35th Annual International Conference of the IEEE EMBS
Osaka, Japan, 3 - 7 July, 2013

Feedback Compensation of Intrinsic Muscle Properties during Torque Regulation Tasks

Xiao Hu, *Member, IEEE*, Wendy M. Murray, and Eric J. Perreault, *Member, IEEE*

Abstract— **Many functional tasks require regulating appropriate forces or torques even under unpredictable disturbances. However, how this regulation can be achieved remains poorly understood. Limb impedance describes the relationship between externally imposed displacements to the limb and the changes in force or torque generated in response. Low limb impedance is preferred during torque regulation tasks. However, low-frequency impedance increases with muscle activation, which is counterproductive to torque regulation. The purpose of this study was to quantify the ability to voluntarily reduce limb impedance during torque regulation tasks, and to assess if the observed performance is near optimal given the challenges posed by activation-dependent muscle properties and time delays in the neuromuscular system. By examining elbow impedance measured in experiments and predicted by a biomechanical model with an optimal controller, our results demonstrated that individuals can reduce the low-frequency components (below 1Hz) of elbow impedance during forceful contractions, and that this performance is similar to those predicted by an optimal feedback controller. These findings suggest that neural feedback can compensate for intrinsic muscle properties in a near-optimal manner, thereby allowing torque to be regulated at frequencies below ~ 1 Hz.**

I. Introduction

Many functional tasks, including the handling of delicate objects, require producing and regulating appropriate endpoint forces or joint torques even in the face of unpredictable disturbances. Though the ability to generate constant forces has been studied extensively [1, 2], how such forces can be maintained when interacting with unpredictable environments remains poorly understood.

Maintaining a constant force or torque when perturbed requires low impedance. Limb impedance describes the relationship between externally imposed displacements to the limb and the changes in force or torque generated in response [3]. For small perturbations limb impedance can be approximated by the inertia, viscosity and stiffness of the limb. Inertia dominates the limb impedance for rapid perturbations, and remains constant for a given posture. For slower perturbations (<~2Hz for human arm), arm impedance is largely described by stiffness, which increases with muscle activation [4]. This activation-dependent stiffness is advantage when trying to regulate position, but it would limit the ability to regulate force or torque in the presence external disturbances since high stiffness leads to a high change in force or torque for an imposed displacement.

The central nervous system (CNS) may employ feedback to compensate for the counterproductive effects of intrinsic muscle properties during torque regulation tasks. When sensing the change of torque caused by an external perturbation, the CNS could adjust muscle activations to keep muscle force and the corresponding net torque about the relevant joints constant. Mugge et al. [5] showed that low-frequency ankle impedance can be regulated in torque control tasks to be lower than that when subjects were instructed not to react to imposed perturbations. The lowered impedance was attributed to the reflexive force feedback from Golgi tendon organs. However, the subjects were only required to maintain a passive baseline torque caused by the weight of the foot, thereby requiring no muscle activation. Tasks that require non-zero muscle forces are likely to be more challenging due to the force-dependent increase in muscle stiffness. Stretch reflexes that increase muscle stiffness also increase with muscle activation [6]. Therefore, it remains unclear to what extent humans can reduce limb impedance during tasks that require active torque generation.

The purpose of this study was to quantify the ability to voluntarily reduce limb impedance during torque regulation tasks, and to assess if the observed performance is near optimal given the counterproductive intrinsic properties of muscles and the time delays inherent in the neuromuscular system. This was accomplished by experimentally quantifying elbow impedance during the exertion of volitional torques at 10% and 20% of maximum voluntary contraction (MVC). Two tasks were considered: a "do not intervene" (DNI), in which subjects were instructed not to respond to the perturbation, and a "torque control" task, in which subjects were instructed to keep the elbow torque constant even when perturbed. We hypothesized that subjects would be able to reduce low-frequency impedance during the torque control task. To examine if this compensation is near-optimal, a simple biomechanical model of elbow was constructed that incorporated the activation-dependent stiffness properties of muscles and a delayed optimal feedback pathway to regulate torque. Our results highlight the importance of feedback in compensating for the intrinsic properties of muscle during torque control tasks.

