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Evidence of bilinearity in the relationship between rate of neuromuscular excitation and rate of force development

Micah D. Josephson[a,*], William C. Rose[b], Christopher A. Knight[b]

[a] Doctor of Physical Therapy Program, Alvernia University, Reading, PA, USA
[b] Department of Kinesiology and Applied Physiology, University of Delaware, Newark, DE, USA

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ABSTRACT

The purpose was to examine the relationship between the rate of neural excitation (rate of rise in the electromyogram, EMG) and the rate of isometric force development (RFD) to determine whether surface EMG measures can detect nonlinearity that is expected due to underlying motor unit discharge behavior and the summation of progressively larger motor unit potentials throughout recruitment. Due to interest in obtaining a change point, a bilinear model was hypothesized to provide the best fit of the EMG-RFD relationship compared to a linear model, exponential model and log-transformed data. 21 young adult participants performed isometric dorsiflexion contractions to 40% of their maximal voluntary contraction (MVC) force. Contractions were performed in RFD conditions ranging from slow (20 %MVC/s) to fast (peak volitional rate). The Akaike Information Criterion supported nonlinear best fit models in 16 of the 21 participants with the greatest overall support for the bilinear model (n = 13). The bilinear models indicated a mean change point at 204%MVC/s. The present data do not identify the specific motor unit control mechanisms at play and the influence of amplitude cancellation on the electromyogram must be carefully considered.

1. Introduction

Examining the relationship between neuromuscular excitation (NE) and force production provides a means to study topics such as impaired motor control (Chou et al., 2013; Jahanmiri-Nezhad et al., 2014; Ng et al., 1997), the effects of exercise training (Van Cutsem et al., 1998) and neuromuscular efficiency (Paquin and Power, 2018). In some instances, physical function is predicted more strongly by the rate of force development (RFD) than the peak force achieved (Bento et al., 2010; Hazell et al., 2007). NE primarily determines RFD (Maffiuletti et al., 2016), and is quantifiable using electromyography (EMG). EMG represents the electrical sum of active motor units (Robertson et al., 2004) and is primarily determined by motor unit (MU) recruitment and rate coding mechanisms of force control (Kamen and Gabriel, 2010). While one must not over-interpret measures from surface EMG with respect to MU behavior, some recognize that nonlinearities in the EMG-force relationship may reflect “different motor unit pool activation strategies” and have demonstrated that parameters from a bilinear fit of the EMG-force relationship can be sensitive to experimental manipulations such as contraction history (Paquin and Power, 2018).

At the MU level, the relationship between the rate of increase in current applied to the motoneuron and RFD is linear (Baldissera and Campadelli, 1977). This linearity is due to bilinear firing behavior of the alpha motor neuron offsetting the nonlinear input-output transform of muscle which mimics a low-pass filter (Baldissera et al., 1998; Partridge, 1965). The bilinear relationship between input to the motor neuron and its response (i.e. firing rate) includes a primary range of firing rates typically observed during slow contractions and a secondary range of firing rates observed during rapid contractions or movements (e.g. Harwood et al., 2011; Kernell, 1965b). The two linear ranges intersect at a change point and the secondary range has a greater slope. Feline studies have demonstrated that both rapid muscle contractions from rest and higher frequency sinusoidal force modulations depend on brief instances of secondary range MU discharge rates (Baldissera et al., 1998) and the bilinear relationship between movement velocity and MU firing rates has been successfully documented in humans (Harwood et al., 2011).

The dynamics of MU recruitment may also contribute to possible nonlinearity in the NE-EMG relationship since higher threshold MUs have greater electrophysiological sizes (Masakado et al., 1994) and are more likely to be recruited earlier in a contraction as RFD increases (Desmedt and Godaux, 1977; Yoneda et al., 1986). In slow muscle contractions, the greatest NE occurs close to peak force, whereas during fast muscle contractions the greatest NE occurs closer to force onset

* Corresponding author at: Alvernia University, Doctor of Physical Therapy Program, 400 Saint Bernadine St., Reading, PA 19607, USA.
E-mail address: micah.josephson@alvernia.edu (M.D. Josephson).

