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EMG Versus Torque Control of Human-Machine Systems: Equalizing Control Signal Variability Does Not Equalize Error or Uncertainty

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EMG versus torque control of human-machine systems: equalizing control signal variability does not equalize error or uncertainty

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Abstract— In this paper we asked the question: if we artificially raise the variability of torque control signals to match that of EMG, do subjects make similar errors and have similar uncertainty about their movements? We answered this question using two experiments in which subjects used three different control signals: torque, torque+noise, and EMG. First, we measured error on a simple target-hitting task in which subjects received visual feedback only at the end of their movements. We found that even when the signal-to-noise ratio was equal across EMG and torque+noise control signals, EMG resulted in larger errors. Second, we quantified uncertainty by measuring the just-noticeable difference of a visual perturbation. We found that for equal errors, EMG resulted in higher movement uncertainty than both torque and torque+noise. The differences suggest that performance and confidence are influenced by more than just the noisiness of the control signal, and suggest that other factors, such as the user's ability to incorporate feedback and develop accurate internal models, also have significant impacts on the performance and confidence of a person's actions. We theorize that users have difficulty distinguishing between random and systematic errors for EMG control, and future work should examine in more detail the types of errors made with EMG control.

Index Terms—EMG, myoelectric control, uncertainty, upper limb prosthesis, uncertainty

I. INTRODUCTION

MYOELECTRIC control is non-invasive and widely used for human-machine interfaces, but performance is far from able-bodied standards [1] and inferior to able-bodied control interfaces such as joint torque or joint angle [2], [3]. The decoded electromyographic (EMG) signals used in myoelectric control are highly variable, and this variability is thought to be a major performance limitation of EMG as a control signal [4]. Many research efforts focus on improving filters and algorithms to lower the variability of EMG control signals (e.g. [5]). However, other factors also make EMG control difficult, such

as the lack of direct biological feedback and the lack of experience modulating EMG to use as an explicit control input. EMG is often simply compared against other control signals, with no way of knowing how each of those factors affect performance. We need to clarify the influence of control signal variability on performance with EMG control.

The relationship between EMG amplitude and generated torque has been well studied and several excellent reviews are available (e.g. [6]). In certain circumstances, for example during isometric contractions, the EMG amplitude is proportional to muscle torque, so the two signals represent similar movements. However, the variability of EMG signals is not filtered through tissue and muscle redundancies. Instead, the stochastic patterns of EMG signals are sent to the control system, which may transmit variability through to movements. Furthermore, when measured from the skin's surface, the EMG interference signal is comprised of only a subset of active motor units. Thus EMG control signals have higher variability than corresponding torque control signals, which likely contributes to the larger errors that users make when using EMG control.

Errors are often caused by unexpected control signal variability, but may also come from other factors, many of which are common to both EMG control and torque control. However, there are two differences that may affect performance: 1) users do not have feedback on EMG signals in the same way they do with muscle torque, through either efference copy or local feedback loops, and 2) users do not have as much experience explicitly modulating EMG amplitude, whereas torque is often modulated to accomplish everyday tasks. In this paper we seek to determine if variability alone can explain the increased errors with EMG, as compared to torque control.

Increased error generally causes increased uncertainty, which affects the user's behavior and ability to improve performance. Movement uncertainty, or how confident the user is of movement outcomes, is typically inferred through observing adaptation and error behaviors. Scientists manipulate

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feedback variance [7], [8] or motor variance [9], [10], and observe how movement behavior changes in response. In this experiment we dissociated error and uncertainty, and explicitly quantified uncertainty by measuring the just noticeable difference of a visual perturbation.

