Vary Slow Motion

Effect of Task Forces on Movement Variability and Implications for a Novel Skill Augmentation Mechanism

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This article presents the results of a human subject experiment aimed at answering the question, "can increased muscle force variability in low force levels explain increased variability or intermittency of slow movements?" To address this research question, we conducted an experiment with eight subjects, which involved the completion of slow elbow flexion movements at two target speed levels and under five resistive torque fields implemented via an elbow exoskeleton. The results of this experiment demonstrated that increasing levels of resistive torques decreased movement speed variability only until a certain torque level. This observation indicates that a motor-unit pool-based muscle force generation variability, which is known to increase at low force levels, can indeed underlie increased variability in slow movements. Our results imply that resistive torques may be used to significantly decrease movement speed variability, opening up new possibilities for novel assistive devices for motor skill augmentation.

Variability in Slow Movements

In their seminal research, Flash and Hogan [1] proposed the minimum jerk theory (MJT) to explain planning in unconstrained reaching movements. With the MJT, the central nervous system (CNS) chooses the trajectory that minimizes the squared jerk (time derivative of acceleration) among many infinite possible trajectories, leading to an optimally smooth trajectory. The minimum jerk velocity profile is smooth, symmetric, and bell shaped and accurately predicts the velocity profiles observed in unconstrained reaching experiments [1]. A summary of the observations, implications, and assumptions of MJT, as well as those of two other computational motor control theories discussed subsequently in this section, is provided in Table 1.

Flash and Hogan anticipated that MJT would not hold for movements that reached the limits of the neuromuscular system, such as very fast movements. A lower limit for the speed below which the observation of unimodal smooth velocity profiles would break, however, was not initially anticipated. Doeringer and Hogan [2] showed that movements lose their smoothness and become increasingly intermittent with decreasing movement speed as demonstrated by distinct peaks in the velocity profile. Although many studies interpreted the intermittency to be caused by corrective actions [3], [4], which is correct under certain circumstances, Doeringer and Hogan showed that the submovements persisted under no visual feedback, indicating that not all submovements can be attributed to corrective actions. They concluded that increased movement intermittency in slow movements is a very robust characteristic of the human motor control system: people cannot avoid moving intermittently during slow movements [5]. It is also important to note that similar highly intermittent behavior is observed in the movements of stroke patients, and smoothness of movement is used as a reliable and objective measure of motor function recovery [6]–[9].

Doeringer and Hogan [2] proposed two potential sources of movement intermittency: neuromuscular noise and

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submovements-based central planning. However, they did not arrive at a final conclusion about the source of intermittency, and a satisfactory explanation for the origins of intermittency has remained elusive.

An alternative theory of movement planning and control, the minimum variance theory (MVT) proposed by Harris and Wolpert [10], has been remarkably successful in predicting the well-known and experimentally well-documented Fitts' law [11], bell-shaped velocity profiles of arm reaching movements, saccadic eye movements, and even the two-thirds power law [12]. MVT proposes that principles for minimizing the effects of the noise present in biological processes and mechanisms underlie movement planning rather than cost functions (such as jerk), which are difficult to be sensed or integrated by CNS. MVT relies on the assumption of a linear relationship between the standard deviation (SD) of the control signals and their mean levels, an assumption known as *signal-dependent noise (SDN)*. According to this assumption, during the planning of a rapid goal-directed movement, moving as fast as possible should be avoided, otherwise the end-point error will be very large due to the large control signals involved in the movement. Therefore, it places a tradeoff between movement duration and end-point variability.

Todorov and Jordan [13] proposed the optimal feedback control model (OFCM) to overcome the shortcomings of MVT. Specifically, Todorov [14] pointed out that despite the success of MVT in providing a unified explanation for numerous seemingly unrelated experimental observations in motor control, it is limited to open-loop control scenarios and, hence, rapid goal-directed movements with no disturbances. However, tasks in daily life are often slow to allow enough time for feedback to be incorporated and involve various disturbances. OFCM considers noise in both control and sensing (or state estimation) and provides a variable structure feedback controller that is allowed to change its parameters during the movement, based on disturbances or feedback. The noise in motor commands is still assumed to comply with SDN. Unlike MJT and MVT, where motor planning and execution are considered to be two separate processes, in the OFCM, they take place simultaneously [15].

It is important to highlight that both MVT and OFCM rely on one essential assumption: SDN. With the SDN assumption, movements involving smaller control signals will always result in less variability. In fact, Jordan and Wolpert state that "longer movements can always be made smoother than short movements," [16] which is in contradiction with Doeringer and Hogan's experimental results. Therefore, MVT and OFCM fall short of providing an explanation for intermittency in slow movements and are concerned with only rapid movements.

