Practical Course

EMG-based Robotic Control

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Final Presentation

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Introduction

- **Motivation:**
  - EMGs control human movements.
  - Popularity of EMG-based systems and their application fields (e.g. upper-limb prostheses).
  - Analyse and understand the signal profiles.
- **Purpose:**
  - Build an EMG-based control of a robotic arm.
- **Challenges:**
  - EMG data collection methodology.
  - Design of an accurate classifier.
  - Robot Arm control.

System Overview

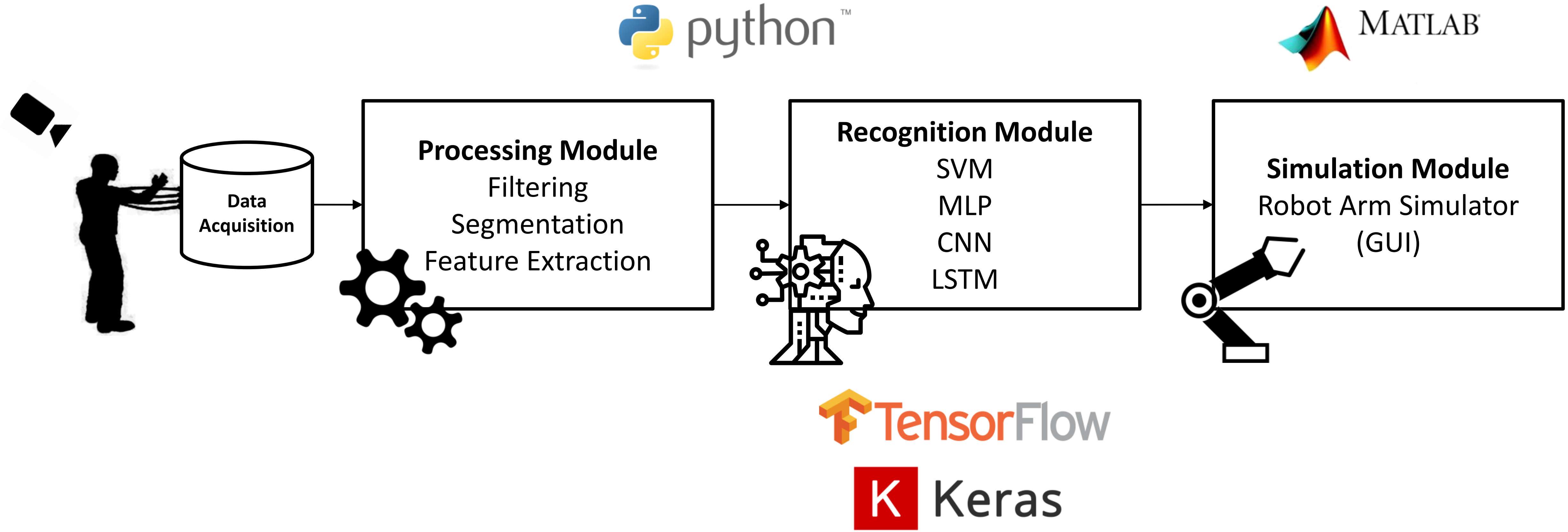


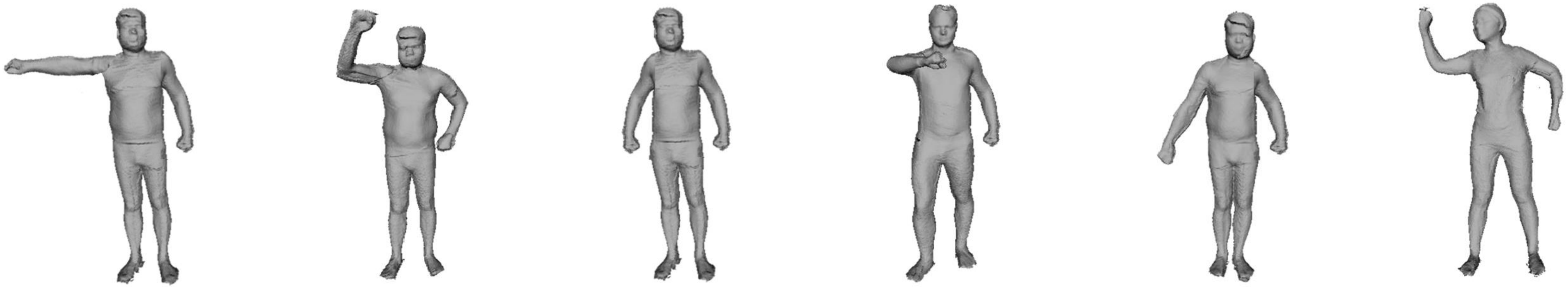
Figure: System Overview

Data Acquisition

1. Target muscles definition:

- Biceps &Triceps

2. Movement classes definition:



Movement 1 Movement 2 Movement 3 Movement 4 Movement 5 Movement 6

Data Acquisition

3. **Shimmer Hardware configuration:**
   - Sampling frequency 120Hz.
4. **Camera calibration:**
   - Making sure a continuous tracking of the marker.
5. **EMG and Camera data synchronization (Trigger).**

Input:
Human movements
Output:
RAW EMG signal

Data Acquisition

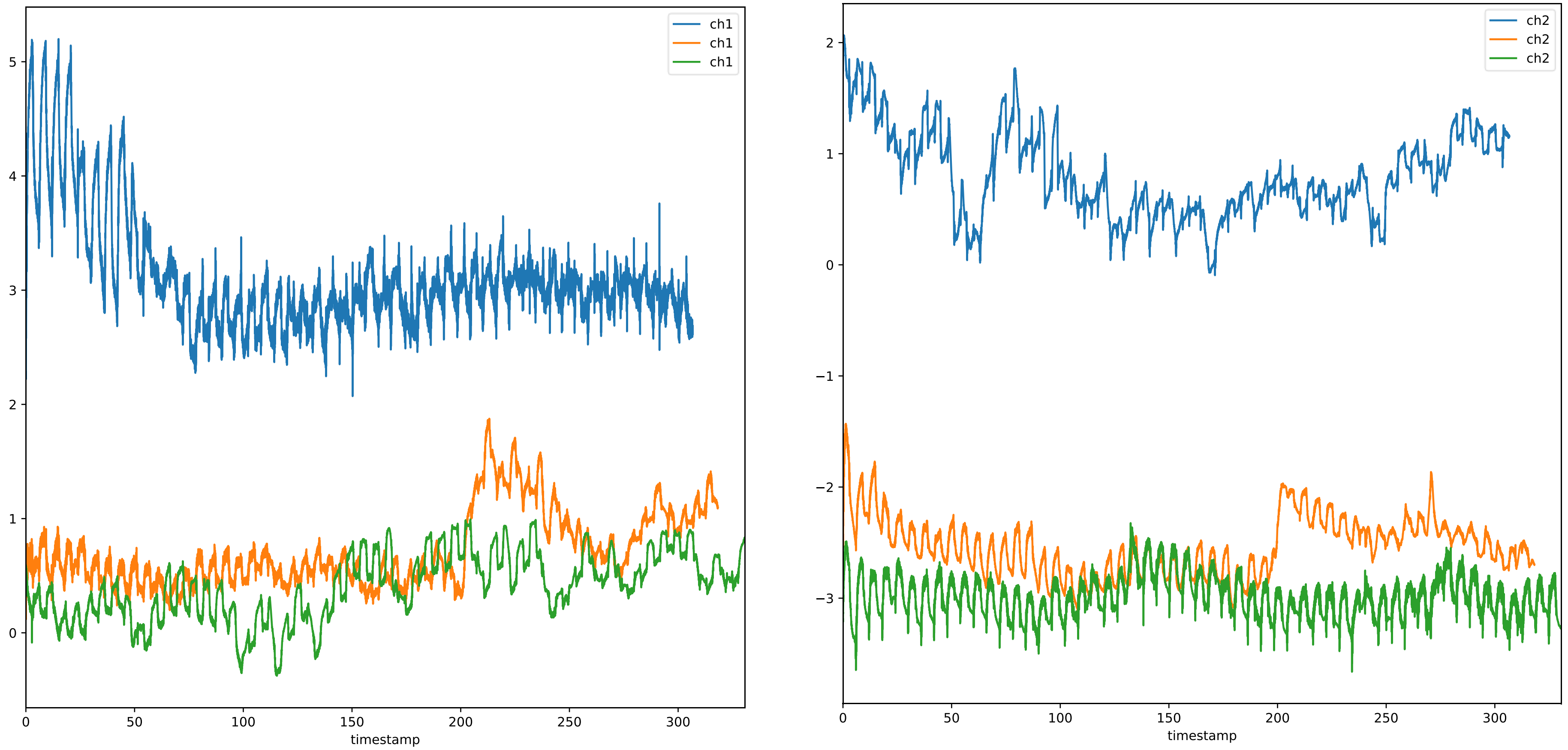


Figure: 3 recording sessions with 2 movement per session, links: biceps – right: triceps

