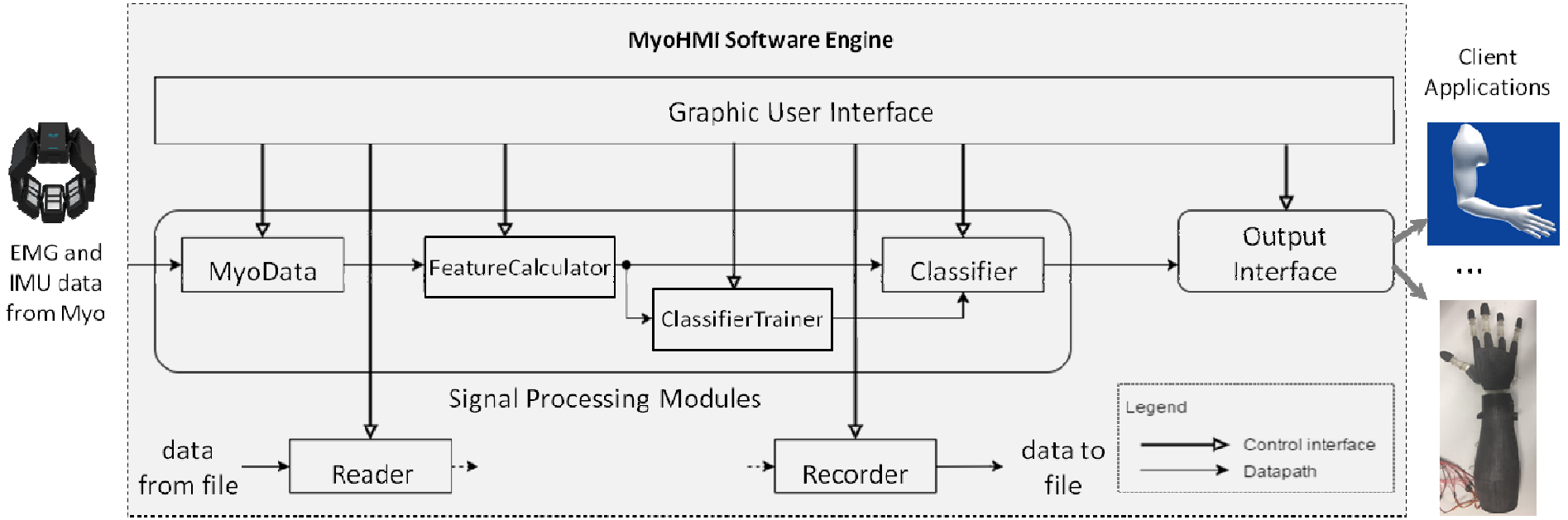
[EMBC 2017] Ian M. Donovan et al. "Simple Space-Domain Features for Low-Resolution sEMG Pattern Recognition

[ASEE PSW 2017] Jeffrey Yan et al. "Engaging Community College Students in Computer Engineering Research through Design and Implementation of a Versatile Gesture Control Interface"

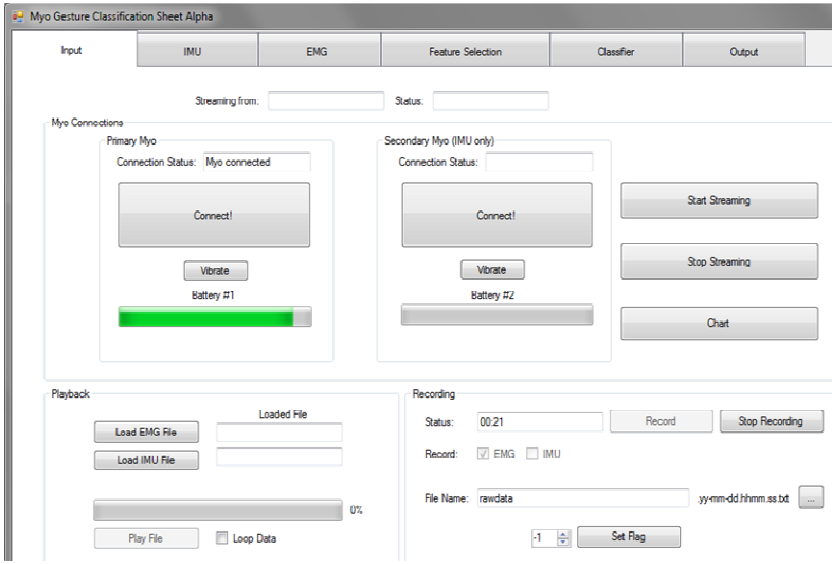
[SMC 2016] Ian Donovan, "MyoHMI: A Low-Cost and Flexible Platform for Developing Real-Time Human Machine Interface for Myoelectric Controlled Applications"

[ASEE PSW 2016] Muslim Razi et al., "Engaging Community College Students in Engineering Research through Design and Implementation of a Human-Machine Interface for Gesture Recognition"

