Fine muscular activity recognition using Electromyography

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Outline

- What is Electromyography?
- A little Biology.
- Surface EMG (sEMG) Signal
- Classifying sEMG.
- Myoelectric Control strategies.
- Our approach in fine muscular activity recognition.

Electromyography

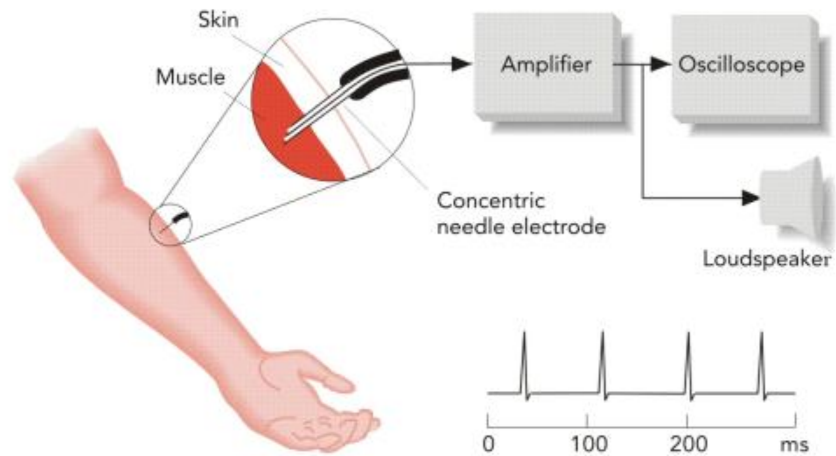
- Medicinal electro-diagnostic technique for measuring and evaluating the **electrical output (action potential)** of skeletal muscles.

- Signals can be analyzed to detect medical abnormalities, activation levels, recruitment order, or to analyze the the biomechanics of human or animal environment.

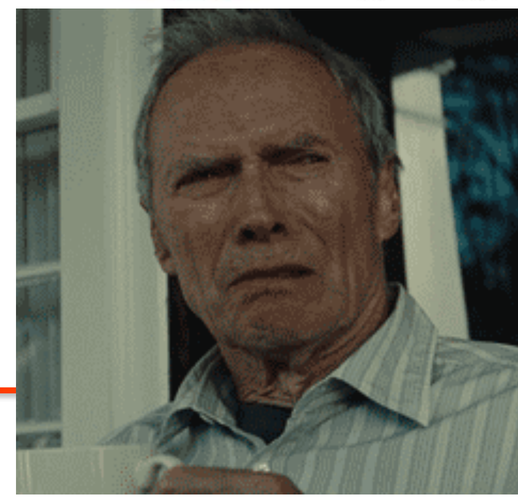
- **Two** types:
  1. **Intramuscular EMG**
  2. **<u>Surface EMG</u>**

Intramuscular EMG

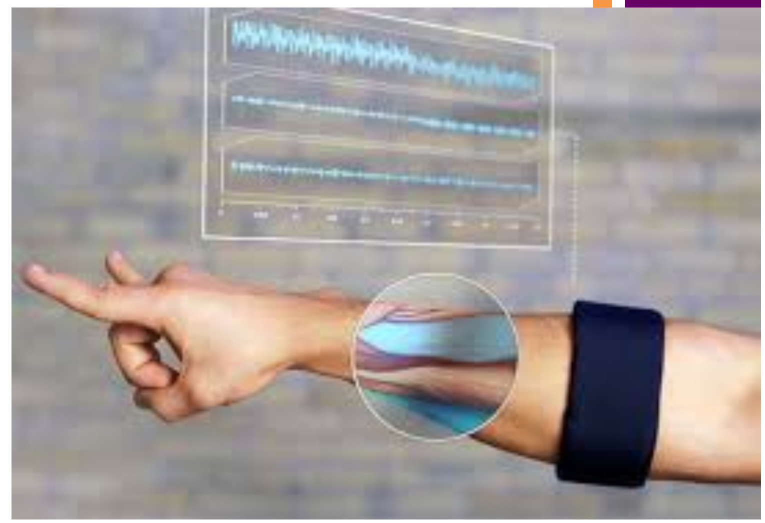
- Typically performed using **monopolar needle electrode**
  - A fine wire inserted into a muscle with a surface electrode for reference, **or**
  - Two fine wires inserted into the muscle referenced to each other.
- Need pre-injections and skin preparations.
- **Less noise**



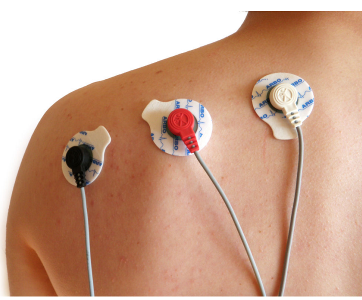
Invasive, painful.