Processing Module

1. Filtering:

- Low pass filter with cut-off frequency of 55Hz.
- Notch filter, 50Hz.

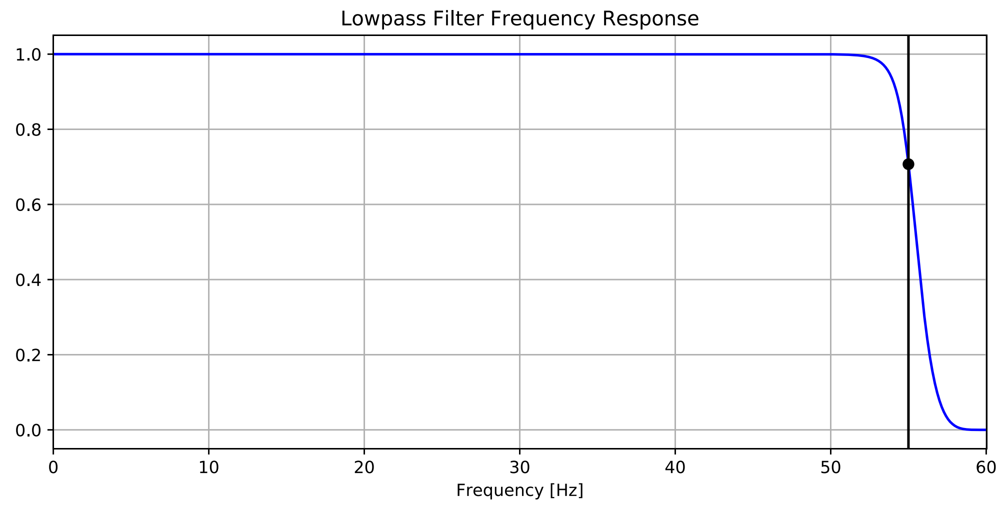


Figure: Low pass filter

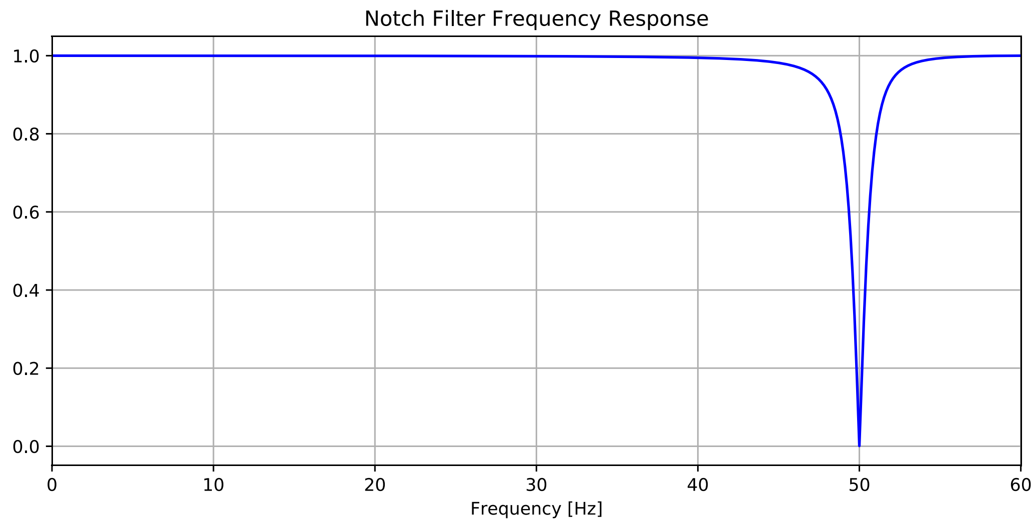


Figure: Notch filter

Processing Module

2. Normalization:

- Statistical normalization (unbiased, unit variance).
- Standard normalization (range [-1, 1]).

