

Neuromuscular physiology, signal processing and statistical inference

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Outline

- Filtering, aliasing, and resampling timeseries data in Matlab
- Neuromuscular physiology properties of electromyographic (EMG) signals
- Bayesians and frequentists, tests of central tendency (t-tests and ANOVA)
- Interactive visualization and statistical analysis of clinical behavioral research data in Matlab
- Statistical analysis and inference with EMG signals with wavelet-based functional ANOVA (wfANOVA)

Homework (due Thursday, 11/17)

- Complete **one** of the homework problems described during the lecture and return to Dr. McKay by email by 11:59 PM Thursday, 11/17.
- j.lucas.mckay@emory.edu
- Attach the exercise as a PDF named “BMI500 Lastname Firstname.pdf”
- Make the subject of the email “BMI500 Lastname Firstname.pdf”

Filtering, aliasing, and resampling

Spatial aliasing (Moiré pattern) resulting from image size reduction

Spatial frequency of brick pattern much lower than pixel spatial frequency



Spatial frequency of brick pattern equivalent to pixel spatial frequency



Temporal aliasing (wagon-wheel effect) resulting from video frame rate

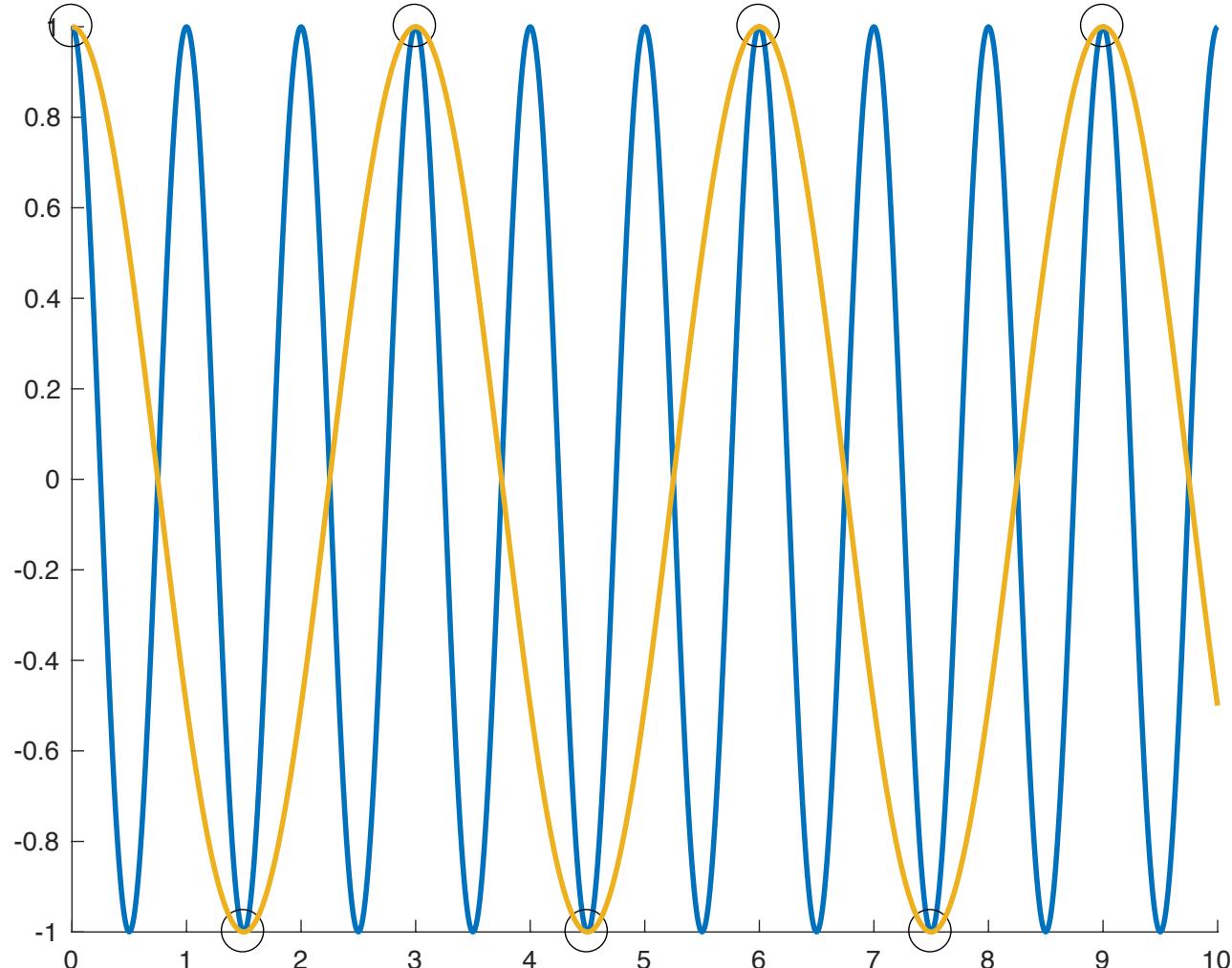


**Photographing a fast-moving
propeller at video speed**

What exactly is happening here?

- “In signal processing and related disciplines, aliasing is an effect that **causes different signals to become indistinguishable when sampled**. It also refers to the distortion or artifact that results when the signal reconstructed from samples is different from the original continuous signal.” (wikipedia)
- Notice that the same concept results in either spatial aliasing (Moiré pattern) or temporal aliasing (wagonwheel effect)

What exactly is happening here?



What exactly is happening here?

- Note that the underlying signal can alias to signals of **lower** or **higher** frequency.
- This makes it possible to alias certain frequency bands to different regions of the frequency spectrum (this is how kHz audio signals can be transmitted in the MHz range). 😊
- This means that in some cases it is impossible to recognize aliasing once it occurs or to reconstruct the underlying signals. 😬

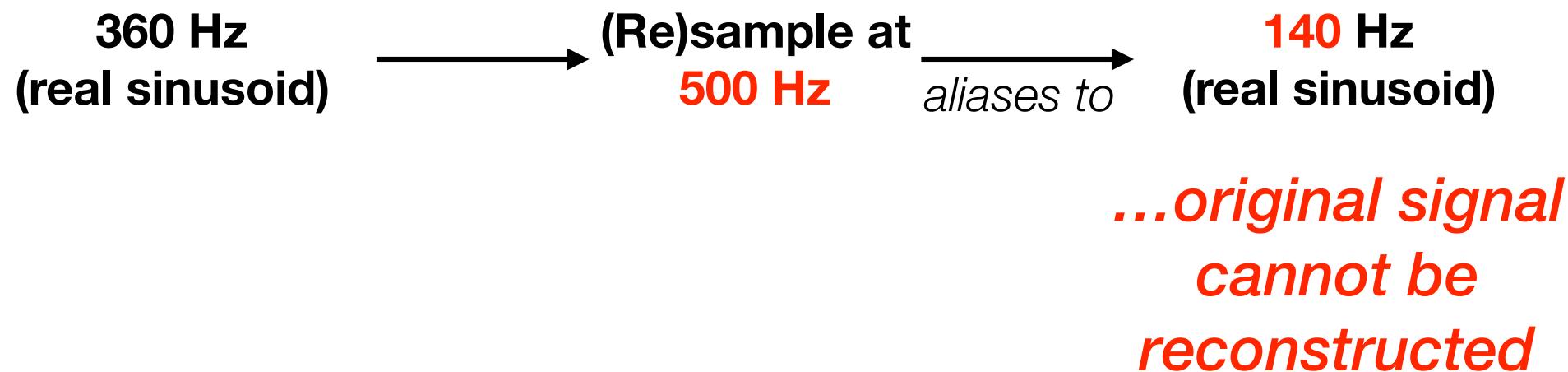
When does aliasing happen?

1. When **sampling** continuous data into an analog-to-digital converter (often built in to commercial equipment)
2. When **resampling** data that has already been digitized, i.e., when changing sampling rates (what we will consider)

Frequencies in the source signal less than 1/2 sampling rate alias correctly

360 Hz
(real sinusoid)

Frequencies greater than 1/2 the sampling rate do not alias correctly



Exercise: “dumb” and safe resampling in Matlab

- `aliasing.m`
- note in sample code:
 - anonymous functions (similar to lambda in python)
 - `eval('arbitrary string')` for macro execution; ! to escape to system environment
 - manipulation of graphics object properties (`graphicobject.Property = ...`)
 - table data structure (indexed with (), { }, variable names or numbers depending on context)

Homework exercise: aliasing

- Plot and compare the time-varying power spectrum of each signal we created in aliasing.m. Use built-in functions as much as possible.
- Look up, describe, and explain the “Nyquist rate.” (1-2 paragraphs or so.)

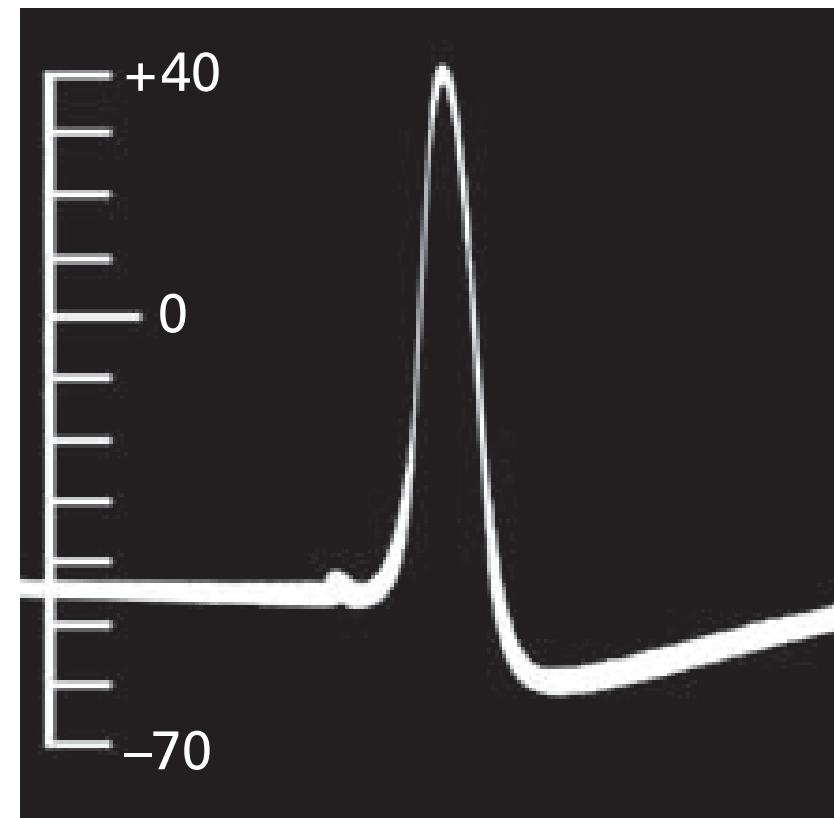
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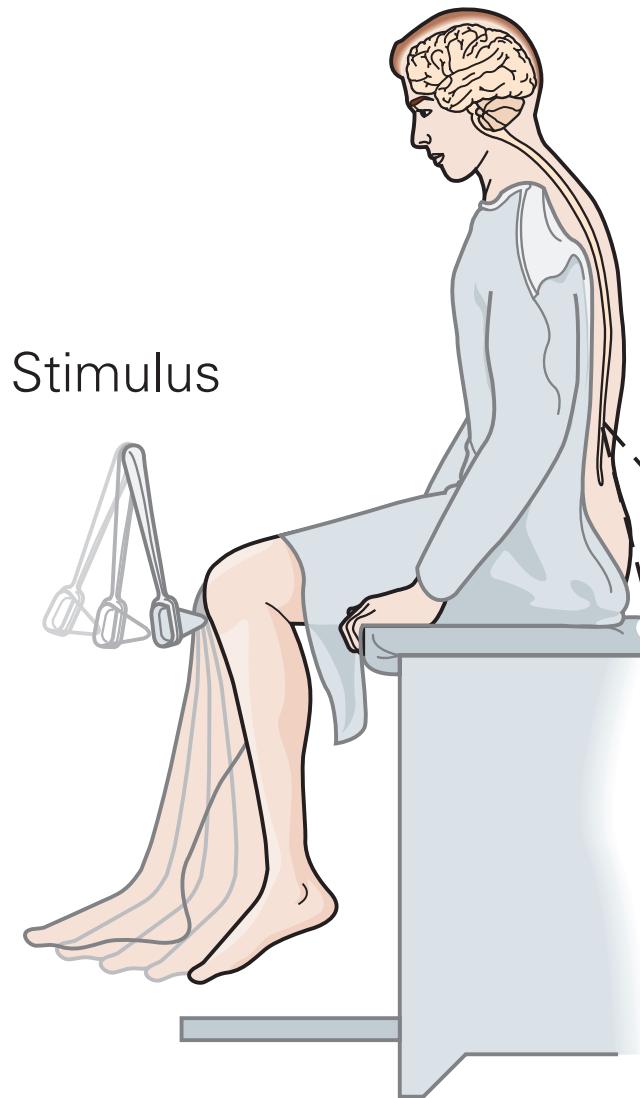
The motor unit, muscle action, and electromyography (EMG)

Information in the nervous system is exchanged primarily through action potentials