We measured the user’s uncertainty in movement predictions using a two-alternative forced choice (2AFC) technique [11]. This technique is used extensively to quantify feedback uncertainty [12] and shows promise for quantifying feedforward uncertainty [13]. In a 2AFC paradigm, the subject is given two options and must decide which is correct. In our specific task, the subject makes two movements. Visual feedback is only given at the movement endpoints and is visually perturbed on one of the movements. The subject must decide which movement was perturbed. This task measures how precisely the subject estimates movement distance. The size of the visual perturbation is adjusted using an adaptive staircase pattern [14], [15]. When the subject answers correctly, the perturbation size decreases; when the subject answers incorrectly, the perturbation size increases. The staircase hones in on the threshold at which the subject can detect a perturbation, called the Just Noticeable Difference (JND), which serves as a measure of movement uncertainty.

In this study we raised the variability of torque control signals to match that of EMG, and assessed the effect on error and uncertainty. Does matching the control signal variability across torque and EMG equalize any performance differences? Here we studied the movement performance and corresponding movement uncertainty during use of three control interfaces in a virtual dynamic environment: torque (low variability), EMG (high variability), and torque+noise (variability manipulated to match that of EMG). We measured variability of each control signal, observed the average errors during the target-directed task, and quantified movement uncertainty by measuring the JND of visual perturbations.

II. METHODS

A. Subjects

Eighteen able-bodied subjects completed this experiment, which was approved by the Northwestern University Institutional Review Board (7 female, 11 male; between the ages of 23 and 34).

B. Protocol

Subjects sat comfortably in front of a computer display screen (Fig. 1). They used isometric elbow extension to move a cursor clockwise around a circular single degree-of-freedom track. The starting position was held fixed at 180 degrees on the left-hand side of the screen.

Target Task

For each trial, subjects began moving the cursor when a GO signal appeared on the screen. They were allowed 3 seconds to complete the movement. The end of the trial was triggered

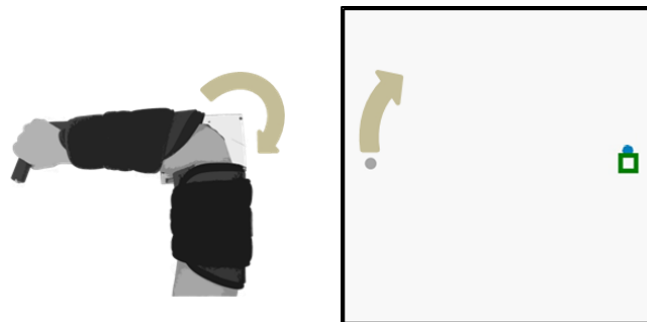


Fig. 1. Experimental setup for EMG and torque control interfaces. The elbow was immobilized in a brace. Isometric elbow extension torque and EMG signals were mapped to clockwise movement of the cursor around the circular track.

when subjects brought the cursor to a stop. If they did not end the movement within the allotted time, a TOO SLOW signal appeared on the screen and the trial was not counted. Subjects were instructed to end the movement as close to the target as possible. The target position was drawn from a uniform distribution across the right-hand side of the screen (between -45 and +45 degrees).

To focus on feedforward variability and feedforward uncertainty, as opposed to feedback, visual feedback was taken away during each movement and returned at the end of the trial. For a training phase (first 10 trials), subjects were given visual feedback on cursor position throughout the movement. The training phase gave subjects information to form estimates of the task dynamics and variability. For the testing phase (last 75 trials), the cursor disappeared after 15 degrees of movement and reappeared at the end of the movement to show subjects the cursor endpoint. Thus during the testing phase, subjects had to rely on feedforward predictions to successfully complete this “reaching in the dark” task, instead of relying on visual feedback throughout the movement.

2AFC Task

Immediately after the target-testing task for each control interface, subjects began the 2AFC testing. Each trial was composed of two movements. For each movement, subjects moved to the right-hand side of the circle over the course of three seconds, without aiming for a displayed target. The cursor was visible only for the first 15 degrees of movement and reappeared at the end of movement to display the cursor endpoint. Subjects were instructed beforehand that one of the two movements would be perturbed visually in the clockwise direction, and that their job was to decide which of the two movements was perturbed (movements were perturbed in only one direction to maintain a standard 2AFC paradigm—the MSSM design [11]).

