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 biomechanics of human or animal environment.

- Two types:
  1. Intramuscular EMG
  2. Surface EMG
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 **composite** 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 **contraction** and **relaxation**.
  - Generate forces, movements, & ability for expression.

- 4 main functions of muscles:
  1. Produce motion.
  2. Moving substance w/i body.
  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**
sEMG Electrodes

• Electrodes measuring the sEMG signal form an emg channel.

• 3 main types:
  – Bipolar configuration
  – Monopolar configuration
  – Laplacian 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 higher effect on classification accuracy than classifier type.

• 3 qualities determine quality of feature space:
  1. Maximum class separability.
  2. Robustness
  3. Computational complexity
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

- **EMG Features**
  - 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

- **IMU Features**
  - 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

Results:
• 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.

Results:
• Typing or not typing:
  – Majority vote.
    • Window chopped into subwindows.
    • Subwindows are classified.
  – ~100% accuracy using LDA, Perceptron, and SVM regardless of typing speed.
• Finger classification
  – 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

<table>
<thead>
<tr>
<th>Feature vector</th>
<th>Classifier</th>
<th>Classification accuracy (%)</th>
<th>Classes</th>
<th>Bipolar electrodes</th>
<th>Subjects</th>
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