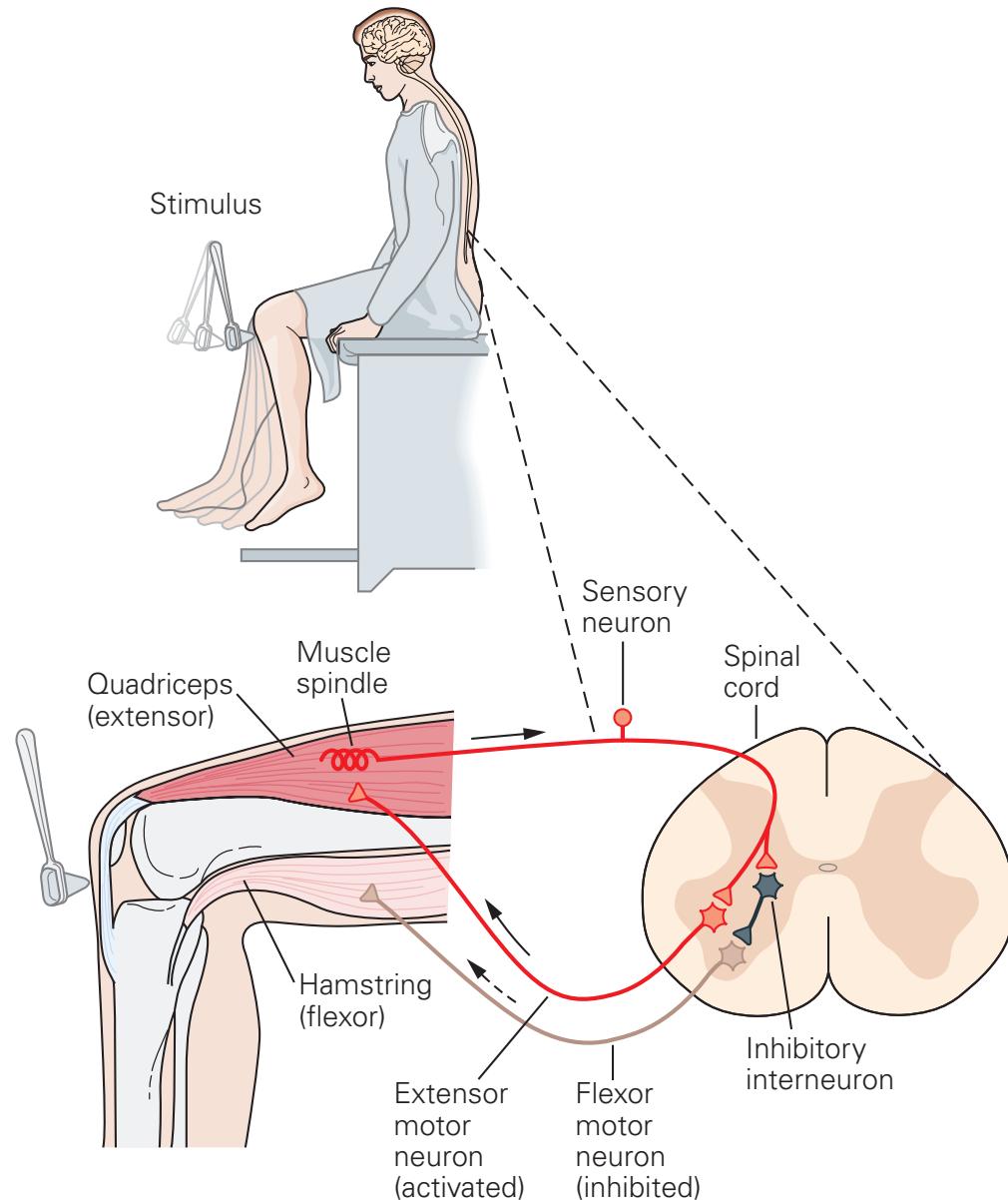
- Neurons are the signaling units of the nervous system.
- Neuronal **axons** convey electrical signals over 0.1 mm - 2 m.
- Neurons that synapse onto muscles are called **motor neurons**.
- The **action potential**, the cell's conducting signal, is initiated at the initial segment of the axon and propagates to the synapse.



Action potentials travel through circuits of sensory and motor neurons



Action potentials travel through circuits of sensory and motor neurons



Dorsal / Back
(sensory signals
goes in)

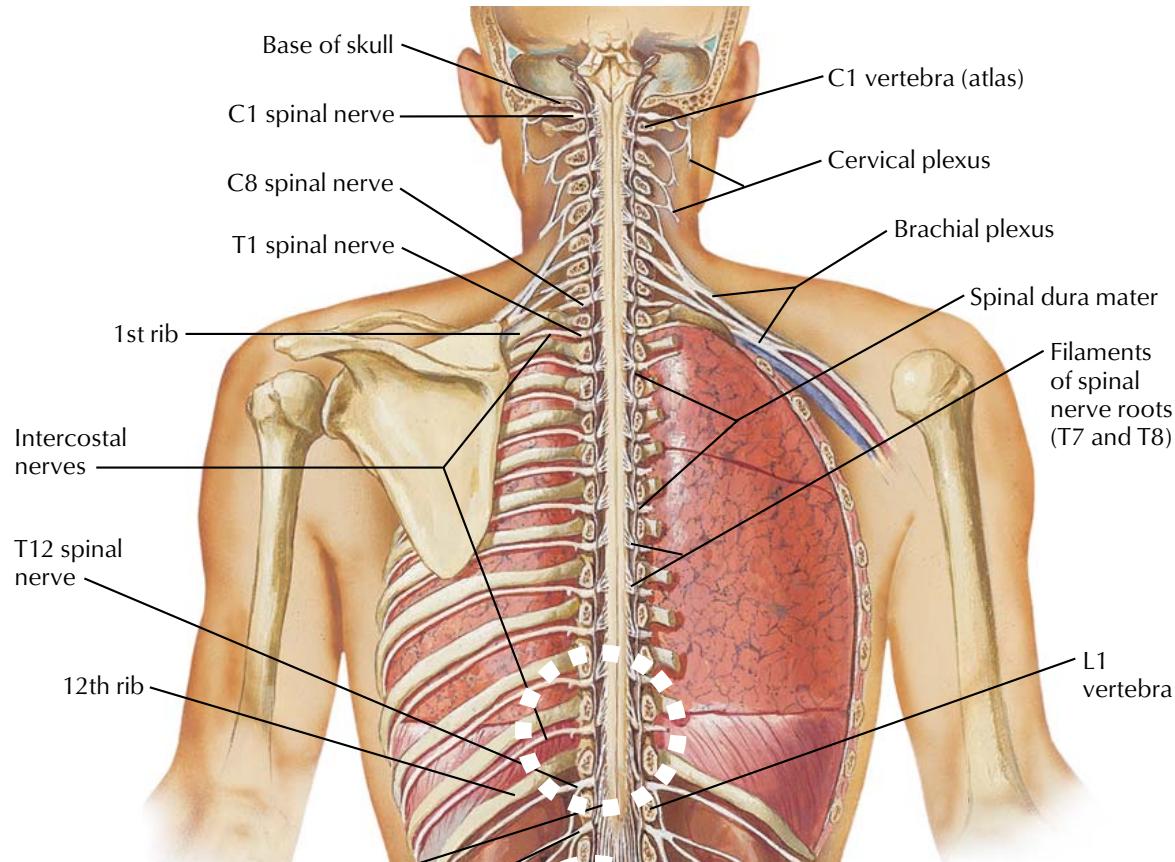
Most neurons
are only excitatory
or inhibitory

Ventral / Front
(motor signals
come out)

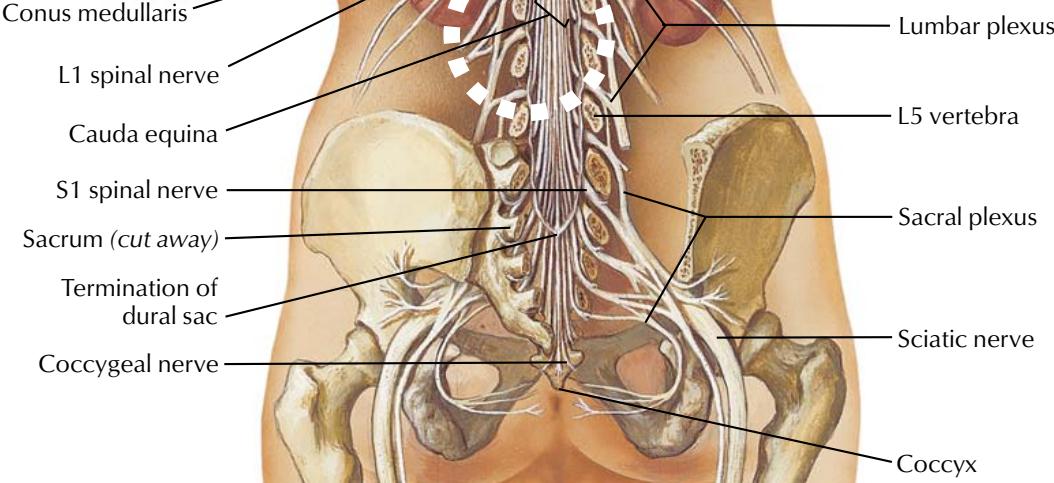
The motor unit is the elementary unit of motor control

- The nervous system controls muscle force with action potentials sent from motor neurons in the spinal cord to the muscle fibers. A motor neuron and the muscle fibers it innervates are known as a *motor unit* (Sherrington, 1925).
- A typical muscle is controlled by a few hundred motor neurons whose cell bodies are clustered in a motor nucleus in the spinal cord or brain stem.
- In most mature vertebrate muscles each fiber is innervated by a single motor neuron. The number of muscle fibers innervated by one motor neuron, the innervation number, varies with the muscle type and function. In human skeletal muscles it ranges from average values of 5 for an eye muscle to 1,800 for a leg muscle.

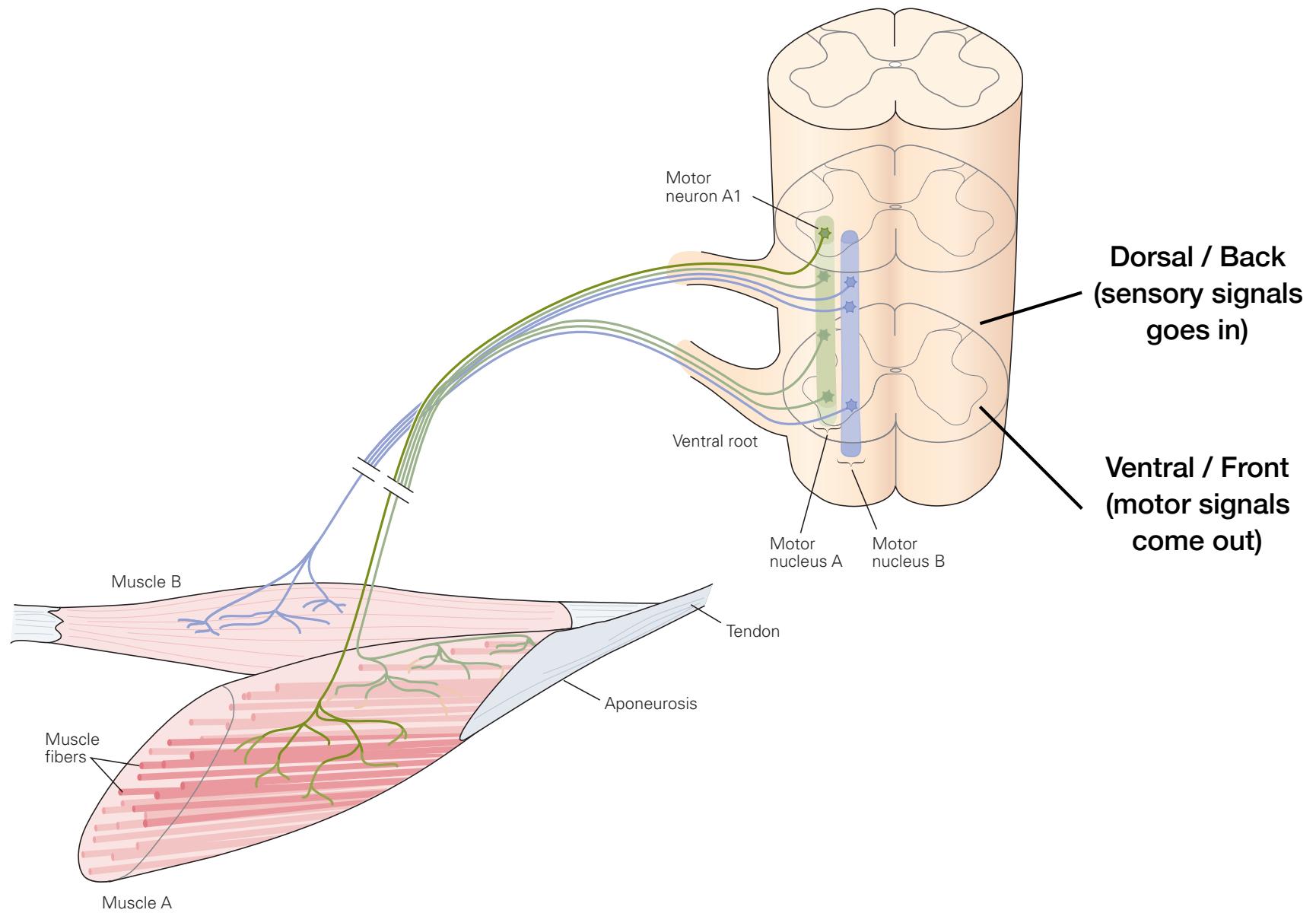
**reflex arc
circuitry
at \approx T10-12**



**mixed nerves
innervating
quadriceps at \approx L2-4**



A motor unit consists of a motor neuron and the muscle fibers it innervates



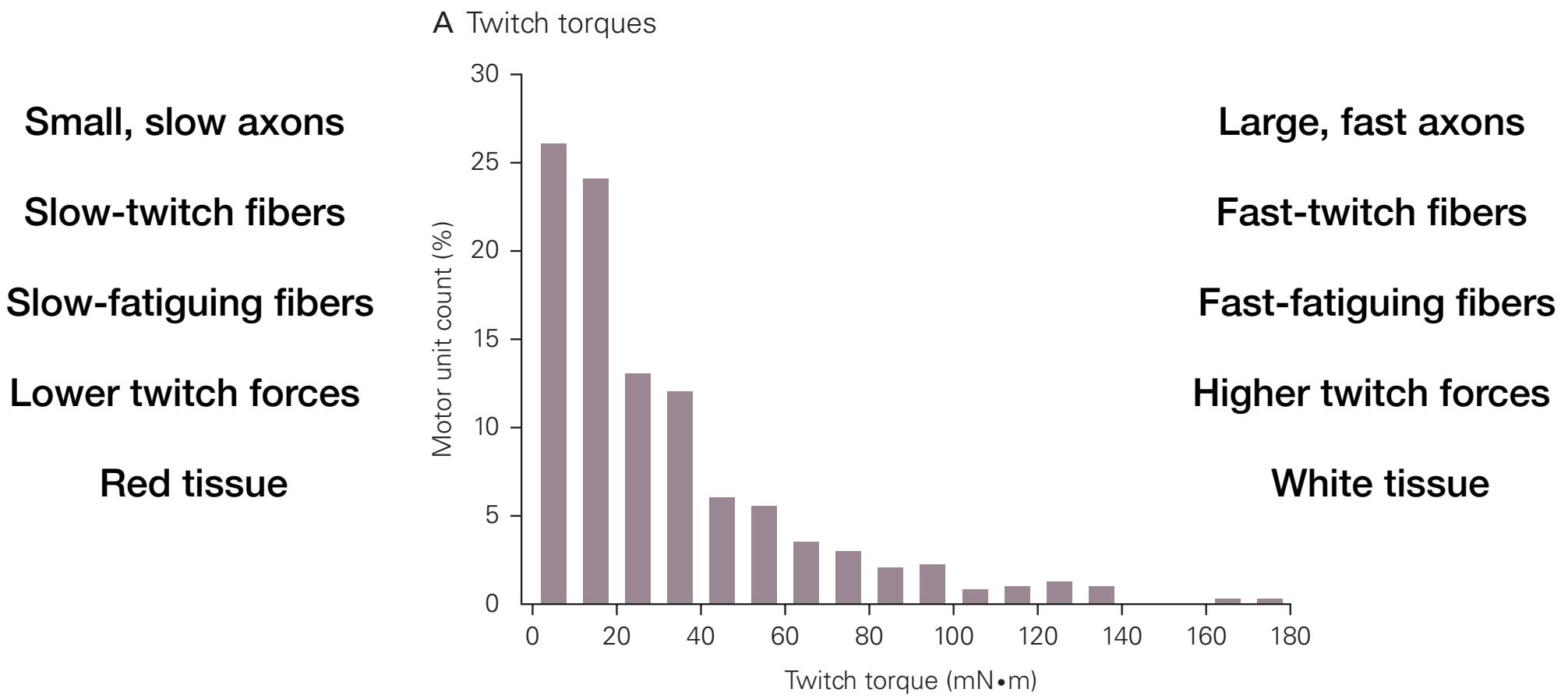
A typical muscle is comprised of 100's – 1000's of motor units

Table 34–1 Innervation Numbers in Human Skeletal Muscles

Muscle	Alpha motor axons	Muscle fibers	Innervation number
Biceps brachii	774	580,000	750
Brachioradialis	333	>129,200	>410
Cricothyroid	112	18,550	155
Gastrocnemius (medial)	579	1,042,000	1,800
Interossei dorsales (1)	119	40,500	340
Lumbricales (1)	96	10,269	107
Masseter	1,452	929,000	640

How do these numbers compare to the number of cortical neurons?