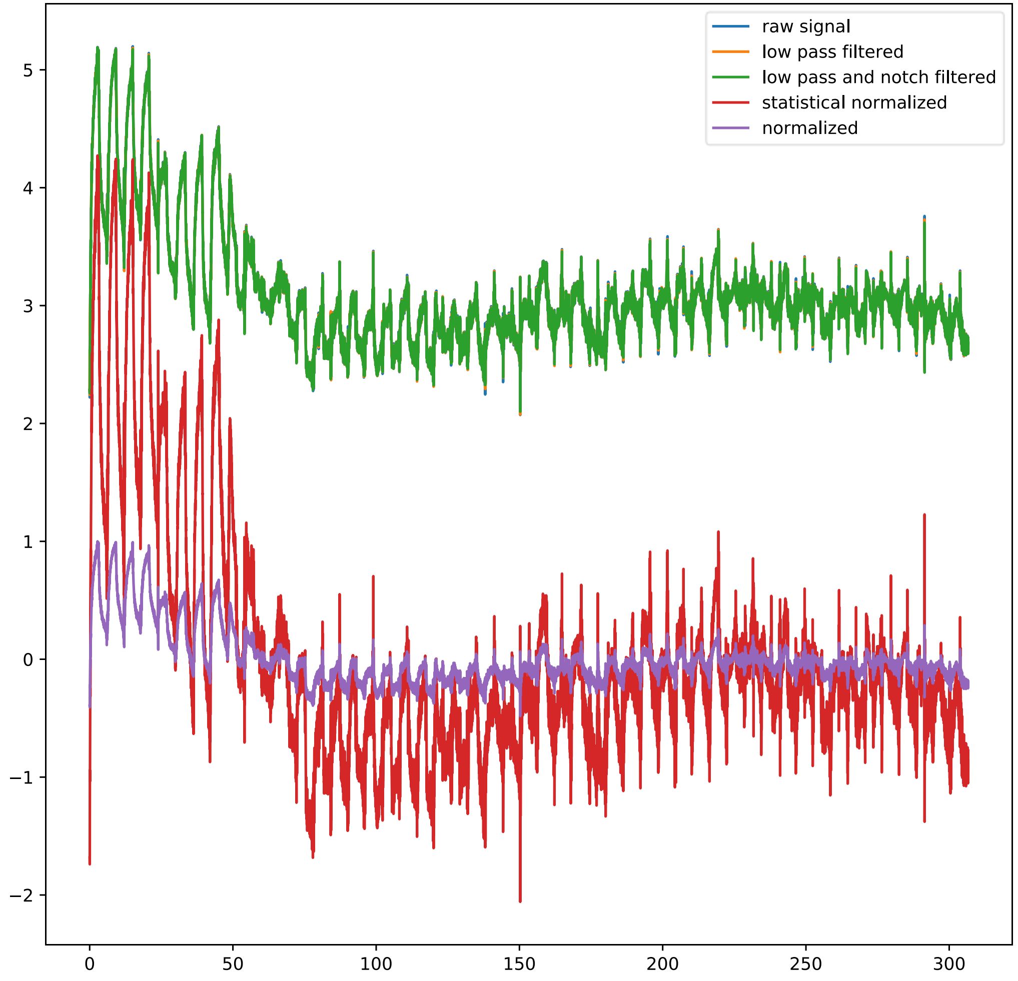


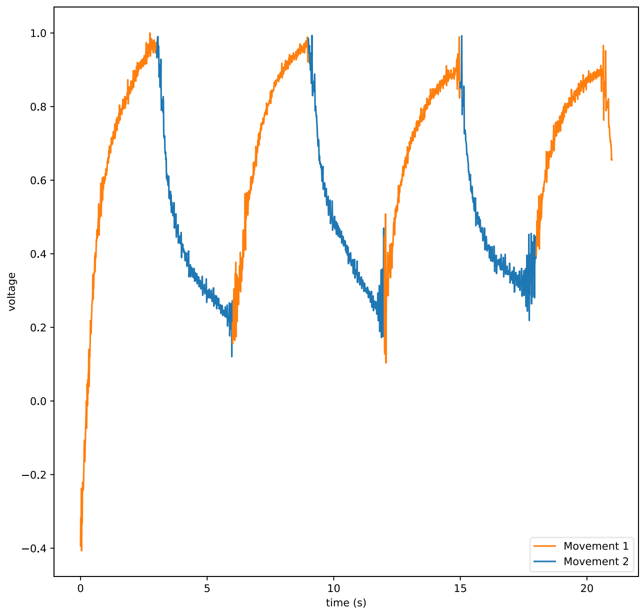
Figure: Filtered and normalized signals

Processing Module

3. Segmentation:

- **Full segements:** Extract labeled samples from the recording sessions by the means of camera data.
- **Partial Segments:** From the full semgents extract subsegments of 200ms.

Figure: Label and preprocessed EMG data



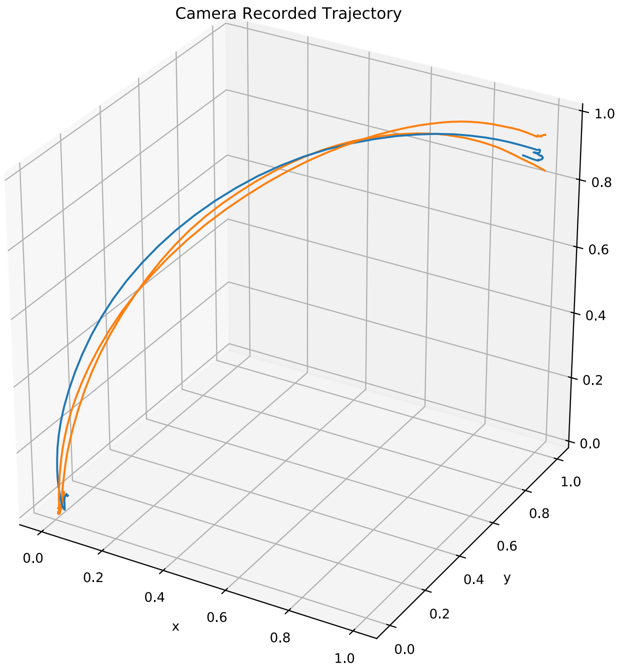
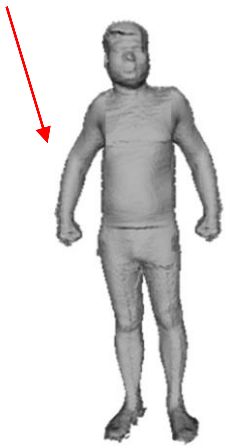


Figure: 3D Representation of Marker Trajectory (Camera data)

Processing Module

Challenge:



Movement 3

VS.

Movement 5

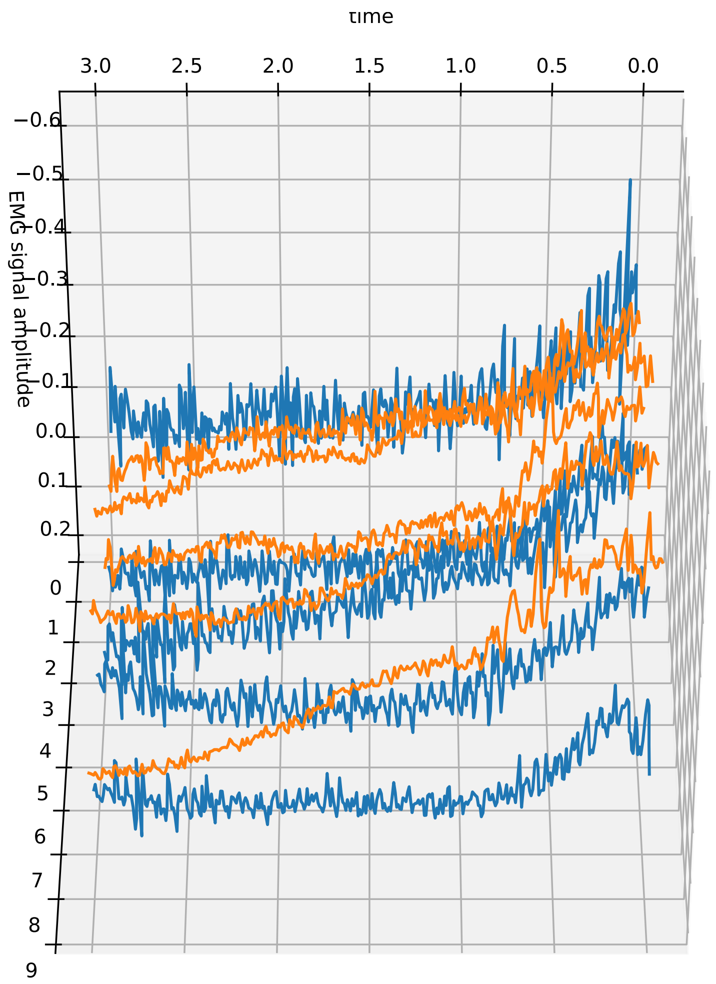


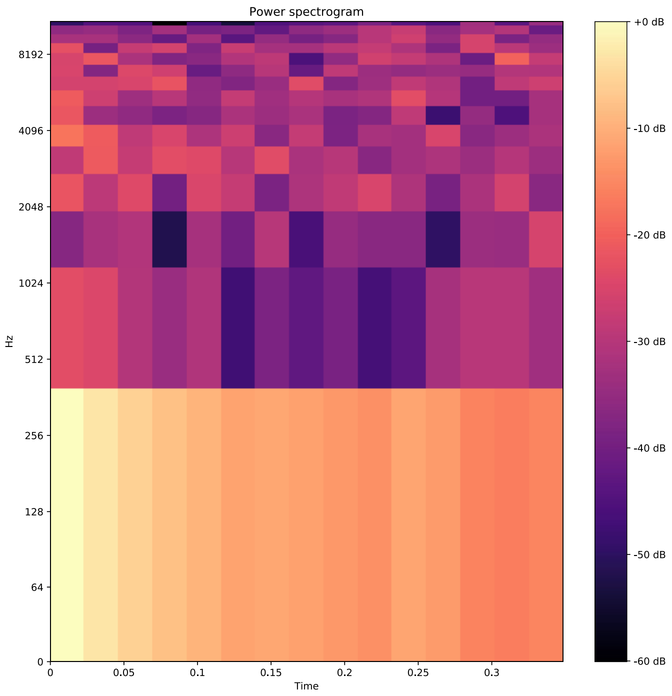
Figure: 3D representation of EMG signals associated to class 3 and 5.

Processing Module

4. Features Extraction:

- **TD features:** Mean Absolute Value, Mean Root Square, Variance, Slope Sign Change, maximum amplitude, minimum amplitude
- **Spectrograms (TD/FD combination):**

Figure: Spectrogram of a random sample from the class 2.



