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Feedforward impedance control efficiently reduce motor variability

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Abstract

Despite the existence of neural noise, which leads variability in motor commands, the central nervous system can effectively reduce movement variance at the end effector to meet task requirements. Although online correction based on feedback information is essential for reducing error, feedforward impedance control is another way to regulate motor variability. This Update Article reviews key studies examining the relation between task constraints and impedance control for human arm movement. When a smaller reaching target is given as a task constraint, flexor and extensor muscles are co-activated, and positional variance is decreased around the task constraint. Trial-by-trial muscle activations revealed no on-line feedback correction, indicating that humans are able to regulate their impedance in advance. These results demonstrate that not only on-line feedback correction, but also feedforward impedance control, helps reduce the motor variability caused by internal noise to realize dexterous movements of human arms. A computational model of movement planning considering the presence of signal-dependent noise provides a unifying framework that potentially accounts for optimizing impedance to maximize accuracy. A recently proposed learning algorithm formulated as a V-shaped learning function explains how the central nervous system acquires impedance to optimize accuracy as well as stability and efficiency.

1. Motor noise and possible strategies to cope with it

Humans can generate skillful and precise movements in daily life, such as threading a needle and reaching a small target. To realize such dexterity, the central nervous system (CNS) computes appropriate motor commands that regulate the activations of arm muscles, and thus generate actual movement.

However, these motor commands are corrupted by neural noises, whose standard deviation increases with the level of motor commands (Harris and Wolpert 1998; Jones et al. 2002). Such signal-dependent noise (SDN) plays an undesirable role in movement accuracy through the muscle dynamics, leading to variability in movements. Therefore, even after extensive training, movement variability continues to exist. The CNS must have the ability to cope with the variability arising from such neural noises to achieve task goals.

One possible strategy to cope with variability is online correction based on somatosensory or visual feedback information. Although it has been believed that feedback-based control does not work for rapid movement, because of the delay in biological feedback loops that causes instability (Mehta and Schaal 2002), recent studies emphasize that any movements are realized by optimal feedback control with the help of state estimators (Todorov 2005; Todorov and Jordan 2002). This stochastic optimal feedback control schema assumes that all the redundancy problems and task optimization problems are solved simultaneously at the feedback level without a reference trajectory. Because the motor noise causes a positional error on the actual

current state, the motor command of the next state is estimated by using the updated sensory feedback and efference copy so that only the deviations that interfere with the task goals are corrected. Therefore, deviations irrelevant to task goal are not corrected. Todorov and Jordan investigated the effects of task constraints on realized trajectories and positional variability, and their results indicated that movement accuracy increased with task-relevant movement parameters and decreased with task-irrelevant ones, consistent with the optimal feedback control schema (Todorov and Jordan 2002). Since computation of optimal feedback gain would require considerable neural costs, especially for nonlinear systems, the schema has to assume relatively slow feedback loops including the cerebral cortex. Therefore, it is open to question whether the schema is applicable to rapid movements or not.

Another possible strategy to obtain the required accuracy is to co-activate flexor-extensor arm muscles and regulate impedance to reduce variability in the end effector. Muscles have an intrinsic spring-like property; their spring constant, that is, stiffness, increases as muscle activation increases. The CNS is able to regulate the stiffness of a joint by changing the activation of antagonistic muscles around that joint (co-activation, co-contraction). Joint stiffness produces stiffness at the hand and stabilizes movements when the hand is interacting with environments (Hogan 1985; McIntyre et al. 1996). Because there is little delay in the muscle spring-like property, the muscle instantaneously responds to external perturbation to restore joint angle, and thus, the hand position, to the initial equilibrium state. Through regulating the magnitude of this restoring force by muscle co-activation, humans realize movements

with variable flexibility (Burdet et al. 2001; Franklin et al. 2007; Franklin et al. 2004).

Although impedance works effectively to reduce external noise, even for quick movements, it is only recently that it has been shown to possibly reduce motor variability caused by intrinsic noise such as SDN.

2. Co-contraction and movement accuracy

Since an increase in muscle activation causes an increase in SDN, co-contraction leads to a trade-off between increased noise and reduced consequences owing to the changed impedance.

