Classification and Diagnosis of Myopathy from EMG Signals

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Diagnosing Myopathy

- **Myopathy (muscle disease):** neuromuscular disorder causing muscle weakness due to dysfunctioning skeletal muscle fibers
- Many forms of myopathy identified
  - Some serious and often debilitating conditions (e.g., muscular dystrophy)
- Difficult to accurately diagnose and treat
  - Can be inherited or acquired
  - Multiple pathologies can be present
- Early detection can ease patient suffering and reduce medical expenses

**Gowers' sign:** patient uses arms/hands to reach an upright position due to weakness of the hip/thigh muscles common to several forms of myopathy
Our Contributions

- Proof of concept of a novel methodology for classification and diagnosis of myopathy from electromyograph (EMG) signals
- Frequency domain analysis of EMG signals measured at full muscle contraction
- Consider multiple subjects and multiple muscles
- DMMH paper results: classification of EMG traces from healthy patients vs. patients with myopathy
- Our recent results: predicting the severity of myopathy from EMG signals
Intramuscular Electromyography (EMG)

Standard technique for diagnosing neuromuscular disease

Physician inserts an electrode into muscle tissue and observes electrical activity

Audible characteristics of EMG trace are diagnostic for different pathologies

Figure credit: adam.com
Laboratory Criteria Also Assist in Making the Diagnosis

Diagnosing Myopathy from EMG Measurements

Healthy Muscle

Motor Unit Action Potentials (MUAPs)

EMG signal w.r.t. muscle contraction

Muscle with Myopathy

Small, polyphasic MUAPs

EMG signal w.r.t. muscle contraction

Increased high frequency “noise”

Figure credits: Rowland, [2000]
Common Approach: MUAP Decomposition

Issues

- Assumes:
  1. Temporally-regular firing pattern (i.e., evenly-spaced MUAPs)
  2. Separable MUAPs
- Observed MUAP firing pattern decreasingly regular with disease severity
- Borderline pathologies difficult to diagnose at low contraction
  - At low contraction levels: MUAPs more separable
- Separating individual MUAP trains difficult at high contraction
  - At high contraction levels: many MUAPs recruited
Example EMG Trace:
Diagnostic Considerations

- **Issue:** portions of EMG signal not diagnostic due to:
  - Activity from needle insertion / muscle probing
  - Instrument tuning effects (e.g., saturation)

- **Solution:** consider **diagnostic regions** identified by physician

- **Issue:** signal amplitude often uninformative
  - High variability between patients, muscle contraction levels
  - Captures instrument effects
  - Only diagnostic in severe cases

- **Solution:** classify **normalized** EMG signals in the **frequency domain**
Our Approach:
EMG Classification in the Frequency Domain

- **Sample** = fixed-duration slice of length $ns$ seconds from a particular diagnostic region
- **Normalization**: each time-domain sample $x = x / ||x||_2$
- **Classification**:
  1. Balance the number of samples from each class via sampling with replacement
  2. 5-fold cross-validation:
     I. Split samples into train/test (50/50%) sets via stratified random sampling
     II. Ensure train/test sets consist of samples from different subjects
### Experimental Data

- **Myo1**=borderline myopathy, **Myo4**=severe myopathy
- **Myo**= set of all (Myo1,....,Myo4) data
- **DMMH paper results**: classify samples into Normal vs. Myo* classes
- **Our recent results**: classify samples into Normal vs. Borderline/Mild (MyoLo) vs. Moderate/Severe (MyoHi) classes

<table>
<thead>
<tr>
<th>Muscle</th>
<th>#</th>
<th># sec</th>
<th>Normal</th>
<th>MyoLo</th>
<th>MyoHi</th>
<th>Myo*</th>
</tr>
</thead>
<tbody>
<tr>
<td>Biceps</td>
<td>4</td>
<td>51.0 (4)</td>
<td>0.0 (0)</td>
<td>7.5 (1)</td>
<td>0.0 (0)</td>
<td>35.0 (2)</td>
</tr>
<tr>
<td>Deltoid</td>
<td>6</td>
<td>53.0 (6)</td>
<td>26.0 (3)</td>
<td>8.5 (1)</td>
<td>0.0 (0)</td>
<td>18.5 (2)</td>
</tr>
<tr>
<td>Triceps</td>
<td>2</td>
<td>18.5 (2)</td>
<td>0.0 (0)</td>
<td>0.0 (0)</td>
<td>10.0 (1)</td>
<td>0.0 (0)</td>
</tr>
<tr>
<td>VL</td>
<td>3</td>
<td>51.5 (3)</td>
<td>0.0 (0)</td>
<td>0.0 (0)</td>
<td>21.5 (1)</td>
<td>12.0 (1)</td>
</tr>
<tr>
<td>Total</td>
<td>15</td>
<td>174.0 (8)</td>
<td>26.0 (3)</td>
<td>16.0 (2)</td>
<td>31.5 (2)</td>
<td>47.5 (4)</td>
</tr>
</tbody>
</table>

Table: Summary of EMG data for each muscle with sample duration

- The number of seconds of data for each class is provided
- Values in parenthesis give the number of unique subjects for each muscle with respect to each class

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DMMH 2013

B. Bue, E. Merényi, J. Killian
DMMH Paper Results:
Normal vs. Myo* Accuracy vs. Sample Length (ns)

- **Goal:** evaluate prediction accuracy vs. sample length $ns$
- **Classifier:** linear Support Vector Machine (SVM)
- **Results:**