Surface EMG (sEMG)



- Surface electrodes only provide a limited assessment of the muscle activity.
  - Array of electrodes typically used
- Signal is a **<u>composite</u>** of all the muscle fiber action potentials occurring in the muscles underlying the skin.
- **Prone to noise, artifacts**
- **Non-invasive**



Muscles

- Composed of bundles of **specialized cells** that are responsible for <u>contraction</u> and <u>relaxation</u>.
  - Generate forces, movements, & ability for expression.
- 4 main functions of muscles:
  1. Produce motion.
  2. Moving substance w/i body.
  3. Stabilization.
  4. Generate heat.

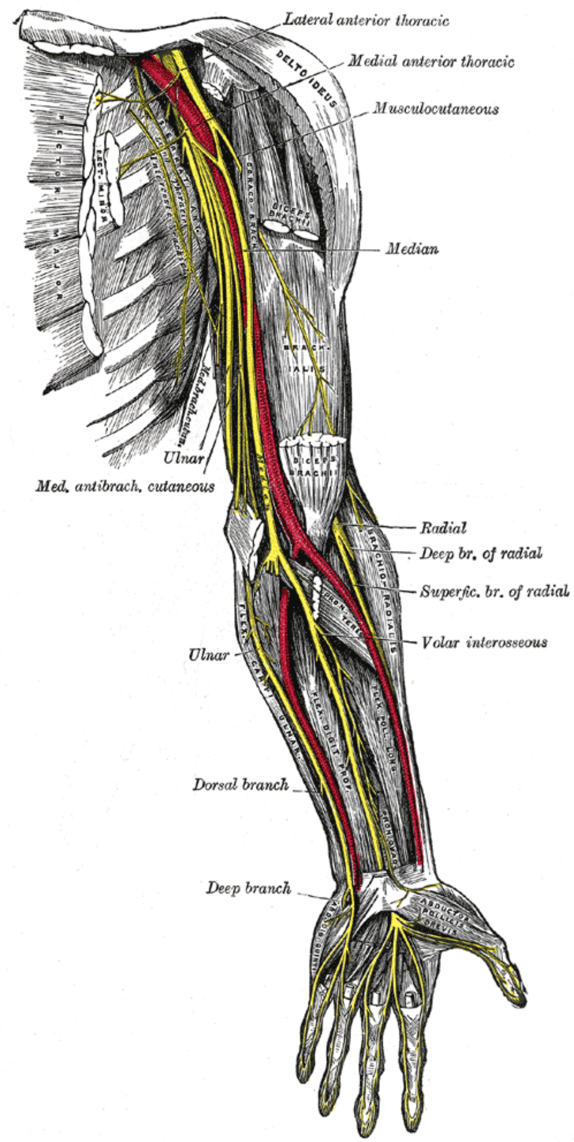
Muscles

- **3 types of muscle tissue**:
  1. Skeletal muscle.
  2. Smooth muscle.
  3. Cardiac muscle.

- **Skeletal muscles** are a form of muscle tissue that is under the control of the somatic nervous system.
  - Voluntarily controlled.

- Attached to the bone by bundles of collagen fibers, known as **tendons.**

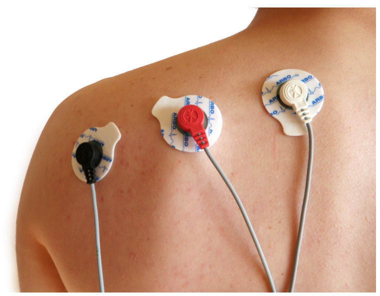
- **When muscles contract and relax, they release a tiny bioelectric pulse called the Action Potential**

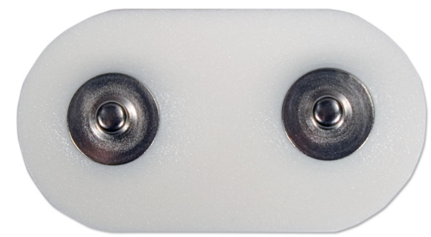


WiSeR
Wireless System Research Group

sEMG Electrodes

- Electrodes measuring the sEMG signal form an **emg channel**.
- 3 main types:
  - Bipolar configuration
  - Monopolar configuration
  - Laplacin configuration