Although speed–accuracy tradeoff [11] and planning and execution of rapid goal-directed movements have garnered significant research interest [1], [10], [13], [17], [18], far fewer studies have reported results on the lower end of the movement speed spectrum. Not only do very interesting observations exist for slow movements but an explanation of these observations is highly relevant to motor function recovery and motor skill learning, where movements are typically slow at the initiation of therapy or learning and movement speed increases through practice, exercise, or therapy. Understanding the mechanisms behind movement intermittency in slow movements can help: 1) establish objective, accurate, and biologically plausible measures of motor function recovery for stroke and spinal cord injury rehabilitation and 2) develop novel motor skill augmentation methods or devices that can reduce movement variability in critical or high-precision tasks that normally require a significant amount of motor skill training.

Table 1. Computational motor control theories for reaching movements.

Theory	Implications and Observations	Underlying Assumptions
MJT proposed by Flash and Hogan [1]	The smooth, symmetric, and bell-shaped minimum jerk velocity profile accurately predicts the velocity profiles observed in unconstrained reaching experiments.	For reaching movements, the central nervous system chooses the trajectory that minimizes the squared end-point jerk among infinitely many possible trajectories.
MVT proposed by Harris and Wolpert [10]	Principles for minimizing the effects of the noise present in biological mechanisms underlie movement planning rather than cost functions (such as jerk), which are difficult to be sensed by the CNS. MVT successfully predicts Fitts' law, bell-shaped velocity profiles of arm reaching movements, saccadic eye movements, and even the two-thirds power law.	MVT relies on the assumption of a linear relationship between the SD of the control signals and their mean levels, an assumption known as *SDN*.
OFCM proposed by Todorov and Jordan [13]	MVT is limited to open-loop control scenarios and, hence, only rapid goal-directed movements with no disturbances. Tasks in daily life are slow enough to allow feedback and involve various disturbances. OFCM takes into account noise in both control and sensing and provides a variable structure feedback controller that changes its parameters during the movement based on disturbances or feedback.	The noise in motor commands is still assumed to comply with SDN.

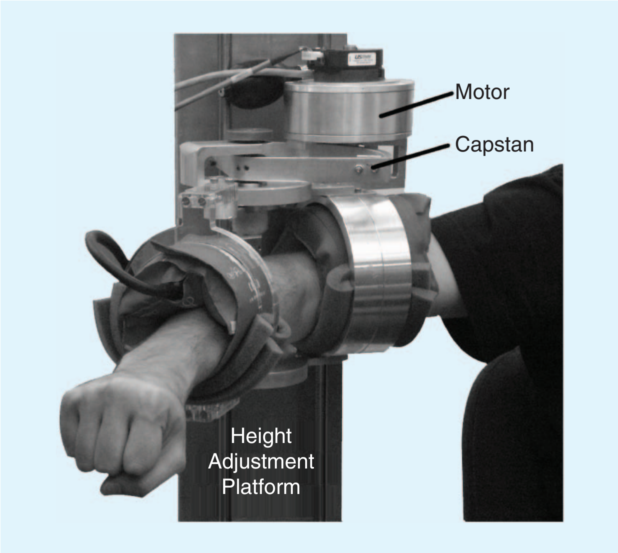

Figure 1. The elbow exoskeleton. The subject's right arm was attached to the device via foam padding and pressure cuffs to provide a comfortable and tight fit. The height of the device was adjusted for each subject so as to have his or her arm moving in the horizontal plane at shoulder level throughout the experiments.

Newell et al. [19] provided experimental evidence that movements slower than 15 cm/s became less accurate and more variable in terms of movement timing. They provided insight into the origins of this increased variability by showing that even movements with a duration as short as 100 ms demonstrated increased variability and, therefore, cannot be attributed solely to a feedback mechanism. Rather, they pointed out that the source of this variability should be sought in actuation. Although the main variability measure in this study was time and not speed, the results in [19] are considered to be relevant to and indicative of the same type of variability observed in movement speed.

In this article, we propose to explore the origins of the intermittency problem from a movement variability point of view. We define movement intermittency as within-trial variability rather than trial-to-trial variability, which is a common type of variability measure used for rapid goal-directed movements [10]. This point of view provides a framework to study movement intermittency as a special case of movement variability observed in slow movements.

In our earlier work [20], we showed that intermittency of various joints along the arm during a multijoint tracking task increased in the distal direction along the arm. Considering that muscle size decreases in the distal direction along the arm, this result is in agreement with the results of Hamilton et al. [21], which showed that larger muscles are capable of producing force with less variability than small muscles. Hamilton et al. complemented their results with a motor unit pool-based isometric neuromuscular model and suggested that a similar mechanism due to the number of active motor units may be responsible for the significant increase in muscle force variability at low force levels. More precisely, this range of low force levels corresponds to 20–30% of the maximum voluntary contraction force [22]. We propose that this range may as well be the range of forces involved in slow movements.

This article reports the results of a human subject experiment that aimed to evaluate whether increased muscle force variability in low force levels can explain increased variability or intermittency in slow movements.

Methods

Participants

A total of eight subjects (four male and four female) participated in the experiment. The mean age was 25.5 years (SD 3.1), ranging from 21 to 29. One subject was left-handed. All subjects had normal or corrected-to-normal vision, none had any movement disorders affecting their upper extremities, and all provided their informed consent for the experimental protocol approved by the Rice University Institutional Review Board.