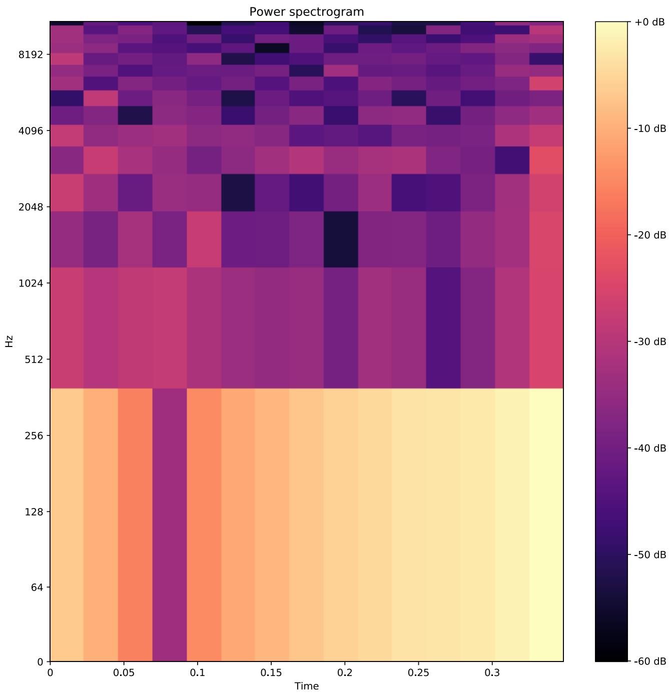
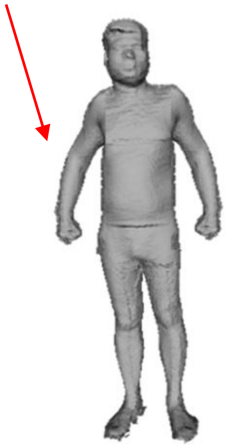


Figure: Spectrogram of a random sample from the class 4.

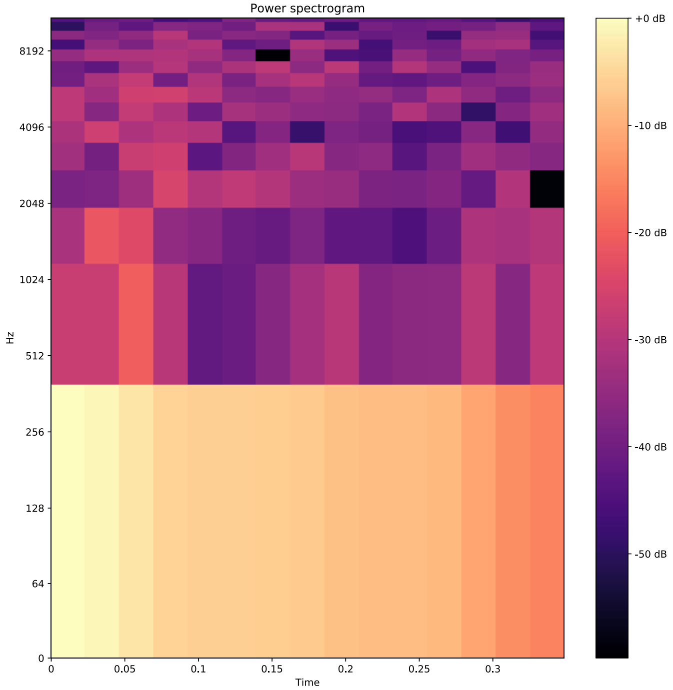
Processing Module

Again Challenge:

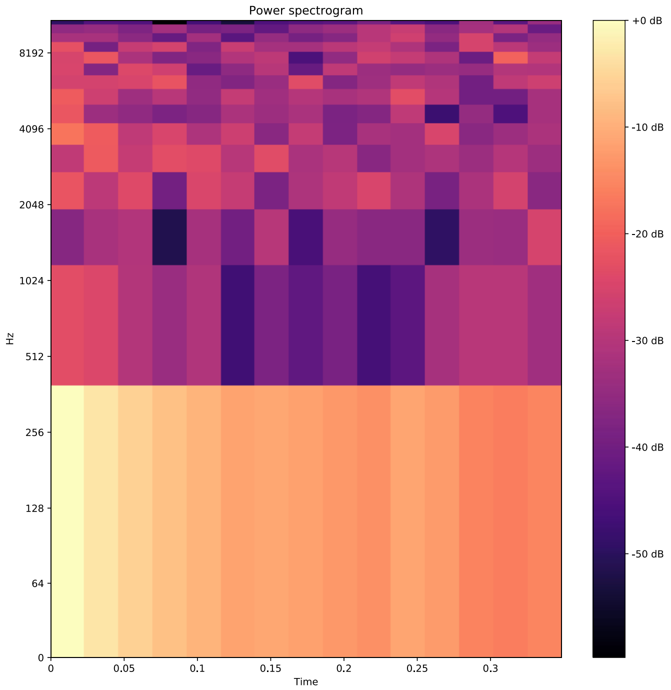


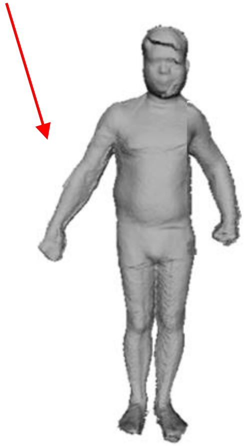
Movement 3

Figure: Label and preprocessed EMG data



VS.





Movement 5

Figure: Label and preprocessed EMG data

Processing Module

Input: RAW EMG and Camera Signals **Output:** Processed and labeled EMG samples

"full-segments dataset" (#636 @ 3s per sample)

"partial-segments dataset" (#3180 @ 200ms per sample)

"TD features dataset"

"spectrograms dataset"