*This work was supported by the NSF program in Cyber-Physical systems, grant 0939963.

X. Hu is with the Department of Biomedical Engineering, Northwestern University, Evanston, IL, 60208, and with the SMPP, the Rehabilitation Institute of Chicago, Chicago, IL 60611 USA (fax: 312-238-2208, phone: 312-238-1416, e-mail: xiaohu2011@u.northwestern.edu).

W. M. Murray is with the Departments of Biomedical Engineering and Physical Medicine and Rehabilitation, Northwestern University, Evanston, IL, 60208 USA, and with the SMPP, the Rehabilitation Institute of Chicago, Chicago, IL 60611 (e-mail: w-murray@northwestern.edu).

E. J. Perreault is with the Departments of Biomedical Engineering and Physical Medicine and Rehabilitation, Northwestern University, Evanston, IL, 60208 USA, and with the SMPP, the Rehabilitation Institute of Chicago, Chicago, IL 60611 (e-mail: e-perreault@northwestern.edu).

II. Methods

A. Experiment

1) Subjects

Ten subjects (7 men and 3 women) with an age range of 23~45, and no prior history of neurological disease or injury to the elbow, participated in this study. All experimental procedures were approved by the Institutional Review Board of Northwestern University (IRB protocol STU00009204) and required informed consent.

2) Equipment

Subjects were seated in an adjustable chair (Biodex, NY); movement of the trunk was minimized using straps placed across the torso (Fig. 1). The wrist joint was immobilized in neutral position using a custom-made plastic cast. The cast was attached to a rotary motor, aligned such that the motor axis was in line with the elbow flexion/extension axis. The rotary motor (BSM90N-3150AX; Baldor Electric Company, Fort Smith, AR) was controlled using Matlab xPC®. It was configured as a rigid position servo with a stiffness of 35kNm/rad, and used to apply small angular position perturbations to the elbow joint. Elbow moments were measured using a six degree-of-freedom load cell (630N80; JR3, Inc, Woodland, CA). Displacements were measured using an encoder with an effective resolution of 6.3×10^{-5} rad.

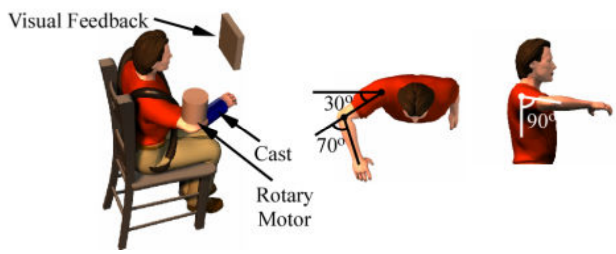

Figure 1. Experimental setup. The right forearm of each subject was positioned in the horizontal plane at a nominal posture of 90° shoulder abduction, 30° shoulder flexion and 70° elbow flexion.

3) Protocol

MVCs were collected at the start of each experiment and later used to normalize the target torque to the strength of each subject. Before the main experiment, subjects were given specific instructions about how to perform the DNI and the torque control tasks. For both tasks, subjects were first instructed to exert a specified torque against rotary motor, and to maintain that torque for 5 seconds. After this time the perturbation commenced, lasting for 35 seconds. During the DNI task, subjects were instructed to keep the muscle activation the same as before the perturbation started, and not to react with the perturbation. For the torque control task, subjects were instructed to keep their torque constant by voluntarily activating their muscles, as needed. Two target torque levels, 10% and 20% MVC, were evaluated for each task. All target torques were in elbow flexion.

Visual feedback of elbow torque was provided to assist with task completion. The feedback was filtered differently in each task. In the DNI task, the visual feedback was filtered by a 2nd order low-pass Butterworth filter with a cutoff frequency of 0.1Hz to prevent drift from the target torque, while also reducing visual information related to the applied perturbation. For the torque control task, the visual feedback was filtered by a 2nd order low-pass Butterworth filter with a cutoff frequency of 2Hz, to allow for subject intervention. The feedback was scaled to keep the variance of the displayed torque constant for all tested torque levels.

