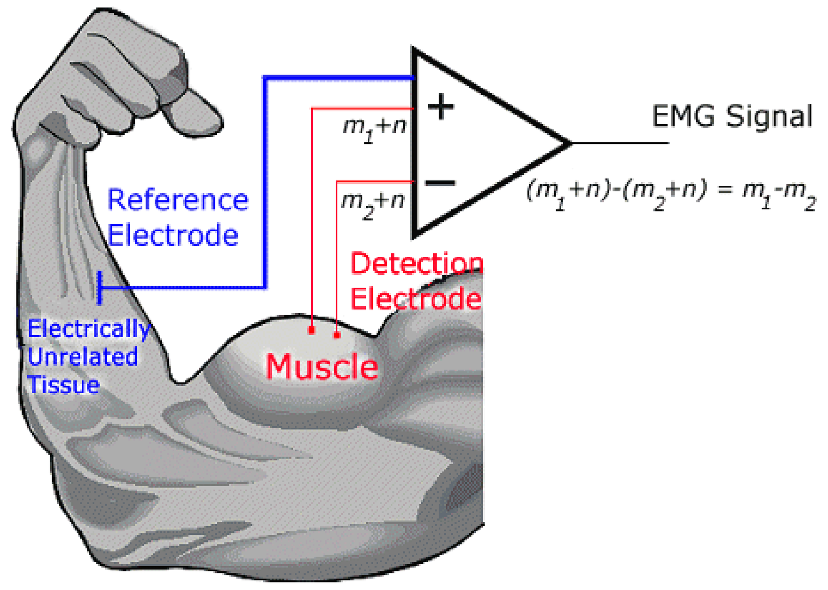
Classification of Hand Gestures using Surface Electromyography Signals for Upper Limb Amputees

Greg Luppescu, Michael Lowney, Raj Shah

Stanford University

MOTIVATION

Approximately 38 to 50 percent of patients with upper-limb amputations discontinue use of their prosthetic because the cost of carrying it outweighs its (limited) usage. After a patient loses a limb, they still contain all the necessary nerves to control their non-existing limb. By using EMG to measure the electrical signals sent through these nerves, amputees can potentially control a robotic prosthetic in the same way that they once controlled their original limb.



DATASET & FEATURES

- Our dataset consists of raw EMG signals recorded from four transradial amputees.
- The subjects performed 6 different hand gestures at 3 different force levels. Ten channels were used per subject.
- Eighteen features were used to classify signals. Six features were Time Dependent Power Spectrum Density (TD-PSD) features, three features were from the frequency domain, and nine were from the time domain.

$$\overline{m}_0 = \sqrt{\sum_{j=1}^{N-1} x[j]^2}$$

$$\overline{m}_2 = \sqrt{\sum_{j=1}^{N-1} (\Delta x[j])^2}$$

$$\overline{m}_4 = \sqrt{\sum_{j=1}^{N-1} (\Delta^2 x[j])^2}$$

$$m_i = \frac{\overline{m}_i \lambda}{\lambda}$$

TD-PSD

(1)	$log(m_0)$
(2)	$log(m_0 - m_2)$
(3)	$log(m_0 - m_4)$
(4)	$log\left(\frac{m_0}{\sqrt{m_0-m_2}\sqrt{m_0-m_4}}\right)$
(5)	$\frac{m_2}{\sqrt{m_0 m_4}}$
(6)	$log\left(\frac{\sum_{j=1}^{N-1} \lvert\Delta x\rvert}{\sum_{j=1}^{N-1} \lvert\Delta^2 x\rvert}\right)$

Time Domain

(7) Mean Absolute Value
(8) Integrated EMG
(9) Variance
(10) RMS
(11) Waveform Length
(12) Log Detector
(13) Slope Sign Change
(14) Wilson Amplitude
(15) Zero Crossing

Frequency Domain

(16) Mean Frequency
(17) Median Frequency
(18) Modified Mean Frequency

METHODOLOGY

Raw Data → Filtering & Windowing → Feature Extraction → Feature Selection → Training → Classification → Output Gesture