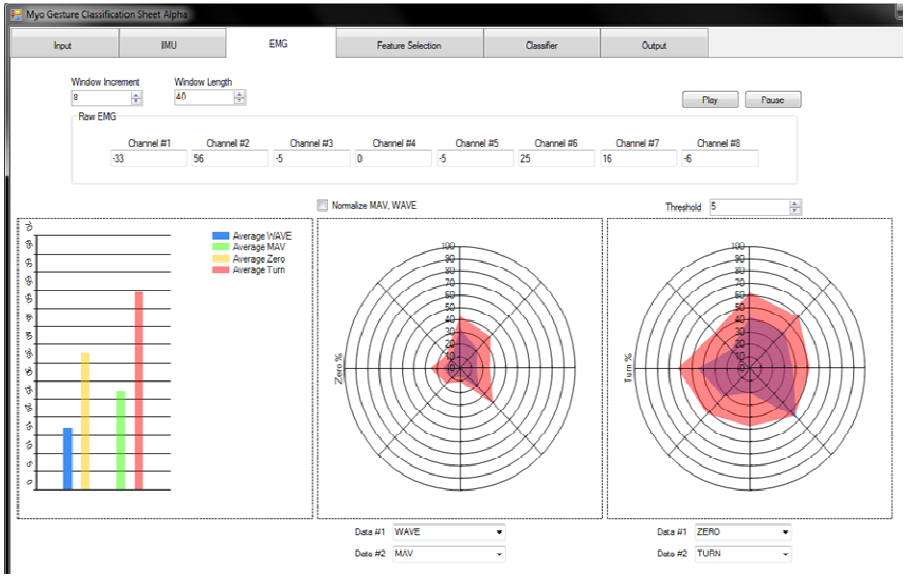
MyoHMI: A Low-cost, Flexible NMI for Myoelectric Controlled Applications (I. Donovan et al. *SMC 2016*)



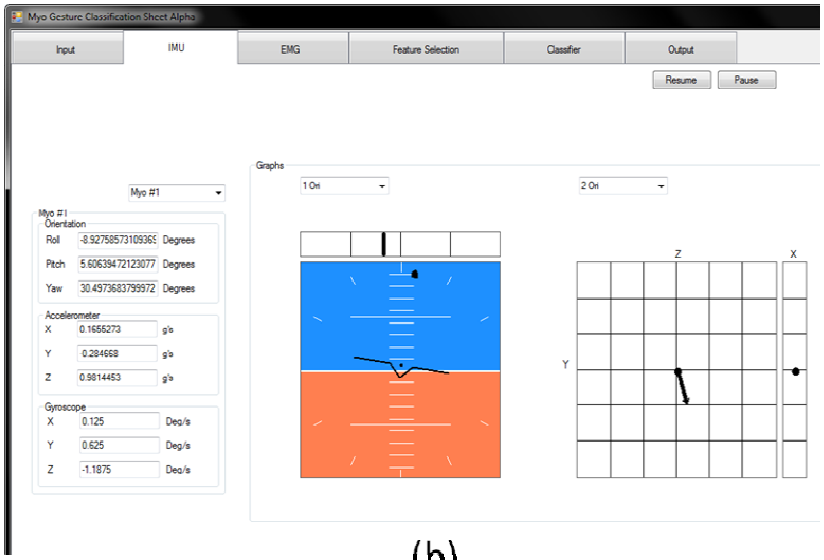
MyoHMI


Myo Gesture Classification Sheet Alpha
Input
IMU
EMG
Feature Selection
Classifier
Output
Streaming from:
Status:
Myo Connections
Primary Myo
Connection Status:
Myo connected
Connect!
Vibrate
Battery #1
Secondary Myo (IMU only)
Connection Status:
Connect!
Vibrate
Battery #2
Start Streaming
Stop Streaming
Chart
Playback
Load EMG File
Load IMU File
Loaded File
0%
Play File
Loop Data
Recording
Status:
00:21
Record
Stop Recording
Record:
EMG
IMU
File Name:
rawdata
yy-mm-dd.hhmm.ss.txt
-1
Set Flag

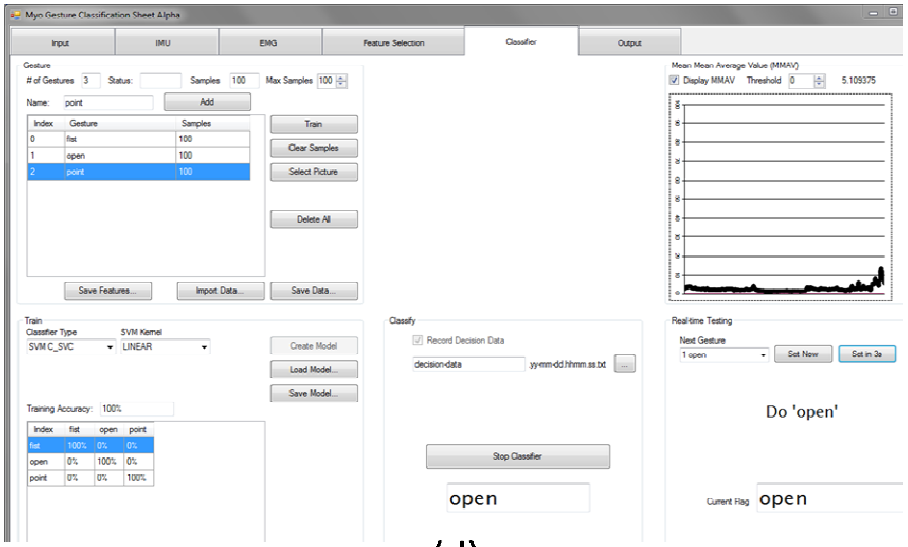
(a)