Each subject completed a training session of about 1 hour to become familiar with the tasks. On a separate day, the testing session evaluated the two tasks (DNI and torque control), each at two levels of MVC (10% and 20%). Each of these 4 conditions was repeated three times, yielding a total of 12 trials. The trials were grouped into two randomized blocks according to task; within each task block, trials were randomized in terms of MVC level. A one-minute rest period was imposed between trials to avoid fatigue.

Stochastic displacement perturbations were used to estimate elbow impedance. These consisted of a "full power" component with a flat power spectra up to 1Hz and an amplitude (std. dev.) of 1.5 degrees, and a "reduced power" component with an amplitude of only 0.3 degrees but power up to 20 Hz, so that the impedance of the elbow could be characterized adequately [7].

4) Data Analysis and Statistics

The ability to maintain a constant torque in the presence of stochastic perturbations was assessed by comparing the standard deviation of the measured torque and the elbow impedance estimated during the DNI and torque control tasks. All analyses were performed on the final 30-seconds of collected data, to avoid possible transients at the beginning of each perturbation. Nonparametric system identification [8] was used to estimate the elbow impedance transfer functions. The estimated transfer functions were scaled by the subject-specific target torques at 10% and 20% MVCs, so as to facilitate comparisons across subjects.

The hypothesis that low-frequency impedance is smaller in a torque control task than in a DNI task was tested at each frequency up to 10Hz using a linear mixed effect model with subject as a random factor. The same analysis was used to assess the task-dependent change in the standard deviation of the torque. All analyses were performed in MATLAB®. Significance was tested at the level of 0.05.

B. Modeling and Simulation

A biomechanical model of the elbow was constructed in Matlab/Simulink (The Mathworks, Natick, MA) to examine whether the performance in the torque control task was similar to optimal feedback control (Fig. 2). The elbow joint was approximated by a 2nd order system containing inertia (I), viscosity (B) and stiffness (K), which were matched to the average values identified across all subjects. The stiffness K was assumed to vary linearly with joint torque, a reasonable assumption for this range of torques [9]. Changes in joint torque were assumed to arise from changes in muscle activation. Muscle activation dynamics were modeled as a linear 2nd order system with a low frequency gain of 1.6, a natural frequency of 2.4Hz and a damping ratio of 1.2 [10, 11]. This feedforward model was used to simulate the DNI task. A separate feedback loop with time delays was used to simulate the torque control task, in which the neural controller was approximated by an optimal linear quadratic regulator (LQR) [12] of the linearized system.

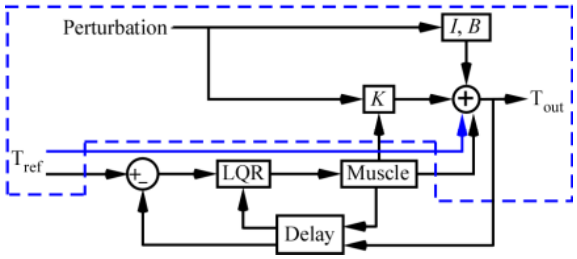

Figure 2. Block diagram of the simulated biomechanical model of the elbow. Muscle block contains muscle activation dynamics. T_{out} represents torque output. The DNI task was simulated by feeding the T_{ref} directly to the comparison point without the LQR controller and feedback loop, as highlighted by the blue pathway and dashed box.

Both tasks were simulated for a target torque (T_{ref}) corresponding to 10% of the average MVC (6.2Nm) recorded for all subjects. Two transmission delays (100 and 200ms) were considered based on a separate analysis of muscle activities, which showed that the activation of the elbow flexors muscles started to differ between two tasks within this time window [13]. Separate feedback controller parameters were estimated for each delay. The perturbation used in this simulation study had the same spectral characteristics as that used in the experiments. The impedance transfer function of the resulting model was obtained by linearization within Simulink. The simulated impedance transfer functions were scaled by the target torque, as was done in the experiment.