C. Control Interface

Subjects used each of the three control interfaces (torque, torque+noise, and EMG) in the same session with a randomized order. For each control interface, the target task was performed

first, immediately followed by the 2AFC task. Each subject completed all three protocols in one sitting, but were not told which control interface they were using.

Subjects placed their arm in an elbow brace that minimized movement (ProCare Elbow RANGER Motion Control, modified). Isometric torque about the elbow was measured by a reaction torque sensor (Futek TFF40). EMG activity of elbow extensors was measured by a self-adhesive bipolar electrode (Delsys Bagnoli) placed over the lateral head of the triceps brachii. The lower arm portion of the brace was fixed to a horizontal link that coupled to the shaft of the torque sensor. The upper arm portion of the brace was fixed to the housing of the torque sensor.

A calibration was performed to set the gains of each control interface. Subjects exerted isometric elbow extension torque and held the muscle contraction at a series of low, medium, and high effort levels. Each contraction was held for 5 seconds and each effort level was repeated 3 times. The average mean absolute value (MAV) of the medium effort level was used to set the gains so that effort was equalized between torque and EMG control (note that the medium MAV did not set a ceiling for control signals, instead only a benchmark for the average effort needed to complete a movement). EMG signals were high-pass filtered at 0.1 Hz, rectified, low-pass filtered at 5 Hz, and normalized to the MAV recording during calibration. Torque signals were low pass filtered at 5Hz and normalized.

To create the torque+noise condition, additive and multiplicative white random Gaussian noise was added to the raw torque signal. At the surface of the muscle, EMG can be modeled as Gaussian noise with additive and multiplicative components [5]. We recreated these Gaussian noise sources, based on measured EMG properties, and added them to torque control signals for the torque+noise condition. The standard deviation of additive noise was set according to the baseline standard deviation of EMG signals during the calibration. The standard deviation of multiplicative noise was proportional to control signal amplitude. The torque+noise signal was then low-pass filtered at 5 Hz and normalized.

For all three interfaces, processed control signals were mapped to cursor angle with the following transfer function (given in the Laplace frequency domain representation):

$$\frac{\theta(s)}{u(s)} = \frac{1250}{s^2 + 11s}. \quad (1)$$

Eq. 1 represents the dynamic relationship between the subject's control input and the cursor movement—a relationship that was designed to imitate a clinical EMG filter for powered upper limb prostheses [16]. Particular values were chosen to emulate the dynamics of a typical prosthetic arm—the LTI Boston Digital™ elbow [17] in velocity control mode [4].

The control interface was designed to focus on the question at hand: how does control signal variability affect error and uncertainty? Thus, we tested only one degree of freedom to minimize the confounding effects of coordination and tuning a multi degree of freedom control system. We used elbow

extension as the control movement to give EMG signals the best possible chance at performing similarly to torque signals: a large muscle with minimal crosstalk from nearby muscles.

Data are available from the Dryad Digital Repository: <http://doi.org/10.5061/DRYAD.80150>.

III. ANALYSIS

A. Target Task

Signal-to-noise ratio (SNR) was measured in the normalized processed control signals (Fig. 2) with rest intervals between trials removed. SNR was calculated as the mean of the processed control signal divided by the standard deviation [18]. A higher SNR indicates a signal with less variability, or a cleaner signal.

We used repeated-measures general linear models to test for differences between mean SNR and mean error across control interfaces. For the mean SNR test, SNR was the within-subjects factor and control interface (torque, torque+noise, EMG) was the between-subjects factor. For the mean error test, error was the within-subjects factor and control interface was the between-subjects factor. The mean error test was performed twice: once for the mean error of all trials, and once for the mean error of the last 10%, or 8 trials (to study the practiced performance at the end of the experiment). Significance was assessed at $\alpha=0.05$ and Bonferroni corrections were applied for all post-hoc comparisons. Analyses were processed with IBM SPSS Statistics for Windows (IBM Corp., Armonk, N.Y., USA).