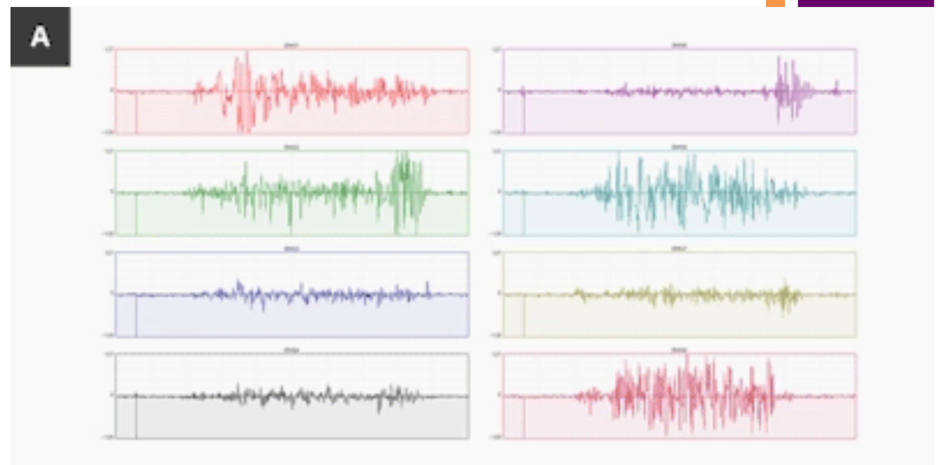


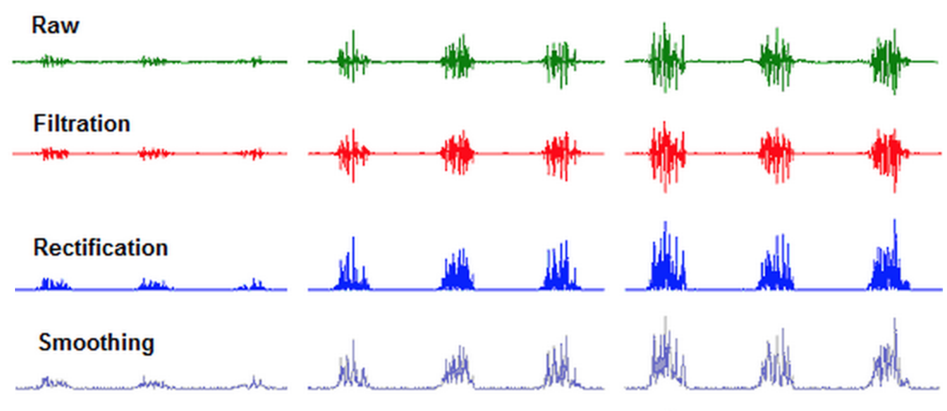
- **One channel** bipolar derivation typical.
- Recent interest has also increased toward **high-density sEMG (HD-sEMG).**

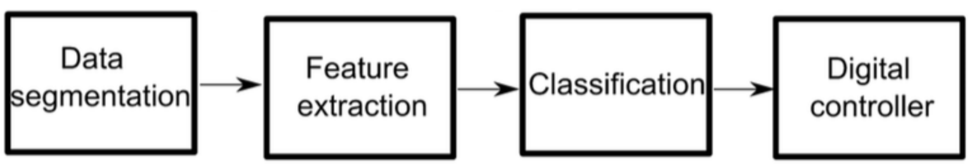
sEMG Signal

- Raw EMG signals typically come in a somewhat useless form.

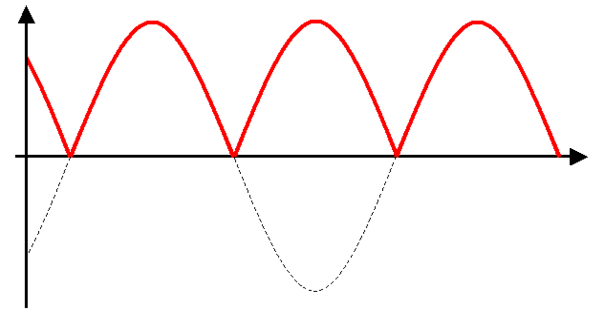
- Before beginning pattern recognition, several steps are typically followed:
  1. Cleanup
  2. Segmentation
  3. Analysis & preprocessing