Myo Gesture Classification Sheet Alpha
Input
IMU
EMG
Feature Selection
Classifier
Output
Window Increment
Window Length
Play
Pause
Raw EMG
Channel #1
Channel #2
Channel #3
Channel #4
Channel #5
Channel #6
Channel #7
Channel #8
-33
56
-5
0
-5
25
16
-6
Normalize MAV, WAVE
Threshold
Average WAVE
Average MAV
Average Zero
Average Turn
Zero %
Turn %
Data #1
WAVE
Data #2
MAV
Data #1
ZERO
Data #2
TURN

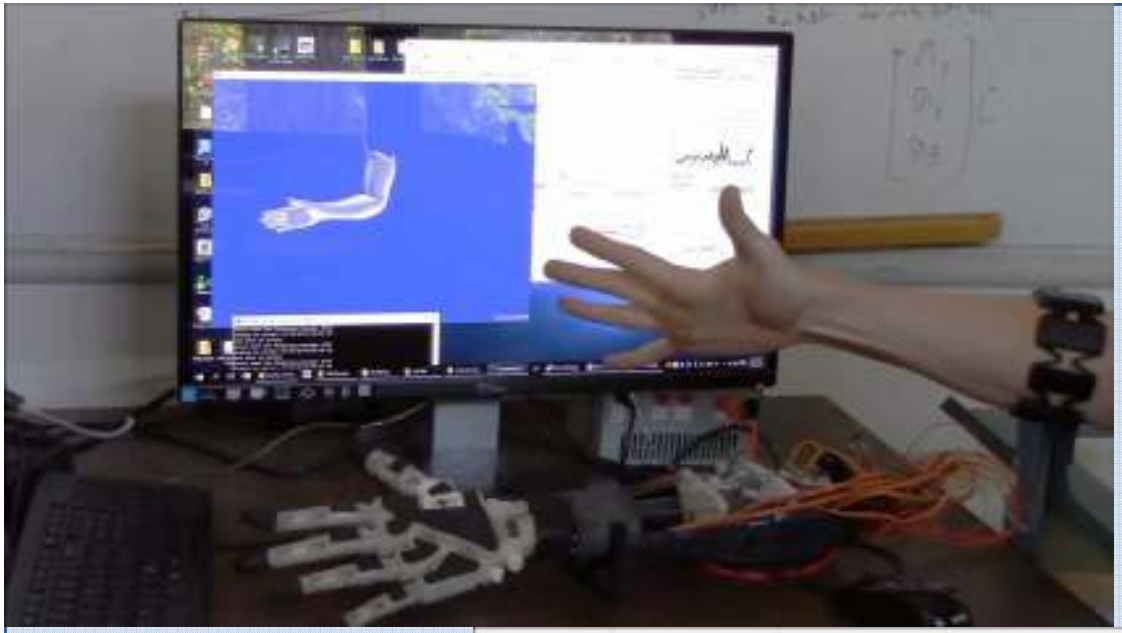
(c)


Myo Gesture Classification Sheet Alpha
Input
IMU
EMG
Feature Selection
Classifier
Output
Resume
Pause
Graphs
Myo #1
1 Ori
2 Ori
Orientation
Roll
Pitch
Yaw
Degrees
Accelerometer
Gyroscope
Deg/s
Z
X
Y

(b)

