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

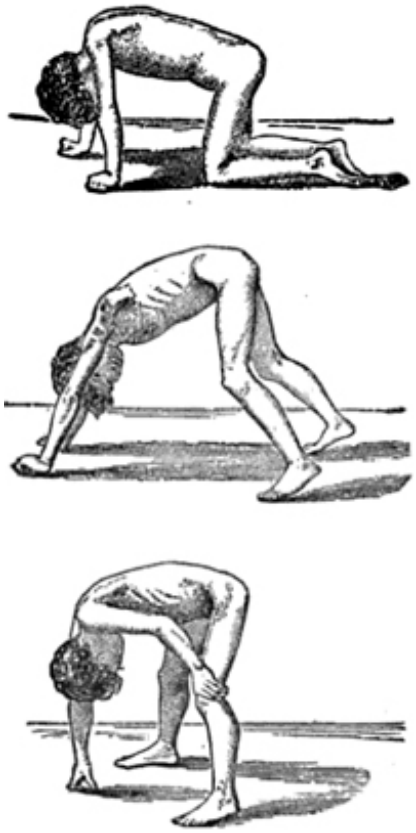


Figure credit: http://neuromuscular.wustl.edu/

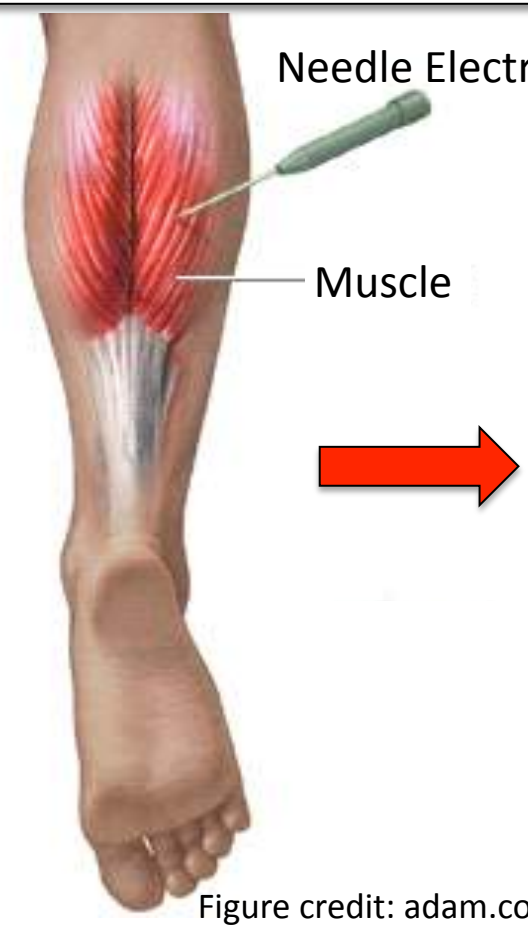
Gowers' sign: patient uses arms/hands to reach an upright position due to weakness of the hip/thigh muscles common to several forms of myopathy

Our Contributions

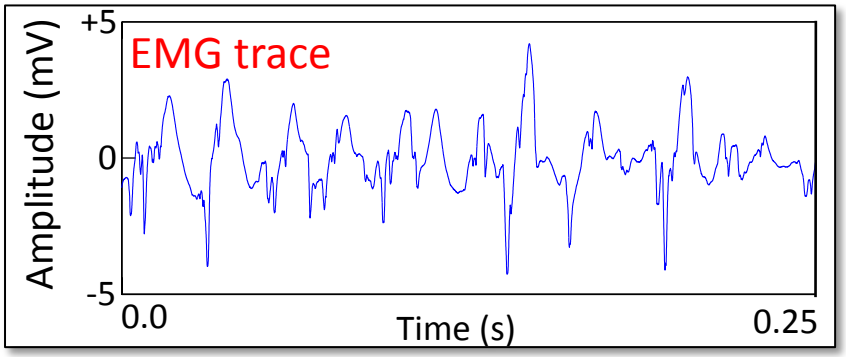
- **Proof of concept of a novel methodology for classification and diagnosis of myopathy from electromyograph (EMG) signals**
- Frequency domain analysis of EMG signals measured at full muscle contraction
- Consider multiple subjects and multiple muscles
- DMMH paper results: classification of EMG traces 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