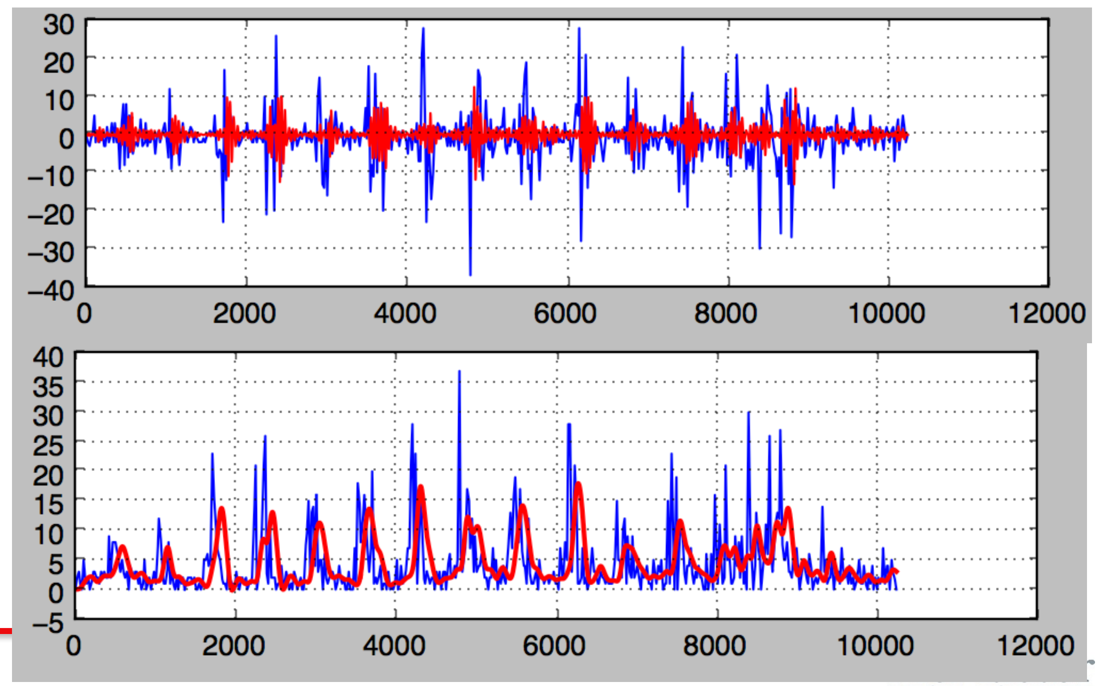


sEMG Signal Cleanup



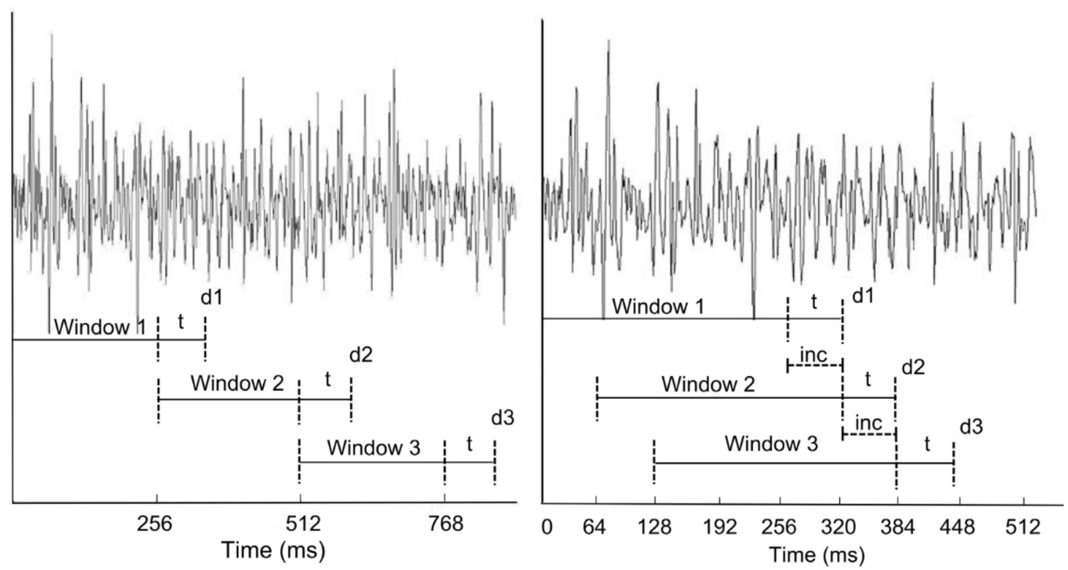
- Consists of several sub-steps:

  1. Filtration & De-noising.
     - LPF most typical
     - HPF or Bandpass also used.
     - Wavelet Transforms
  2. Rectification.
     - Half wave.
     - Full wave.



sEMG Signal Segmentation

- Two windowing techniques:
  1. Overlapped windowing
  2. Adjacent windowing



Features

- Features selected can have <u>higher</u> effect on classification accuracy than classifier type.
- 3 qualities determine quality of feature space:
  1. Maximum class separability.
  2. Robustness
  3. Computational complexity

	Mathematical definition
Time domain features	
Energy and complexity information methods	
Mean absolute value	$MAV = \frac{1}{N}\Sigma_{i=1}^{N}\lvert x_i\rvert$
Integrated EMG	$IEMG = \Sigma_{i=1}^{N}\lvert x_i\rvert$
Variance	$VAR = \frac{1}{N-1}\Sigma_{i=1}^{N}x_i^2$
Root mean square	$RMS = \sqrt{\frac{1}{N}\Sigma_{i=1}^{N}x_i^2}$
Waveform length	$WL = \Sigma_{i=1}^{N-1}\lvert x_{i+1} - x_i\rvert$
Log detector	$LOGDET = e^{1/N\Sigma_{i=1}^{N}\log(\lvert x_i\rvert)}$
Frequency information methods	
Zero crossing	
Wilson amplitude	$WAMP = \Sigma_{i=1}^{N-1}[f(\lvert x_n - x_{n+1}\rvert)]$
Slope sign change	$SSC = \Sigma_{i=2}^{N-1}[f(\lvert(x_i - x_{i-1}) \times (x_i - x_{i+1})\rvert)]$ where $f(x) = \begin{cases} 1, & \text{if } x \geq \text{throshold} \\ 0, & \text{otherwise} \end{cases}$
Prediction model methods	
Autoregressive coefficients	$x_n = \Sigma_{i=1}^{P} a_{i,n}x_{n-i}$, P = model order, $a_{i,n}$ = ith AR coefficient at time instant n
Cepstral coefficients	$c_n = -a_n - \Sigma_{k=1}^{n}\left(1 - \frac{k}{n}\right)a_k c_{n-k}$, $c_1 = -a_1$, c_n = nth cepstrum coefficient, a_i = AR coefficient
Time-dependence methods	
Mean absolute value slope	$MAVS_i = MAV_{i+1} - MAV_i$; $i = 1, \ldots, K-1$; K = number of segments covering the signal
Histogram of EMG	HEMG divides elements in the EMG signal into equally spaced segments and returns number of signal elements for each segment.
Frequency domain features	
Mean frequency	$MNF = \Sigma_{j=1}^{M} f_j P_j / \Sigma_{j=1}^{M} P_j$
Median frequency	$\Sigma_{j=1}^{MDF} P_j = \Sigma_{j=MDF}^{M} P_j = \frac{1}{2}\Sigma_{j=1}^{M} P_j$
Modified mean frequency	$MMNF = \Sigma_{j=1}^{M} f_j A_j / \Sigma_{j=1}^{M} f_j A_j$
Time-frequency domain features	
Short time Fourier transform	$STFT(k, m) = \Sigma_{r=1}^{N-1} x(r)g(r-k)e^{-j2\pi mi/N}$; g = window function; k = time sample; m = frequency bins
Continuous wavelet transform	$WT_x(\tau, a) = \frac{1}{\sqrt{a}}\int x(t)\Psi\left(\frac{t-\tau}{a}\right)dt$; t = translation parameter; a = scale parameter; Ψ = mother wavelet function
Discrete wavelet transform	DWT splits the signal into an approximation and detail coefficients by passing it through complementary low- and high-pass filters. The approximation coefficients are further split into a second-level approximation and detail coefficients. By repeating the process, one signal is broken down into many lower resolution components.
Stationary wavelet transform	SWT does not decimate the signal at each stage, avoiding the problem of nonlinear distortion of the DWT and WPT.
Wavelet packet transform	WPT is a generalized version of DWT that is applied to both low-pass results (approximations) and high-pass results (details).
Spatial domain features	
Experimental periodogram	$\gamma(h) = \frac{1}{2n(h)}\Sigma_{i=1}^{n(h)}[x(z_i) - x(z_i + h)]^2$; h = distance vector, $x(z_i)$ = measurement at location z_i. $n(h)$ = number of pairs h units apart in the direction of the vector h

EMG Features

- Raw sEMG signals typically mapped into smaller-dimension feature vectors.
- Classifiers perform faster.
  - Improves real-time properties of the system.
- Can be grouped into **4 categories:**
  - Time domain (TD) features
  - Frequency domain (FD) features
  - Time-frequency domain (TFD) features
  - Spatial domain (SD) features.