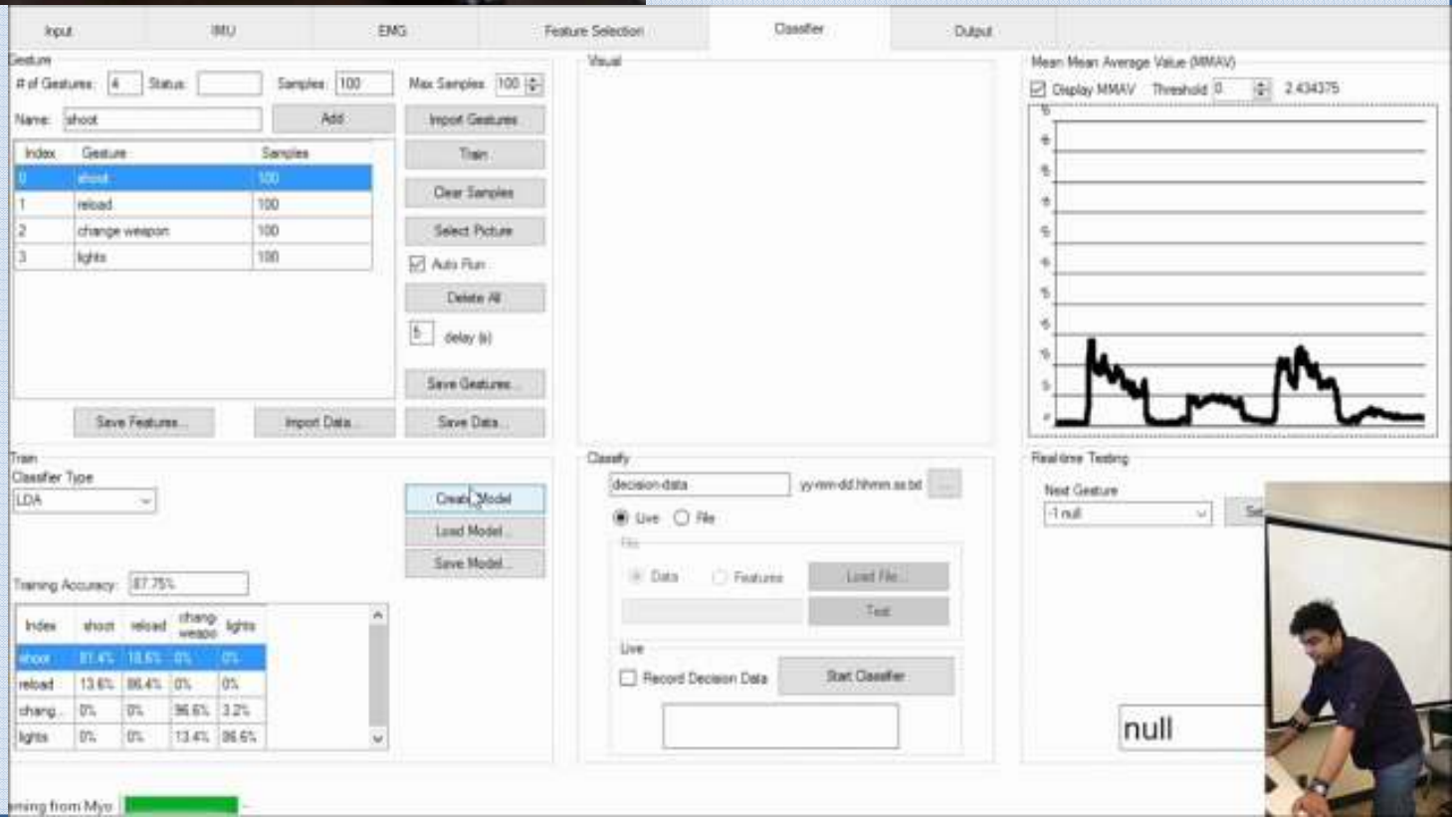

Myo Gesture Classification Sheet Alpha
Input
IMU
EMG
Feature Selection
Classifier
Output
Gesture
# of Gestures
Status:
Samples
Max Samples
Name:
point
Add
Index
Gesture
Samples
0
fist
100
1
open
100
2
point
100
Train
Clear Samples
Select Picture
Delete All
Save Features...
Import Data...
Save Data...
Mean Mean Average Value (MMAV)
Display MMAV
Threshold
Train
Classifier Type
SVM C_SVC
SVM Kernel
LINEAR
Create Model
Load Model...
Save Model...
Training Accuracy:
100%
Classify
Record Decision Data
decision-data
yy-mm-dd.hhmm.ss.txt
Stop Classifier
open
Real-time Testing
Next Gesture
1 open
Set Now
Set in 3s
Do 'open'
Current Flag
open

(d)



MyoHMI controlling a 3D printed prosthetic hand and a virtual hand

MyoHMI controlling a first-person-shooter (FPS) VR game



Education and Outreach Activities

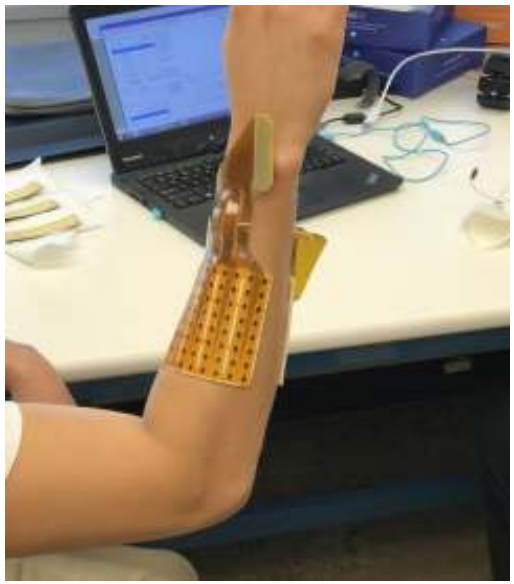
Cañada College and SFSU School of Engineering Cooperative Summer Internship Program

Projects presented at *ASEE PSW 2016, 2017*

Research Progress

Simple Space-Domain Features for Low-Resolution sEMG Pattern Recognition (I. Donovan, J. Puchin et al. *EMBC 2017*)