Gribble et al. examined the relationship between muscle activations (surface EMG activity) and endpoint variability in multi-joint reaching movements (Gribble et al. 2003). By changing the size of a reaching target, they experimentally manipulated the accuracy requirement of a task. They showed that trajectory variability decreased and endpoint accuracy improved as the target size decreased, and that this improvement in accuracy was accompanied by an increase in co-contraction of antagonist muscle at the shoulder and elbow. Osu et al. further demonstrated in single-joint elbow movements (Osu et al. 2004) that optimal impedance is selected for task achievement in the presence of SDN. They not only changed target size, but also explicitly asked subjects to increase co-contraction during reaching movements. They showed that when subjects were asked to increase co-contraction during movements, EMG activity increased in variability, but the final positional error at the target was smaller. The effects of co-contraction on various movement variables were examined on the basis of

correlation coefficients between the co-contraction magnitude (an index of muscle co-contraction around the joint (IMCJ)) and EMG deviation, torque deviation, position deviation, endpoint deviation, and endpoint error (Fig. 1). Correlation coefficients between EMG activity magnitude and EMG variability were very close to 1, demonstrating the existence of SDN. However, the correlation coefficients between co-contraction magnitude and movement variable degraded as the movement variables transformed from kinetics towards kinematics. That is, SDN is attenuated as the space shifts from intrinsic motor command space to extrinsic task space.

Although signal-dependent noise was increased with increased muscle activation, the variability of parameters in task space, such as endpoint error was reduced. The results demonstrate a trade-off between increased noise and reduced consequence owing to the changed impedance. Since there was no explicit external perturbation in these experiments, the observed reduction of final task error could be ascribed to the reduction of internally generated noise, although the detailed mechanism underlying is still an open question.

3. Task constraints at the middle of the trajectory

Morishige et al. recently extended these studies and examined how muscle activations and movement variability are affected by task constraints visually presented in the middle of the movements (Morishige et al. 2006). Subjects performed simple point-to-point movements without a task constraint, or with a task constraint that required precision for going through a visual gate allocated at the middle point between

the start and end points (Fig. 1A). As expected, positional variability was significantly smaller around the gate in the condition with task constraint than in the condition without it (Fig. 2B). Movement variability was improved depending on the required accuracy. From the surface EMG activity of related six muscles, the IMCJ was computed to evaluate joint stiffness during movements (Fig. 2C). Comparison of root mean square EMG values for each period relative to the moment of gate entrance revealed that muscle activations in the gate condition generally got larger than those in the free condition 100 ms before gate entrance (Fig 3). Consequently, the muscle activation resulted in increased shoulder IMCJ, which was significantly high at the gate entrance and remained high until the end of movements. Since stabilization in the transverse direction during radial movements generally requires shoulder joint control, shoulder impedance just before the gate that requires transverse dexterity is a plausible response. On the other hand, elbow IMCJ started to increase after the gate entrance, which may contribute to decelerating the movements as well as control accuracy in a radial direction to reach the target. No case was observed where EMG or IMCJ with a task constraint were significantly smaller than those without a task constraint.

Taken together, these findings show that subjects increased their muscle impedance around the task constraint, and movement accuracies were improved in conjunction with muscle impedance. Increased co-activation did not lead to movement variability, but rather attenuated it. These results further support the possibility that a relationship exists between muscle impedance and movement accuracy.

4. Feedforward impedance control

In force field experiments under unstable environments that provide external perturbation, feedforward impedance control was clearly demonstrated by catch trials where, after extensive learning of **an unstable force field**, the force field was unexpectedly removed (Franklin et al. 2003). Even if there was no external perturbation in a catch trial, subjects showed a similar level of impedance, suggesting that muscle activation increases without on-line correction. Therefore, impedance can be pre-programmed against the external perturbation by learning the property of the environmental instability. In stable environments with no explicit external perturbation, it is difficult to elucidate whether the increased activation is pre-programmed or in response to the feedback information, because catch trial experiments are impossible. Although it has been suggested that co-contraction of flexor and extensor muscles contributes to the realization of accurate movements, the observed prior increases in co-activation shown in Figs 2 and 3 are not free from possible averaging artifacts; that is, taking the mean of the on-line corrective response in each trial could generate an apparent co-activation increase in the average with no actual increase in each trial.