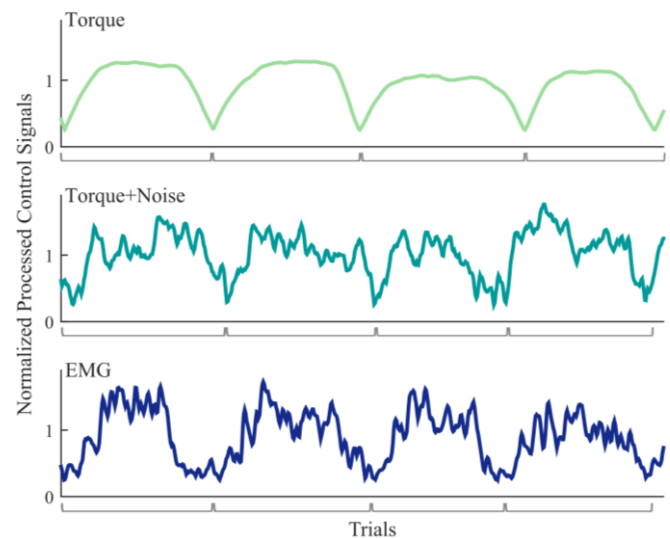


Fig. 2. Representative processed control signals for torque, torque+noise, and EMG. Four representative trials are shown for each control signal. Because the end of the trial was triggered by subjects bringing the cursor to a stop, trial lengths varied slightly. Intervals between trials, in which subjects were generally at rest, were removed from this plot and from the data used to calculate SNR. Normalized processed control signals are plotted from 0 to 1, where 1 indicates the mean absolute value (MAV) calculated during the medium effort level of the calibration.

B. 2AFC Task

The perturbation size was determined by an adaptive staircase that targeted the 75% JND [14], [19]:

$$x(n+1) = x(n) - \frac{C}{n_{shift+1}} [z(n) - \phi] \quad (2)$$

where x is the perturbation magnitude, n_{shift} is the number of reversals, ϕ is the target probability, z is the subject's decision ($z = 1$ when correct and $z = 0$ when incorrect) and C is the initial step size (set to 0.5σ , where σ is the spread of the psychometric curve). Here we used staircase parameters of $\sigma=40$ degrees (set by the spread of the psychometric curve calculated from pilot testing), $C = 20$ degrees, $\phi = 0.75$, and ran the staircase until the subject reached 25 reversals (Fig. 3). The resulting JND was used to quantify feedforward uncertainty.

We used a repeated measures general linear model to test if JND was the same between control interfaces. To assess JND as a function of mean error for each control interface, we used a general linear model with JND as the dependent factor, mean absolute error (of the last 10% of the experiment, which was 8 trials) as a continuous covariate, control interface as a fixed factor, and subject as a random factor. The mean error of the last 8 trials was used as the best estimate of each subject's error: this block of trials occurs after the subject has had plenty of practice with the control interface, and right before the JND measurement test. Significance was assessed at $\alpha=0.05$ and Bonferroni corrections were applied to post-hoc comparisons. Analyses were performed using SPSS Statistics.