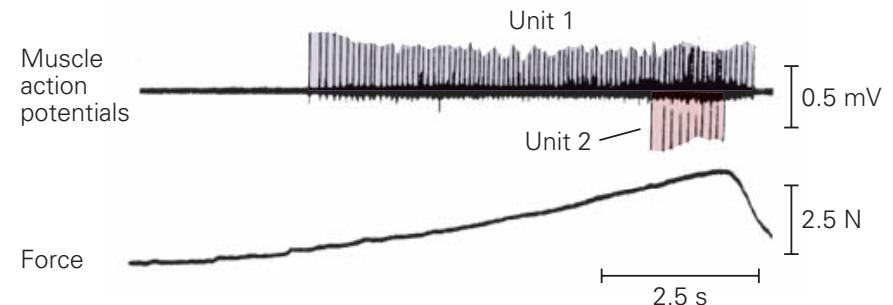
Motor units vary widely with muscle fiber type



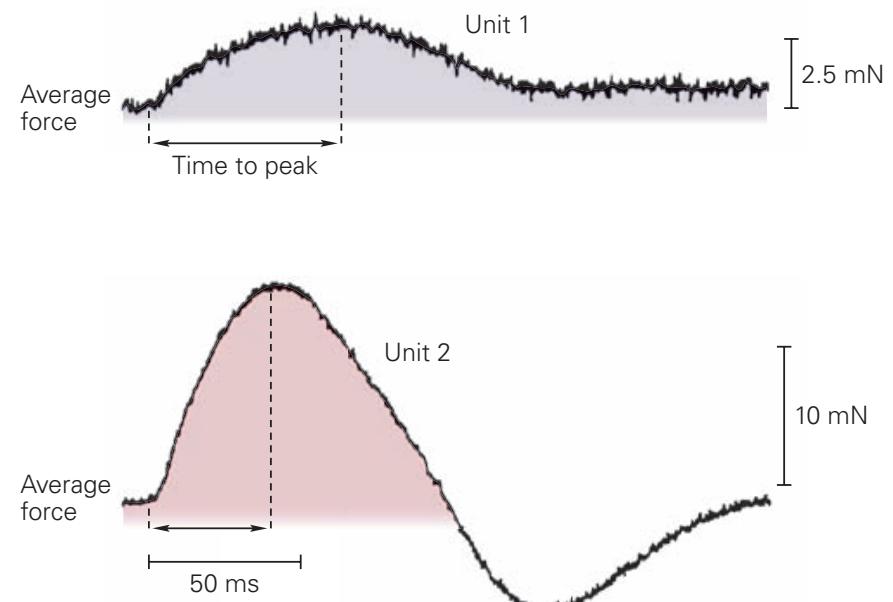
Muscle force is controlled by the orderly recruitment and discharge rate of motor units

- The order in which motor units are recruited is highly correlated with several indices of **motor unit size**.
- Force is increased during a muscle contraction by the activation of additional motor units, which are recruited **progressively from the weakest to the strongest**.
- This is accomplished **by the spinal cord**, not by conscious control.

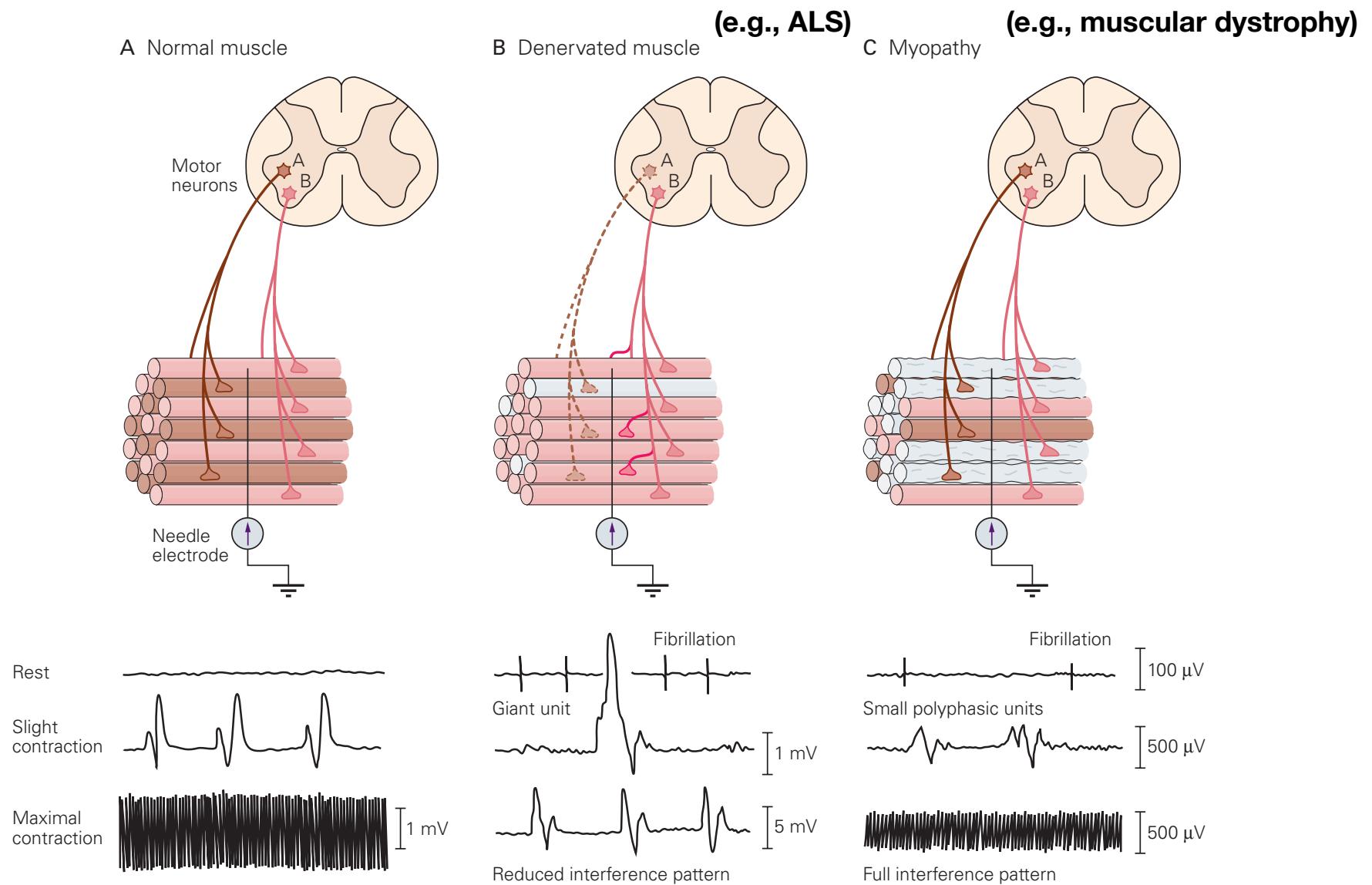
A Action potentials in two motor units



B Force produced by the two units

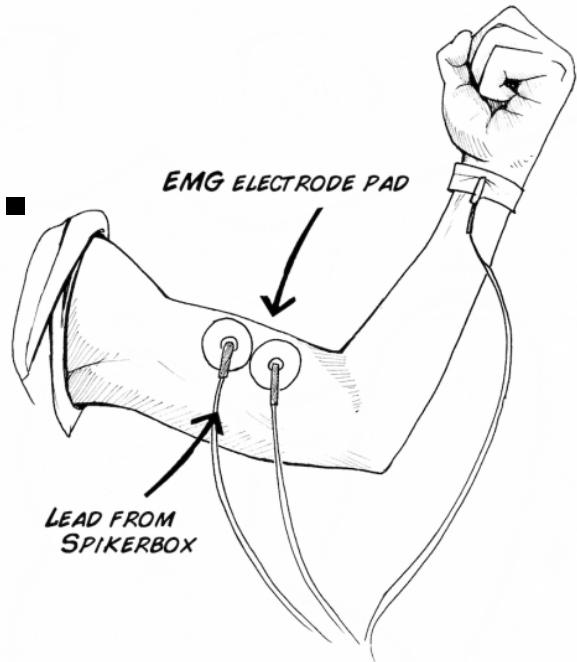


Information contained in EMG can be used to diagnose neuromuscular disorders

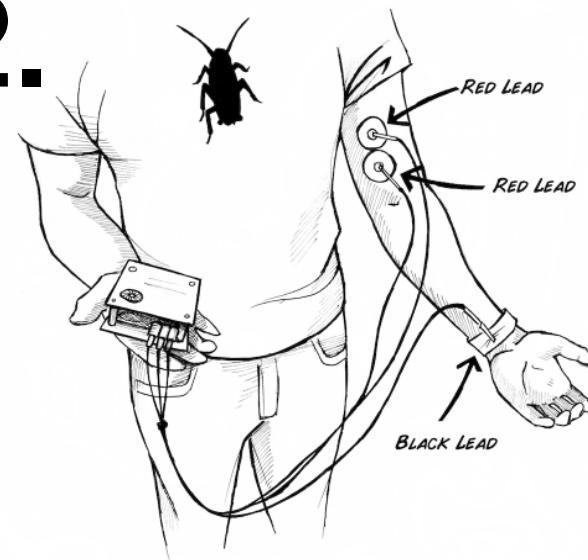


Whole muscle activation can be measured with surface electromyography (EMG)

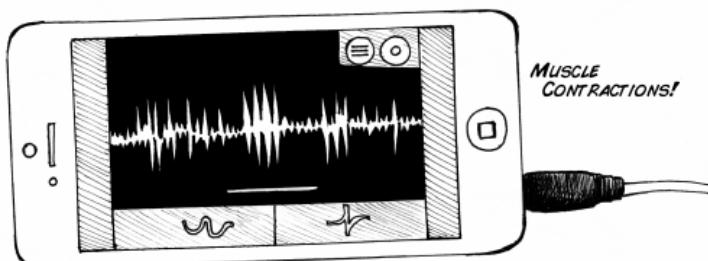
1.



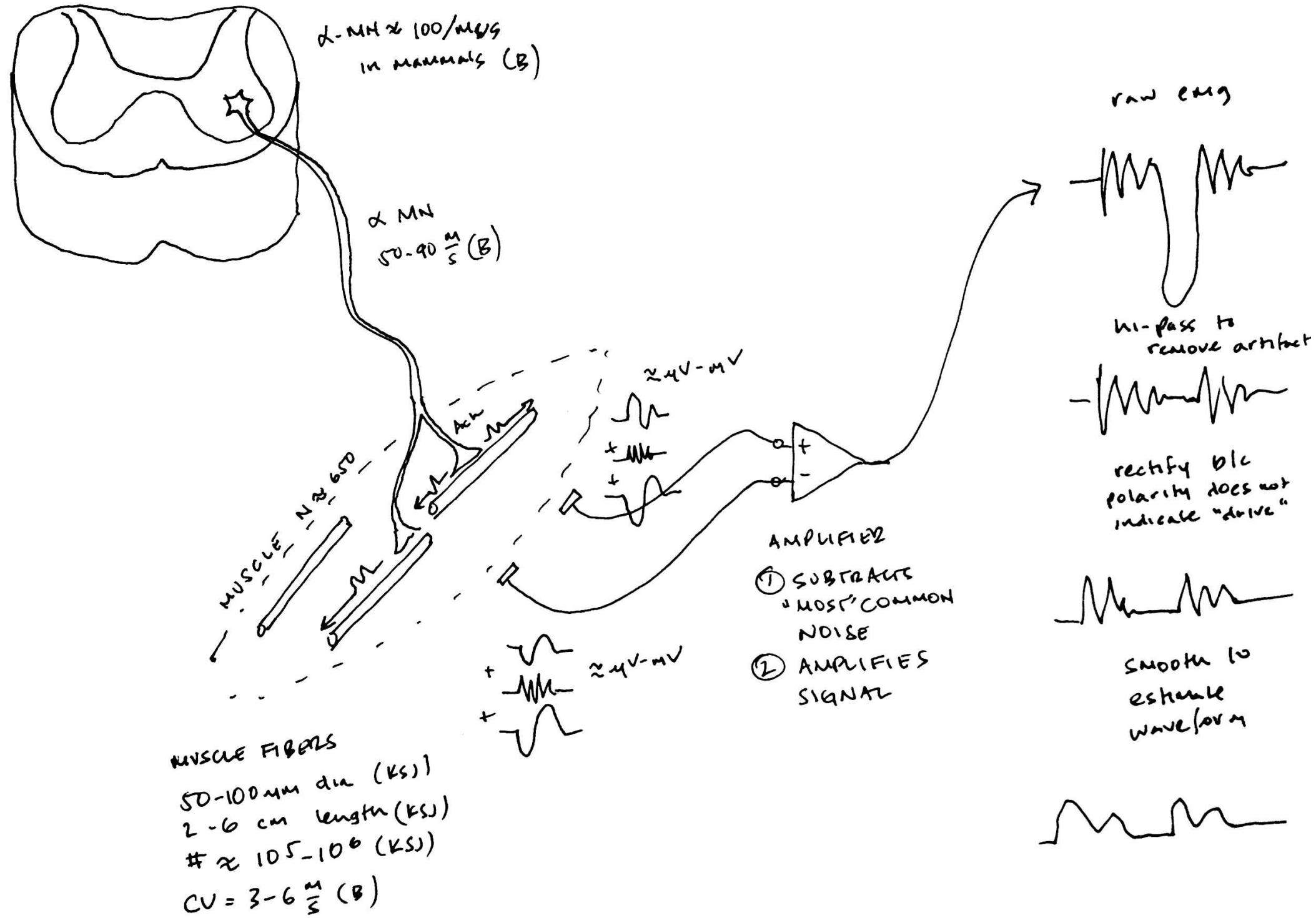
2.