Experimental Setup

Subjects were seated at a 17-in liquid crystal display computer screen, and their right arms were attached to an elbow exoskeleton device via foam padding and pressure cuffs, which provided a comfortable and tight fit, as shown in Figure 1. The exoskeleton allowed elbow flexion and extension movements in the horizontal plane and was capable of applying controlled torques on the elbow. The device used a Platinum ServoDisc U9D-E pancake motor from Kollmorgen Motion Technologies with a E3-2048-500-H optical encoder from US Digital with 2048×4 counts/rev resolution in quadrature mode. The output torque and position sensing resolution were further improved via a 1:11.25 ratio cable drive mechanism, leading to a maximum torque capability of 5.48 Nm and 0.0039° position reading resolution at the elbow joint. The inherent friction of the device was predominantly of columbic nature and was canceled via a motion-based friction cancellation algorithm [23]. It was verified that the movements of the exoskeleton were essentially frictionless after friction cancellation. A platform allowed the height of the exoskeleton to be properly adjusted for each subject so as to have the right arm moving in the horizontal plane at shoulder level throughout the experiments. An emergency stop button placed within easy reach of the subject's left hand and hard stops at the fully extended and at approximately 100° flexed positions of the elbow constituted the safety precautions. Also the maximum elbow torque that the device could apply was limited to 3 Nm in the software. MATLAB and SIMULINK by Mathworks Inc. and QUARC by Quanser Inc. were used for the real-time control software and experiment interface. The feedback control loop ran at 1 kHz, and the data capture rate was 100 Hz.

Experimental Protocol

The subjects were asked to always look at the screen and not at their arms and to make a fist with their right hands and keep it in this consistent posture throughout the experiment. On the screen, the subjects could see a time plot of their elbow movement speed (°/s) and three numerical indicators. The plot was not updated in real time but rather generated after every 4-s-long trial, displaying the speed profile of the last trial. This configuration ensured that visual feedback during the trials did not lead to corrective actions. At the end of each trial, the first indicator displayed the mean speed of subjects' movement during the trial. Two additional numerical indicators displayed the current trial number and time in seconds (a chronometer with ms precision) during the trial, as depicted in Figure 2.

The task assigned to the subjects was to complete constant speed elbow flexion movements against free or constant resistive torque fields generated by the exoskeleton so as to match a target constant speed profile. There were two target speed levels (5 and 10°/s) and five resistive torque levels (0–2 Nm, with 0.5-Nm increments). All subjects completed all ten speed and torque level combinations, following a full factorial design. One experiment session took around 45 min, and all subjects completed the experiment in two sessions with different target speed levels on two consecutive days. The presentation order of speed and an increasing or a decreasing order for resistive torque levels within a speed level were counterbalanced and randomized among subjects. For example, 5°/s target speed on the first session (or day) with an increasing order for torque levels and 10°/s target speed on the second session (or day) with a decreasing order for torque levels constituted one specific presentation order. A total of eight possible combinations for the presentation order of speed and torque levels were randomly assigned to the eight subjects.

Each session consisted of five blocks, with each block involving a specific resistive torque level. In each block, subjects completed 40 trials in around 6 min, and subjects were required to have a 2-min rest between blocks to avoid fatigue. Each trial started with the subject's initiation of movement from a fully extended elbow position (the chronometer started counting to indicate the start of the trial, as subjects passed through 1° of flexion). No feedback was available to the subjects during their movement, except proprioception. After the 4-s trial ended, the subjects observed their speed profile time plot in the trial, superimposed with the target speed level as a horizontal line on the computer screen (see Figure 2). The ordinate of the plot was adjusted so that the target speed level always appeared vertically centered. When subjects moved back to the initial fully extended posture, the trial number counter was incremented indicating that they can initiate the next trial when they felt ready.

The experimental task did not involve precision tracking [24] or compensating for unstable dynamic interactions [25], the most common scenarios where cocontraction would be expected, allowing us to neglect existence and confounding effects of cocontraction. When the subjects arrived for their first session, they were given written instructions about the experiment. The instructions explained the experimental setup, protocol, and interface. The primary goal was defined as always making a constant speed flexion movement to match the target constant speed level as closely as possible. The subjects were instructed to always check the mean speed indicator after every trial and adjust their speed in the following trials accordingly. As a secondary goal, they were also instructed to observe the speed profile plots to not only match the mean speed but also to keep their speed constant throughout the trial and avoid increasing or decreasing trends in this plot. The instructions asked them to avoid slowing down or stopping toward the end of the trial but rather to keep a constant speed until the trial ended. After the subjects read the written instructions, example speed profile plots depicting successful and unsuccessful trials (in terms of satisfying target speed levels) were shown to them and explained by the experimenter.