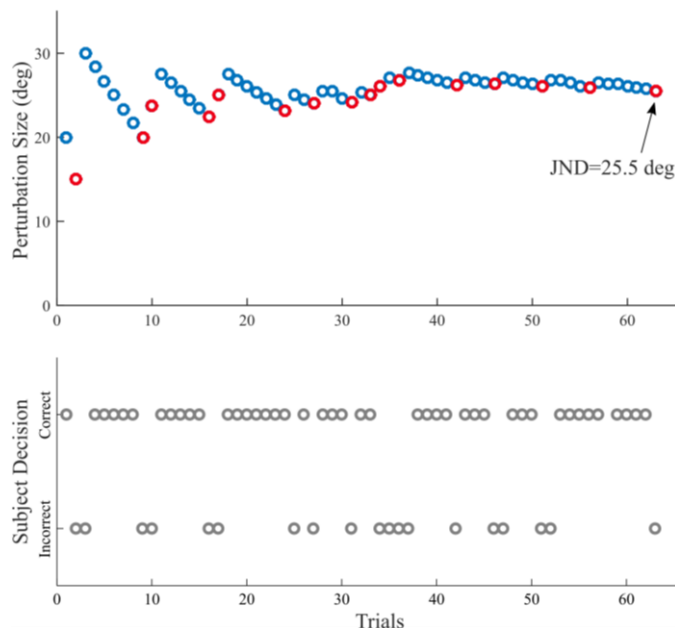


Fig. 3. Representative adaptive staircase used to find the Just Noticeable Difference (JND). The top plot shows that perturbation size was adjusted with the adaptive staircase pattern (Eq. 2), which depends on if the subject detects the perturbation correctly (blue circle) or incorrectly (red circle). The staircase pattern continues until the subject makes 25 reversals. A reversal is when the staircase changes directions—i.e., when the subject decision (bottom plot) switches between a correct choice and an incorrect choice, or vice versa.

IV. RESULTS

In this study, we investigated how increased control signal variability affected the ability of subjects to hit a target in a virtual environment with limited visual feedback. Three control signals were each used to perform the same protocol: torque, torque+noise, and EMG. Performance was evaluated by measuring the error between target and cursor at the end of each movement.

A. Target Task

The artificial variability added to torque signals in the torque+noise condition lowered the signal-to-noise ratio (SNR) (Fig. 4). The SNR of torque control signals was significantly higher than both torque+noise and EMG ($p<0.01$), and no significant difference was found between the SNR of torque+noise and EMG ($p>0.05$). A higher SNR indicates less variability—in other words, a cleaner signal. The difference in SNR was most pronounced at medium and high levels of control signal amplitude (Fig. 5). A frequency spectrum analysis shows that the frequency content of torque+noise and EMG is similar across the frequency range of interest (Fig. 6). These results indicate that we achieved our goal of recreating the variability of EMG in a torque control interface. Thus, we are able to independently study how EMG control influences error, while accounting for control signal variability.

However, subjects performed the task with significantly larger errors when using EMG control than either torque or torque+noise ($p<0.05$, Fig. 7). Torque control resulted in the lowest error. By the last 10% of each protocol (8 trials), the mean error of torque control had significantly decreased from 22.2 degrees to 18.5 degrees, suggesting that subjects learned how to improve their performance when using torque. In contrast, the mean error of EMG control tended to actually increase by the last 10% of the experiment—although this difference was not statistically significant.

B. 2AFC Task

The JND was highest when using EMG control, followed by torque+noise, followed by torque (Fig. 8). The JND measured during EMG control was significantly higher than that of both torque and torque+noise ($p<0.01$). There was no significant difference in JND between torque and torque+noise, although torque+noise tended to result in higher JND values.

JND increased proportionally with mean absolute error, for all three control interfaces (Fig. 9). The factors that influence JND were assessed using a mixed effects general linear model. Mean absolute error was a continuous covariate, meaning that JND varied linearly with mean error, with an estimated slope of 0.53 ± 0.10 deg/deg.

For equivalent errors, EMG result in higher JND than either torque or torque+noise (Fig. 9). Control interface was a fixed factor in the general linear model, meaning that torque, torque+noise, and EMG affected the intercept of the JND vs Error curve. Torque and torque+noise control resulted in 4.88 ± 2.23 and 4.57 ± 2.11 deg/deg, respectively.