3.



4. signal
processing



Typical surface EMG processing

- Hardware antialias lowpass filtering
- Digitization ($\approx 1\text{kHz}$)
- Highpass filtering (35 Hz) to remove motion artifact
- Full-wave rectification
- Lowpass filtering (40 Hz) to smooth signal

Homework exercise: frequency content in EMG

- Choose 1:
 - Find a surface EMG signal simulation package implemented in Matlab available in the literature. Simulate and plot 1 second of spontaneous EMG activity. Plot the spectrogram.
 - Simulate 1 second of white noise at 2 kHz. Resample it at 1 kHz using `resample.m`. Plot the spectrogram after processing as described for surface EMG. Compare the spectrogram to that obtained by bandpass filtering between 35 and 40 Hz. Explain the difference.

The information contained in EMG is sufficient to control a prosthetic arm (Kuiken Lab)

Jesse Sullivan



54-year-old lineman

May 2001 suffered
7,200 volt burns

Immediate bilateral
shoulder disarticulation

Required revision
surgery



Conventional Prostheses:
Body-powered on right
Motorized on left

Getting it to a clinical trial may be more important than creating the best software

The image shows a screenshot of a medical journal article from JAMA. The title of the article is "Intuitive Control of a Powered Prosthetic Leg During Ambulation". The article is categorized as "Original Investigation". It is a "Randomized Clinical Trial". The authors listed are Levi J. Hargrove, PhD; Aaron J. Young, PhD; Ann M. Simon, PhD; Nicholas P. Fey, PhD; Robert D. Lipschutz, CP; Suzanne B. Finucane, MS; Elizabeth G. Halsne, CPO; Kimberly A. Ingraham, BS; Todd A. Kuiken, MD, PhD. The abstract discusses the development of a real-time control system for a powered prosthetic leg, comparing classification error with and without EMG signals. The results show significantly lower classification error with the inclusion of EMG signals. The article includes sections on importance, objective, design, setting, and participants; interventions; main outcomes and measures; results; and conclusions and relevance. It also lists author affiliations and a corresponding author. The journal issue is JAMA, 2015;313(22):2244-2252, doi:10.1001/jama.2015.4527.

Research

Original Investigation

Intuitive Control of a Powered Prosthetic Leg During Ambulation

A Randomized Clinical Trial

Levi J. Hargrove, PhD; Aaron J. Young, PhD; Ann M. Simon, PhD; Nicholas P. Fey, PhD; Robert D. Lipschutz, CP; Suzanne B. Finucane, MS; Elizabeth G. Halsne, CPO; Kimberly A. Ingraham, BS; Todd A. Kuiken, MD, PhD

IMPORTANCE Some patients with lower leg amputations may be candidates for motorized prosthetic limbs. Optimal control of such devices requires accurate classification of the patient's ambulation mode (eg, on level ground or ascending stairs) and natural transitions between different ambulation modes.

OBJECTIVE To determine the effect of including electromyographic (EMG) data and historical information from prior gait strides in a real-time control system for a powered prosthetic leg capable of level-ground walking, stair ascent and descent, ramp ascent and descent, and natural transitions between these ambulation modes.

DESIGN, SETTING, AND PARTICIPANTS Blinded, randomized crossover clinical trial conducted between August 2012 and November 2013 in a research laboratory at the Rehabilitation Institute of Chicago. Participants were 7 patients with unilateral above-knee ($n = 6$) or knee-disarticulation ($n = 1$) amputations. All patients were capable of ambulation within their home and community using a passive prosthesis (ie, one that does not provide external power).

INTERVENTIONS Electrodes were placed over 9 residual limb muscles and EMG signals were recorded as patients ambulated and completed 20 circuit trials involving level-ground walking, ramp ascent and descent, and stair ascent and descent. Data were acquired simultaneously from 13 mechanical sensors embedded on the prosthesis. Two real-time pattern recognition algorithms, using either (1) mechanical sensor data alone or (2) mechanical sensor data in combination with EMG data and historical information from earlier in the gait cycle, were evaluated. The order in which patients used each configuration was randomized (1:1 blocked randomization) and double-blinded so patients and experimenters did not know which control configuration was being used.

MAIN OUTCOMES AND MEASURES The main outcome of the study was classification error for each real-time control system. Classification error is defined as the percentage of steps incorrectly predicted by the control system.

RESULTS Including EMG signals and historical information in the real-time control system resulted in significantly lower classification error (mean, 7.9% [95% CI, 6.1%-9.7%]) across a mean of 683 steps (range, 640-756 steps) compared with using mechanical sensor data only (mean, 14.1% [95% CI, 9.3%-18.9%]) across a mean of 692 steps (range, 631-775 steps), with a mean difference between groups of 6.2% (95% CI, 2.7%-9.7%) ($P = .00$).

CONCLUSIONS AND RELEVANCE In this study of 7 patients with lower limb amputations, inclusion of EMG signals and temporal gait information reduced classification error across ambulation modes and during transitions between ambulation modes. These preliminary findings, if confirmed, have the potential to improve the control of powered leg prostheses.

Author Affiliations: Center for Bionic Medicine, Rehabilitation Institute of Chicago, Chicago, Illinois (Hargrove, Young, Simon, Fey, Lipschutz, Kuiken); Department of Physical Medicine and Rehabilitation, Northwestern University, Chicago, Illinois (Hargrove, Simon, Fey, Lipschutz, Kuiken); Department of Biomedical Engineering, Northwestern University, Evanston, Illinois (Hargrove, Young, Kuiken).

Corresponding Author: Levi Hargrove, PhD, Center for Bionic Medicine, Rehabilitation Institute of Chicago, 345 E Superior St, Room 1309, Chicago, IL 60611 (l-hargrove@northwestern.edu).

jama.com

JAMA. 2015;313(22):2244-2252. doi:10.1001/jama.2015.4527

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2244

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Research data vs. Health data

- High-density, high-quality research data
($\approx 2M$ bit/s)
- Highly structured (cf. paper records)
- Amenable to supervised, unsupervised learning, pattern recognition, etc.
- “Vanilla” methodologies are often good enough
- $\approx 95\%$ prototyped off-line in Matlab, implemented in other software to achieve realtime performance



Amanda Kitts, http://www.npr.org/sections/pictureshow/2010/01/bionics_now_science_nonfiction.html

Homework exercise: information content in EMG

- Estimate the amount of information (in bits) contained in 10 seconds of simultaneous 128-channel electromyogram recorded at 16 bits, 1080 Hz, critically sampled.
- Compare it to the amount of information contained on this sheet of paper from earlier in the course. Be explicit about your assumptions for correlations between EMG channels, but do not assume independence.

19-0505 Blood: Venous ORDERED BY: TNT HED CL - AT&T ACCOUNT:		COLLECTED: 04/19/89 10:10 AM RECEIVED: 04/19/89 10:51 AM ACCESSIONED: 04/19/89 10:59 AM					
HEMATOLOGY							
NORMAL RANGE							
HGB	5.5	K/uL	(4.0 - 11.0)				
RBC	4,52	ILL/uL	(Female) 3.8 - 5.2 (Male) 4.4 - 5.9)				
HBD	14.2	gm/dL	(Female) 11.7 - 15.7 (Male) 13.5 - 17.7)				
HCT	42.0	%	(Female) 35 - 47 (Male) 40 - 52)				
HCV	95.	FL	(80 - 100)				
HCH	31.4	pg	(27 - 34)				
HCRC	33.1	g/dL	(32 - 36)				
RDW	13.1	%	(less than 14.5%)				
DIFF							
POLY	BAND	NEUT	LYMPH	MONO	EOS	BAZO	REAC-LYN
56			27	13	2	2	
HYEL	FRON	BLAS	LYMPHOMA	OTHER	NRBC/100W	CELLS..COUNTED	
						100	

Figure 2.9. Laboratory reporting forms record medical data in a consistent, familiar format.

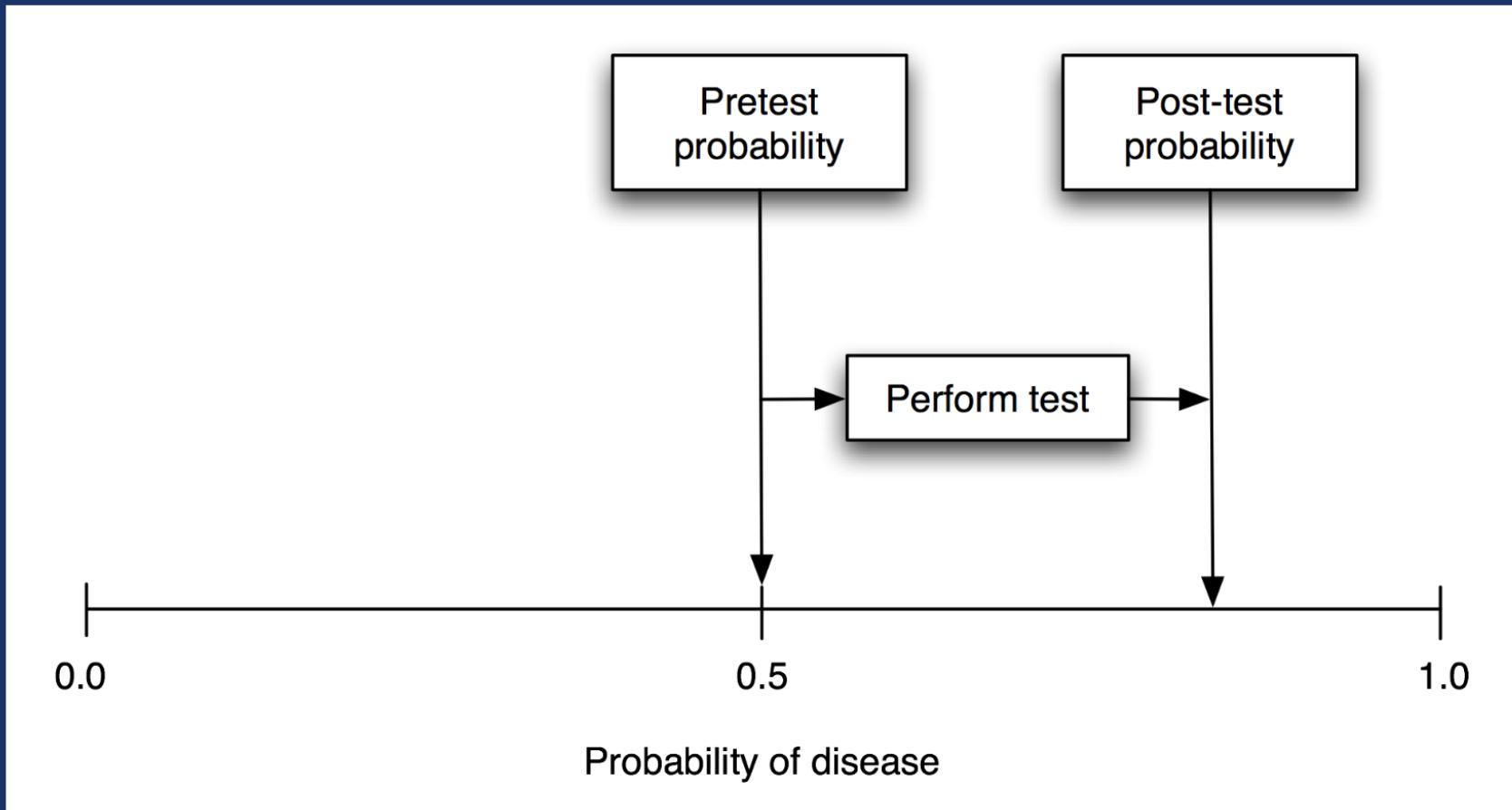
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Bayesians and frequentists, tests of central tendency (t-tests and ANOVA)



Updating Probability



In frequentist statistics, there are no priors (for better or for worse)

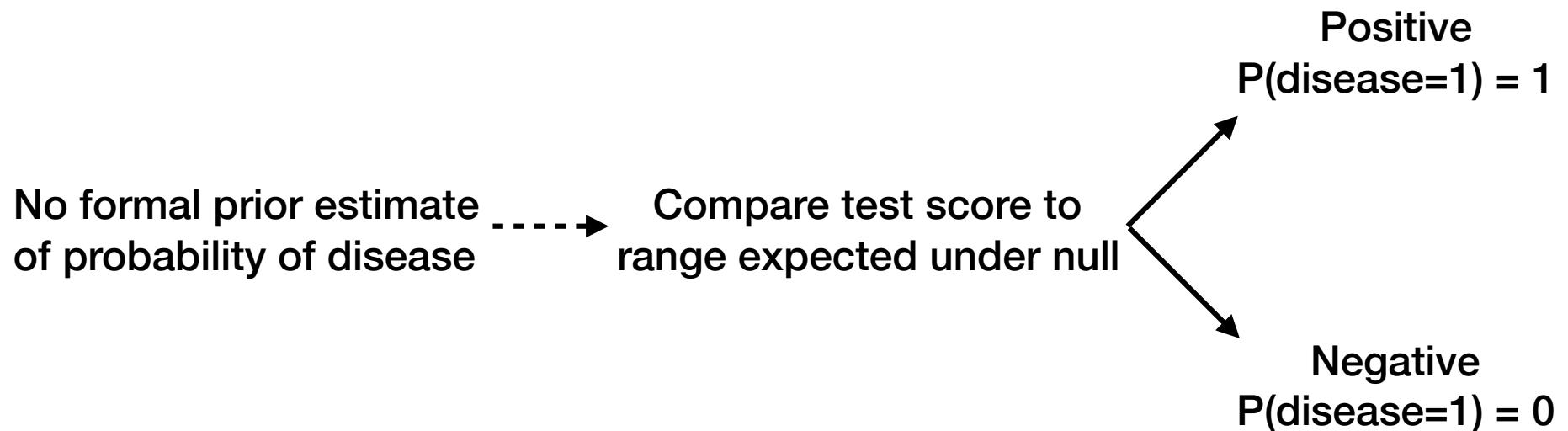


Table 3—Criteria for the diagnosis of diabetes

1. A1C $\geq 6.5\%$. The test should be performed in a laboratory using a method that is NGSP certified and standardized to the DCCT assay.*
OR
 2. FPG ≥ 126 mg/dl (7.0 mmol/l). Fasting is defined as no caloric intake for at least 8 h.*
OR
 3. 2-h plasma glucose ≥ 200 mg/dl (11.1 mmol/l) during an OGTT. The test should be performed as described by the World Health Organization, using a glucose load containing the equivalent of 75 g anhydrous glucose dissolved in water.*
OR
 4. In a patient with classic symptoms of hyperglycemia or hyperglycemic crisis, a random plasma glucose ≥ 200 mg/dl (11.1 mmol/l).
-