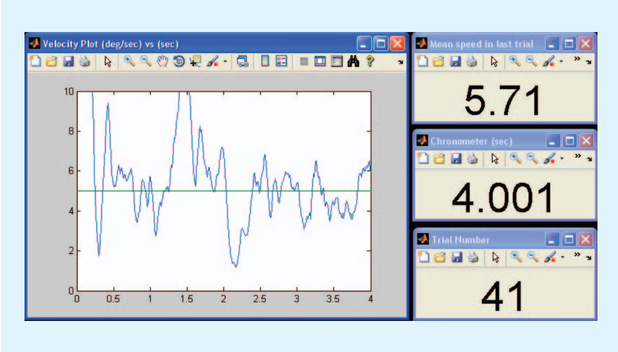

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Figure 2. The computer interface for the experiment. At the end of every 4-s-long trial, the speed profile of the subject during the last trial was displayed together with the target speed level. The first indicator displayed the mean speed of the subject's movement for the last trial. Two additional numerical indicators displayed the current trial number and time in seconds (a chronometer with ms precision) during the trial.

At the beginning of each session, the subjects were allowed to practice as many trials as they wanted until they were convinced that they were able to successfully and consistently complete the constant speed movement task. Only the last 20 trials out of 40 for each block was included in data analysis. Also, the last 3 s of each 4-s trial was used in the analyses to avoid the sudden jerks that occasionally occurred at movement initiation and during movements near the joint limits. Note that the experiment's focus was on the sustained constant speed movements rather than the initiation of the movements.

Analysis of Movement Speed Variability

In the literature, various measures are used to quantify movement intermittency or variability. Usually, a number of significant peaks in the speed profile quantifies movement intermittency [6], [7], [20]. Movement variability measures, on the other hand, are most commonly defined as end-point error or variability [8], [10], quantifying only trial-to-trial variability [14]. In contrast, within-trial variability measures are commonly used for force variability, such as SD of force, and most importantly a normalized version of SD, coefficient of variation (CV) of force. CV facilitates comparing the results of different studies [22] and is defined as SD of force normalized by the mean level of force.

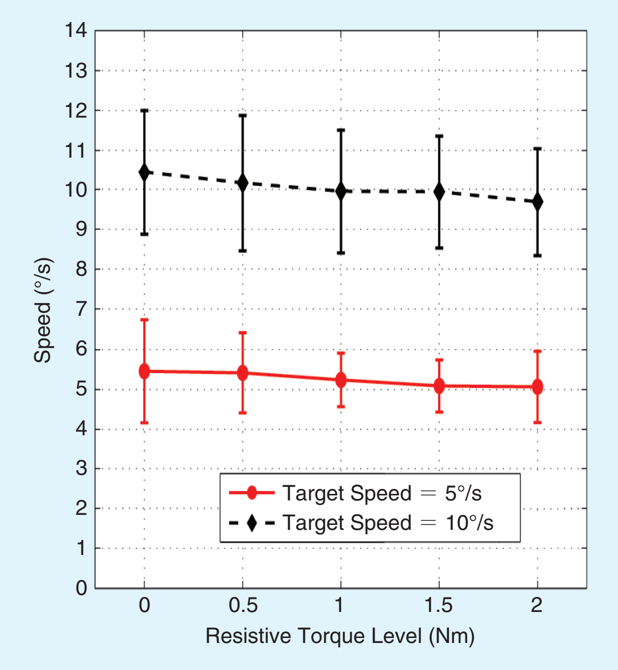

Figure 3. The subjects were successful in matching the target speed level on average. The error bars denote the SD of speed.

Although trial-to-trial variability measures are well suited to discrete movement tasks, such as reaching, a within-trial variability measure is much better suited to continuous movement tasks, such as maintaining a constant speed during movement. Hence, we use the CV of speed (CV_{speed}) as the measure of movement variability in this article. For each trial in the experimental protocol described in the previous section, CV_{speed} during the last 3 s of the trial quantified the speed variability. The speed was obtained from encoder readings via Euler's forward difference method and was bidirectionally filtered offline (for zero-phase shift) with a second-order low-pass Butterworth filter with 20-Hz cutoff frequency.

Statistical Analysis

We used a repeated measures analysis of variance (ANOVA) with no between-subjects factors and with subject, trial, speed, and torque within-subjects factors. CV_{speed} constituted the dependent measure. The trial had 20 levels, speed had two levels (5 and 10°/s), and torque level had five levels (0–2 Nm with 0.5-Nm increments). The subject (eight levels) is treated as a random factor. Out of 1,600 total observations, three data points were not included in the statistical analysis. In these three trials, the subject mistakenly thought that the trial did not initiate properly and quit moving at before the midpoint of the trial. We used the Kenward-Rogers adjusted degrees of freedom method to account for Type I error risk. The alpha level was set at 0.05 for all significance tests. Since the trial did not lead to any significant results when included as a factor main or interaction effects, we report only the main and interaction effects of speed and torque on CV_{speed}. Tukey-Kramer's post hoc analysis test was used for pairwise comparisons of the main and interaction effects of torque. We used Statistical Analysis System (SAS) software by SAS Institute Inc. for conducting the statistical analyses. We used a MIXED procedure