Previous studies [10, 11] have shown that muscle activation dynamics can have quite variable natural frequencies and damping ratios. Thus, Monte Carlo simulations were used to evaluate the sensitivity of the model to these parameters. For each set of simulations in the torque control task, these two parameters were selected from uniform distributions ranging from 1 to 5Hz for the natural frequency, and from 0.5 to 1.5 for the damping ratio based on plausible ranges shown in previous experimental studies [10, 11]. Two hundred simulations were performed, and the results quantified by the standard deviation of the impedance transfer functions estimated across all simulations.

III. Results

Subjects were able to complete the torque control task, reducing the change in elbow torque due to the applied perturbations, relative to that measured during the DNI tasks. This was first demonstrated by the reduced low-frequency torque amplitude in the torque control task (Fig. 3A). Accordingly, the standard deviation across all subjects in this task was significantly lower than that in the DNI (10%MVC: $F_{1,9}$ = 10.9, P = 0.0093; 20%MVC: $F_{1,9}$ = 10.8, P = 0.0095; Fig 3B). This reduction was not due to changes in the mean torque between two tasks (10% MVC: $F_{1,9}$ = 1.4, P = 0.27; 20%MVC: $F_{1,9}$ = 0.0, P = 0.998; Fig. 3C).

This ability to control torque was associated with reduced low-frequency elbow impedance during torque control. Below ~1 Hz, the impedance magnitude was smaller in the torque control task than in the DNI task at both 10% and 20% MVCs (Fig. 4). In the range of 1~4Hz, there was a small increase of elbow impedance during the torque control task relative to the DNI task. In the range above 4 Hz, elbow impedance showed no significant difference between two tasks. This is because the limb inertia dominated impedance in this frequency range and remained invariant across tasks.

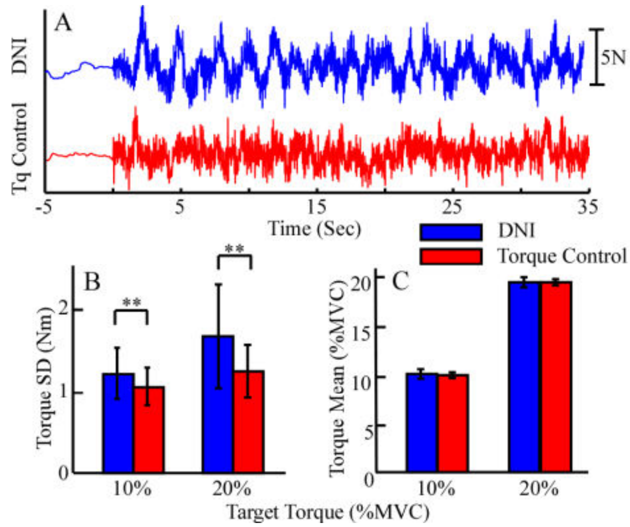

Figure 3. (A) Raw torque trajectories from subject S5. The subject was exerting a torque of 10% MVC during the DNI task (upper trace) and the torque control task (lower trace). (B) The comparison of the average standard deviation of the torques measured in each task. (C) Comparison of the average of measured torques. Error bars indicate standard deviations. The asterisks ** correspond to a significant difference (P < 0.01).

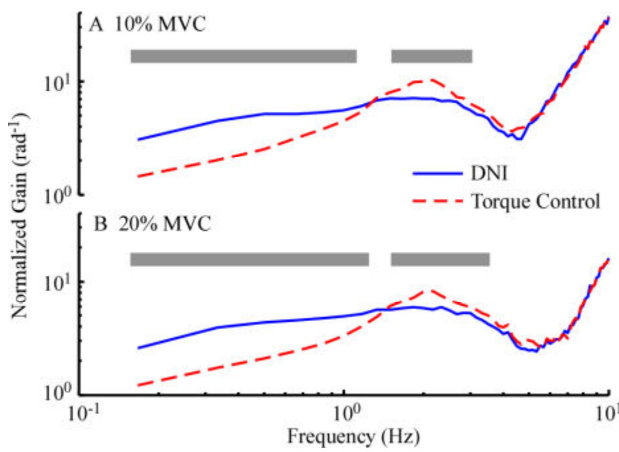

Figure 4. Group average of stiffness transfer functions estimated in DNI (solid curve) and torque control (dashed curve) tasks. The bars at the top of each panel indicate frequencies for which the impedance gain was significantly different (P < 0.05) between tasks.