The correlation between trial-by-trial EMG and positional errors is one possible way to answer the above question by clarifying what kind of information defines the muscle activations (Morishige et al. 2006). If on-line feedback control mainly causes muscle activations depending on required accuracy, some correlations should be expected between trial-by-trial EMG and positional errors. Conversely, if feedforward control regulates muscle impedance without depending on the on-line

feedback information, there should be less correlation between them. Therefore, correlation coefficients were examined between positional errors at hand and muscle activation of the data shown in Figs 2 and 3. Essentially, if positional error to the right side of the movement direction (assigned as positive) had occurred, shoulder flexor muscles should be activated to correct the error, resulting in a positive correlation. By contrast, if positional error to the left side of the movement direction (assigned as negative) had occurred, an increase in shoulder extensor muscle activations should be observed, resulting in a negative correlation. However, there were hardly any significant correlations between positional errors and EMG.

This result corroborates the possibility of feedforward impedance control in reducing the effects of internally generated noises on the final endpoint variability. At least for well-learned rapid reaching movements, online feedback does not explain the task-relevant decrease in variability.

5. Computational models

These experimental results examining feedforward impedance control and movement accuracy suggest that feedforward movement control is executed considering not only the reference trajectory represented as a mean of actual trajectory, but also the variance in actual trajectory caused by neural noise. These experiments further demonstrated that without the need for greater accuracy, subjects accepted worse performance, but with low impedance, meaning that minimizing the endpoint deviation or endpoint deviation is not the sole consideration of task optimization (Osu et al. 2004).

A computational model of movement planning (task optimization in the presence of signal-dependent noise (TOPS)) maximizes accuracy considering the presence of SDN (Harris and Wolpert 1998). Since this model considers only movement accuracy as an objective of the motor planning, it contradicts the above observation of allowing worse performance with fewer motor commands. Miyamoto et al and Nagata et al extended this model by adding a cost term in the motor command magnitude multiplied by α (TOPS- α) (Miyamoto et al. 2004; Nagata et al. 2002). TOPS- α model combines maximization of task achievement and minimization of motor command magnitude, and the relative contributions of these two components is determined by weight α . Therefore, it can explain the observation that without the need for the greatest accuracy, subjects accept worse performance but reduced motor command magnitude; that is, lower stiffness. The TOPS- α model gives a better prediction of trajectories than the TOPS model for a large number of point-to-point movements.

Although these models for movement planning do not explicitly include the noise-reducing effect of impedance and the resultant trade-off between impedance and SDN, a recently proposed motor learning algorithm provides a unified framework to learn force and impedance that optimizes stability, accuracy and efficiency (Franklin et al. 2008). The algorithm is formulated as a V-shaped nonlinear learning function between error on one trial and adjustment of feedforward motor commands on the next trial in muscle space, in contrast to most of the previous learning schemas formulated as a linear function in joint space. First, the feedforward muscle activity increases in response to unexpected muscle lengthening (positive error) on the previous trial. Second,

even when a muscle is unexpectedly shortened (negative error), the feedforward muscle activity increases on the subsequent trial, although the magnitude of the increase is smaller than when the error is positive. **These two principles result in increased impedance that reduces motor variability (van Galen and de Jong 1995).** Then, as the third principle, the CNS reduces the feedforward activation of a muscle if the error is small enough (below a certain threshold). This corresponds to an energy efficiency term that allows lower impedance without the need for greater accuracy. Through these processes, the CNS gradually forms an internal representation between motor commands and motion output, which is generally called an internal model. This learning algorithm provides a good prediction of human motor learning under novel environmental interaction. Simulated motor learning shows human-like evolution of muscle activation, force and impedance in both stable and unstable environments.

The V-shaped learning algorithm can simulate trial-by-trial adaptation behavior in internal model formation, but does not predict the preplanned reference trajectory, based on which error is computed. On the other hand, the TOPS- α model predicts the desired trajectory, but is irrelevant to learning. In actual movements, the adaptation to a new environment (internal model formation in control) and the computation of the optimal reference trajectory under that environment (modification in plan), will probably occur simultaneously. A unified schema is expected, combining motor planning, control and learning, taking into account accuracy as well as efficiency and stability.