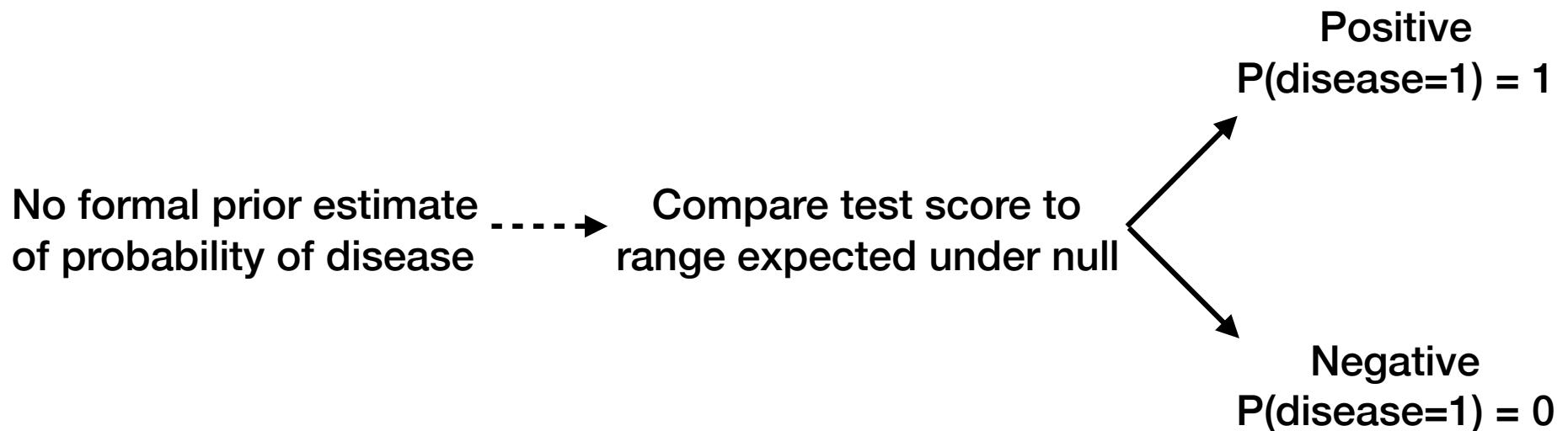
*In the absence of unequivocal hyperglycemia, criteria 1–3 should be confirmed by repeat testing.

What is the *a priori* probability of disease assumed by this test?

What are the *a posteriori* probabilities of disease resulting from this test?

How do physicians use these results?

In frequentist statistics, there are no priors (for better or for worse)



Can incorporate tests into Bayesian framework (e.g., automated decision making)

Usually Bayesian framework is implemented in clinician expertise

DID THE SUN JUST EXPLODE? (IT'S NIGHT, SO WE'RE NOT SURE.)

THIS NEUTRINO DETECTOR MEASURES WHETHER THE SUN HAS GONE NOVA.

THEN, IT ROLLS TWO DICE. IF THEY BOTH COME UP SIX, IT LIES TO US. OTHERWISE, IT TELLS THE TRUTH.

LET'S TRY.

DETECTOR! HAS THE SUN GONE NOVA?

ROLL

YES.



FREQUENTIST STATISTICIAN:

THE PROBABILITY OF THIS RESULT HAPPENING BY CHANCE IS $\frac{1}{36} = 0.027$.

SINCE $p < 0.05$, I CONCLUDE THAT THE SUN HAS EXPLODED.



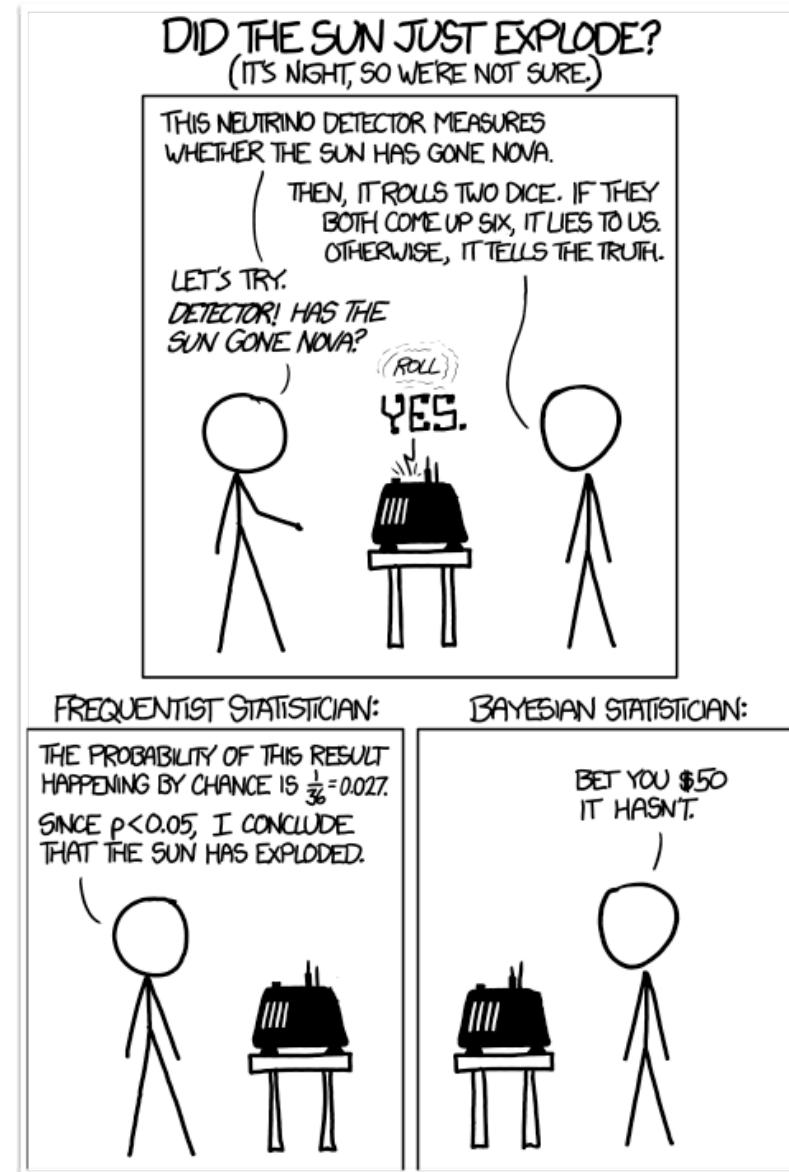
BAYESIAN STATISTICIAN:

BET YOU \$50 IT HASN'T.



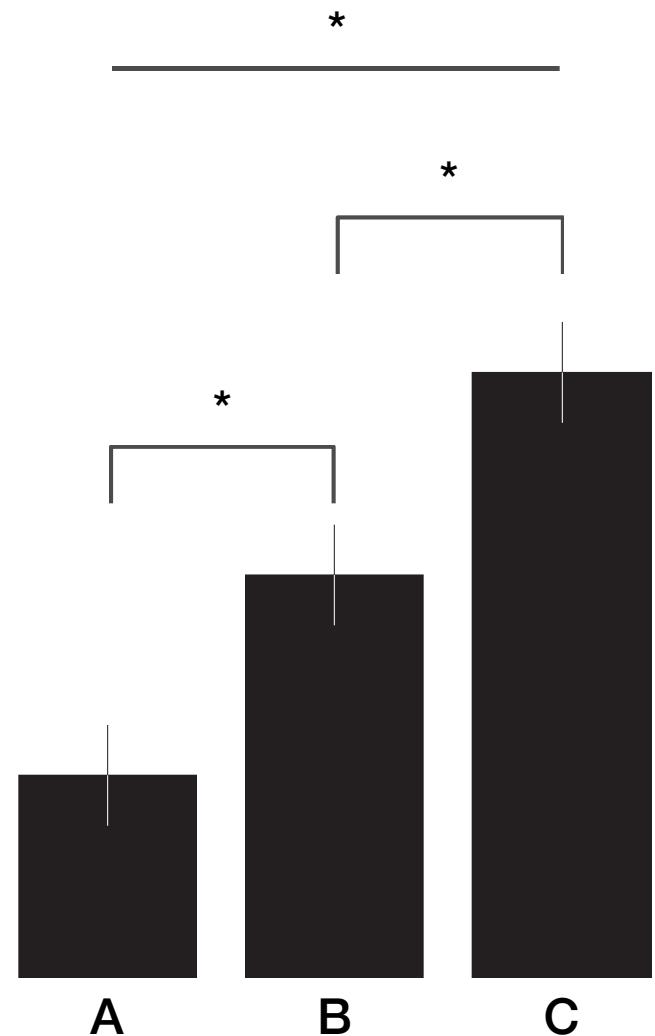
Homework exercise: Bayesians and frequentists

- Use Baye's rule to explain this joke.
- Define events.
- Describe the hypothesis test performed by the Frequentist statistician.
- Describe the calculation performed by the Bayesian statistician.



Some tests of central tendency: t-tests and ANOVA

- Calculate the probability that the means of **2** independent samples are drawn from populations with identical means: **t-test**.
- Calculate the probability that the means of **≥3** independent samples are drawn from populations with identical means: analysis of variance (**ANOVA**)
- If an **initial ANOVA** provides evidence to reject the null hypothesis that the means of the samples are drawn from populations with identical means, the different samples can be compared with **post-hoc tests**.



“Last Observation Carry Forward” imputation of missing data

- Missing follow-up data in clinical trials is inevitable and must be dealt with in some way.
- Complete case analyses (e.g., throw out incomplete records) can introduce bias (e.g., if patients that die are excluded from analyses).
- In “Last Observation Carry Forward” imputation, the last observed value is perpetuated forward.
- Many (better) techniques exist to address this problem, but LOCF is still relatively common in smaller trials, and is useful in some circumstances.
- I do not recommend LOCF data for entry into statistical analyses, but find it to be useful for visualization.

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An example visualization and analysis of clinical research data in Matlab

- `outcomedata.m`
- note in sample code:
 - importing column-oriented .csv data into table data type
 - embedding arbitrary data in graphics objects
 - callback functions for interactive plots
 - hypothesis testing with inverse-CDF and canned methods

“Wide” and “tall” data structures

“Wide”

Patient	Arm	Outcome.1	Outcome.2	Outcome.3
---------	-----	-----------	-----------	-----------

yyu9	Rx	34	34	36
ry76	Sham	30	30	30
yyu6	Sham	29	30	29
uu77	Rx	34	38	38

“Tall”

Patient	Arm	Obs	Outcome
---------	-----	-----	---------

yyu9	Rx	1	34
yyu9	Rx	2	34
yyu9	Rx	3	36
ry76	Sham	1	30
ry76	Sham	2	30
ry76	Sham	3	30
yyu6	Sham	1	29

:

Homework exercise: clinical research data

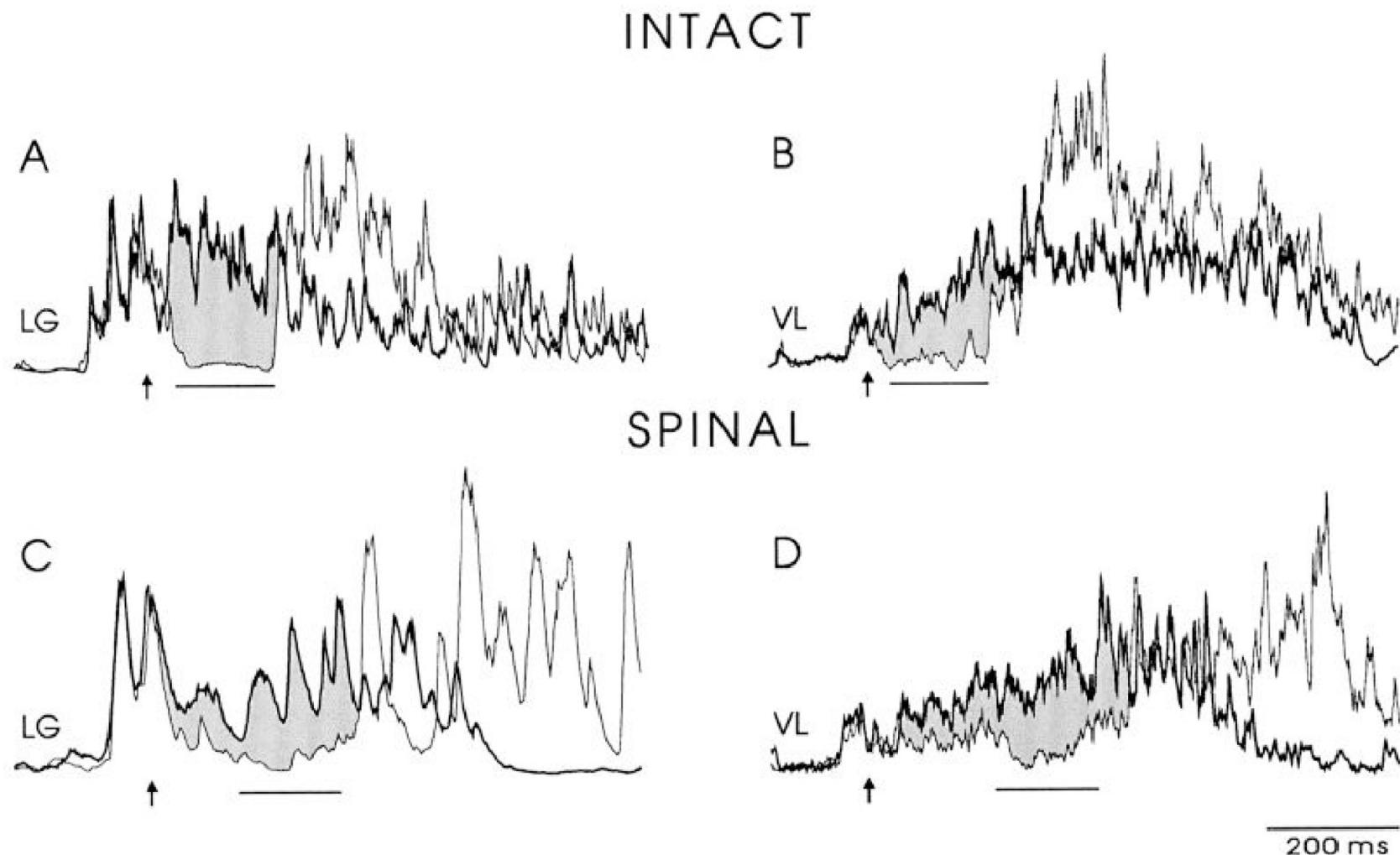
- The data table outcomes2 is in “tall” format. Write a Matlab function capable of creating a new table with the same data in “wide” format. Derive the number of time points from the data table.
 - Include only the variables ‘uniqueid’, ‘assess_group’, ‘timepoint’, and ‘fab’.
 - Use built-in functions as much as possible.