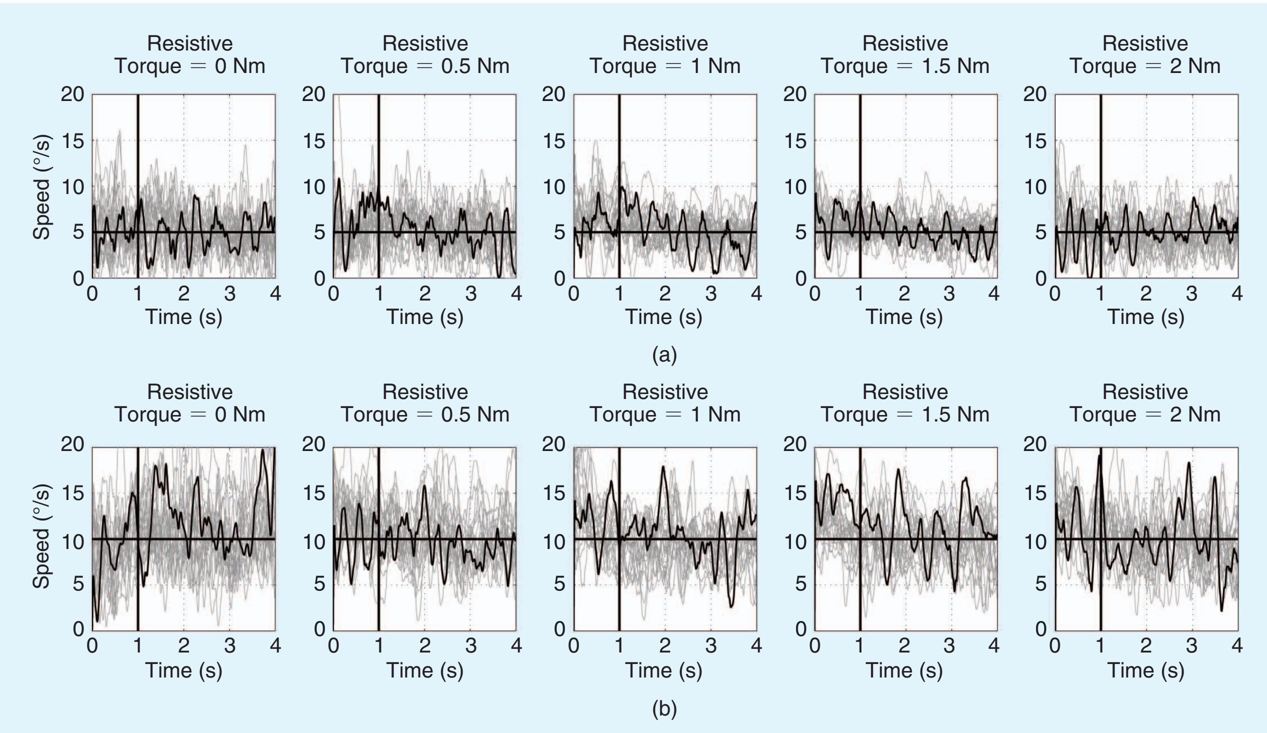

Figure 4. The representative speed profiles achieved by subject 5 under all torque and speed condition combinations. The last 20 of 40 trials are plotted in gray, with the final trial in black. The horizontal lines correspond to the target speed levels, and the vertical lines mark the range (1–4 s) for which the measure CV_{speed} was calculated. (a) Target speed = 5°/s. (b) Target speed = 10°/s.

(PROC MIXED) design (due to both random and fixed effects), with the trial treated as a repeated measure and with a compound symmetry structure for the covariance matrix. This design allows for the incorporation of all available observations, excluding only missing individual observations, without having to drop a group or condition of data points [26], [27], and therefore provides higher statistical power for data sets with missing data points.

Results

Figure 3 shows the mean speed values achieved by the subjects in the experiment with error bars depicting the SD of speed. The subjects were able to perform the constant speed flexion task reasonably well but with high variability, which is an expected observation for slow movements. Increasing resistive torque levels led to a weak and insignificant decreasing speed trend. It can be observed that variability generally decreases as the resistive torque level increases. The variability is lower for the target speed level of 5°/s, but this is simply due to the effect of scaling. A fair comparison of the variability of speed for different levels of mean speed necessitates the use of the CV_{speed} measure that normalizes the SD of speed by mean speed.

Figure 4 shows the raw speed profile data from a representative subject (Subject 5) from all ten speed and torque level condition combinations. Only profiles in the last 20 of 40 trials are plotted in gray and the final trial in black. The horizontal lines correspond to the target speed levels, and the vertical lines mark the range (1–4 s) for which the measure CV_{speed} was calculated.

The results of the ANOVA indicate a significant main effect of speed $[F(1, 1390) = 465.4,\ p < 0.05]$ and a significant main effect of torque $[F(4, 1390) = 42.53,\ p < 0.05]$ on CV_{speed}. The interaction effect of torque by speed is also significant $[F(4, 1390) = 5.57,\ p < 0.05]$. The results of the post hoc Tukey-Kramer test for pairwise comparison of torque are summarized in the bar plot in Figure 5. The error bars indicate standard errors. This plot indicates that CV_{speed} is significantly higher for the no resistive torque condition in comparison with all other torque levels $(p < 0.05)$. Although there is initially a decreasing trend for CV_{speed} with increasing resistive torque levels, after 1.5 Nm the trend reverses direction and CV_{speed} starts to increase. CV_{speed} for $T_r = 2$ Nm is significantly higher than it is for $T_r = 1.5$ Nm.