Optimal Features

- Little consensus on studies trying to find the optimal features for classification of sEMG signals
- Comparative studies show TD features achieve higher accuracy for LDA classifier.
  - TFD features outperform them for SVM.
  - TD features classified with LDA have been suggested as optimal for sEMG classification.
- Conclusions not reliable.
  - Made in low-noise lab environment.

Time domain (TD) features

- Most common feature group in sEMG signal classification.

- No mathematical transformations needed.
  - Fast calculations, suitable for real-time
  - Sensitive to noise and artifacts.

- Phinyomark et al. divided TD features into **4 main types**
  1. Energy and complexity information methods.
  2. Frequency information methods.
  3. Prediction model methods.
  4. Time-dependence methods.

Time domain (TD) Features

- Several attempts to determine the optimal TD feature vector for several classifiers.

- Most common combination: LDA classifier with Hudgin's feature vector
  - Mean absolute value (MAV)
  - Waveform length (WL)
  - Zero crossing (ZC)
  - Signal slope changes (SSC)

- Low computational complexity, high accuracy.

Frequency domain (FD) features

- Calculated from power spectral density (PSD).
  - Can be determined by firing rate of recruited motor units or morphology of MUAPs traveling along respective muscle fibers.
    - Depends on muscle being measured.

- Phinyomark studied the properties of 37 TD and FD features
  - TD features superior to FD features.
  - FD features computationally more complex, less accurate classification.
  - What about TD + FD feature vector?
    - Better than single TD feature vector.

Time-frequency Domain (TFD) Features

- Describe signal in both time and frequency domains simultaneously.

- Computationally more complex than TD features.
  - Implemented with fast algorithms.
  - Shown to be capable of meeting real-time requirements in sEMG classification using appropriate dimensional reduction and segmentation techniques.

- Yield high dimensional feature vector that requires dimensionality reduction to increase speed and accuracy of classification.

Time-frequency Domain (TFD) Features

- TFD features typically used in sEMG classification include:
  - Short time Fourier transforms (STFT)
  - Discrete wavelet transform (DWT)
  - Continuous wavelet transform (CWT)
  - Wavelet packet transform (WPT)
- STFT cannot increase both time and frequency resolution simultaneously.
- CWT, DWT, WPT overcome this somewhat.
  - Good frequency resolution and poor time resolution in low frequency band.
  - Bad frequency resolution and good time resolution in high frequency band.
  - DWT most popular due to being computationally more efficient

Spatial domain (SD) features

- Regions of muscle activated differentially.
  - Depends on the position of the joint and duration and strength of the contraction.

- HD-sEMG measurements have made it possible to extract spatial information from sEMG recordings.

- Improve differentiation between postures and force levels.
  - Provide information about MUAPs and load-sharing between muscles.

- Recently adopted, few studies investigated and designed SD features for this purpose.

Myoelectric Control Strategies in sEMG

- 2 control strategies:
  1. Pattern recognition based.
  2. Non-pattern recognition based.

- Pattern recognition based control uses classifiers.
  - Map feature vectors to desired commands
  - Allows more versatile control scheme than non-pattern recognition based control.

- Non pattern recognition based control compares value of single feature to predetermined threshold.

Pattern recognition-based control

- Relies on assumption:
  - Classifier is capable of recognizing input values introduced in training session and assign each input value to one of a given set of classes.
- Input: feature vectors calculated of the sEMG signal.
- Classes:
  - Different control commands sent to the device.
  - Different “poses” made by muscles.
- Comparative studies show most classifiers have similar classification accuracy.
  - Using appropriate feature sets and sufficient number of channels.
  - Best classifiers are fast to train, simple to implement, meet real-time contractions.
    - LDA, SVM, HMM
    - LDA most commonly used.