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(Ricard et al., 2005). Thus, bilinearity in rate coding and the nonlinear summation of progressively larger MU action potentials are both considered as the basis of the present hypothesis that a bilinear relationship between neural excitation and RFD can be observed with surface EMG measures. A more complete understanding of this relationship will benefit applications of electromyography to the study of neuromuscular function during rapid movements in health, pathology, and performance.

2. Methods

2.1. Participants

Twenty-one healthy young adults, ten females and eleven males, (mean ± SD: age = 21.7 ± 2.7 years, body mass = 73.6 ± 20.2 kg, height = 1.7 ± 0.1 m, maximal grip strength = 39.5 ± 10.2 kg) participated in this study. Nine participants self-reported as consistently participating in high-intensity physical activity for at least the previous six months. All participants were university students and free of neurological impairment, lower body dysfunction, and recent (< 6 months) lower extremity injuries. All participants signed a university approved informed consent before beginning the study.

2.2. Procedures

EMG and isometric force recordings were obtained during a single testing session. Participants were seated on a custom wooden bench with the left foot fastened with an inelastic strap to a plate affixed to a strain gauge force transducer (Model SM-100, Interface Force Inc., Scottsdale, AZ). Force was amplified and low-pass filtered at 50 Hz at the time of recording (Model SGA, Interface force Inc., Scottsdale, AZ). The skin above the belly of the tibialis anterior muscle was shaved, abraded, and cleansed with ethyl alcohol. A pre-amplified double differential surface electrode was secured to skin above the mid-belly region of the tibialis anterior muscle (MA-300, Motion Lab Systems, Baton Rouge, LA). The surface electrodes were 12 mm diameter medical grade stainless steel disks with a 17 mm inter-electrode distance. A 13x3 mm reference bar separated the sensors and a ground electrode was placed on the lateral malleolus. Amplification ranged from 2000 to 5700. Input impedance for this system is > 100 MΩ with a common mode rejection ratio > 100 dB at 65 Hz and noise < 1.2 uV RMS. Signals were digitized at 2 kHz with 24-bit resolution (cDAQ-9178, module NI9239, National Instruments, Austin TX). DASYLab v.13 (National Instruments, Austin, TX) was used to control data acquisition and to provide real-time force biofeedback.

2.3. Experimental conditions

Participants performed three maximum voluntary isometric contractions (MVCs) with the maximum force achieved used to present relative force levels (%MVC) in visual feedback. Participants were asked to produce force to match static plots of different linear ramp force-time curves (Fig. 1). There were five different ramp force RFD conditions (20 %MVC/s, 40 %MVC/s, 80 %MVC/s, 160 %MVC/s, and 200 %MVC/s) and one condition of rapid force pulses. All conditions were performed to 40 %MVC. Each condition was practiced and performed for multiple trials. Each ramp force within a trial was separated by 2 s and rapid pulses by 1 s. Each trial contained six ramps with one minute of rest between recordings. With feedback based on visual inspection by the investigator, participants practiced each RFD ramp condition until five ramps of adequate performance were obtained. To reduce order effects, the ramp conditions were counterbalanced across participants followed by two trials of rapid force pulses. After the conservative exclusion of contractions that exhibited poor performance (typically excessive RFD at the onset of a ramp, large corrections during a ramp, or poor amplitude control in pulses) an average of 57 contractions were analyzed in each individual.

2.4. Signal processing

Force and EMG data were processed using LabVIEW v. 2014 (National Instruments, Austin, TX). All values derived from the force-time curve were normalized to MVC force. An RFD time series was calculated from the force-time curve as the slope from a linear fit line of all data points within a .1s moving window (± 0.05 s around each data point). After adjusting for gain, removing DC offset, and bandpass filtering between 10 and 990 Hz, the EMG was absolute value rectified. Based on recent work involving EMG and rapid contractions, peak rate of EMG rise (RER) was selected to quantify NE because it had the greatest correlation with RFD among measures that do not require the determination of EMG onset, which would have been impractical and highly variable in the slowest RFD conditions (Josephson and Knight, 2018). Using the same .1s window size as RFD computation, RER was calculated as the slope of the rectified, filtered (zero-lag 4th order low-pass Butterworth, 20 Hz cutoff) electromyogram. The EMG recordings were normalized to the RMS amplitude of EMG in the maximal MVC trial (± 0.250 s window surrounding MVC) which was filtered similarly.