Figure 6 summarizes the results of pairwise comparison tests for interaction effects of resistive torque level by speed on speed variability in an interaction plot format. Although the CV_{speed} versus torque level curves under two different target speed level conditions mostly follow a parallel trend, the overall interaction effect is significant because of the nonparallel subtrends, such as those observed between $T_r = 1$ Nm and $T_r = 1.5$ Nm.

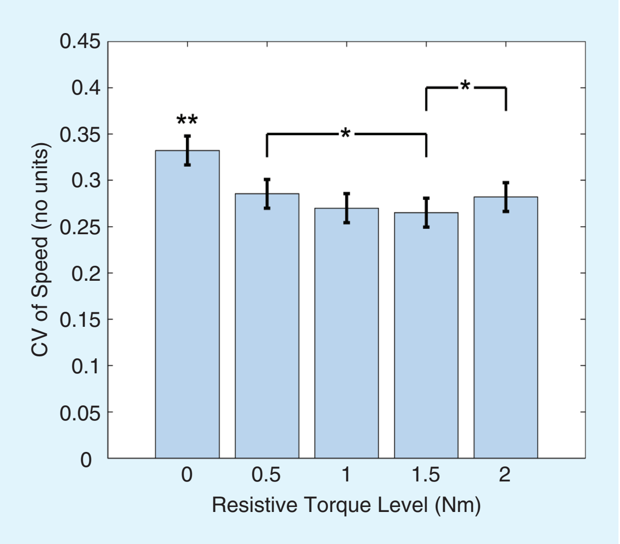

Figure 5. The main effect of resistive torque level on speed variability is significant. The mean and standard error values are displayed. A pairwise comparison of effect of torque levels indicates that, when speed level is not taken into consideration, CV_{speed} is significantly higher for the no resistive torque condition in comparison with all other torque levels (denoted by **, $p < 0.05$). Additional pairwise significant differences are denoted by * $(p < 0.05)$. Although initially there is a decreasing trend for CV_{speed} with increasing resistive torque levels, after 1.5 Nm, the trend reverses direction and CV_{speed} starts to increase. In fact, CV_{speed} for $T_r = 2$ Nm is significantly higher than it is for $T_r = 1.5$ Nm. See the "Discussion" section for details about these results.

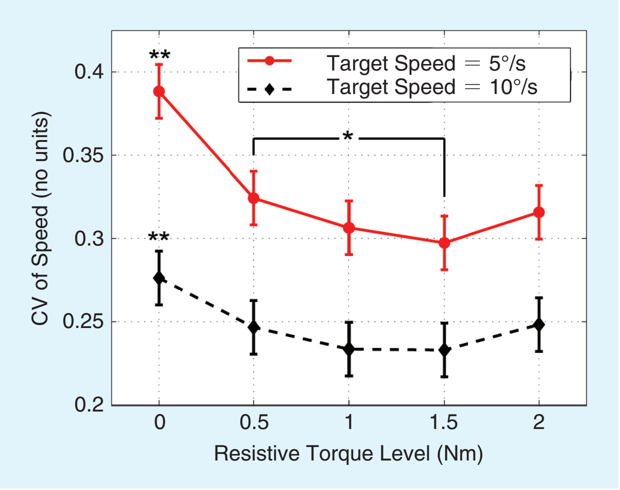

Figure 6. The interaction effect of resistive torque level by speed level on speed variability is significant. The mean and standard error values are displayed. A pairwise comparison of the effect of torque levels indicates that, when different speed level results are grouped and analyzed separately, CV_{speed} is significantly higher for the no resistive torque condition in comparison with all other torque levels (denoted by **, $p < 0.05$) in the same speed level. The only other significant difference is between $T_r = 0.5$ Nm and $T_r = 1.5$ Nm (denoted by *, $p < 0.05$). See the "Discussion" section for details about these results.

Discussion

The significant main effect of speed on movement speed variability is in agreement with findings using movement intermittency [2], [20] or timing [19] as the measure of variability in the literature. This possibly indicates a single mechanism of variability behind all, as we have proposed in the "Variability in Slow Movements" section.

The nonmonotonic relationship between speed variability and resistive torques observed in Figures 5 and 6 is a novel finding. These experimental results indicate that increased muscle force variability in low force levels can indeed explain increased variability or intermittency in slow movements. Increasing resistive torque levels increase the force requirement of the task and, hence, may push the muscle forces out of the low force range with increased force variability [21], [22]. However, the speed variability increases after a certain torque level. This might be due to entering the region where SDN takes hold, with force SD linearly increasing with mean force.

From a dynamics point of view, one can question whether the effect of increasing resistive torques is equivalent to applying increased dry friction and whether decreased variability can be attributed to increased friction. Although resistive torques and dry friction are indeed functionally equivalent, the nonmonotonic nature of the relationship helps dismiss this alternative explanation for decreased variability.