Recognition Module

Support Vector Machine

1. Dimensionality Reduction: Principle Component Analysis (PCA)

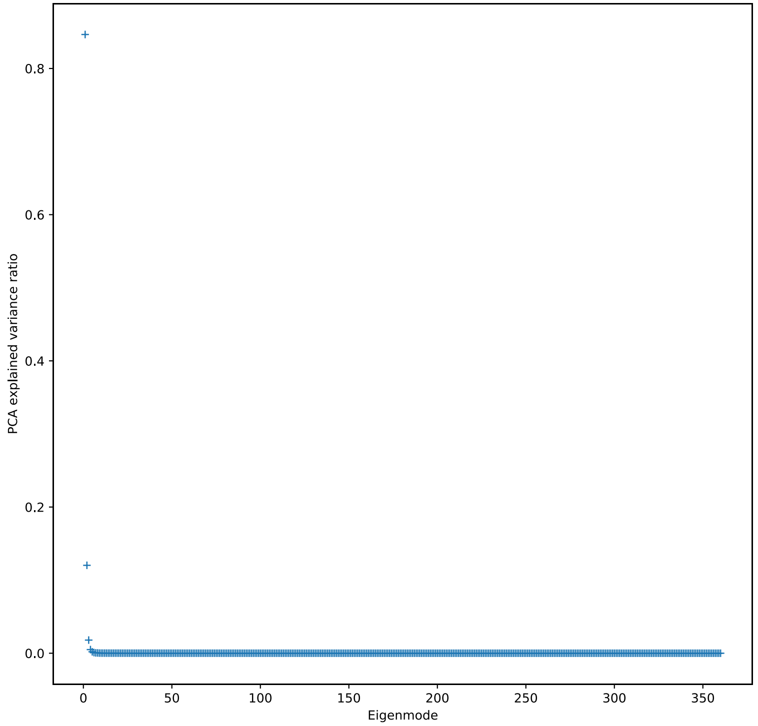


Figure: Full explained variance ratio

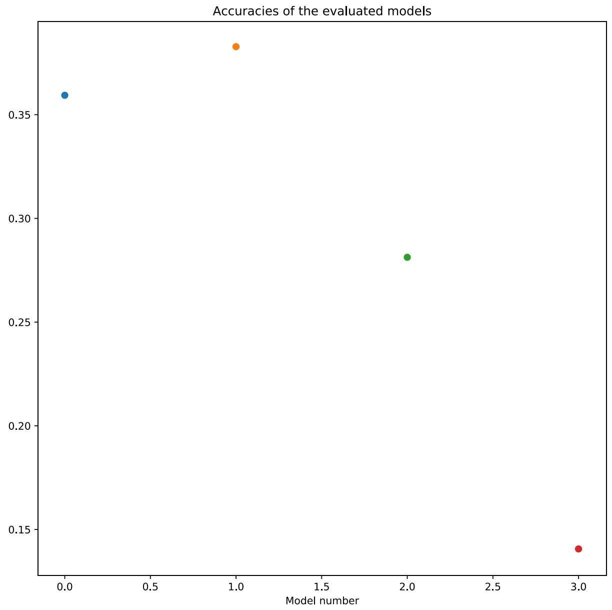
2 Principle Components preserved

Recognition Module

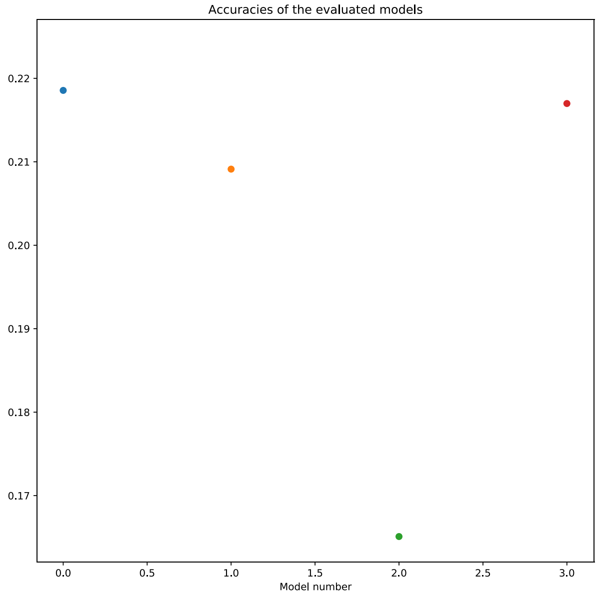
Support Vector Machine

2. Training and Evaluation

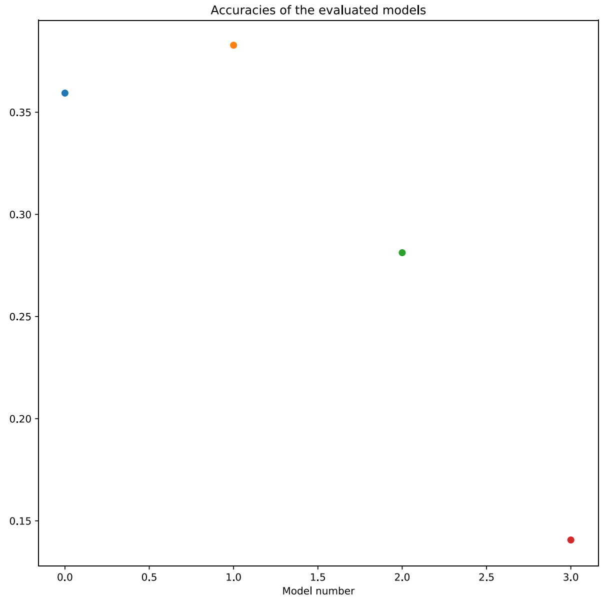
- Train on the 4 dataset types
- Hyperparameter Tuning: Kernel function (linear, RBF, poly, sigmoid)



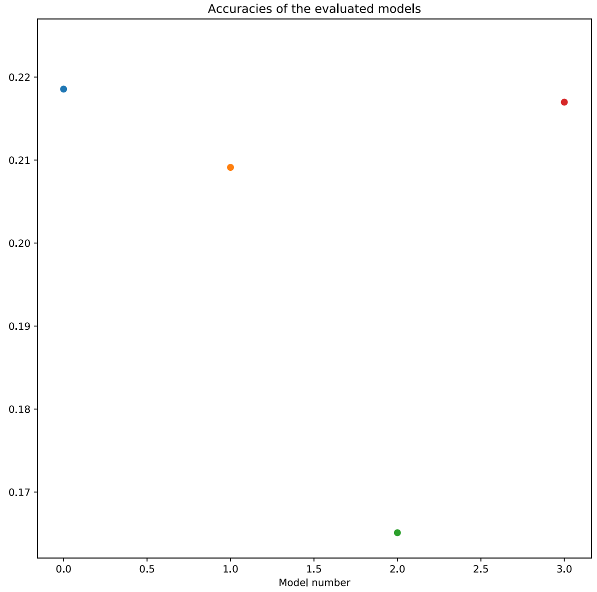
Full segments dataset



Partial segments dataset



TD features dataset



Spectrograms

Recognition Module

Support Vector Machine (SVM)

2. Training and Evaluation

Data-set	Kernel	Accuracy
Full segments	RBF	**38.28%**
Partial segments	Linear	21.85%
TD features	Linear	16.41%
Spectrograms	Sigmoid	17.96%

Table: SVM achieved accuracies

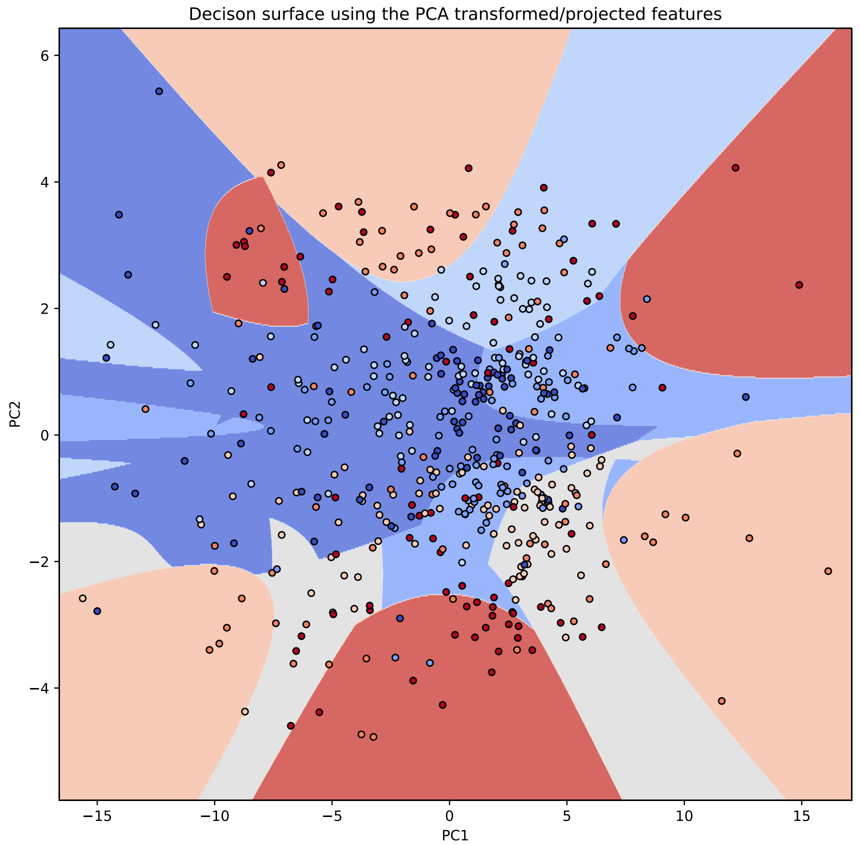


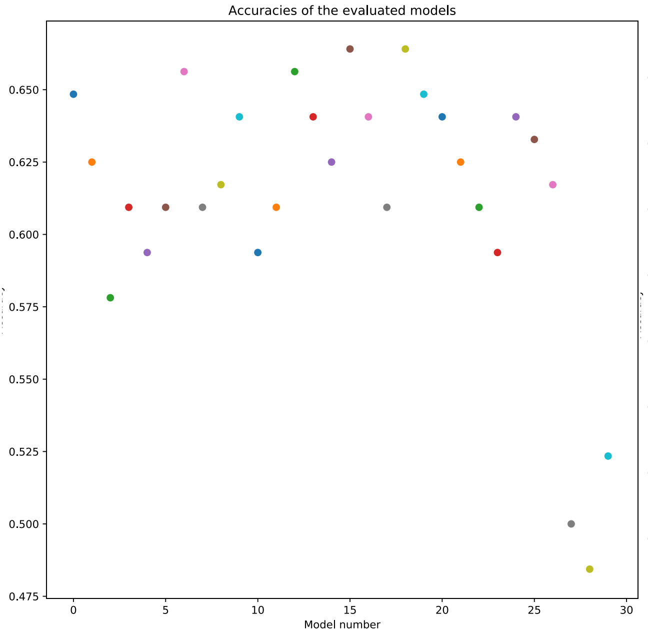
Figure: Best SVM model decision boundaries