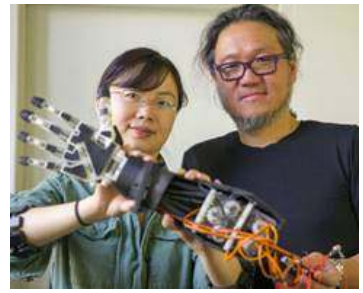
- Exploit spatial relationships of sEMG signals from sensor array
- Develop computational efficient space-domain features for real-time embedded system design
- Classification accuracy increased by 7% compared to Hudgins' time-domain features



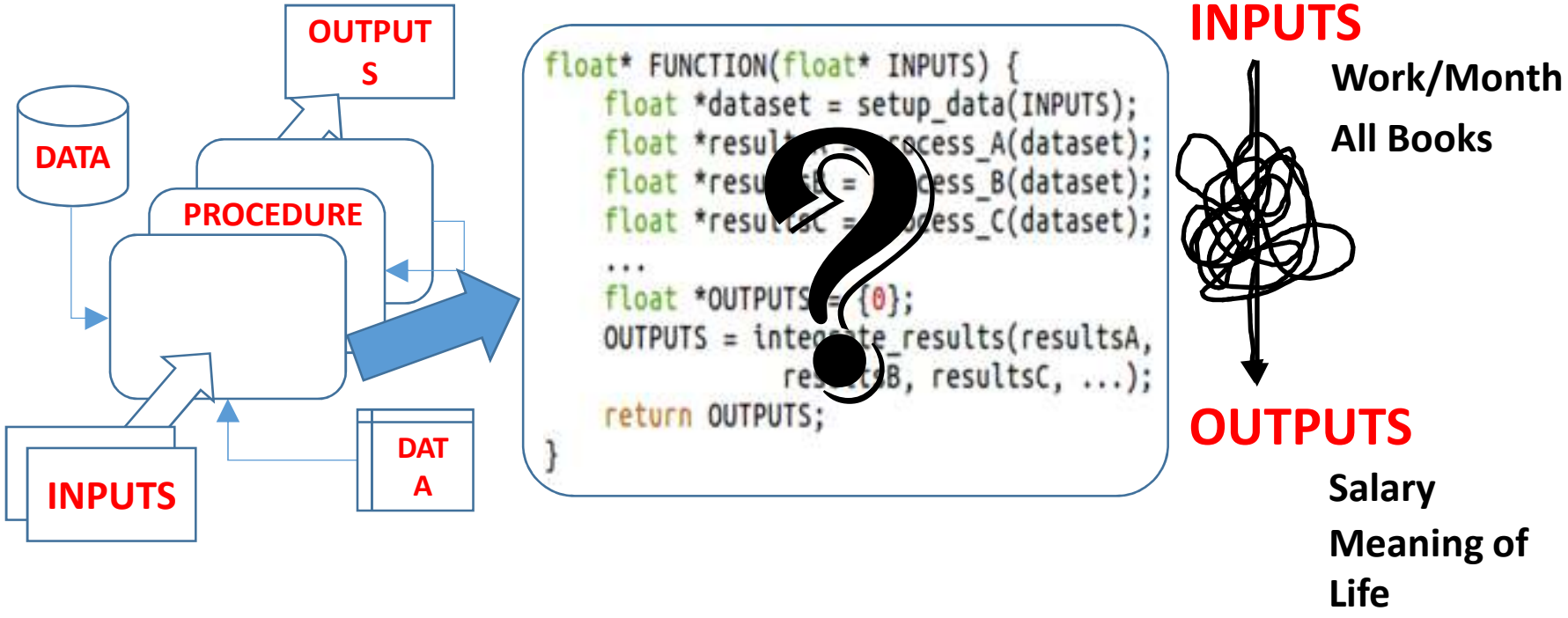
Toward improving the life of amputees: Machine Learning Technologies

BIDAL

Dr. Kaz Okada & Members of BIDAL group
Department of Computer Science, COSE
San Francisco State University