2.5. Model selection

Based on the evidence of bilinearity in neuromuscular function cited above and with interest in observing a potential change point, a strict bilinear model of the data was our primary model of interest. Two other models were tested using guidance from research on blood lactate concentration curves. Beaver et al. (1985) determined that the best bilinear fit for this relationship is achieved with a log-log transformation. Later researchers suggested that exponential model was most representative of the underlying physiology (Hughson et al., 1987). A linear relationship between surface EMG measures of NE and RFD, establishing our fourth model. Therefore, the models tested in the present study were linear, bilinear, log-log transformation, and exponential.

The referent model (model 1) is a strict linear relationship, which is defined as:

$$y = ax + b$$

where ‘a’ is the slope of the line, ‘x’ is the peak RFD, and ‘b’ is the y-intercept.

Model 2 is based on a strict bilinear relationship and is defined as:

$$y = \begin{cases} a_0 + a_1 x & if \quad x \le x_0 \\ b_0 + b_1 x & if \quad x > x_0 \end{cases}$$

where

$$x_0 = \frac{a_0 - b_0}{a_1 - b_1}$$

where ‘y’ represents the estimated peak rate of NE, ‘x’ represents the peak rate of force development, ‘a_0’ represents a constant of the first linear relationship, ‘a_1’ represents the slope of the first linear relationship, ‘b_0’ represents a constant of the second linear relationship, ‘b_1’ represents the slope of the second linear relationship, and x_0 is the change point where the two relationships intersect.

Model 3 is a bilinear fit following a log-log transformation. For this model, the log values were found for both peak RFD and peak RER prior to fitting it into the same bilinear relationship listed above.

Model 4 is based on an exponential relationship. This relationship is defined as:

$$y = ae^{(bx)} + c$$

where ‘y’ represents the estimated peak rate of neuromuscular activation, ‘x’ represents the peak rate of force development, ‘a’ is the y-