Recognition Module

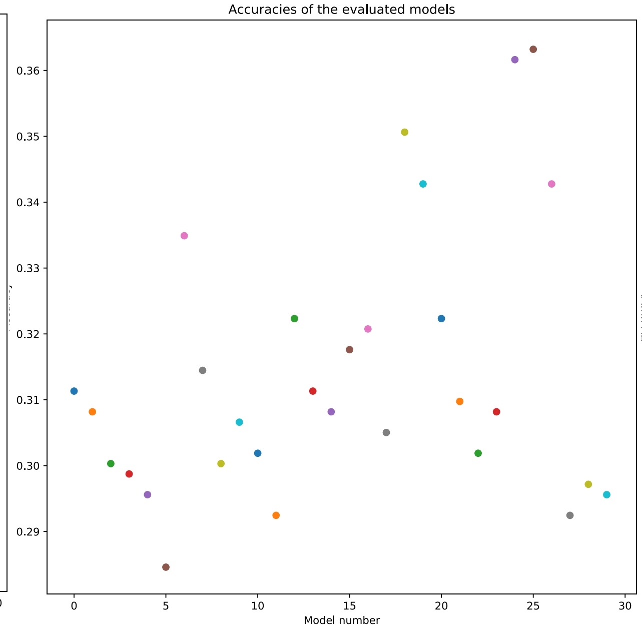
Multilayer Perceptron (MLP)

1. Training and Evaluation

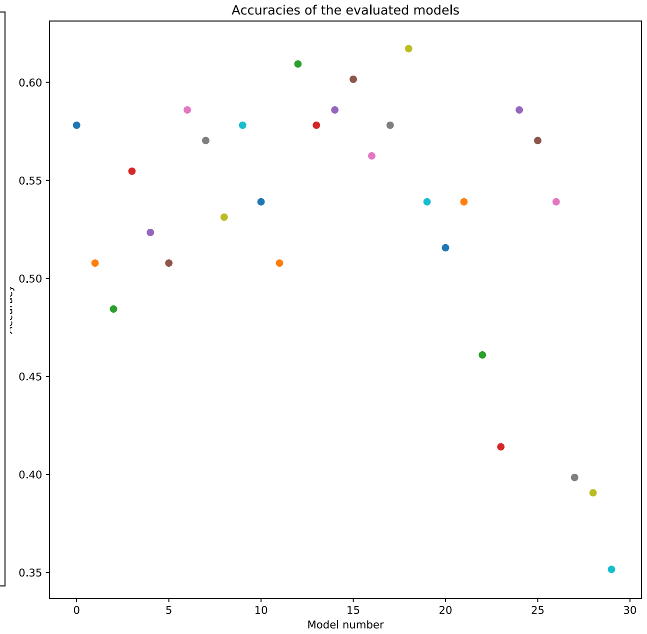
- Train on the 4 dataset types
- Hyperparameter Tuning: Number of Neurons, dropout rate, batch size



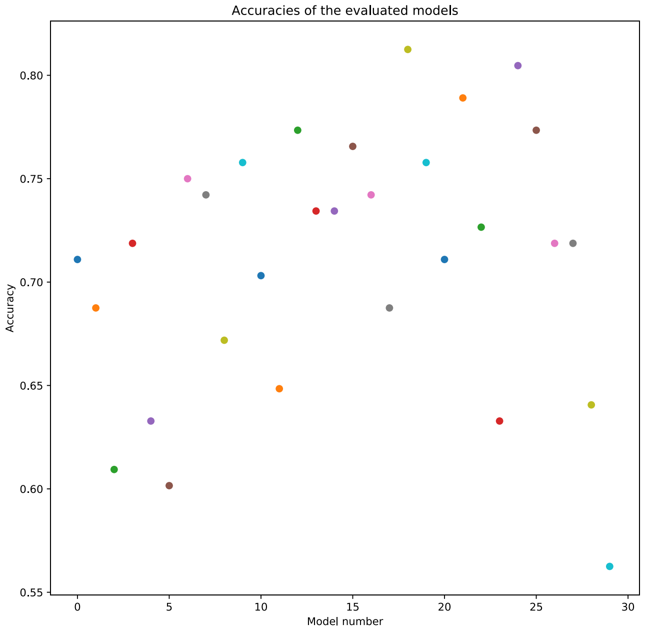
Full segments dataset



Partial segments dataset



TD features dataset



Spectrograms

Recognition Module

Multilayer Perceptron (MLP)

1. Training and Evaluation

Data-set	Number of Neurons	Dropout	Batch Size	Accuracy
Full segments	256	0.5	32	66.40%
Partial segments	64, 32, 16	0.2	64	36.32%
TD features	64, 32	0.2	32	61.71%
Spectrograms	64, 32	0.2	32	**81.25%**