Non-pattern recognition-based control

- Simple structure.
  - Limitation: only so many commands can be recognized.
- Shown to provide intuitive interface for navigation menus, wheelchairs, and assistive robotics.
  - All of which require fewer commands than other applications, like prosthesis.
- Methods included in non-pattern recognition-based control:
  - Proportional control
  - Onset analysis
  - Finite state machines (FSM)

Fine muscular activity recognition

- Now we know the “magic” behind muscular signals and EMG.
  - We can begin to talk about what we are able to explore with this knowledge.

- Fine activity recognition is not yet a “hot topic” like EMG controls and regular activity recognition.
  - Easy to tell if someone is standing or sitting.
  - We do many activities with our fingers.
    - Typing, writing, eating, etc.
    - Many neuromuscular diseases show symptoms at the finger level
      - Parkinson’s, Muscular Dystrophy, MS, Carpel Tunnel

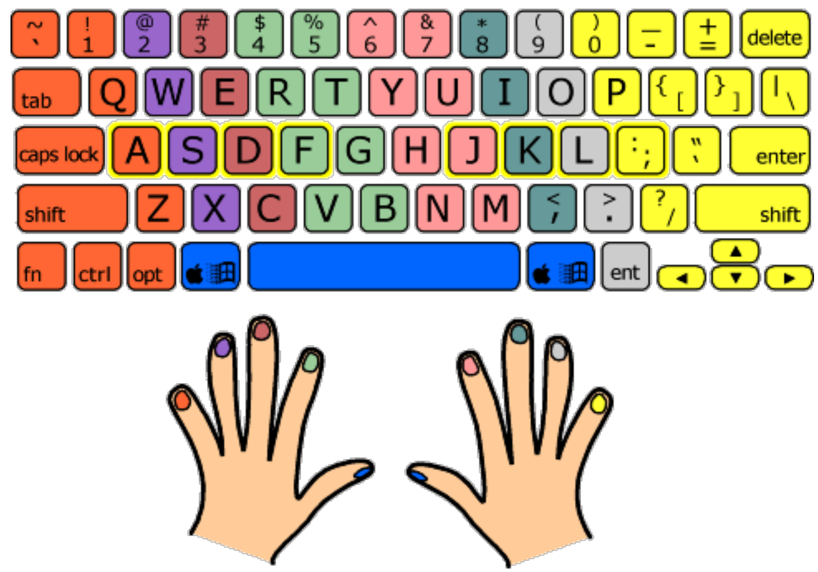
Overall structure

- We need to be able to:

Collect data → Extract Features → Classify → Predict finger

Myo Data Recognition

- While typing in a "naturalistic setting", is it possible to extract what fingers users are utilizing?
  - Allows for finger movement analysis
  - Unobstructive, uninvasive.
- Using standard QWERTY keyboard
  - Standard finger positioning
- Using **two** MYO armbands
  - Collecting EMG data at 200Hz
  - Collecting IMU data at 50Hz



Myo Data Recognition

- <u>EMG Features</u>
  - TD Features:
    - Mean Absolute Value (MAV)
    - Waveform Length (WL)
    - Slope Sign Changes (SSC)
    - Zero Crossings (ZC)
  - TFD Features:
    - EMG Short Time Fourier Transform
    - IMU Short Time Fourier Transform

Myo Data Recognition

- <u>IMU Features</u>
  - Average of acceleration for x, y, z axes.
  - Standard deviation of each x, y, z axes.
  - Average Absolute Difference.
  - Average Resultant Acceleration.

- These features don't tell us much about acceleration changes when typing, since the movements are mostly along one axis, and are very small in the grand scheme.
  - Other features still under consideration.