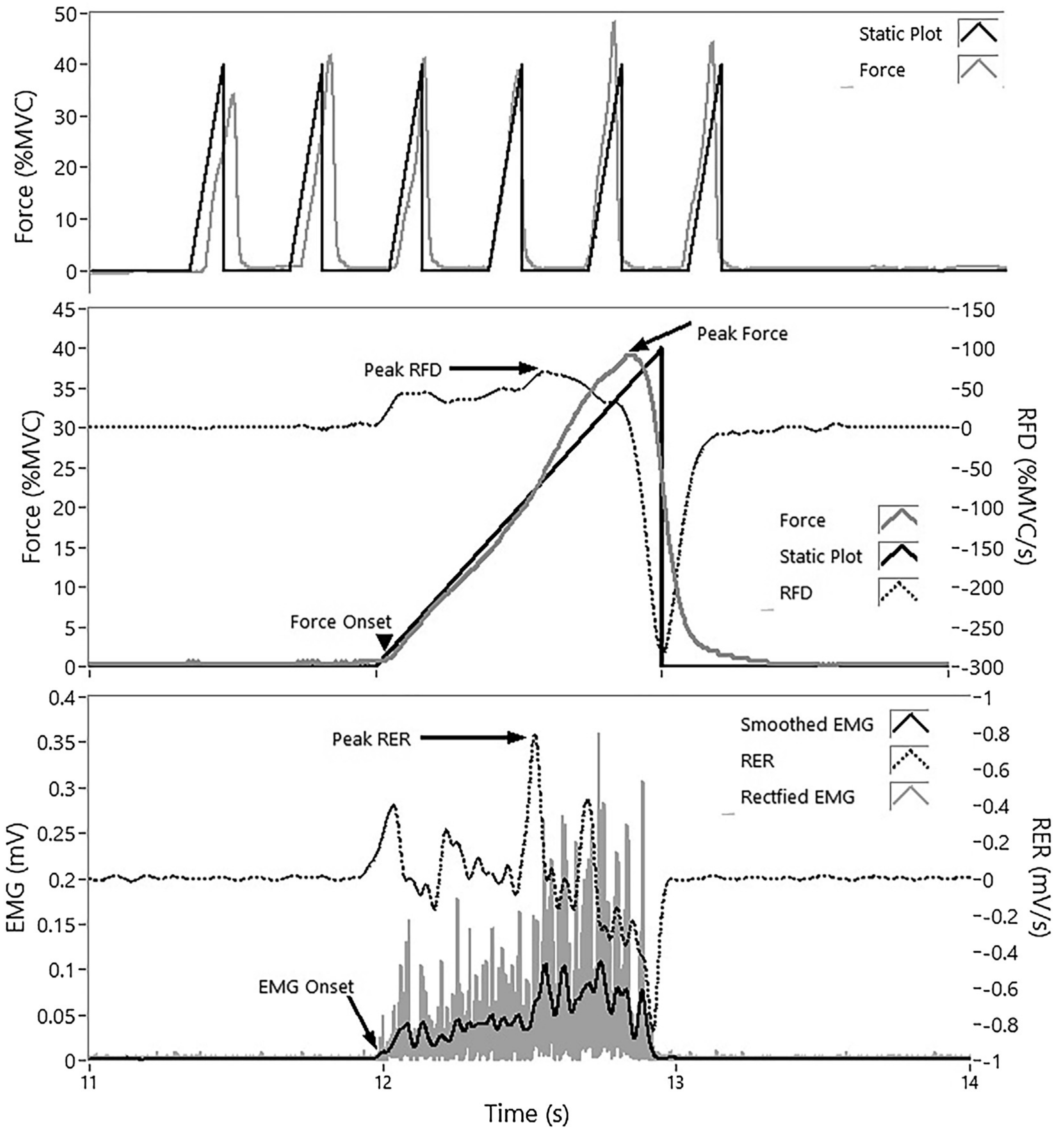

Fig. 1. A sample force-trace for the ramp force-matching condition (top) and graphs showing details of data analysis (middle and bottom). The top graph contains a static plot of the 40 %MVC/s ramp condition (black line) and the force produced for the entire trial by the participant (gray line). The middle graph is isolates a single ramp between from the top graph with the addition of the dF/dt (RFD, dotted line). The bottom graph is the rectified (gray line), smoothed (black line), and dEMG/dt (RER, dotted line) EMG from the same ramp.

intercept, 'b' is the growth factor, and 'c' is a constant.

2.6. Data analysis

The data from each participant was fitted with each model, using a custom LabVIEW program (National Instruments, Austin, TX) to adjust model parameters until the mean squared error (MSE) was minimized. The corrected Akaike Information Criterion (AICc, explained below) was computed for each model. According to information theory, the model with the lowest AICc is most likely to be the best model. The Akaike Information Criterion accounts for models with more adjustable parameters tending to have lower mean squared error, even when not the best model (Akaike, 1973; Katsanevakis, 2006). The formula for AIC is

$$AIC = n\log(MSE) + 2K + n(1 + \log(2\pi))$$

where n is the number of data points and K is the number of fitted parameters. Note that K should include one extra parameter for the hidden estimate of residual variance (Burnham et al., 2002), and therefore K = 3 for the linear model, K = 5 for the bilinear and log–log models, and K = 4 for the exponential model. The formula for AICc (which is AIC corrected for small sample size (Akaike, 1973; Shono, 2000) is:

$$AICc = AIC + 2K(K + 1)/(n - K - 1)$$

When the sample size, n, is large, AICc approaches AIC.

The normalized model likelihood (Akaike weight, w_i) is the probability that model i is the best model, among the considered models (Burnham et al., 2002; Wagenmakers and Farrell, 2004). Akaike weight, is calculated as:

$$w_i = \frac{\exp(-0.5\Delta_i)}{\sum_{k=1}^{4}\exp(-0.5\Delta_k)}$$

where Δ_i is the difference between AICc for model i and AICc for the best model for that set of data:

$$\Delta_i = AICc_i - AICc_{best}$$

Table 1
Detailed model comparison in participant 1. Mean square error (MSE), corrected AIC (AICc), AICc difference (Δ), and normalized model likelihood (w) for each model. n = 42 data points for this participant.