Table: MLP achieved accuracies

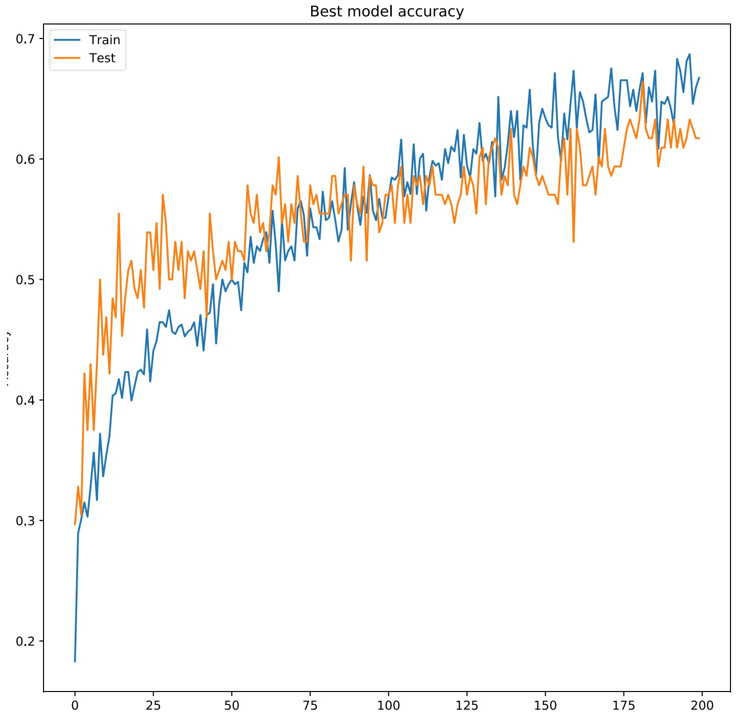


Figure: Best MLP model training and test accuracies

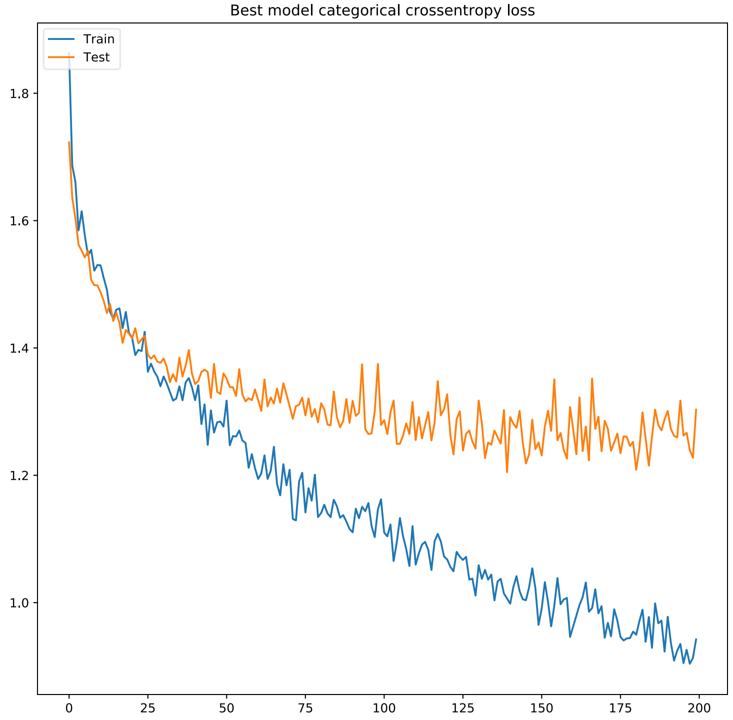


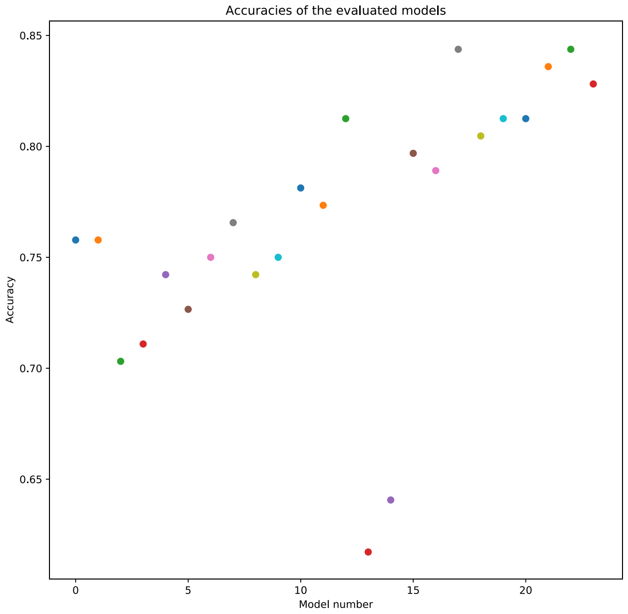
Figure: Best MLP model training and test loss

Recognition Module

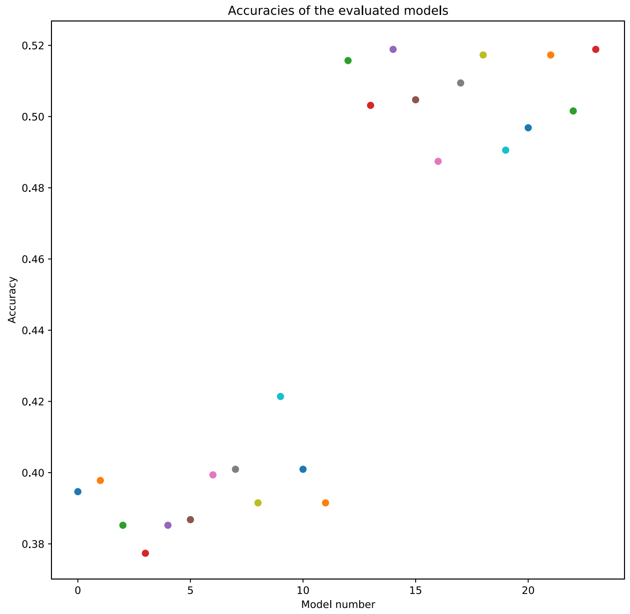
Convolutional Neural Network (CNN)

1. Training and Evaluation

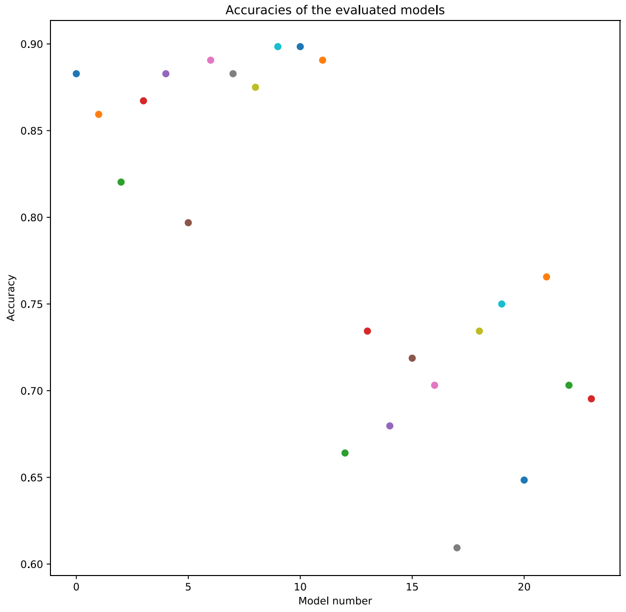
- Train on the 3 dataset types (TD features dataset is not relevant).
- Hyperparameter Tuning: # filters, kernel size, pooling size, # neurons, dropout, batch size



Full segments dataset



Partial segments dataset



Spectrograms

Recognition Module

Convolutional Neural Network (CNN)

1. Training and Evaluation

Data-set	Number Filters	Kernel Size	Pooling Size	Number Neurons	Dropout	Batch Size	Accuracy
Full segments	64, 32, 16	3	2	512	0.5	64	84.43%
Partial segments	64, 32, 16	3	2	512	0.5	128	51.88%
Spectrograms	64	3	2	512	0.5	64	**89.84%**