<table>
<thead>
<tr>
<th>$ns$</th>
<th># samp</th>
<th>Dims</th>
<th>Accuracy (std.dev.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.05</td>
<td>10528</td>
<td>1600</td>
<td>0.760 (0.058)</td>
</tr>
<tr>
<td>0.1</td>
<td>5256</td>
<td>3200</td>
<td>0.815 (0.059)</td>
</tr>
<tr>
<td>0.2</td>
<td>2616</td>
<td>8000</td>
<td>0.878 (0.042)</td>
</tr>
<tr>
<td>0.5</td>
<td>1048</td>
<td>16000</td>
<td>0.904 (0.033)</td>
</tr>
<tr>
<td>1</td>
<td>512</td>
<td>32000</td>
<td>0.966 (0.028)</td>
</tr>
<tr>
<td>2</td>
<td>256</td>
<td>64000</td>
<td>0.971 (0.041)</td>
</tr>
</tbody>
</table>

- Accuracy increases with sample length
- Limited data: # samples decreases with sample length => increased variance in predictions (e.g., $ns=1$ vs. $ns=2$)
In this work, we evaluated a novel methodology for classifying normal subjects versus myopathic patients. Our hypothesis is that the biceps and deltoid muscles are misclassified more often due to significant variability in the EMG data. After training a linear SVM classifier, we tested it on 1024 samples from the biceps and deltoid muscles. The average classification accuracy for normal subjects was 0.852 (0.028) and for myopathic patients it was 0.936 (0.050). The classification accuracy for myopathic patients is significantly higher than that of normal subjects for both muscles, as a possible reason for this is that the biceps and deltoid muscles tend to be more disparate, but appear similar to the triceps and VL muscles.

<table>
<thead>
<tr>
<th>Subject</th>
<th>Average</th>
<th>Muscle</th>
<th>Class</th>
<th>Trace Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>S02</td>
<td>0.936 (0.050)</td>
<td>Biceps</td>
<td>Myo*</td>
<td>0.936 (0.050)</td>
</tr>
<tr>
<td>S03</td>
<td>0.958 (0.037)</td>
<td>Deltoid</td>
<td>Myo*</td>
<td>0.937 (0.055)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Triceps</td>
<td>Myo*</td>
<td>1.000 (0.000)</td>
</tr>
<tr>
<td>S04</td>
<td>1.000 (0.000)</td>
<td>VL</td>
<td>Myo*</td>
<td>1.000 (0.000)</td>
</tr>
<tr>
<td>S07</td>
<td>0.986 (0.022)</td>
<td>Biceps</td>
<td>Myo*</td>
<td>0.972 (0.043)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Deltoid</td>
<td>Myo*</td>
<td>0.984 (0.025)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>VL</td>
<td>Myo*</td>
<td>1.000 (0.000)</td>
</tr>
<tr>
<td>S08</td>
<td>0.888 (0.007)</td>
<td>Deltoid</td>
<td>Nor</td>
<td>0.888 (0.007)</td>
</tr>
<tr>
<td>S09</td>
<td>0.975 (0.035)</td>
<td>Biceps</td>
<td>Myo*</td>
<td>0.951 (0.068)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Deltoid</td>
<td>Myo*</td>
<td>1.000 (0.000)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Triceps</td>
<td>Myo*</td>
<td>1.000 (0.000)</td>
</tr>
<tr>
<td>S10</td>
<td><strong>0.789 (0.128)</strong></td>
<td>Biceps</td>
<td>Myo*</td>
<td><strong>0.622 (0.171)</strong></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Deltoid</td>
<td>Nor</td>
<td><strong>0.691 (0.056)</strong></td>
</tr>
<tr>
<td></td>
<td></td>
<td>VL</td>
<td>Myo*</td>
<td>1.000 (0.000)</td>
</tr>
<tr>
<td>S15</td>
<td>0.852 (0.028)</td>
<td>Deltoid</td>
<td>Nor</td>
<td>0.852 (0.028)</td>
</tr>
</tbody>
</table>
Our Recent Results:
Predicting Disease Severity

- **Goal:** predict disease severity; Normal vs. MyoLo = (Myo1, Myo2) vs. MyoHi = (Myo3, Myo4)
- **Classifiers:** Linear SVM vs. Neural Network classifier of Merényi et al., [1993]

**Current Results:**
- Linear SVM = 63.51% (stddev: 8.6%) accuracy
  - Most mispredictions between MyoLo vs. MyoHi classes, normal accuracy 85-90%
  - Sample balancing improves overall prediction accuracy
- Neural Network = 78.85% (stddev: 3.8%) accuracy
  - MyoLo and MyoHi accuracy 80-100%, normal accuracy 50-80%
  - Sample balancing does **not** affect accuracy; majority classes (MyoLo, MyoHi) learned well, poor generalization on minority (normal) class
  - Expect to improve results with more sophisticated balancing schemes
Conclusions and Future Work

- Frequency-space analysis enables classification of EMG signals measured at full-contraction
  - Requires no MUAP segmentation
  - Capable of discriminating normal vs. myopathic traces

- Validation in progress:
  - Incorporating additional normal traces from new subjects
  - Achieving similar results for fixed muscle groups

- Feature-selection techniques could potentially improve our results and aid interpretation
  - Example: identifying diagnostic frequencies for particular pathologies

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DMMH 2013
References