Quantity	Linear	Bilinear	Log-Log	Expon.
M.S.E.	21,369	11,011	199,270	13,272
AICc	544.5	521.7	643.4	527.0
Δ	22.8	0.0	121.6	5.3
w	0%	93%	0%	7%

3. Results

The mean dorsiflexion strength was 34.04 ± 7.30 N-m. During the rapid contractions, the peak RFD observed ranged from 287 to 623 % MVC/s with a mean peak RFD of 446 %MVC/s. The mean absolute peak RFD was 149 ± 34.2 N-m/s.

For aggregate data, an exponential line of best fit had the lowest AICc (16,015) and w_i = 91.2%. Considering the potential for aggregate data to hide individual differences in best fit, model testing was performed on an individual level, an approach consistent with the individual computation of blood lactate curves (Hughson et al., 1987) and serves an interest in computing bilinear regression parameters such as the change point for individual research participants.

Table 1 shows mean squared error (MSE), corrected AIC (AICc), AICc difference (Δ), and relative model likelihood (w, in percent) for the four models, for participant 1, to illustrate their computation and relationships. In this participant, the bilinear model has the lowest AICc, and therefore has the greatest likelihood of being the best model. The AICc difference, Δ, is zero for the model with the lowest/best AICc. The relative likelihoods of the four models add up to 100% (Fig. 2**)**.

Table 2 shows the AICc differences (Δ) and the model likelihoods (w) for each participant. The data in Table 2 indicate that a linear fit was best in five of the twenty-one participants while a non-linear fit was best in the remaining sixteen. A chi square test indicated a significant (X^2 = 5.76, p = 0.01) departure from an equal distribution across linear and nonlinear models. More specifically, linear model was the strongest for five participants and had a better-than-5% chance of being the best model in two other participants. The bilinear model was the strongest fit for thirteen participants and had a better-than-5% chance of being the best model for the remaining eight participants. Log-log transformation was the strongest fit for no participants and had a better-than-5% chance of being the best model in one participant. Exponential was the strongest fit for three participants and had a better-than-5% chance of being the best model in twelve additional participants.

Each bilinear fit has a change point: X-coordinate separating the primary range from the secondary range. Table 3 provides the primary slope, change point, and secondary slope for each participant in whom the bilinear model was most likely along with the coefficient of variation for each parameter. The mean primary range slope was 0.51, the mean secondary range slope was 3.21, and the mean peak RFD where NE changed from primary to secondary range was 204 %MVC/s. The change point exhibited the least coefficient of variation.

4. Discussion

This study sought to add to the current understanding of the rate of neural excitation (EMG rate of rise, RER) throughout a wide range of isometric contraction rates. The aim was to determine whether there is support for a bilinear model of the NE-RFD relationship, considering the known bilinearity in MU discharge behavior (Baldissera et al., 1998; Harwood et al., 2011; Kernell, 1965b) and the nonlinear summation of MU potentials in the electromyogram as larger MUs are recruited (Masakado et al., 1994). Although we borrow the terms primary range and secondary range from studies that observed bilinearity in MU firing rates, we do not suggest the observed bilinearity in the surface electromyogram is due specifically to this MU control mechanism.