Table: CNN achieved accuracies

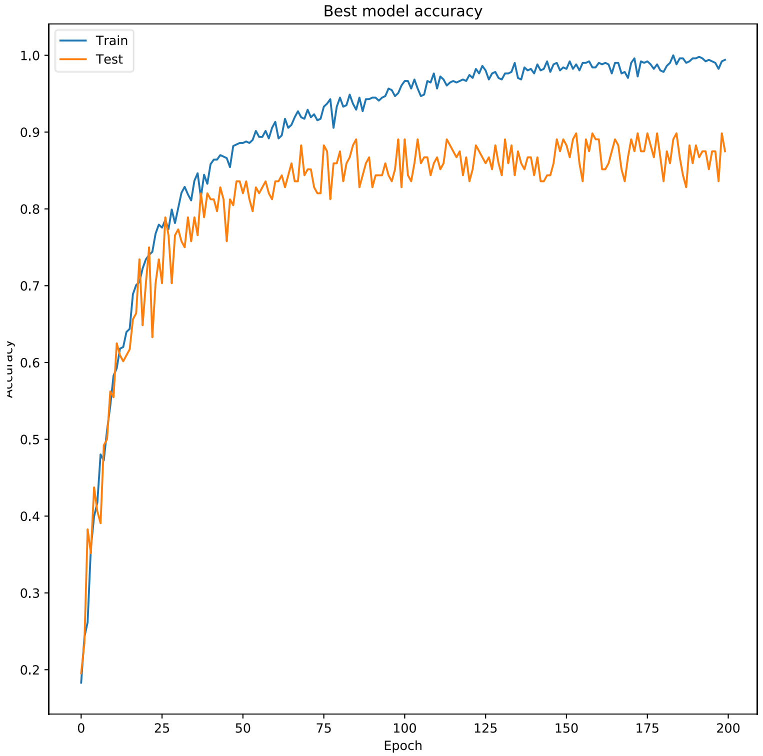


Figure: Best CNN model training and test accuracies

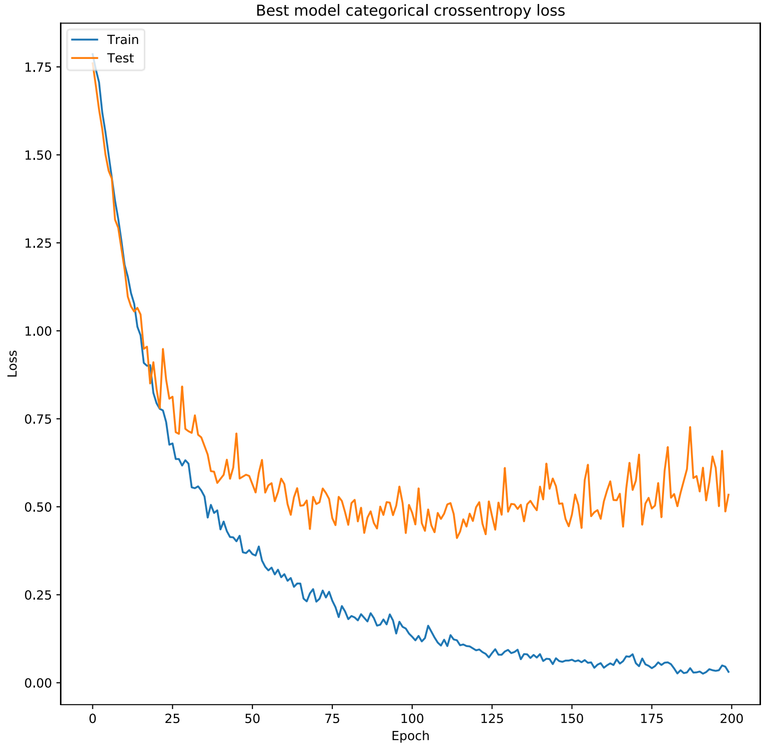


Figure: Best CNN model training and test loss

Recognition Module

Long-Short-Term Memory (LSTM)

1. Training and Evaluation

- Train on the 3 dataset types (TD features dataset is not relevant).
- Hyperparameter Tuning: # units, dropout, # neurons, batch size

Data-set	Number of Units	Dropout	Number of Neurons	Batch Size	Accuracy
Full segments	64	0.5	64	32	28.90%
Partial segments	32	0.2	64	128	25.00%
Spectrograms	64	0.2	64	64	**82.03%**

Table: LSTM achieved accuracies

Recognition Module

Input:

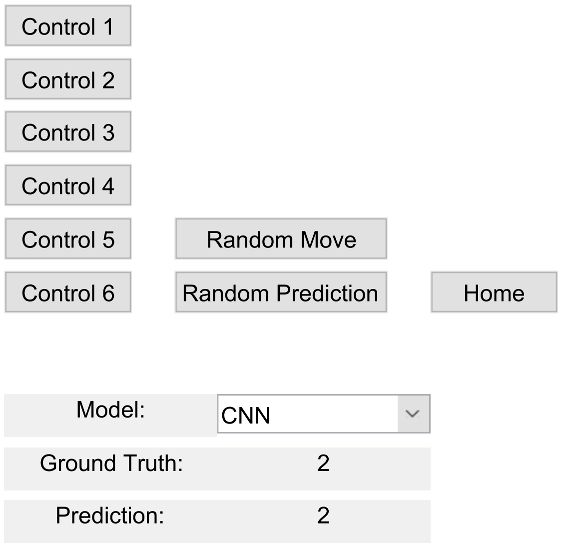
Processed and labeled EMG samples

Output:

Predicted Movement Class

Simulation Module

1. **Robot arm model selection**
   - 6DoFs, PUMA robot of Walla University.
2. **Robot kinematic and inverse kinematics Solvers**
   - From joint-angles to 3D target coordinates and vice-versa.
3. **Control panel construction**
   - GUI for visualizations.
4. **Link of the classifiers with the simulator**
   - Predictions of samples from the test-set

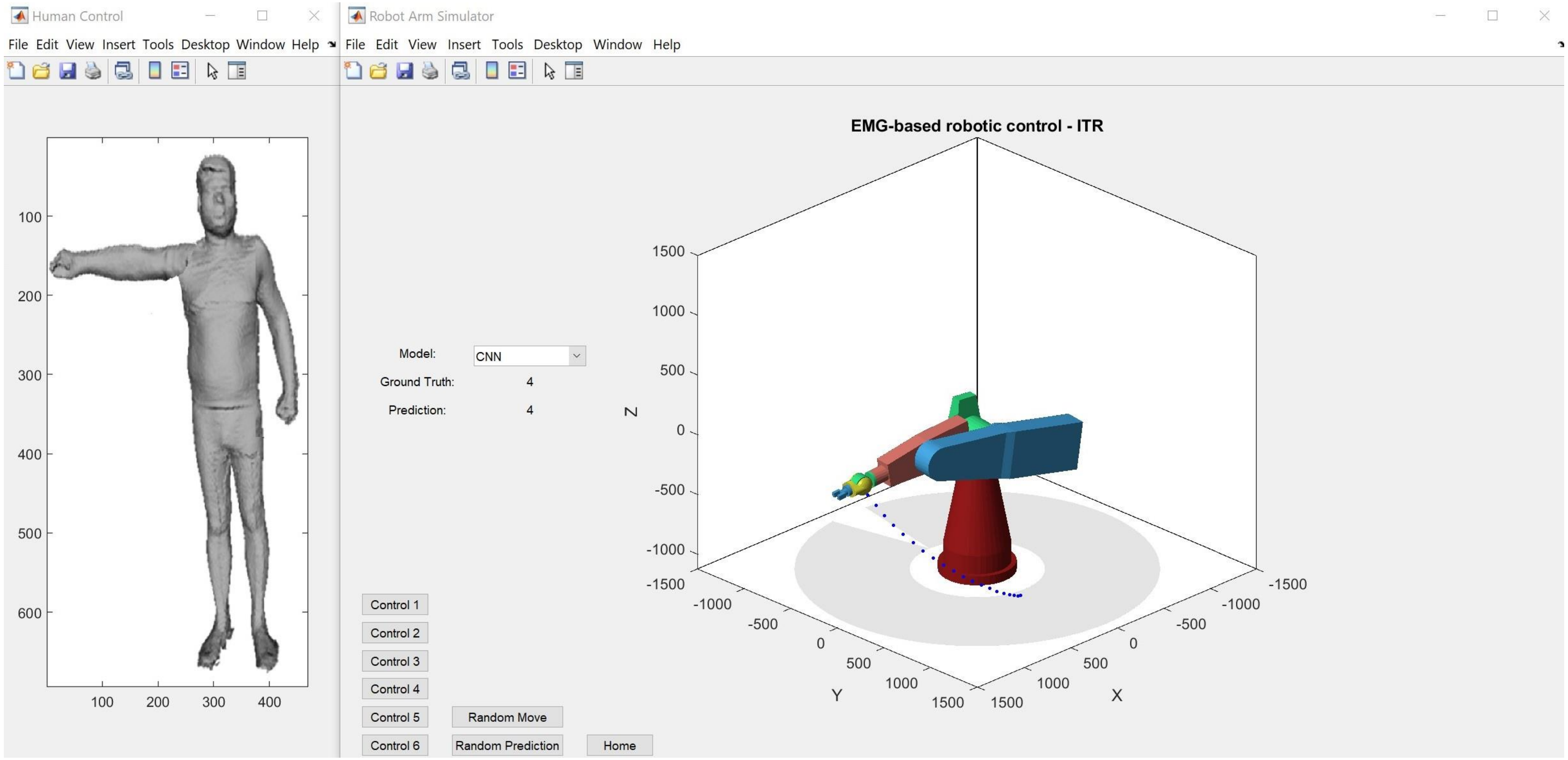


Simulation Module

Input:
RAW EMG samples
Output:
Robot joint positions

Simulation Module

DEMO



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