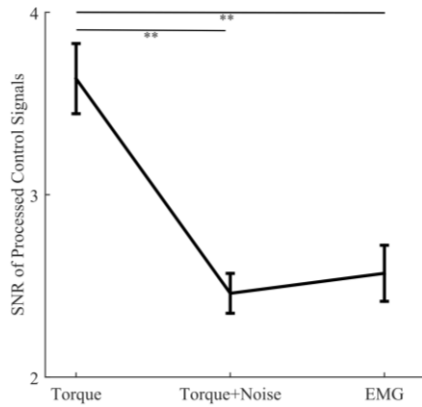


Fig. 4. The signal-to-noise ratio (SNR) of EMG and torque+noise were not significantly different. The SNR of torque was significantly higher than both torque+noise and EMG (** indicates $p < 0.01$). A higher SNR indicates less variability (a cleaner signal). Bars show standard errors of the mean.

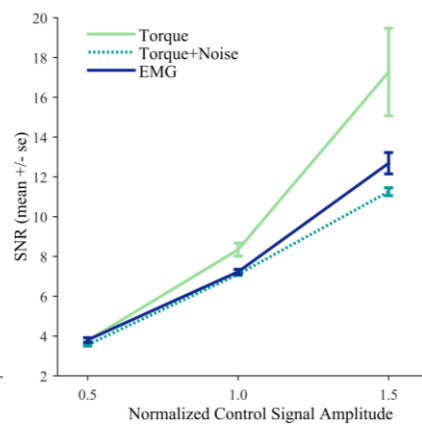


Fig. 5. The SNR of torque+noise is similar to or lower than that of EMG across the entire amplitude of control signals used. Amplitude was normalized to the MAV of the medium level contraction during the calibration. Bars show standard errors of the mean.

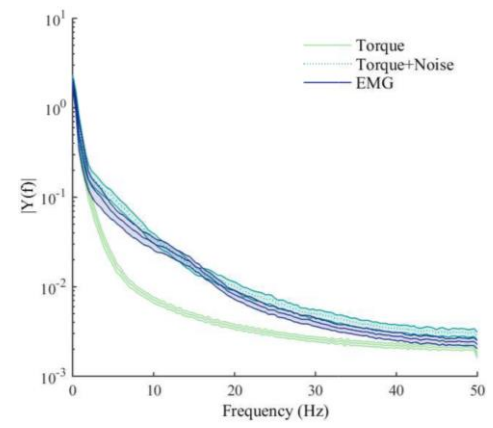


Fig. 6. The magnitudes of the torque+noise and EMG signals are similar across the entire frequency range of 0-50 Hz. Above the human movement frequencies (~5Hz), the magnitude of torque is less than both torque+noise and EMG, indicating lower noise levels. Magnitude spectra were computed with a fast Fourier transform.

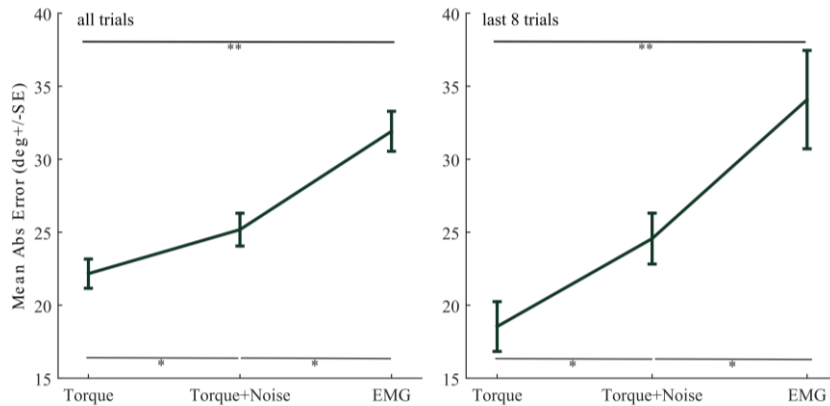


Fig. 7. EMG control resulted in significantly larger errors than torque+noise control. Torque control resulted in significantly smaller errors than both torque+noise and EMG. Left plot shows the average across-subjects error throughout the entire experiment. Right plot shows the average across-subjects error during the last 8 trials, or 10%, of the experiment. (*) indicates $p < 0.05$, (**) indicates $p < 0.01$ for a repeated measures general linear model with Bonferroni corrections.