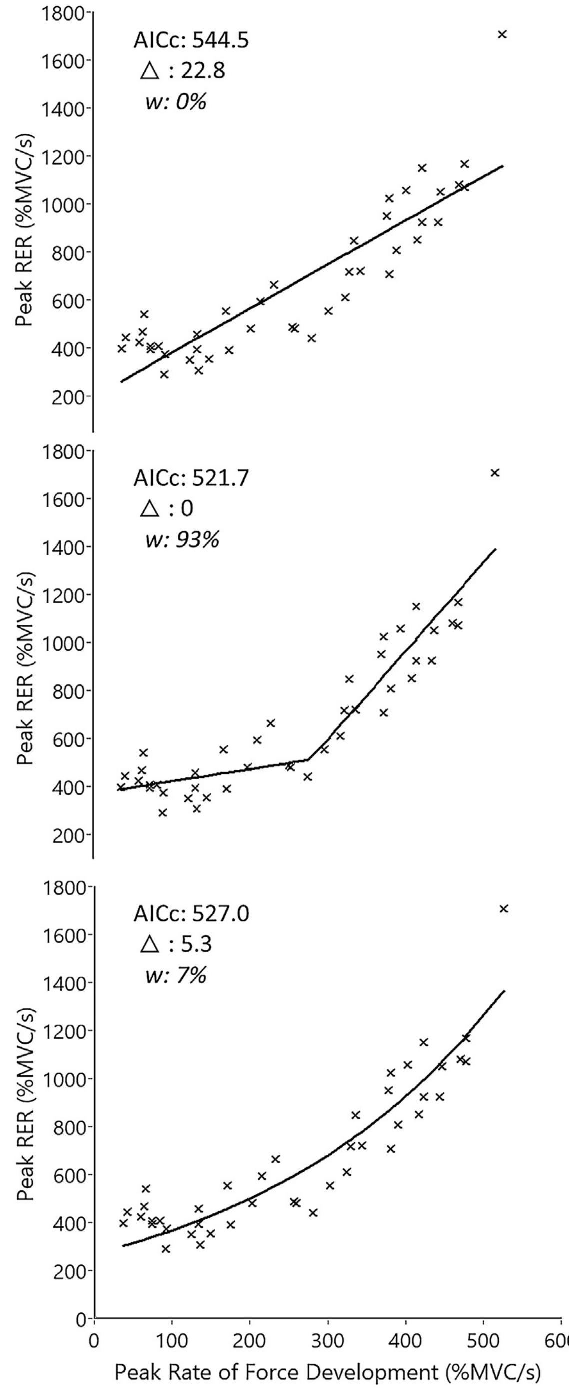

Fig. 2. Linear (top), bilinear (middle), and exponential (bottom) fit for participant 1. AICc, AICc delta, and Akaike weight of each fit are listed on each figure. AICc delta is the difference between the AICc of that particular model and the lowest AICc observed among the three. Akaike weight is the likelihood (percent) of a particular model being the best fit for that dataset.

The AICc provided objective support for the bilinear model compared to linear, log-log, and exponential alternatives. While nonlinearity was not the best fit model in all participants, that 76% of the participants demonstrated a nonlinear best fit and all participants had a better-than-5% chance specifically for bilinearity supports the application of this model to the study of NE across increasing rates of force development. Bilinear model parameters from the 13 best-fit participants provided slopes of the primary and secondary excitation ranges

Table 2
Model comparison in all participants. Table shows AICc difference (Δ) and normalized model likelihood (w, in percent) for each model in each participant. Bold indicates most likely model for each participant, among the tested models.

Participant	Linear		Bilinear		Log-Log		Expon.	
	Δ	w	Δ	w	Δ	w	Δ	w
1	22.8	0%	0.0	**93%**	121.6	0%	5.3	7%
2	6.4	2%	0.0	**55%**	1.2	30%	2.8	13%
3	10.8	0%	0.0	**78%**	136.3	0%	2.5	22%
4	10.7	0%	0.0	**97%**	93.7	0%	7.7	2%
5	30.4	0%	2.6	22%	106.4	0%	0.0	**78%**
6	0.0	**78%**	4.0	10%	110.8	0%	3.9	11%
7	5.5	5%	0.0	**80%**	126.0	0%	3.3	15%
8	6.9	2%	0.4	44%	113.8	0%	0.0	**55%**
9	8.5	1%	0.0	**98%**	129.7	0%	10.7	0%
10	4.3	8%	0.0	**71%**	120.2	0%	2.4	21%
11	14.2	0%	0.0	**96%**	176.0	0%	6.4	4%
12	0.0	**61%**	3.7	10%	69.5	0%	1.5	29%
13	0.0	**64%**	1.1	36%	169.5	0%	17.3	0%
14	5.7	3%	0.0	**57%**	116.3	0%	0.7	40%
15	0.5	30%	0.3	33%	72.4	0%	0.0	**38%**
16	0.0	**49%**	1.1	29%	131.6	0%	1.6	22%
17	21.2	0%	0.0	**86%**	162.4	0%	3.7	14%
18	0.0	**71%**	4.4	8%	67.9	0%	2.4	21%
19	22.3	0%	0.0	**98%**	132.1	0%	7.4	2%
20	5.6	5%	0.0	**81%**	132.8	0%	3.5	14%
21	16.2	0%	0.0	**100%**	174.2	0%	10.9	0%