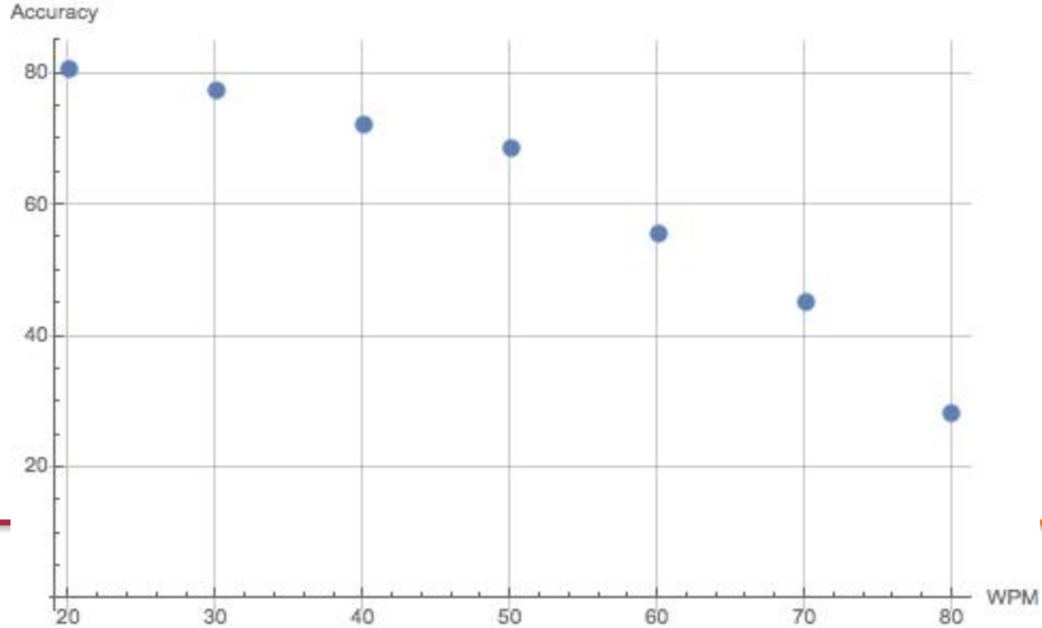
Conditions

- Wearing a Myo armband on each arm, user types out an article.
- Typing speed has to be slow, in order to get larger window sizes.
  - Approx. 20 words/minute or less
- User holds the key down when pressed for approx. **1 second.**

"Traditional" classification

<u>Results:</u>

- 50%-60% accuracy in identifying which finger was used at **normal** typing speed (~60 wpm).
- ~76% - 80% accuracy at **slow** typing speed (~20 wpm).
- Why?



Hierarchical classification

Collect data → Extract Features → Classify

Window data
- “chop” data up into windows

Typing activity
- Classify whether the user is typing or not.

Fingers used
- Once we know an activity is occurring, we can extrapolate fingers

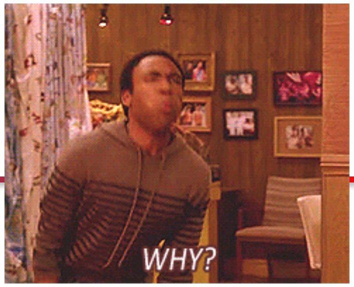
Hierarchical classification

- First check if typing activity is happening.
- If yes, classify finger.

<u>Results:</u>

- <u>Typing or not typing:</u>
  - Majority vote.
    - Window chopped into subwindows.
    - Subwindows are classified.
  - ~100% accuracy using <u>LDA</u>, <u>Perceptron</u>, and <u>SVM</u> regardless of typing speed.
- <u>Finger classification</u>
  - 55%-60% accuracy in identifying which finger was used at **normal** typing speed (~60 wpm).
  - ~78% - 82% accuracy at **slow** typing speed (~20 wpm).

- WHY?!?!?!



Culprit

- Muscle Action Potential at supinators/pronators rate is ~500Hz
- Myo claims sampling rate is ~200Hz, actually closer to ~150Hz.
- Window sizes may still be too small. Classification accuracy suffers.

Thank you

TD feature vectors used in sEMG interfaces

Feature vector	Classifier	Classification accuracy (%)	Classes	Bipolar electrodes	Subjects
MAV, WL, ZC, SSC	SVM	96	6	4	11H
MAV, WL, ZC, SSC, AR6	LDA	97	10	3	12H
MAV, WL, ZC, SSC, AR6, RMS	GMM	97	6	4	12H
MAV, WAMP, VAR, WL	ANN	98	12	32	1H
MAV, WAMP, AR, CC	LDA	70[1], 78[2], 87[3]	4	2	8H
MAV, WL, AR, CC	LDA	70[1], 78[2], 88[3]	4	2	8H
WL, LOGDET, AR, CC	LDA	70[1], 78[2], 88[3]	4	2	8H
SE, CC, RMS, WL	LDA	98	11	4	4H
IEMG, WL, VAR, ZC, SSC, WAMP	GRA	96	11	7	12H
AR6, MAV	LDA	98H, 79A	11	4	5H, 5A
AR6, ZC	LDA	97H, 75A	11	4	5H, 5A
AR6, SSC	LDA	97H, 74A	11	4	5H, 5A
AR6, WL	LDA	98H, 79A	11	4	5H, 5A
AR6, RMS	SVM	96	6	4	11H
AR, HIST	CKLM	93A, 97H	8	3	2A, 1H