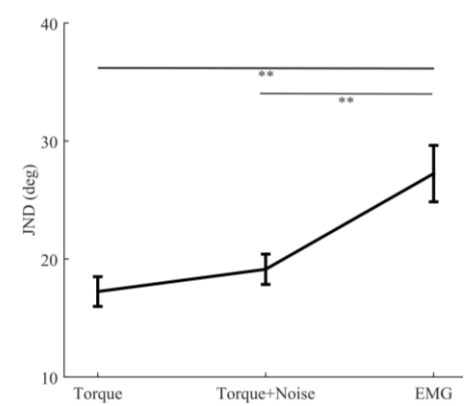


Fig. 8. EMG caused larger Just Noticeable Difference (JND) than torque+noise. Larger JND indicates higher feedforward uncertainty.

V. DISCUSSION

We studied the influence of control signal variability on EMG performance by comparing three control interfaces: torque, torque+noise, and EMG. For all three interfaces, we measured movement error during a target-hitting task and quantified movement uncertainty by measuring the just-noticeable difference of a visual perturbation.

We found that even when variability was equal across EMG and torque+noise control signals, EMG resulted in larger errors during the task (Fig. 7). This result suggests that control signal variability does not fully explain increased errors with EMG. One reason might be that the user has internal feedback loops to provide information about generated torque (e.g. Golgi tendon organs), and does not have the same feedback information for decoded EMG amplitude. Another reason

might be that users have less experience using EMG as a control signal. In sum, the increased variability did increase error size, but users still made the largest errors using EMG control.

EMG caused larger JND than torque and torque+noise at equivalent error levels (Fig. 9). Because JND served as our measure of movement uncertainty, we suggest that subjects were more uncertain of their movement endpoints when using EMG control. This increase in uncertainty with EMG can also be attributed to less feedback and less experience. Thus, subjects made larger errors and were more uncertain of their movements with EMG control, even when accounting for the effect of control signal variability.

One theory behind the increased errors and uncertainty of EMG is that users have difficulty distinguishing between random and systematic errors [20]. In response to random variability, the optimal strategy is correct slowly to the average

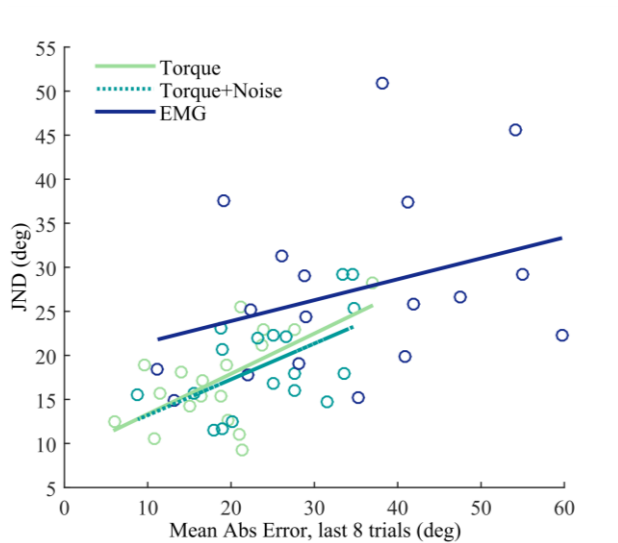


Fig. 9. JND increased as mean absolute error increased. EMG increased JND compared to torque and torque+noise (intercept of JND vs Error curve was significantly larger for EMG, $p < 0.05$). No significant difference was found between the slopes of all three regression lines ($p = 0.21$). Significance was assessed with a general linear model. Points show subjects.

error over many previous trials [10]. But EMG control may introduce more inconsistencies that make these decisions more difficult [21], [22]. Subjects in this experiment may have inappropriately responded to random variability: we see that performance with EMG control does not improve over the experiment, but if anything deteriorates (Fig. 7). This may be due to subjects overcorrecting to random variability and causing additional miscalibrations of their internal model.