Table 3
Bilinear fit results. Primary range slope, change point, and secondary range slope, in each participant for whom the bilinear model was most likely. A paired *t*-test revealed a significant difference between the primary and secondary slopes ($t = -6.67$, $p < 0.001$).

Subject ID	Primary Range Slope	Change Point (RFD%MVC)	Secondary Range Slope
1	0.499	285.1	3.624
2	0.196	162.1	0.894
3	0.737	232.0	2.941
4	−0.174	154.0	1.954
7	−0.795	154.7	1.858
9	−0.186	120.5	1.793
10	0.102	126.3	1.796
11	1.334	256.7	6.024
14	1.249	222.0	3.986
17	0.675	181.8	2.063
19	1.611	367.3	7.994
20	1.692	256.8	4.386
21	−0.279	131.9	2.459
Mean	0.512	203.9	3.213
Standard Deviation	0.788	73.8	1.994
Coefficient of Variation (%)	154	36	62

and a change point. Among these three values the change point (203.9 ± 73.8 %MVC/s, coefficient of variation (CV) = 36%) had the least variance across participants followed by the secondary range slope (3.21 ± 1.99, CV = 62%). The slope of the relationship between RER and RFD in the primary range was the most variable (0.512 ± 0.788, CV = 154%).

While recognizing the limitations of surface electromyography to determine underlying MU activity, one can still consider the possible contributions of rate coding and recruitment to the observed bilinearity in EMG rate of rise. Specifically, one would expect a bilinear or exponential increase in EMG as greater rates of descending excitation elicit secondary range firing rates (Baldissera et al., 1998; Harwood et al., 2011) and/or recruit larger, high threshold motor units with larger electrophysiological potentials (Masakado et al., 1994; Stalberg, 1980). The main challenge to this expectation is the influence of amplitude cancellation (Keenan et al., 2005) in which the electromyogram is increasingly attenuated at greater levels of excitation due to the summation of negative and positive phases of MU action potentials. Since the effect of amplitude cancellation is more pronounced at greater levels of excitation, the present findings of bilinearity in the relationship between EMG rate of rise and RFD might be considered a possible underestimation of its true nature.

Determining why most, but not all, individuals had a nonlinear RFD-NE relationship requires further consideration. Exploratory analysis comparing linear to non-linear subsets of participants was performed for sex, grip-strength normalized-to-body mass, dorsiflexion MVC normalized-to-body mass, BMI, body mass, and participation of high intensity activity in the previous year. Due to the small sample size (N = 21), Fisher's Exact Test was used for the influence of sex and activity. Independent t-tests comparing linear and non-linear groups were used for BMI, body mass, normalized TA-MVC, and normalized handgrip. The Fisher's Exact test revealed no differences in best fit by sex ($p = 0.635$) or regular participation in high intensity activity ($p = 0.611$). No differences in BMI ($t = 0.853$, $p = 0.440$), body mass ($t = 1.068$, $p = 0.342$), dorsiflexion MVC normalized to body mass ($t = 0.737$, $p = 0.470$), or normalized handgrip strength ($t = -0.424$, $p = 0.677$) existed.