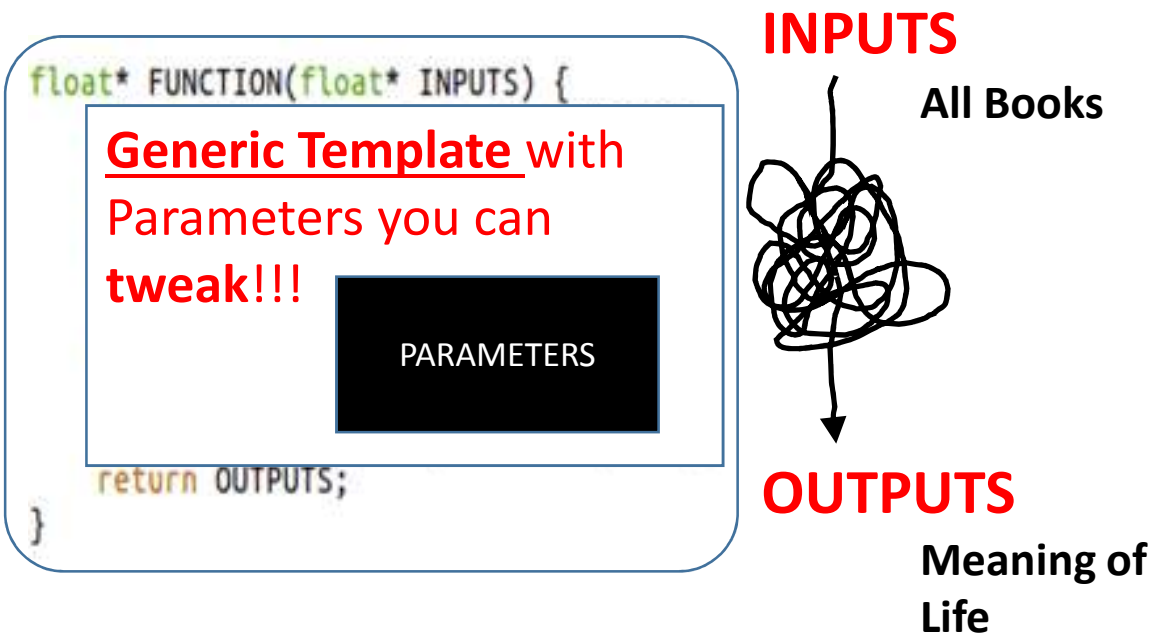


Computer Science?



Machine Learning: Computer Science Perspective

- Machine learning (ML): Automate this parameter tweaking
- With examples: if you select the template well



$$\{(Book1, Meaning1), (Book2, Meaning2), \dots, (BookN. MeaningN)\}$$

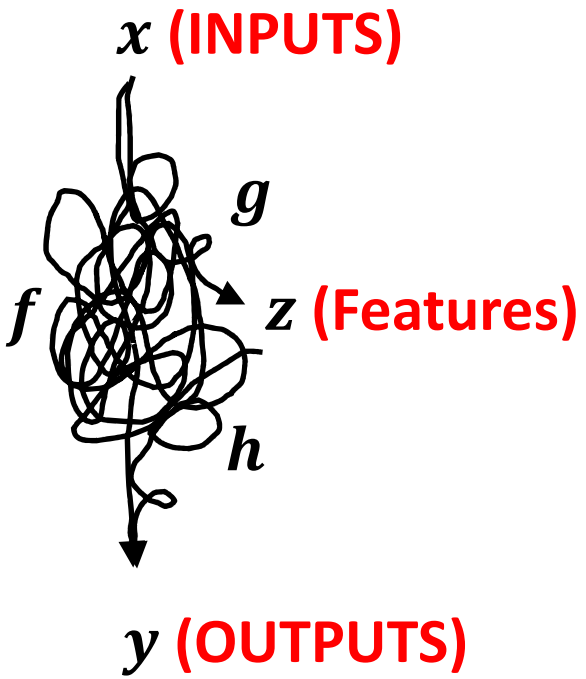
Two-Step Approach: Feature Engineering & Model Selection

$$y = f(x) = h(g(x))$$

$z = g(x)$ Feature transformation (Domain-specific)

$y = h(z)$ Classifiers (Domain-independent)

- Best g for a problem? (Feature Engineering)
- Best h for a problem? (Model Selection)



Question1: What sensors should we use?


Juris Puchin

Myo Band

8 channels
Low resolution
Portable
In-expensive

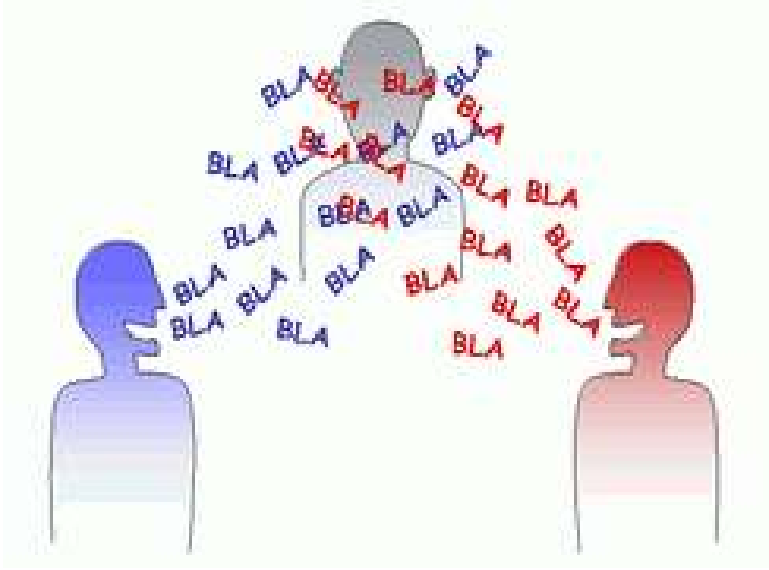
Grid Sensor

128 channels
High resolution
Not portable
Expensive

- Grid gives more information but signals can be awfully entangled…
- Feature engineering: **can we transform signals to untangle them?**
- Built a database of 47 gestures for 11 subjects