The difficulty of inconsistent control can be reduced by providing additional feedback information [22]. In our tasks, subjects were deprived of visual feedback during movements and could only see their endpoint error after movement completion. The only source of feedback for online error correction during the movement was from muscle spindle feedback loops or mechanoreceptors. The lack of visual feedback was designed to test feedforward predictions while using EMG control. In contrast, a previous study also compared EMG and torque control on a single-degree-of-freedom task, but provided visual feedback throughout the movement [23]. Interestingly, Corbett et al. found that EMG control performed similarly to torque control. The additional sensory feedback may have lowered feedback uncertainty, which allowed subjects to update feedforward predictions while still minimizing inappropriate corrections to random variability.

Many typically assume that when a person performs a task, an increase in error proportionally increases the brain's estimation of uncertainty [9], [24]–[26]. We also found that uncertainty (as measured by JND) increased as error increased; however, the baseline level of uncertainty was higher with EMG control (Fig. 9). Thus, the signal modality also caused a difference in uncertainty. This result is a reminder that although error is an important factor in determining uncertainty, other factors such as experience and feedback information should not be neglected.

The variability added to torque was sufficient to recreate the SNR of EMG across a range of frequencies and muscle amplitudes, even during dynamic contractions (Fig. 4, Fig. 5, and Fig. 6). However, it is possible that SNR is not the best measure of the true noise in EMG – for example, the noise might be more Laplacian in nature than Gaussian [27]. The artificial noise added may also not precisely affect the non-stationary nature of the EMG noise. In this experiment, however, these subtleties were likely mitigated by the interface dynamics (Eq. 1), which low-passed the noise and accordingly made it more Gaussian in nature due to the Central Limit Theorem. In addition, metrics only used end-point position, and users were only exposed to end-point position, adding another filter that again increased the Gaussian nature of the data. Thus, for the purposes of this experiment, it seems likely that a Gaussian model, which is commonly used in the field [28], was sufficient to explore user's response to the inherently noisy EMG signals. In contrast, factors such as subtle posture shifts, fatigue [29], or skin impedance changes [30] may cause systematic changes in the control mapping, which users may still perceive as random errors. This study did not address systematic changes or a user's ability to distinguish between systematic changes and random changes, although such exploration would be useful in the future.

Users cannot perform as well with EMG interfaces as they can with torque interfaces [23]; even when aggressively filtered, EMG is a noisy control signal. Many groups have understandably focused on reducing the noisiness of the EMG control signal, using methods such as creating nonlinear filters (e.g., [31]). However, by applying recent advances in psychophysics and computational motor control paradigms to the field of myoelectric control, this study suggests that there is more to the story than the noisiness of the signal: even when the variability of the EMG signal is equalized, users still perform worse using EMG control than torque control. And even when we compare equal levels of performance, users are less confident using EMG control than torque control. These results suggest that the noisiness of the EMG control signal may not be the bottleneck in this field—it may be the type and fidelity of feedback, or the ability to form internal models, which in turn depends on the ability to distinguish between random and systematic errors.

This work accordingly sets the foundation to focus attention elsewhere: specifically, on internal models and the ability of various types of feedback to strengthen those internal models. Although many feedback sources have failed to improve performance (e.g. [32]), recent research by others has demonstrated that providing feedback specifically targeted to enable better discrimination of internal models, such as explicitly providing the amplitude of the EMG signal as a form of vibratory feedback, have indeed improved performance [22]. This study demonstrates that other factors such as feedback and internal models play an important role in performance and uncertainty, and that these factors merit focused research in our field's attempt to improve the control of myoelectric prostheses.

In conclusion, there are difficulties inherent in EMG control beyond that of control signal variability. These difficulties

cause larger errors, which in turn cause higher feedforward uncertainty. To improve performance with EMG control, we need to compensate for these difficulties by providing either improved control systems, training methods, or feedback information to make control more predictable for the user. In future work we will seek to provide relevant feedback information that enables users to distinguish between systematic and random error.

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