Filtering & Windowing

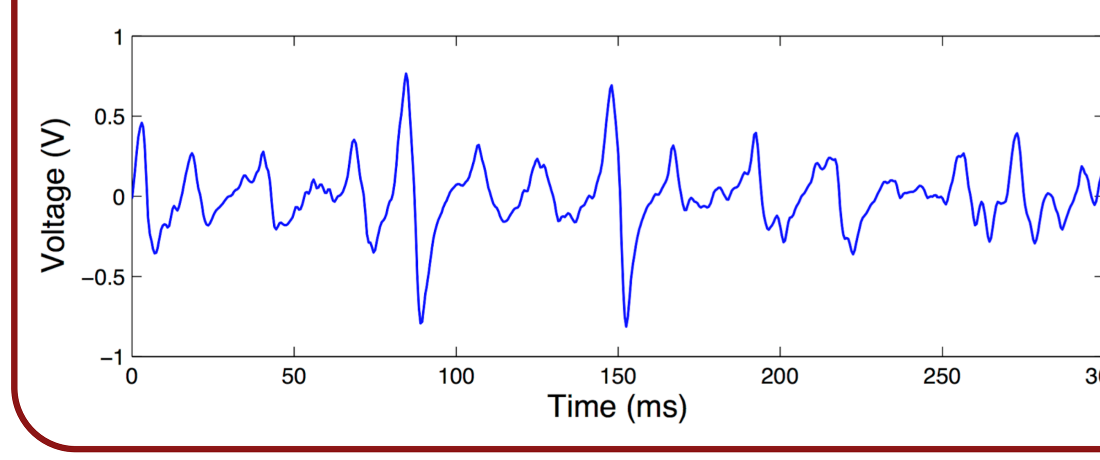
- A cascade of five filters – 20Hz high-pass filter, 450Hz low-pass filter, notch filters with stop bands centered at 50Hz, 150Hz, & 250Hz.
- EMG signals were segmented into windows of length 300ms with 50% overlap.

Feature selection

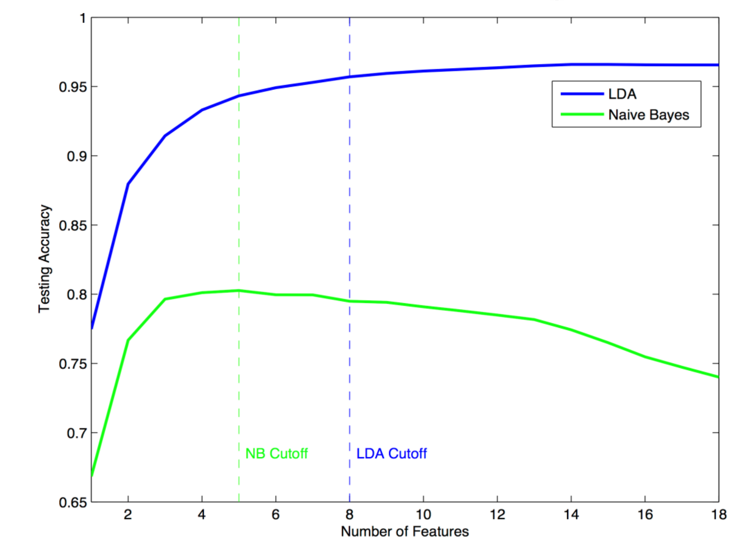
- A forward feature selection with 5-fold cross validation was run on each subject. A voting scheme was used to find the best features across all subjects.

Testing Procedures

- *NO FORCE* - classify the movement (6 classes)
  FORCE - classify both movement and force (18 classes)
- Classifiers were trained for each person individually, and the results were averaged across the four subjects.



$\to \mathbb{R}^{18} \to$



$\to \mathbb{R}^{k}$

RESULTS

Linear Discriminate Analysis

Features used – 1, 6, 10, 4, 11, 5, 3, 8

Procedure	Training accuracy	Testing accuracy
NO FORCE	96.53%	96.18%
FORCE	93.99%	93.11%

94.78	0.20	3.65	1.38	0.00	0.00
0.09	95.99	0.17	0.35	3.40	0.00
4.82	0.00	94.78	0.41	0.00	0.00
0.52	0.21	0.42	97.72	0.93	0.21
0.42	2.35	0.00	2.44	94.70	0.08
0.10	0.39	0.00	0.00	0.10	99.42

Confusion matrix for *NO FORCE procedure*

Naïve Bayes Classifier

Features used – 6, 5, 14, 1, 3

Procedure	Training accuracy	Testing accuracy
NO FORCE	79.09%	78.65%
FORCE	77.59%	76.86%

76.47	3.12	12.21	5.57	2.54	0.10
0.61	80.35	2.98	1.84	11.67	2.54
18.28	0.40	75.62	4.30	1.30	0.10
4.36	1.17	2.02	79.81	11.69	0.96
2.03	8.21	1.18	8.97	77.33	2.28
1.75	3.10	1.45	1.75	4.27	87.68

Confusion matrix for *NO FORCE procedure*

Multi-Class SVM

Features used – 11, 3, 1, 4, 10, 7, 5

Procedure	Training accuracy	Testing accuracy
NO FORCE	100%	88.76%
FORCE	99.94%	86.53%

81.75	0.23	1.52	0.12	7.49	8.89
0.00	89.18	0.11	0.22	4.86	5.63
0.49	0.12	83.97	0.49	8.69	6.24
0.50	0.00	0.87	90.67	4.10	3.86
0.48	0.83	0.00	1.43	91.20	6.06
0.12	0.12	0.12	0.00	9.42	90.21

Confusion matrix for *NO FORCE procedure*