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Statistical inference with EMG signals

Many studies attempt to find differences between EMG waveforms



Comparing curves is hard, even for statisticians!

EMG in condition 1
(baseline stepping)

EMG in condition 2
(stepping in hole)

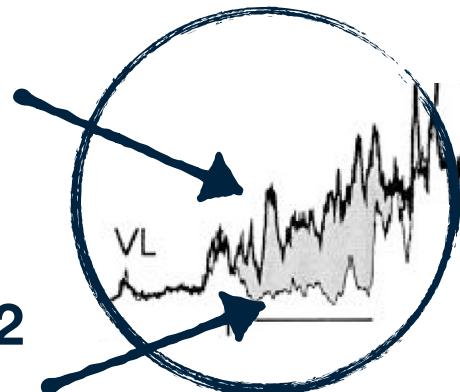
200 ms

*At what time do curves diverge?
How does this difference evolve over time?
Is it statistically significant?*

Problems occur in most studies because differences are spread across time samples

EMG in condition 1
(baseline stepping)

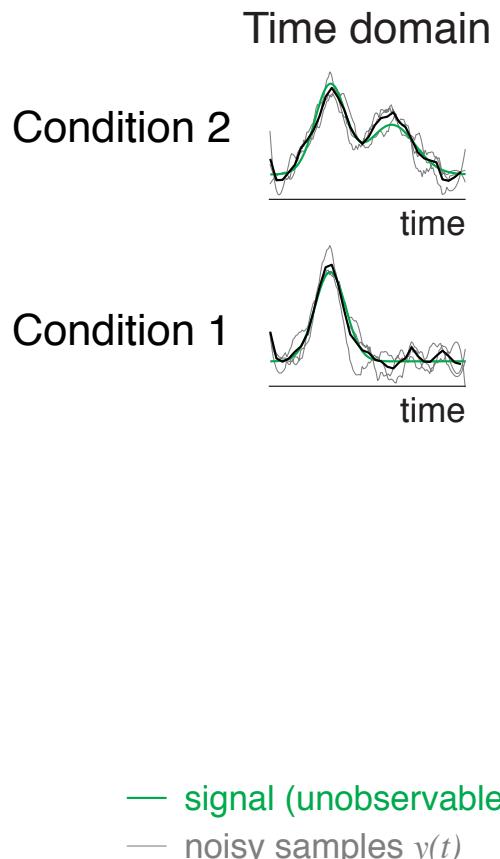
EMG in condition 2
(stepping in hole)



Most studies end up:

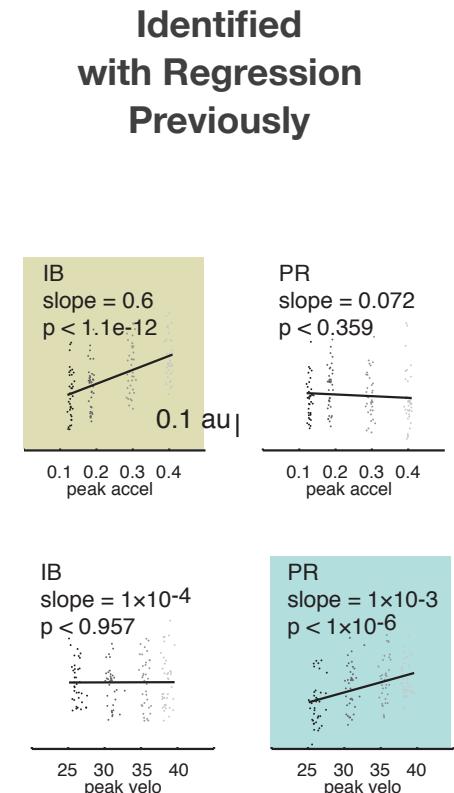
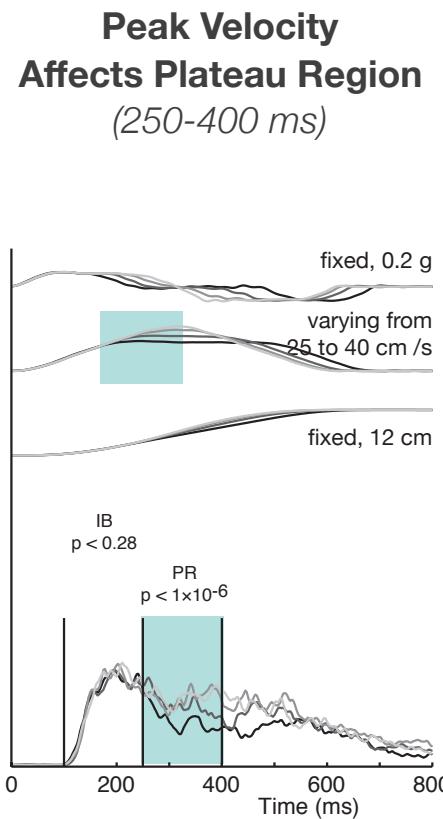
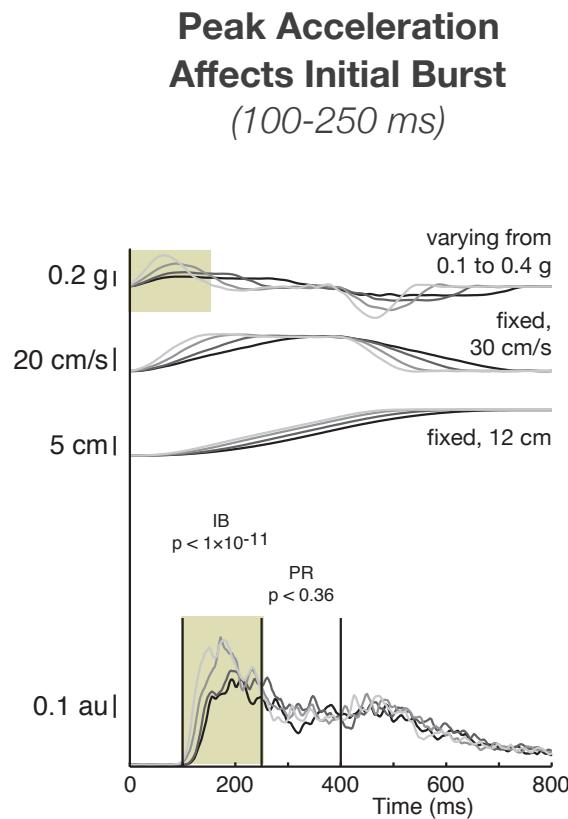
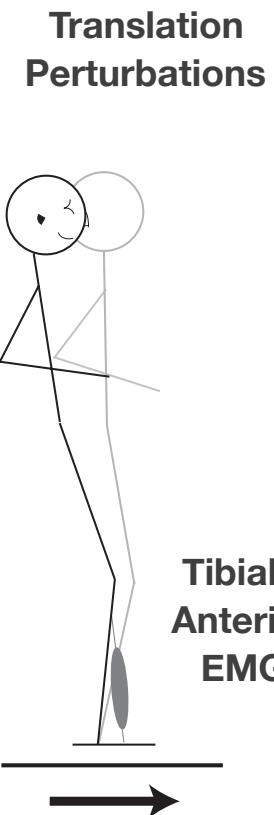
1. Averaging values in a **time window** before performing standard tests (t-tests, ANOVA):
 - *Throws away shape information, can introduce bias*
2. Attempting standard tests on **each sample**:
 - *Many tests of correlated samples, can throw away power*

Wavelet-based functional ANOVA (wfANOVA) does statistics in the wavelet domain



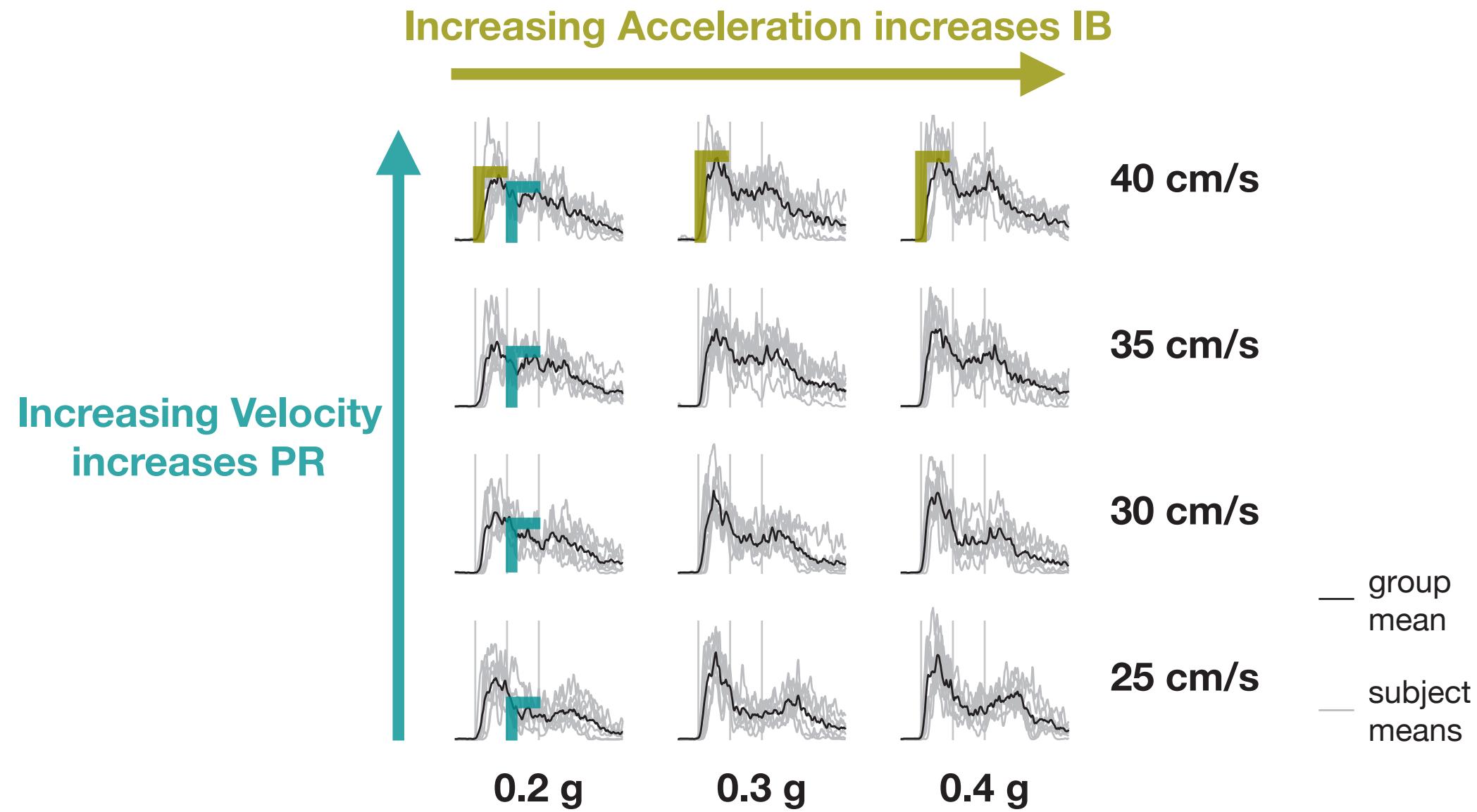
- 1. Transform each signal to wavelet domain.**
 - “Bumps” represented by a few wavelets rather than many time samples.
- 2. Test each wavelet (ANOVA, $\alpha=0.05$).**
 - Differences compressed into a few wavelets, increasing power.
- 3. Test significant wavelets post-hoc (Scheffé, Bonferroni-corrected).**
- 4. Transform back.**

We tested the ability of wfANOVA to confirm EMG trends during balance perturbations