As no significant differences of best-fit based on demographics or descriptive information arose, other options should be considered. One must not only consider possible differences in MU morphology, rate coding, and recruitment, but also the possibility of individual differences in factors that contribute to amplitude cancellation (Keenan et al., 2005). Another possible explanation for the mixed observations of nonlinearity across participants is heterogeneous compliance of the muscle tendon (M–T) unit. As reviewed by Maffiuletti et al., the rate of force transmission through tissue is partly determined by its stiffness and tendon stiffness in the lower extremity is known to be highly variable across individuals (Maffiuletti et al., 2016). Some of the earliest published work on this topic considered the manner in which pairs of electrical stimuli with brief intervals interact with tissue compliance (e.g. Hill, 1949) and perhaps individuals with greater M–T unit stiffness might depend less on secondary range MU firing rates during rapid contractions from rest, compared to individuals with less M–T stiffness.

While extrapolation of specific MU control mechanisms from the surface electromyogram is not recommended (Farina et al., 2014) this observation of nonlinearity in the EMG-RFD relationship is consistent with expectations based on known nonlinearities in both MU rate coding and the summation of progressively larger electrical potentials from higher threshold MUs. However, bilinearity was observed in the MU firing rates of a study examining dynamic elbow extension across multiple angular velocities, but not in surface EMG measures (Harwood et al., 2011). Although one could suggest that differences in the EMG measures used might explain this discrepancy, the isometric equivalent of the measure used by Harwood et al. (RMS amplitude from EMG onset to peak RFD), has a similarly strong correlation with RFD as the rate of EMG rise measure used here (Josephson and Knight, 2018). One could also suggest that surface EMG is more sensitive to recruitment than firing rate (Harwood et al., 2011) but such speculation seems to be based on publications that used slower 10 %MVC/s ramp conditions which are less likely to elicit secondary range firing rates (Christie et al., 2009). It is possible that the present study had greater sensitivity to detect bilinearity due to a greater number of observations used in model fitting at the level of the individual.

Different models have demonstrated the necessity of rapid initial MU firing rates to accomplish rapid contractions (Baldissera et al., 1998; Del Vecchio et al., 2019; Desmedt and Godaux, 1977; Heller, 2010) and found a lower RFD, decreased force, and a force lag when high initial MU firing rates are removed. Considering the importance of RFD in mobility (Bento et al., 2010) and its responsiveness to exercise training (Aagaard et al., 2002), knowledge of an EMG-RFD (or EMG-movement velocity) change point may be informative in the practice of neuromuscular rehabilitation. Variance in the location of the change point in our participants suggests that there may be an individual-specific threshold above which the nonlinearities in recruitment or rate coding are expressed. In addition to differences in M–T stiffness discussed above, it might be the case with humans *in vivo* that the change point will also be influenced by muscle fiber length and contractile velocity. The observed variance in the change point supports the value of examining bilinearity in individual participant data rather than in group data.

As hypothesized, objective quantitative methods provided the greatest support for a bilinear model of the EMG-RFD relationship, despite the known effects of amplitude cancellation which would make such a finding less likely. We consider this finding to be preliminary and one that requires replication as it has not been observed in other related experiments (Harwood et al., 2011) and the results may be dependent on details of experimental design. Two known limitations should be addressed in future studies. First, experimental conditions that produce more data points in the range of the change point may enhance resolution. Second, extending the RFD conditions further into the secondary range by performing force pulses to greater amplitudes would make quantification of the EMG-RFD relationship more complete. Despite the limitations of surface electromyography, a more complete understanding of the relationship between rates of neuromuscular activation and rate of force development will improve our understanding of the neural control of rapid movement in health and disease.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jelekin.2019.102355.

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Micah Josephson completed his PhD in Applied Physiology at the University of Delaware. He is currently an Assistant Professor at Alvernia University in the Doctor of Physical Therapy Program. His research interests focus on neural control of rapid movement and function in special populations.

Bill Rose received his Ph.D. in Biomedical Engineering from the Johns Hopkins University School of Medicine. He is an Associate Professor in the Department of Kinesiology and Applied Physiology at the University of Delaware. His professional interests include teaching anatomy and physiology and investigating neural control of the circulation and neural control of movement.

Christopher A. Knight received a PhD in Kinesiology from the University of Massachusetts – Amherst. He is currently an Associate Professor in the Department of Kinesiology and Applied Physiology at the University of Delaware. His research interests include how aging, Parkinson's disease and exercise training affect neuromuscular function and mobility.