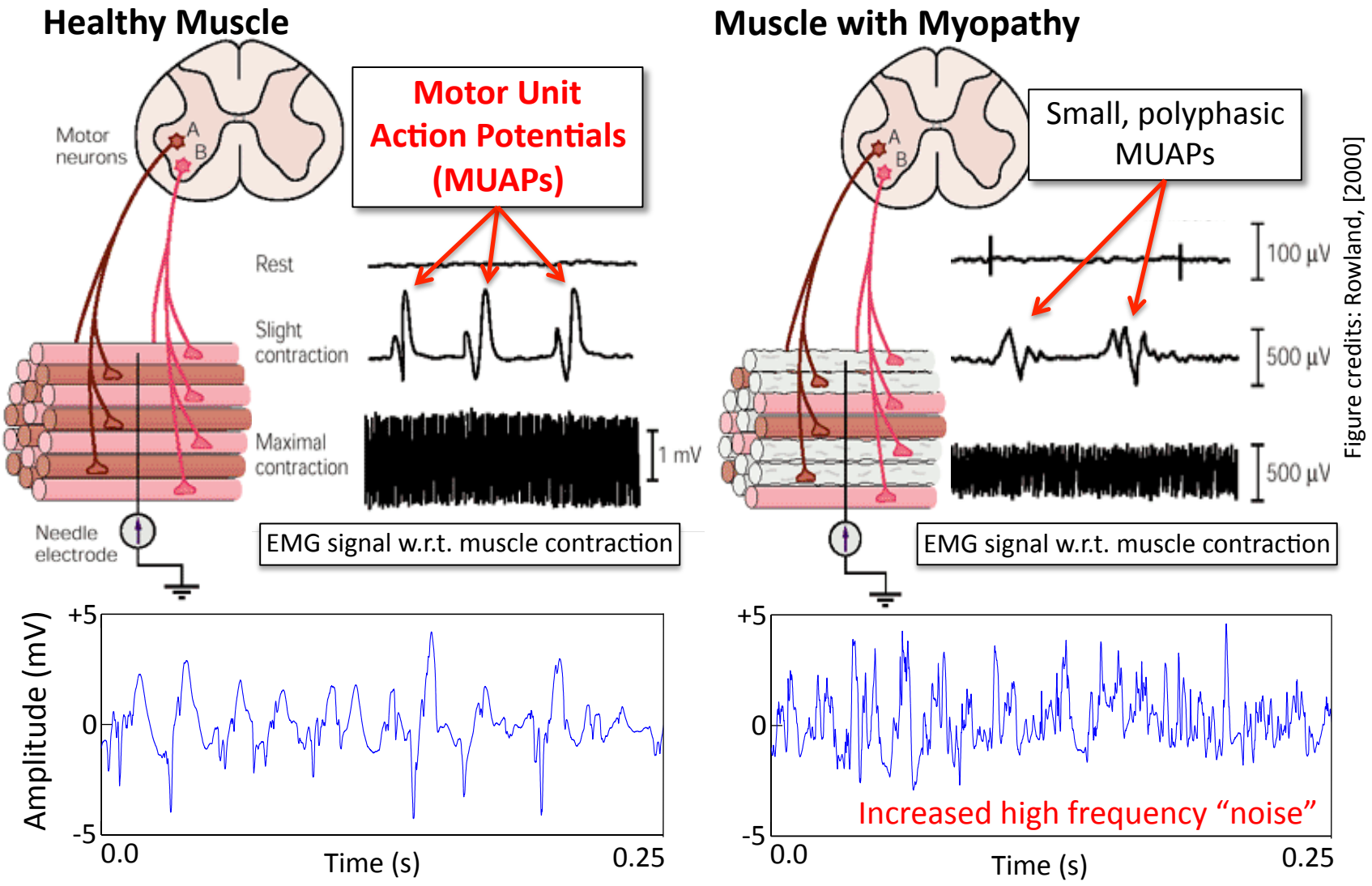
Physician inserts an electrode into muscle tissue and observes electrical activity



Audible **characteristics of EMG trace are diagnostic for different pathologies**