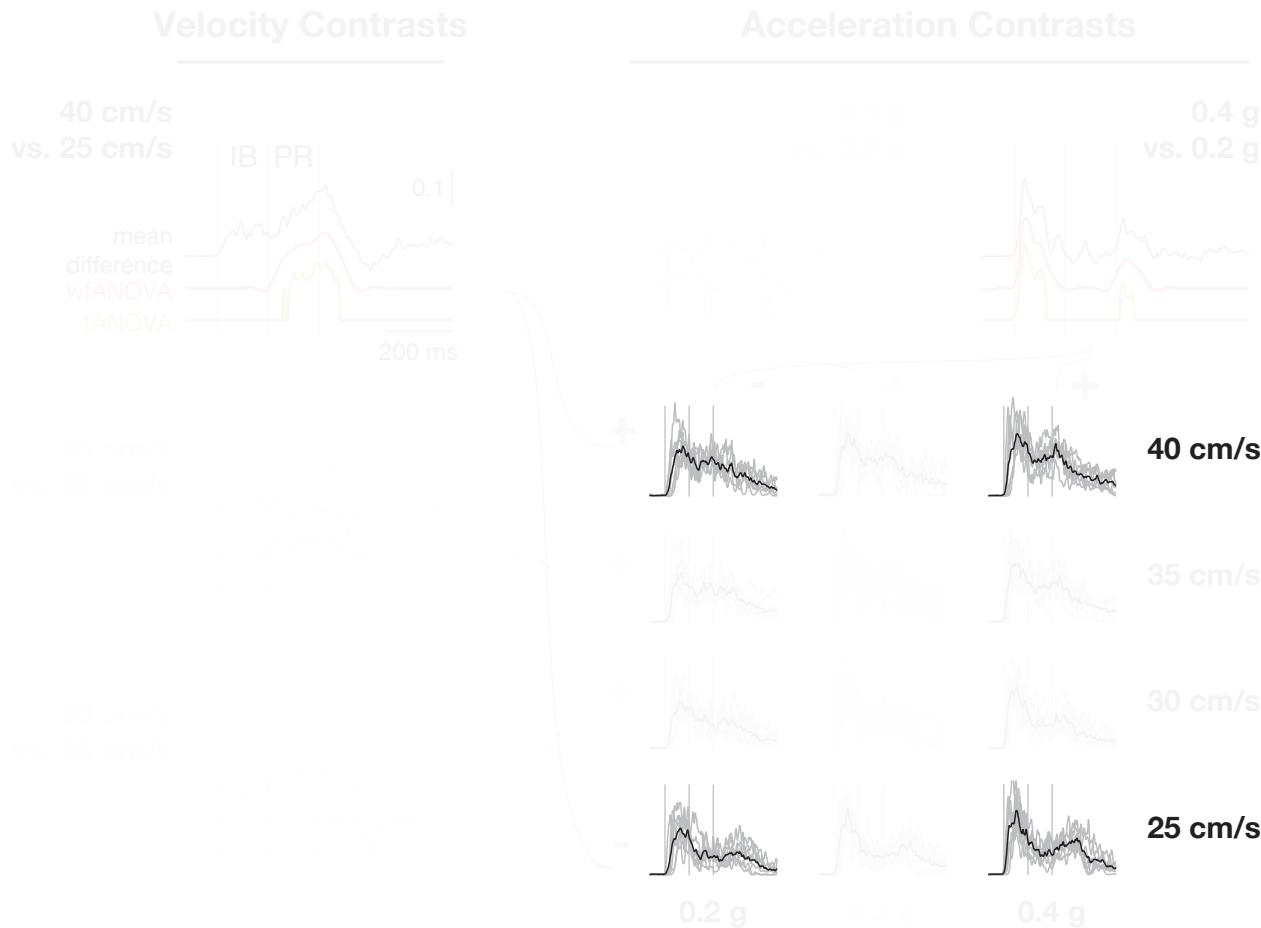


Welch TDJ, and Ting LH.
J Neurophysiol 101:
3294-3309, 2009

We can see acceleration and velocity trends in the raw EMG data



wfANOVA reveals the shape and magnitude of differences over time, superior to tANOVA

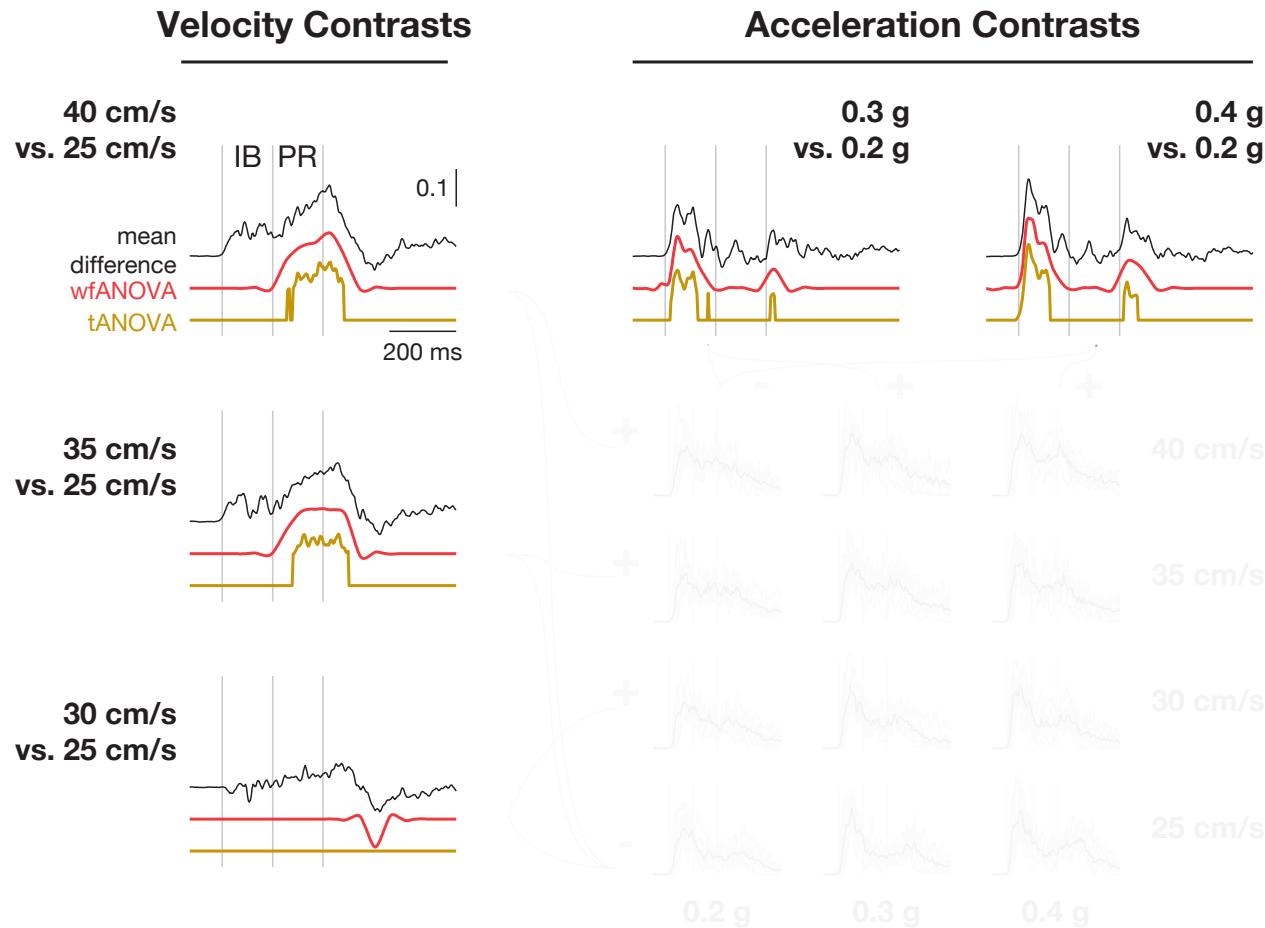


1. wfANOVA confirmed PR velocity scaling, IB acceleration scaling

- Large features in mean difference curves not necessarily significant

2. tANOVA contrast curves have sharp boundaries and missing features due to reduced power

wfANOVA reveals the shape and magnitude of differences over time, superior to tANOVA

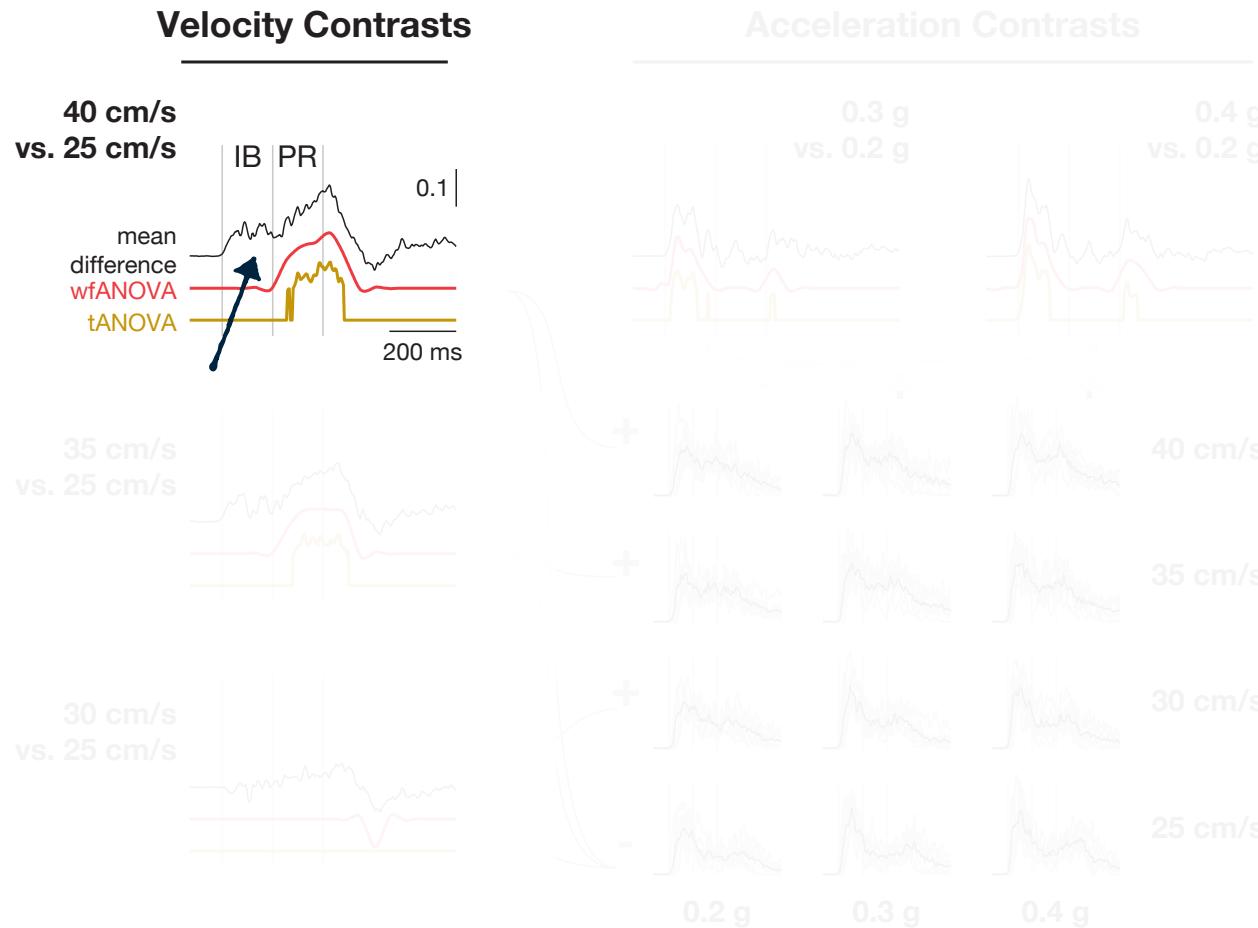


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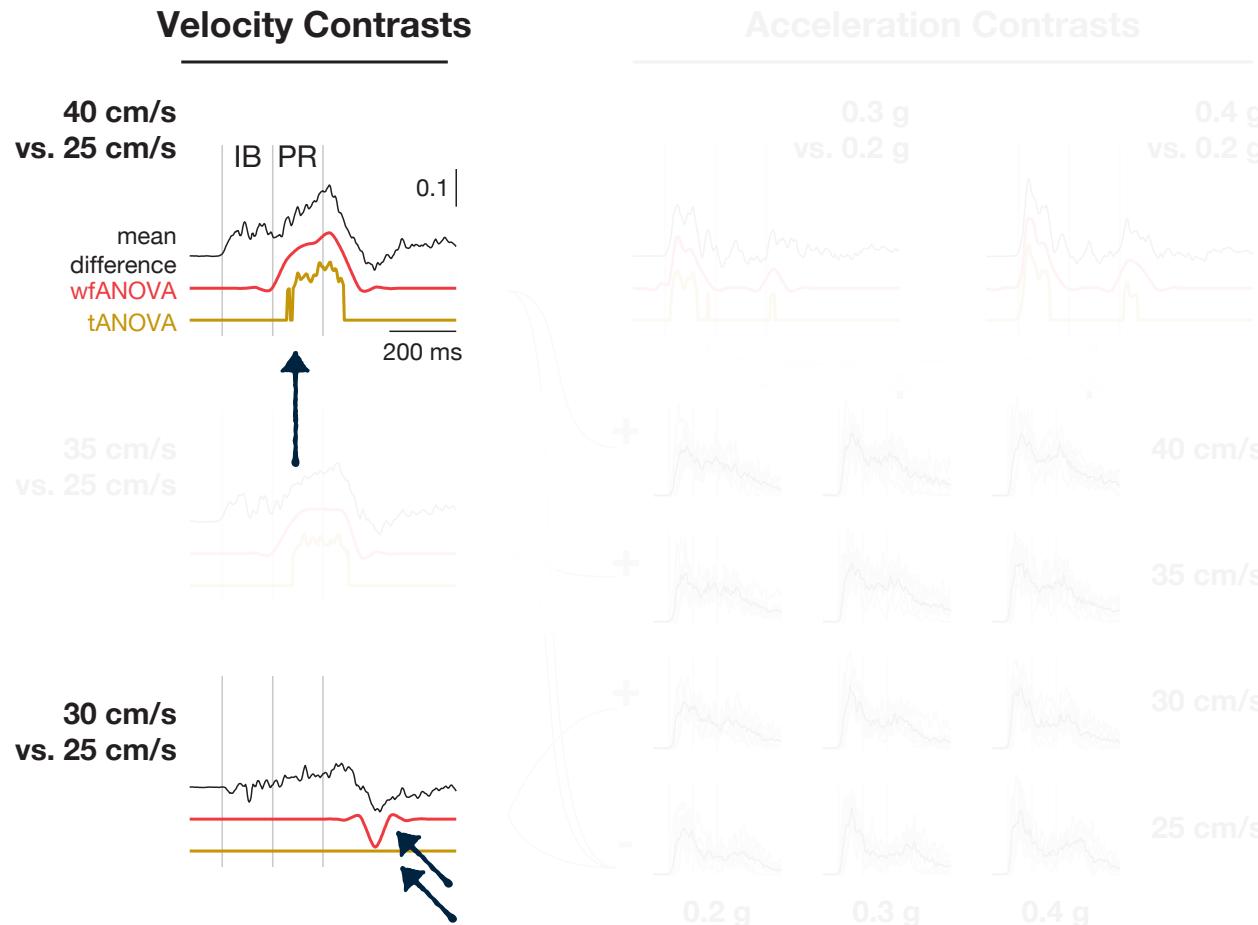