The simulation of our biomechanical model with the LQR controller behaved in a manner similar to the experimental results (Fig. 5). The simulated impedance transfer functions resembled the overall trend of those estimated in experiment. Below ~0.9Hz, the simulated torque control task had a lower impedance gain than the simulated DNI task. When the transmission delay increased from 100ms to 200ms, the low frequency portion of the impedance transfer function shifted to the right, such that the impedance during the torque control task was lower than that in the DNI task only for frequencies less than ~0.5 Hz. This range in which the impedance during experimental torque control task was less than that during the DNI task was consistent with the range estimated across all subjects (0.86±0.35Hz, Fig. 5 shaded area).

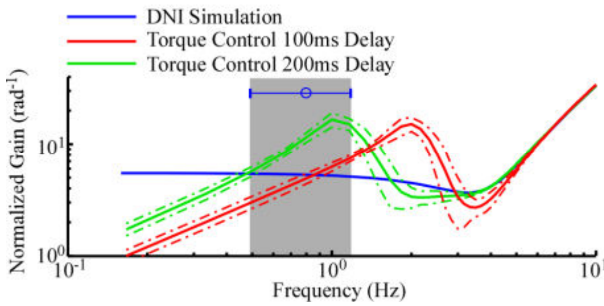

Figure 5. Simulated DNI and torque control tasks. The circle with the error bars and shaded area indicates the average frequency (standard deviation) experimental torque control transfer functions began to be lower than the DNI transfer functions. The dash-dotted curves shows one standard deviation of the Monte Carlo simulations in torque control task.

The impedance of the simulated system was not sensitive to the natural frequency or the damping ratio of muscle activation dynamics. As these parameters were varied over the range of physiologically plausible parameters, the simulated impedance transfer function only varied moderately (Fig. 5, dash-dotted curves). The frequencies at which the transfer functions in the simulated torque control task started to have a lower gain than those in the DNI task varied by less than 0.2 Hz for a simulated delay of 100ms, and by less than 0.1Hz for the simulated delay of 200ms. In contrast, the transmission delay has a larger impact on determining how the elbow impedance is regulated than the parameters used to describe the muscle activation dynamics.

IV. Discussion

This study examined how well humans can maintain a voluntary joint torque in the presence of unpredictable perturbations. This was achieved by estimating elbow impedance during DNI and torque control tasks when subjects were exerting nonzero baseline torques. Our results demonstrated that individuals can reduce the low-frequency components of elbow impedance during forceful contractions. These experimental results were similar to those predicted by an optimal feedback controller designed to minimize elbow torque variance in response to unexpected perturbations. The combined results from our experiment and simulation demonstrate how appropriate feedback can compensate for the intrinsic stiffness properties of muscles, thereby allowing torque to be regulated for frequencies below ~ 1 Hz.

Our finding that elbow impedance can be lowered below ~1 Hz is consistent with previous human operator and prosthetic control studies. In those tracking tasks, performance deteriorated above ~0.7Hz and became completely ineffective above ~2Hz [14, 15]. Similar findings were reported for the regulation of ankle impedance, but only for passive conditions [5]. Our experiments extend those results to active tasks in which feedback is necessary to compensate for the intrinsic properties of muscles.

The observed performance was similar to that predicted by an optimal feedback controller. The degree of similarity was somewhat surprising given the simplicity of our model. Similar near-optimal behavior has been shown in other tasks, such as maintaining standing postures perturbations [12], and generating hand trajectories during reaching [16]. While these studies alone cannot be used to discern the neural mechanisms leading to this near-optimal behavior, they do suggest that the behavior can be replicated with a relatively simple controller. That finding has important implications for the design of artificial systems for restoring motor functions following injury.