Figure credit: adam.com

Diagnosing Myopathy from EMG Measurements



Common Approach:
MUAP Decomposition

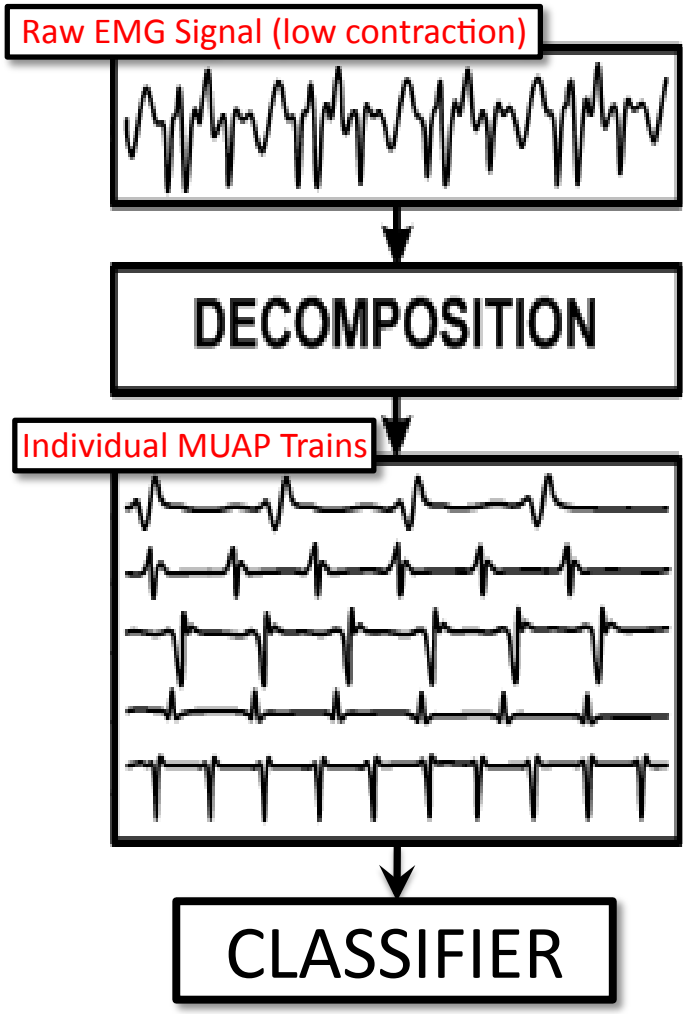


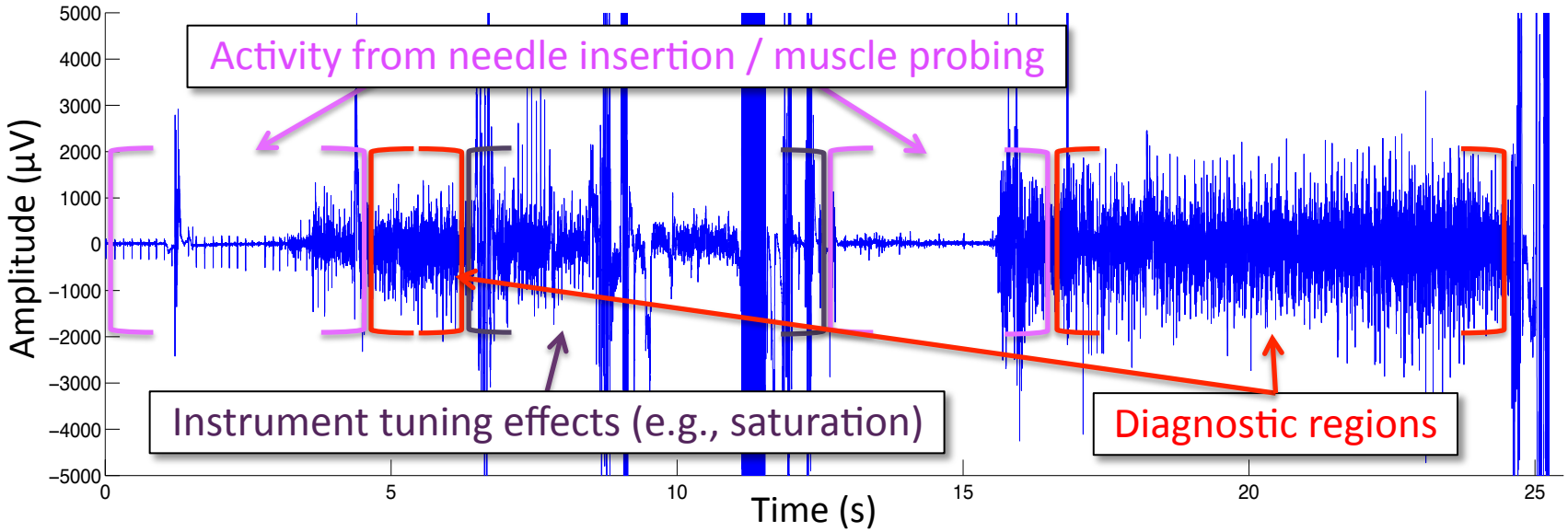
Figure credit: Nawab et al., [2008]

Issues

- Assumes:
  I. Temporally-regular firing pattern (i.e., evenly-spaced MUAPs)
  II. 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