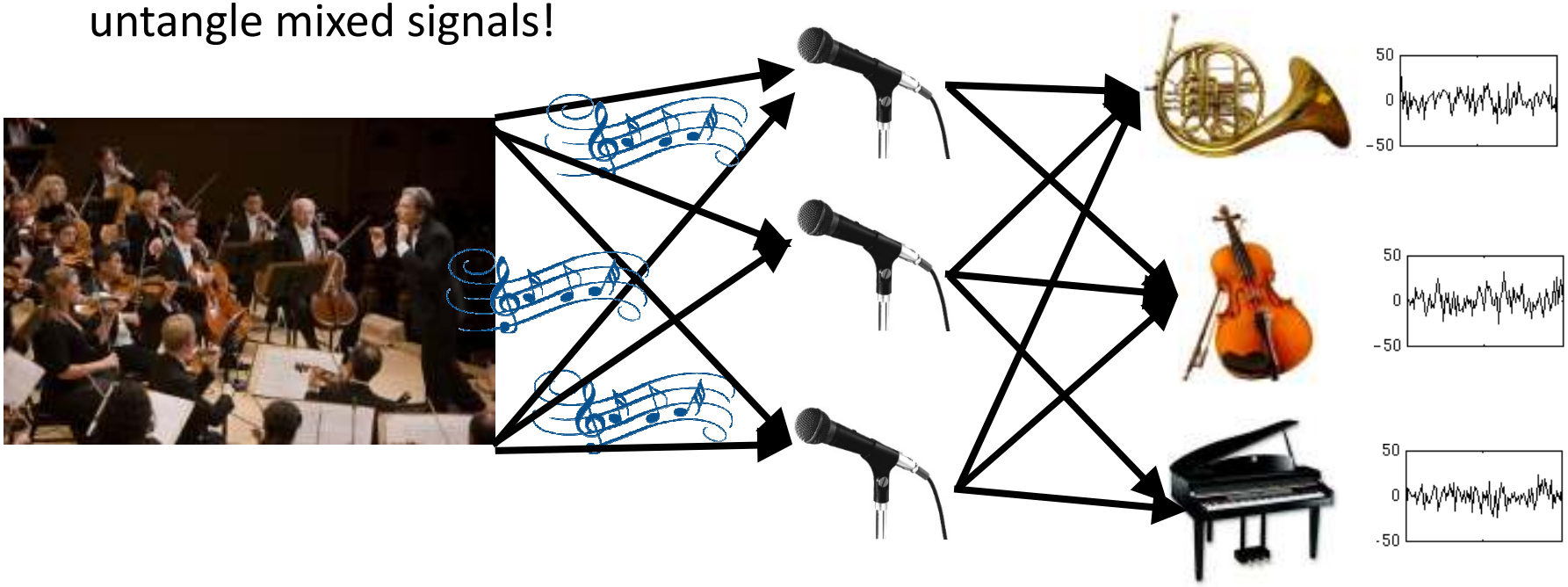
Cocktail Party Problem

- How can we focus on one conversation among cacophony of so many others entangled in what we hear?



ICA solves Cocktail Party Problem

- **Independent Component Analysis (ICA)** is a statistical method to untangle mixed signals!