Our experimental results indicate potential novel methods of human skill augmentation in delicate or critical tasks such as surgery. Existing technologies such as surgical robots [28] allow for the filtering of tremors in a surgeon's movement within a master–slave teleoperation framework. However, the unilateral nature of the existing teleoperation structures for surgical robots causes a deterioration in dexterity due to the loss of haptic feedback [28]. Skill augmentation algorithms based on resistive torques or forces that will be implemented on the master side can enhance surgeons' ability to generate less variable forces and provide better control over slow and critical tasks. Such an algorithm can be implemented with much lower cost and fewer potential safety hazards compared with bidirectional teleoperation algorithms, although it would not improve the dexterity of the surgeon as much. However, it can potentially provide a midpoint solution. In fact, recent research has focused on increasing surgeon dexterity in robotic surgery via safe midpoint solutions without resorting to bidirectional teleoperation algorithms [29].

Similarly, resistive torques may be used in facilitating or accelerating the learning of a new motor skill. Studies in this area concluded that, although task performance can be enhanced during training with various assistance methods, it does not translate to faster or better learning in general [30], [32]. Based on our results, although it may seem counterintuitive, it might be possible to design resistive forces that would make the task easier for a trainee and potentially lead to faster and more complete learning in comparison with virtual practice without any augmented forces. In fact, research in rehabilitation of motor-impaired patients provided evidence for such counterintuitive methods to improve rehabilitation outcomes [33]. Our results here might provide one potential explanation for the mechanisms behind these counterintuitive results.

We show that resistive forces can reduce kinematic variability possibly via moving the task forces into a more favorable region in terms of variability. However, the amount of resistive forces must be adjusted carefully or it might increase rather than decrease variability.

Conclusion

Our results imply that resistive torques may be used to significantly decrease movement speed variability. The relationship between resistive torque levels and speed variability, however, is not monotonic. These results support our hypothesis that the force requirements of the movement are responsible for the observed movement variability in the slow movement range through muscle force generation variability. Our findings also point to the potential for using this mechanism to augment motor skills in slow but delicate tasks that require consistency and precision via controlled delivery of resistive forces and torques by use of assistive exoskeleton or force-feedback devices.

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References

[1] T. Flash and N. Hogan, "The coordination of arm movements: An experimentally confirmed mathematical model," *J. Neurosci.*, vol. 5, no. 7, pp. 1688–1703, 1985.

[2] J. A. Doeringer and N. Hogan, "Intermittency in preplanned elbow movements persists in the absence of visual feedback," *J. Neurophysiol.*, vol. 80, no. 4, pp. 1787–1799, 1998.

[3] S. Pasalar, A. V. Roitman, and T. J. Ebner, "Effects of speeds and force fields on submovements during circular manual tracking in humans," *Exp. Brain Res.*, vol. 163, no. 2, pp. 214–225, 2005.

[4] T. Milner and M. Ijaz, "The effect of accuracy constraints on three-dimensional movement kinematics," *Neuroscience*, vol. 35, no. 2, pp. 365–374, 1990.

[5] J. A. Doeringer, "An investigation into the discrete nature of human arm movements," Ph.D. dissertation, Dept. Mech. Eng., Massachusetts Inst. Technol., Cambridge, MA, 1999.

[6] L. E. Kahn, M. L. Zygman, W. Z. Rymer, and D. J. Reinkensmeyer, "Effect of robot-assisted and unassisted exercise on functional reaching in chronic hemiparesis," in *Proc. IEEE Int. Conf. Engineering Medicine Biology Society*, 2001, vol. 2, pp. 1344–1347.

[7] B. Rohrer, S. Fasoli, H. I. Krebs, R. Hughes, B. Volpe, W. R. Frontera, J. Stein, and N. Hogan, "Movement smoothness changes during stroke recovery," *J. Neurosci.*, vol. 22, no. 18, pp. 8297–8304, 2002.

[8] J. J. Daly, N. Hogan, E. M. Perepezko, H. I. Krebs, J. M. Rogers, K. S. Goyal, M. E. Dohring, E. Fredrickson, J. Nethery, and R. L. Ruff, "Response to upper-limb robotics and functional neuromuscular stimulation following stroke," *J. Rehab. Res. Develop.*, vol. 42, no. 6, pp. 723–736, 2005.

[9] O. Celik, M. K. O'Malley, C. Boake, H. S. Levin, N. Yozbatiran, and T. A. Reistetter, "Normalized movement quality measures for therapeutic robots strongly correlate with clinical motor impairment measures," *IEEE Trans. Neural Syst. Rehab. Eng.*, vol. 18, no. 4, pp. 433–444, 2010.

[10] C. M. Harris and D. M. Wolpert, "Signal-dependent noise determines motor planning," *Nature*, vol. 394, no. 6695, pp. 780–784, 1998.

[11] P. M. Fitts and J. R. Peterson, "Information capacity of discrete motor responses," *J. Exp. Psychol.*, vol. 67, no. 2, pp. 103–112, 1964.