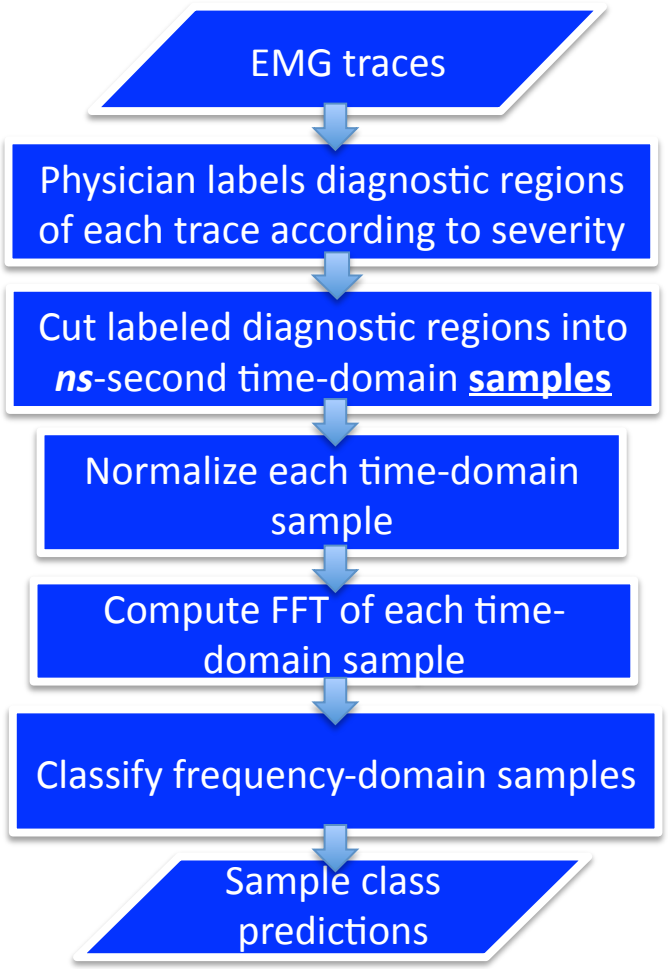
Example EMG Trace: Diagnostic Considerations

- **Issue:** portions of EMG signal not diagnostic due to:



- **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 $\mathbf{x} = \mathbf{x}/||\mathbf{x}||_2$
- **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

				MyoLo		MyoHi		
Muscle	#	# sec	Normal	Myo1	Myo2	Myo3	Myo4	Myo*
Biceps	4	51.0 (4)	0.0 (0)	7.5 (1)	0.0 (0)	35.0 (2)	8.5 (1)	51.0 (4)
Deltoid	6	53.0 (6)	26.0 (3)	8.5 (1)	0.0 (0)	18.5 (2)	0.0 (0)	53.0 (6)
Triceps	2	18.5 (2)	0.0 (0)	0.0 (0)	10.0 (1)	0.0 (0)	8.5 (1)	18.5 (2)
VL	3	51.5 (3)	0.0 (0)	0.0 (0)	21.5 (1)	12.0 (1)	18.0 (1)	51.5 (3)
Total	15	174.0 (8)	26.0 (3)	16.0 (2)	31.5 (2)	65.5 (5)	35.0 (3)	148.0 (6)
				47.5 (4)		100.5 (4)		

- 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

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:**

ns	# *samp*	Dims	Accuracy (std.dev.)
0.05	10528	1600	0.760 (0.058)
0.1	5256	3200	0.815 (0.059)
0.2	2616	8000	0.878 (0.042)
0.5	1048	16000	0.904 (0.033)
1	512	32000	0.966 (0.028)
2	256	64000	0.971 (0.041)

- Accuracy increases with sample length
- Limited data: # samples decreases with sample length => increased variance in predictions (e.g., *ns*=1 vs. *ns*=2)

DMMH Paper Results: Normal vs. Myo* Per-trace Accuracies

Subj.	Average	Muscle	Class	Trace Accuracy
S02	0.936 (0.050)	Biceps	Myo*	0.936 (0.050)
S03	0.958 (0.037)	Deltoid	Myo*	0.937 (0.055)
		Triceps	Myo*	1.000 (0.000)
S04	1.000 (0.000)	VL	Myo*	1.000 (0.000)
S07	0.986 (0.022)	Biceps	Myo*	0.972 (0.043)
		Deltoid	Myo*	0.984 (0.025)
		VL	Myo*	1.000 (0.000)
S08	0.888 (0.007)	Deltoid	Nor	0.888 (0.007)
S09	0.975 (0.035)	Biceps	Myo*	0.951 (0.068)
		Deltoid	Myo*	1.000 (0.000)
		Triceps	Myo*	1.000 (0.000)
S10	0.789 (0.128)	Biceps	Myo*	0.622 (0.171)
		Deltoid	Nor	0.691 (0.056)
		VL	Myo*	1.000 (0.000)
S15	0.852 (0.028)	Deltoid	Nor	0.852 (0.028)

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

References

- Rowland, “Diseases of the Motor Unit,” in Principles of Neural Science, Keller et al. Eds, McGraw Hill, 2000.
- E. Merényi, R. B. Singer, and W. H. Farrand, “Classification of the LCVF AVIRIS test site with a Kohonen Artificial Neural Network,” Summaries of the 4th Annual JPL Airborne Geoscience Workshop, 1993.
- S.H. Nawab, R.P. Wotiz, C.J. De Luca, “Decomposition of Indwelling EMG Signals,” Journal of Applied Physiology, 105: 700-710, Aug. 2008.