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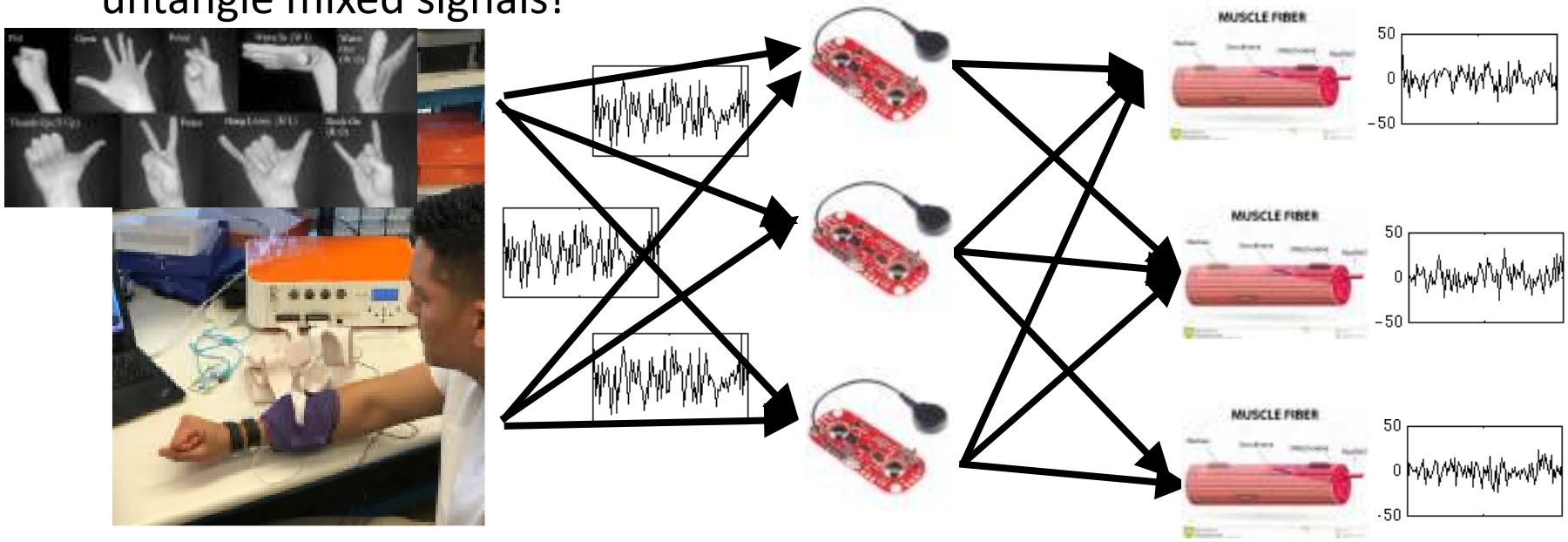
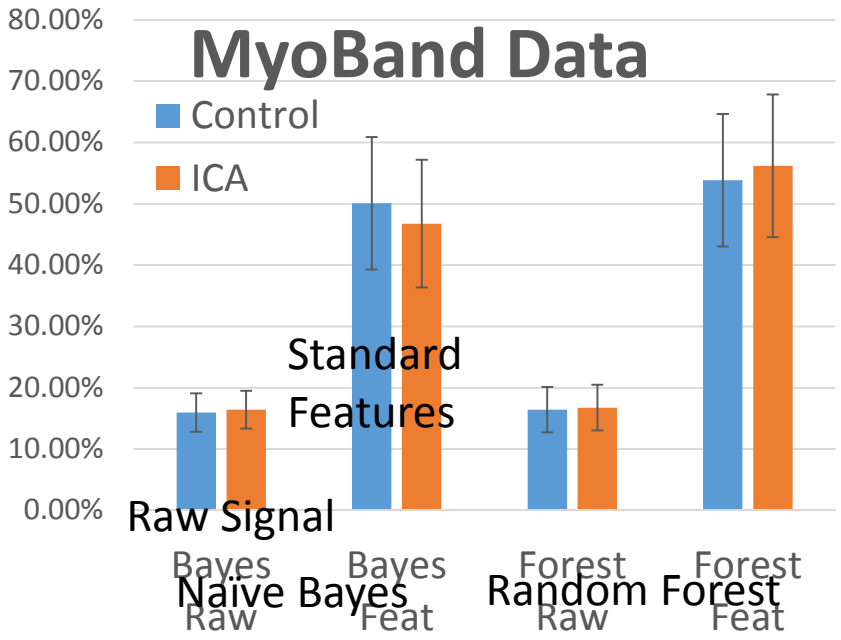
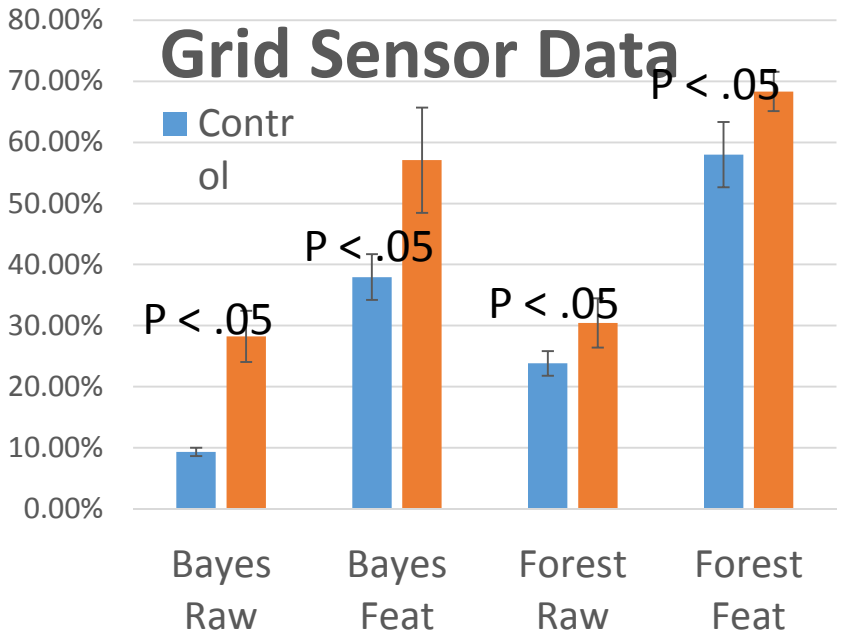


Results: ICA improves for Grid but not Myo…





- Grid sensor data is information rich but they are really entangled

Questions 2: What classifier should we use?

- So many standard classifiers one can use
  - Linear Discriminant Analysis
  - Naïve Bayes classifiers
  - Support Vector Machine
  - Random Forest
  - Logistic Regression
  - Convolution Neural Net
  - ….

Which one?

Model Selection Problem in ML Research

- Team of Undergrads and Grads from multiple depts. & universities.

- 9 classic and advanced classifiers are being tested.
- Careful data collection
- Leave-One-Out experiments: designed for fair parameter tuning and performance evaluation to study different use-case scenarios
- Consideration for time series data …

Outlook

- Application to improve hardships in our lives & society
- Rich field for further challenging investigations
- Exciting collaborations (Robotics? Training for sport/music?)
- Diversity