Through a combination of experiments and simulations, we have demonstrated that individuals have the ability to regulate joint torques possibly through torque feedback. These understanding of torque regulation together with those of position regulation can provide a scientific basis for understanding more general functional tasks involving both torque and position regulation, and for determining how pathologically altered feedback pathways influence the ability to regulate torque.

References

[1] B.L. Tracy and R.M. Enoka, "Older adults are less steady during submaximal isometric contractions with the knee extensor muscles," *J. Appl. Physiol.*, vol. 92, (no. 3), pp. 1004, 2002.

[2] H. Baweja, B. Patel, J. Martinkewiz, J. Vu, and E. Christou, "Removal of visual feedback alters muscle activity and reduces force variability during constant isometric contractions," *Exp. Brain Res.*, vol. 197, (no. 1), pp. 35-47, 2009.

[3] E.J. Perreault, R.F. Kirsch, and P.E. Crago, "Multijoint dynamics and postural stability of the human arm," *Exp. Brain Res.*, vol. 157, (no. 4), pp. 507-517, 2004.

[4] R.E. Kearney and I.W. Hunter, "System identification of human joint dynamics," *Crit. Rev. Biomed. Eng.*, vol. 18, (no. 1), pp. 55, 1990.

[5] W. Mugge, D. Abbink, A. Schouten, J. Dewald, and F. van der Helm, "A rigorous model of reflex function indicates that position and force feedback are flexibly tuned to position and force tasks," *Exp. Brain Res.*, vol. 200, (no. 3), pp. 325-340, 2010.

[6] M.M. Mirbagheri, H. Barbeau, and R.E. Kearney, "Intrinsic and reflex contributions to human ankle stiffness: variation with activation level and position," *Exp. Brain Res.*, vol. 135, (no. 4), pp. 423-436, 2000.

[7] W. Mugge, D.A. Abbink, and F.C.T. van der Helm, "Reduced Power Method: how to evoke low-bandwidth behaviour while estimating full-bandwidth dynamics," in Proc. Rehabilitation Robotics, 2007. ICORR 2007. IEEE 10th International Conference on, 2007, pp. Pages.

[8] E.J. Perreault, R.F. Kirsch, and A.M. Acosta, "Multiple-input, multiple-output system identification for characterization of limb stiffness dynamics," *Biol. Cybern.*, vol. 80, (no. 5), pp. 327-337, 1999.

[9] X. Hu, W.M. Murray, and E.J. Perreault, "Muscle short-range stiffness can be used to estimate the endpoint stiffness of the human arm," *J. Neurophysiol.*, vol. 105, (no. 4), pp. 1633, 2011.

[10] H. Milner-Brown, R. Stein, and R. Yemm, "The contractile properties of human motor units during voluntary isometric contractions," *The Journal of Physiology*, vol. 228, (no. 2), pp. 285-306, 1973.

[11] J. Bobet and R.W. Norman, "Least-squares identification of the dynamic relation between the electromyogram and joint moment," *J. Biomech.*, vol. 23, (no. 12), pp. 1275-1276, 1990.

[12] A. Kuo, "An optimal control model for analyzing human postural balance," *Biomedical Engineering, IEEE Transactions on*, vol. 42, (no. 1), pp. 87-101, 1995.

[13] X. Hu, *Task-dependent Regulation of Arm Mechanics through Feedforward and Feedback Mechanisms*, Ph.D. Thesis, Dept. Biomed. Eng., Northwestern University, Evnaston, IL, USA, 2012.

[14] I. Cathers, N. O'Dwyer, and P. Neilson, "Tracking performance with sinusoidal and irregular targets under different conditions of peripheral feedback," *Exp. Brain Res.*, vol. 111, (no. 3), pp. 437-446, 1996.

[15] E.A. Corbett, E.J. Perreault, and T.A. Kuiken, "Comparison of electromyography and force as interfaces for prosthetic control," *J. Rehabil. Res. Dev.*, vol. 48, (no. 6), pp. 629-42, 2011.

[16] E. Todorov and M. Jordan, "Optimal feedback control as a theory of motor coordination," *Nat. Neurosci.*, vol. 5, (no. 11), pp. 1226-1235, 2002.