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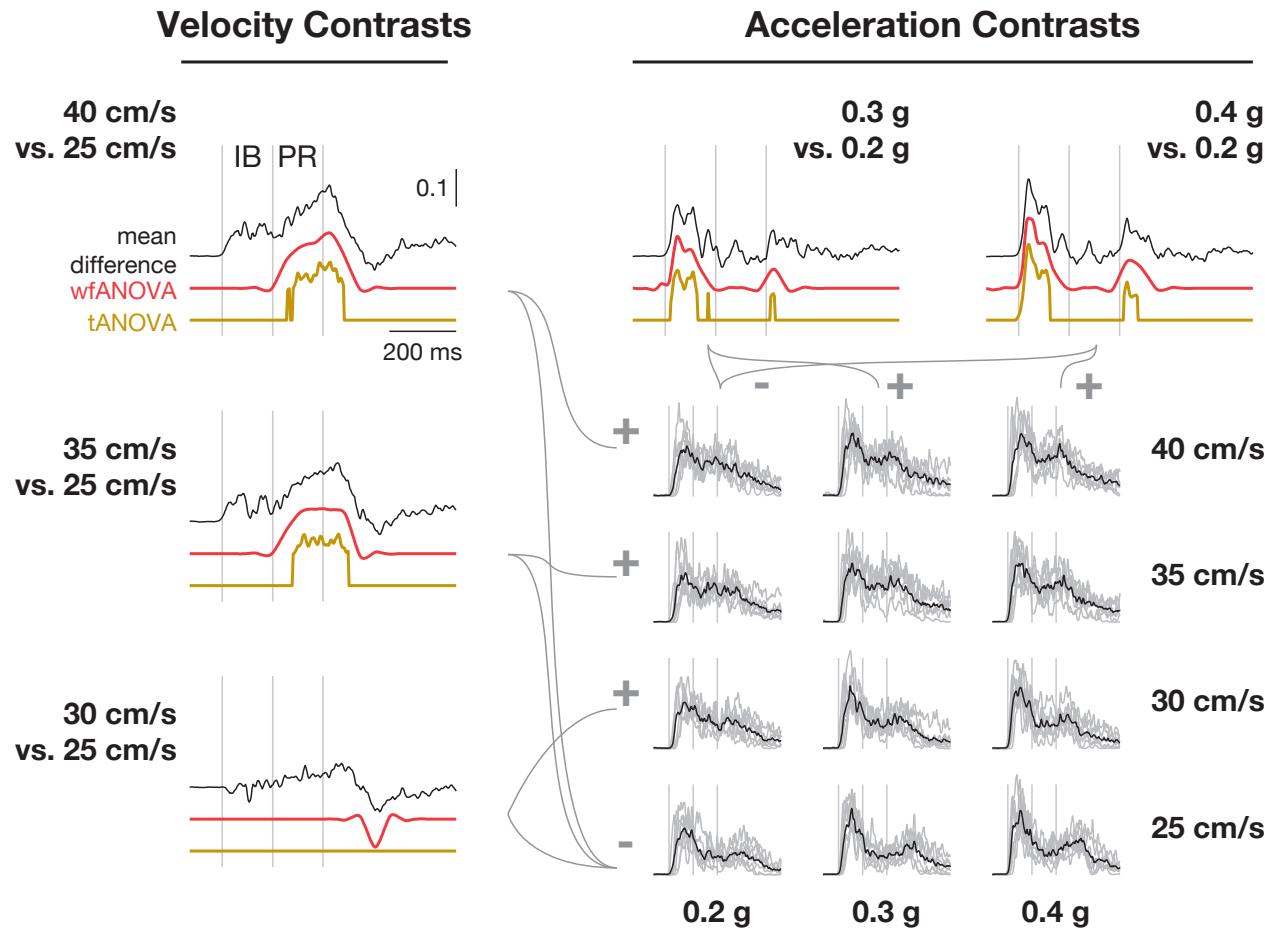


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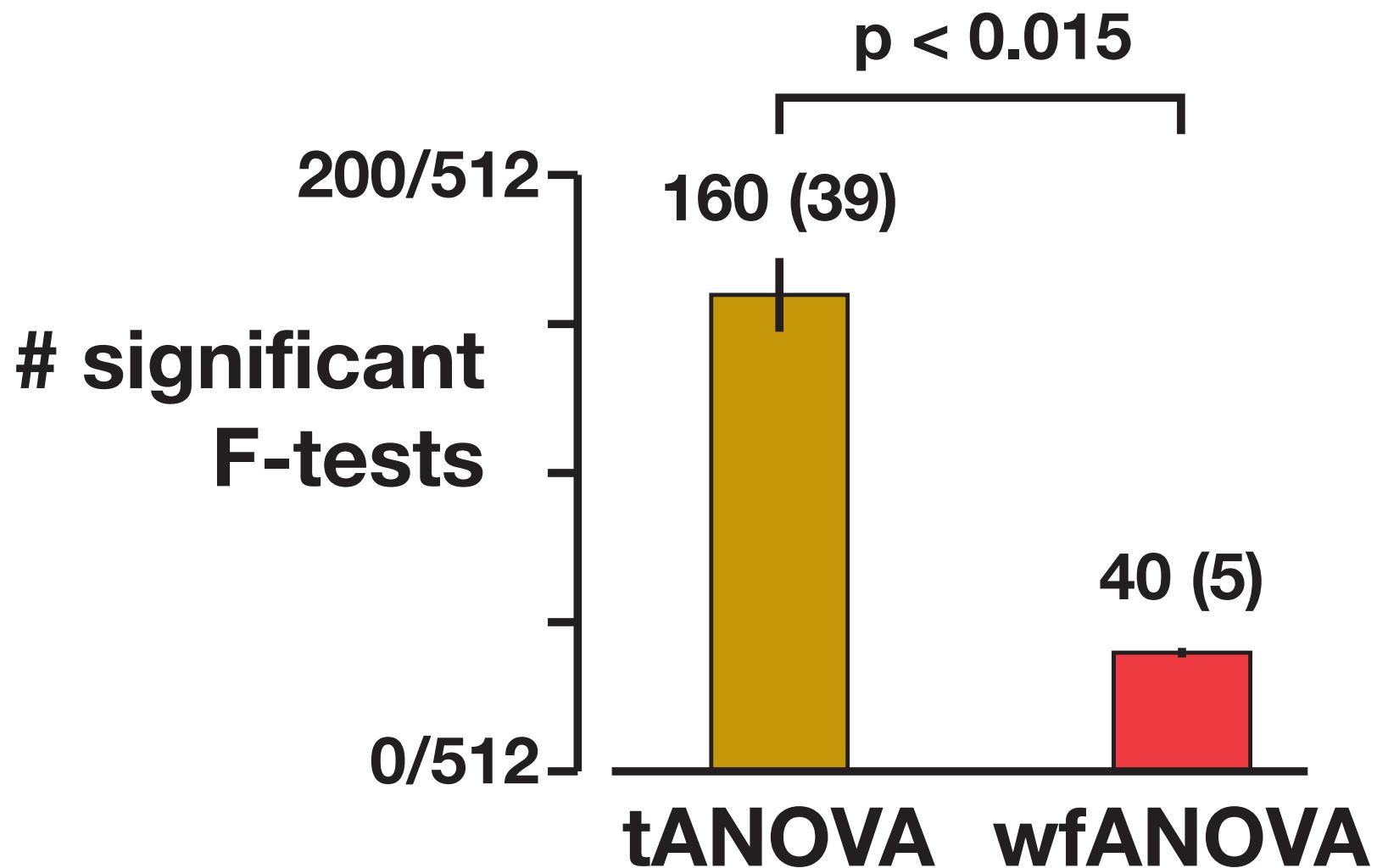
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1. **wfANOVA** confirmed PR velocity scaling, IB acceleration scaling
 - Large features in mean difference curves not necessarily significant
2. **tANOVA** contrast curves have sharp boundaries and missing features due to reduced power

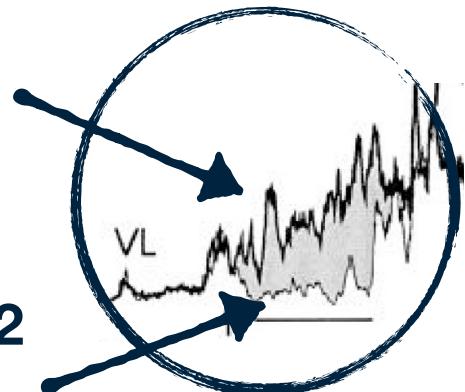
wfANOVA requires 1/4x significant F-tests than **tANOVA**, increasing post-hoc power.



Discussion: wfANOVA is a general tool for identifying differences between curves

EMG in condition 1
(baseline stepping)

EMG in condition 2
(stepping in hole)



1. wfANOVA prevents bias and offers better power than time-domain methods to answer:
 - At what time do curves diverge?
 - How does this difference evolve over time?
2. wfANOVA extends wavelet techniques from imaging applications^{1,2} and EMG analyses³⁻⁶
3. wfANOVA could be extended to other types of data, e.g., kinematics, and other hypothesis tests

¹Raz J and Turetsky B. Wavelet ANOVA and fMRI; Denver, CO, USA, 1999; ²Fadili MJ and Bullmore ET. NeuroImage 2004;

³Flanders M. J Neurosci Methods 2002; ⁴Hart CB, and Giszter SF. Neurosci 2004;

⁵Kumar D, Pah N, and Bradley A. IEEE Trans Neural Syst Rehabil Eng 2003; ⁶Stulen FB and De Luca CJ. IEEE Trans Biomed Eng 1981

wfANOVA is showing up in publications from other laboratories

J Neurophysiol 115: 143–156, 2016.
First published November 11, 2015; doi:10.1152/jn.00263.2015.

CALL FOR PAPERS | Decision Making: Neural Mechanisms

Two-stage muscle activity responses in decisions about leg movement adjustments during trip recovery

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Two-stage muscle activity responses in decision adjustments during trip recovery. *J Neurophysiol*. First published November 11, 2015; doi:10.1152/jn.00263.2015. This article is available online at jneurophysiology.org. © 2015 by the American Physiological Society. This is an open-access article distributed under the terms of the Creative Commons Attribution License (<http://creativecommons.org/licenses/by/4.0/>). The use, distribution or reproduction in other forms is prohibited.

Figure 5 consists of two panels, A and B, showing muscle activity over time from trip onset (s). Panel A shows group mean ± SD for ITA, iGM, iBF, and iRF, along with vertical toe position (m) and vertical toe velocity (m/s). Panel B shows wFANOVA significant contrast T-FZ vs. T trials ($p < 0.05$) for the same variables. The x-axis for both panels ranges from -0.1 to 0.15 seconds. Vertical dashed lines indicate the onset of the trip (T), the landing (T-FZ), and the end of the recovery step (T-TZ). Error bars represent standard deviation. Legend: T trials (average±SD) in blue, T-FZ trials (average±SD) in pink, landing T-TZ trials in black.

Fig. 5. Group average responses (**A**) and significant contrasts (**B**) between normal trips (T, blue) and trips with a FZ (T-FZ, pink), for the ipsilateral leg. Group average data are shown as means \pm SD. All signals are aligned to obstacle contact, indicated by a black vertical line at time 0. Other vertical lines indicate recovery step landing for T (brown line) and T-FZ (solid line) trials. EMG data are normalized to average normal walking and thus are unitless. Contrasts are expressed in the same way, since they represent the difference in normalized EMG data between T-FZ and T trials.

Potocanac Z, Pijnappels M, Verschueren S, van Dieen J, and DuySENS J. *J Neurophysiol* 115: 143-156, 2016. PMID 26561597

frontiers
in Human Neuroscience

ORIGINAL RESEARCH
published: 27 October 2015
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Beta activity in the premotor cortex is increased during stabilized as compared to normal walking

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¹ Department of Human Movement Sciences, MOVE Research Institute Amsterdam, VU University Amsterdam, Amsterdam, Netherlands; ² Department of Orthopaedic Surgery, First Affiliated Hospital, Fujian Medical University, Fuzhou, China

Walking on two legs is inherently unstable. Still, we humans perform remarkable well at it, mostly without falling. To gain more understanding of the role of the brain in controlling gait stability we measured brain activity using electro-encephalography (EEG) during stabilized and normal walking. Subjects walked on a treadmill in two conditions, each lasting 10 min; normal, and while being laterally stabilized by elastic cords. Kinematics of trunk and feet, electro-myography (EMG) of neck muscles, as well as 64-channel EEG were recorded. To assess gait stability the local divergence exponent, step width, and trunk range of motion were calculated from the kinematic data. We used independent component (IC) analysis to remove movement, EMG, and eyeblink artifacts from the EEG, after which dynamic imaging of coherent sources beamformers

were de-
conditi-
local di-
signifi-
sources
power c-
around
involved

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Keywords

FIGURE 8 | Normalized power spectra (estimated via Hilbert transform) of (A) left and (B) right premotor areas during normal (blue) and stabilized (red) walking. Lower panels (C,D) represent differences between conditions, with values below zero representing higher power in the stabilized condition. Red lines in lower panels are the inverse wavelet transform of the significant wavelets, thus indicating the statistically significant differences in power between conditions. Shaded areas represent standard errors.

Bruijn SM, Van Dieen JH, and Daffertshofer A.
Front Hum Neurosci **9:** 593, 2015. PMC 4621867

An example of wfANOVA implementation in Matlab

- `wfANOVAdemo.m`
- Creates the main data figure we discussed
- Note organization of omnibus, post-hoc tests with correction for multiple comparisons

Homework exercise: wfANOVA

- Choose 1:
 - Adapt the wfANOVA.m sample code to use a different basis function of your choice.
 - Adapt the wfANOVA.m sample code to incorporate false discovery rate¹ correction for multiple comparisons.
- Produce plots of contrast curves for the original implementation and the new implementation.

¹**Benjamini Y, Hochberg Y.** Controlling the False Discovery Rate: A Practical and Powerful Approach to Multiple Testing.
J R Stat Soc Series B. 1995; **57**(1):289-300.

Outline

- Filtering, aliasing, and resampling timeseries data in Matlab
- Neuromuscular physiology properties of electromyographic (EMG) signals
- Bayesians and frequentists, tests of central tendency (t-tests and ANOVA)
- Interactive visualization and statistical analysis of clinical behavioral research data in Matlab
- Statistical analysis and inference with EMG signals with wavelet-based functional ANOVA (wfANOVA)

Homework (due Thursday, 11/17)

- Complete **one** of the homework problems described during the lecture and return to Dr. McKay by email by 11:59 PM Thursday, 11/17.
- j.lucas.mckay@emory.edu
- Attach the exercise as a PDF named “BMI500 Lastname Firstname.pdf”
- Make the subject of the email “BMI500 Lastname Firstname.pdf”
- If you were the first to answer the paying attention question, submit that answer as your homework for full credit.