[12] F. Lacquaniti, C. Terzuolo, and P. Viviani, "The law relating the kinematic and figural aspects of drawing movements," *Acta Psychol.*, vol. 54, nos. 1–3, pp. 115–130, 1983.

[13] E. Todorov and M. I. Jordan, "Optimal feedback control as a theory of motor coordination," *Nature Neurosci.*, vol. 5, no. 11, pp. 1226–1235, 2002.

[14] E. Todorov, "Optimality principles in sensorimotor control," *Nature Neurosci.*, vol. 7, no. 9, pp. 907–915, 2004.

[15] F. Campos and J. M. F. Calado, "Approaches to human arm movement control—A review," *Annu. Rev. Control*, vol. 33, no. 1, pp. 69–77, 2009.
[16] M. I. Jordan and D. M. Wolpert, "Computational motor control," in *Cognitive Neurosciences*, M. S. Gazzaniga, Ed. Cambridge, MA: MIT Press, 1999, pp. 601–620.
[17] Y. Uno, M. Kawato, and R. Suzuki, "Formation and control of optimal trajectory in human multijoint arm movement," *Biol. Cybern.*, vol. 61, no. 2, pp. 89–101, 1989.
[18] K. E. Novak, L. E. Miller, and J. C. Houk, "Kinematic properties of rapid hand movements in a knob turning task," *Exp. Brain Res.*, vol. 132, no. 4, pp. 419–433, 2000.
[19] K. M. Newell, L. E. Hoshizaki, and M. J. Carlton, "Movement time and velocity as determinants of movement timing accuracy," *J. Motor Behav.*, vol. 11, no. 1, pp. 49–58, 1979.
[20] O. Celik, Q. Gu, Z. Deng, and M. K. O'Malley, "Intermittency of slow arm movements increases in distal direction," in *Proc. IEEE/RSJ Int. Conf. Intelligent Robots Systems*, St Louis, MO, 2009, pp. 4499–4504.
[21] A. F. C. Hamilton, K. E. Jones, and D. M. Wolpert, "The scaling of motor noise with muscle strength and motor unit number in humans," *Exp. Brain Res.*, vol. 157, no. 4, pp. 417–430, 2004.
[22] K. E. Jones, A. F. C. Hamilton, and D. M. Wolpert, "Sources of signal-dependent noise during isometric force production," *J. Neurophysiol.*, vol. 88, no. 3, pp. 1533–1544, 2002.
[23] N. L. Bernstein, D. A. Lawrence, and L. Y. Pao, "Friction modeling and compensation for haptic interfaces," in *Proc. First Joint Eurohaptics Conf. Symp. Haptic Interfaces Virtual Environment Teleoperator Systems*, IEEE Computer Society, 2005, pp. 290–295.
[24] L. P. J. Selen, J. H. van Dieën, and P. J. Beek, "Impedance modulation and feedback corrections in tracking targets of variable size and frequency," *J. Neurophysiol.*, vol. 96, no. 5, pp. 2750–2759, 2006.
[25] L. P. J. Selen, D. W. Franklin, and D. M. Wolpert, "Impedance control reduces instability that arises from motor noise," *J. Neurosci.*, vol. 29, no. 40, pp. 12606–12616, 2009.
[26] E. B. Moser, "Repeated measures modeling with PROC MIXED," in *Proc. 29th SAS Users Group Int. Conf.*, 2004, pp. 1–19.
[27] W. G. Hopkins. (2000). A new view of statistics [Online]. Available: http://www.sportsci.org/resource/stats/
[28] A. M. Okamura, "Methods for haptic feedback in teleoperated robotassisted surgery," *Ind. Robot: Int. J.*, vol. 31, no. 6, pp. 499–508, 2004.
[29] K. J. Kuchenbecker, J. Gewirtz, W. McMahan, D. Standish, P. Martin, J. Bohren, P. J. Mendoza, and D. I. Lee, "VerroTouch: High-frequency acceleration feedback for telerobotic surgery," in *Proc. Int. Conf. Haptics: Generating Perceiving Tangible Sensations*, 2010, pp. 189–196.
[30] Y. Li, V. Patoglu, and M. K. O'Malley, "Negative efficacy of fixed gain error reducing shared control for training in virtual environments," *ACM Trans. Appl. Perception*, vol. 6, no. 1, pp. 1–21, 2009.
[31] Y. Li, J. C. Huegel, V. Patoglu, and M. K. O'Malley, "Progressive shared control for training in virtual environments," in *Proc. IEEE World Haptics Conf.,* 2009, pp. 332–337.
[32] J. C. Huegel and M. K. O'Malley, "Progressive haptic and visual guidance for training in a virtual dynamic task," in *Proc. IEEE Haptics Symp.*, 2010, pp. 343–350.
[33] J. L. Patton, M. E. Stoykov, M. Kovic, and F. A. Mussa-Ivaldi, "Evaluation of robotic training forces that either enhance or reduce error in chronic hemiparetic stroke survivors," *Exp. Brain Res.*, vol. 168, no. 3, pp. 368–383, 2006.

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