Figure legends

Figure 1

Correlation coefficients between the stiffness (IMCJ) and variability of five quantities. The solid line denotes when subjects were asked to voluntarily change the co-contraction levels. Dashed line denotes when the target size was changed. EMG deviation shows correlation coefficients between EGM activity and EMG variability. Torque deviation shows correlation coefficients between stiffness and torque variability. Position deviation shows correlation coefficients between stiffness and position (trajectory) variability. Endpoint deviation shows correlation coefficients between stiffness and endpoint deviation (deviation from mean). Endpoint error shows correlation coefficients between stiffness and endpoint error (deviation from the target). (Modified from (Osu et al. 2004))

Figure 2

Movement variability and impedance under conditions with and without task constraints.

A Experimental settings. Subjects moved their hand from the start point (a 1-cm radius circle) to the end point (a 3.5-cm radius circle) within a time limit (350 ± 35 ms) under conditions with or without visual task constraints. The gate, which constrains the task, was allocated at the middle point between the start and end points (width: 8 mm, length: 3 cm). The distance between start and end points was 25 cm.

B Comparison of positional variance. Hand trajectories were normalized on the basis of

path, and then positional variance was computed along the path length to remove the temporal effect (Todorov and Jordan (2002)). A black curve shows positional variance with task constraint. A gray curve shows positional variance without task constraint. Gray-shaded areas show the time when the hand was passing through the gate.

C Comparison of stiffness. Surface EMG activity was recorded from a shoulder monoarticular flexor (pectoralis major) and extensor (posterior deltoid), an elbow monoarticular flexor (brachioradialis) and extensor (lateral head of triceps brachii), and a biarticular flexor (biceps brachii) and extensor (long head of triceps brachii). IMCJ, defined as the summation of the absolute values of antagonistic muscle torques around the joint, was computed from the linear relation between surface EMG activity and joint torque. Shoulder and elbow stiffness (IMCJ) were averaged across nine subjects. Black and gray curves show average IMCJ (solid curves) and s.e.m (dashed curves) with and without task constraint, respectively. Gray areas denote the time when the hand was passing through the gate. \triangle and \blacktriangle on the time axis indicate mean start- and end-times of movements without constraint, respectively. ∇ and \blacktriangledown indicates those with constraint. (Modified from (Morishige et al. 2006))

Figure 3

Significant increase in muscle activation and stiffness with the task constraint. To statistically investigate how task constraint affects muscle activations and arm stiffness, a repeated measure ANOVA was conducted on the root mean square of EMG (rmsEMG) values, and the root mean square of IMCJ (rmsIMCJ) of eleven periods:

-300 to -200, -250 to -150, -200 to -100, -150 to -50, -100 to 0, -50 to +50, 0 to +100, +50 to +150, +100 to +200, +150 to +250, and +200 to +300 ms. Zero time was defined as the moment of entering the gate. \triangle , \blacktriangle , ∇ , and \blacktriangledown follow the convention of Figure 2C. Start and end points of each movement were determined using the curvature threshold of $100 \text{ [m}^{-1}\text{]}$. (Modified from (Morishige et al. 2006))

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We thank the reviewer for the comments, which we believe have helped us improve the manuscript. In the following we list the changes that we made in response to each point raised by the Reviewer #1.

Reviewer #1: This paper reviews key studies examining the relation between task constraints and impedance control for human arm movement.

The manuscript is well organized. However, the authors should clarify the subject learned the impedance or force. In section 4, the author indicated that the subject learned the "appropriate" impedance. But the subject learned the force field and as a result, the size and/or orientation of stiffness might be changed.

We have changed the phrase 'learning of appropriate impedance' to 'learning of an unstable force field'.

Also, the author introduced the new experiment in section 3, and a new learning algorithm "V-shaped nonlinear learning function model" in section 5. The author should refer the following paper.

Gerard P. van Galen, and Willem P. de Jong, Fitts' law as the outcome of a dynamic noise filtering model of motor control, Human Movement Science Volume 14, Issues 4-5, November 1995, Pages 539-571

We have cited the suggested paper in Section 5 as follows.

'These two principles result in increased impedance that reduces motor variability (van Galen and de Jong 1995).'