Impedance control: Learning stability in human sensorimotor control*

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Abstract— **The human sensorimotor control system generates movement by adapting and controlling the mechanics of the musculoskeletal system. To generate skilful movements the sensorimotor control system must be able to predict and compensate for any disturbances generated either in our own body or in the external environment. While stable and repeatable perturbations can be easily adapted through iterative learning, instability and unpredictability require a different approach: impedance control. Here I outline the arguments for impedance control as a fundamental process of human adaptation as well as describe evidence suggesting the manner in which such impedance can be learned in order to ensure the stability of the neuro-mechanical system.**

I. Introduction

When humans interact with the world we need to be able to compensate for the mechanical properties of the external environment. Some parts of the environment are stable and predictable allowing them be easily learned. For example, as we pick up a coffee cup the forces that we need to compensate for are repeatable from one sip to the next. Even as we drink the cup of coffee, we can make predictions about the change in weight of the coffee. Iterative learning can compensate for these stable interactions, where the errors at one moment in time can be used to update the model of the external world that is used for the feedforward control [1]. Importantly, a stable interaction with the environment also means that similar motor commands will result in similar movements, with small perturbations and noise having little overall effect of the movement [2]. However, many interactions involve either instability or unpredictability [3]. For example, many cases of tool-use involve inherently unstable interactions [4]. When we use a screwdriver, we need to be able to produce enough force along the length of the driver to hold the screw against the wall. However, if the direction of this force is slightly moved outside of the base, for example through natural variations produced by motor noise, then this force will create a torque about the end of the screwdriver causing it to be further rotated. Equally problematic, however, are conditions of unpredictability. For example, if we are walking a dog or holding the hand of a small child, we cannot predict the sudden pulling in one direction or another as each new object grabs their attention. These issues of unpredictability can also be present in objects with inherent flexibility or internal degrees of freedom [5], [6] which are further affected by noise in the neural system. Therefore, in order to understand how the sensorimotor control system performs such complex tool-use tasks, we need to understand how it adapts to instability and unpredictability.

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II. Control of Impedance

While the sensorimotor control system cannot simply learn a particular pattern of feed-forward joint torques to compensate for either instability or unpredictability, it can employ impedance control. In these tasks, the controller relies on responses arising at multiple delays in order to minimize any errors that occur. The first are those instantaneous responses, occurring to any physical disturbance, produced by the mechanical properties of the body and muscles: the inertia of the body segments, and the intrinsic properties of the muscles (stiffness and damping). Later responses to the perturbations are produced by feedback responses at various delays depending on the circuits. As this delay increases, these responses can be appropriately tuned to the task [7]. However, such tuned feedback responses, delayed by 70ms, may be too late to prevent a task failure, especially in an unstable environment [8]. In these cases the neural feedback pathways may be insufficient to maintain stability. Therefore, in such situations the sensorimotor system tunes the mechanical properties of the muscles, regulating the impedance of the system to ensure stable control.

Mechanical impedance is defined as the resistance to a displacement. In a standard lumped model of impedance, three main components are present: inertia, the resistance to a change in acceleration; damping, the resistance to a change in velocity; and stiffness, the resistance to a change in position. While the inertia can be controlled only by changing limb posture [9], the viscoelastic properties (stiffness and damping) can be controlled by changing muscle activation or endpoint force [10], co-activating muscles [11], changing limb posture [12], and modulating feedback gains [13]. It has been suggested that the sensorimotor system simplifies control by adapting the impedance of the neuromuscular system [9], [14]. This strategy has been supported by several studies demonstrating that subjects increase limb stiffness when reaching in unpredictable [15] or unstable environments [8].

Initial studies trying to demonstrate impedance control in the human limb found only global increases in stiffness with no control or tuning of the stiffness to the environmental perturbations [12]. To demonstrate that humans were able to modulate and tune their impedance independent of changes in endpoint force, subjects reached in a divergent force field in which instability was only present orthogonal to the direction of movement [8]. This force field initially perturbed the subject's movements leading to large errors to either side of the straight reaching path to the target. However, after a period of adaptation subjects learned to make natural reaching movements in the environment. The endpoint stiffness was then estimated by applying position controlled displacements in the middle of the movement and measuring the resulting force compensation [16]. The endpoint stiffness increased only in the direction of the instability, with little or no changes in stiffness in the direction of movement relative to the stiffness in a null force field (no force field condition). This suggested that the sensorimotor control system was able to coordinate the co-activation of muscles, tuning the orientation of the limb stiffness to match the environmental instability [8] independent of changes in endpoint force [17]. To confirm this finding and demonstrate that we have control over the limb impedance, adaptation to multiple levels of instability perpendicular to the direction of movement was examined [18]. If we can modulate the endpoint stiffness then this adaptation should scale with the level of instability in order to ensure stability of the interaction. Indeed, this was found for all subjects after learning to move in the divergent force fields. The endpoint stiffness ellipse scaled with the level of instability, with a specific increase in the component in the direction of the instability, but no change in the orthogonal direction (Fig. 1). Moreover, the net stiffness (limb stiffness + stiffness of the instability) was equivalent to the original null field stiffness across all levels of instability, suggesting that the impedance was tuned to maintain a constant stability margin in all conditions. This illustrates the important balance between generating sufficient impedance for stability while minimizing the metabolic cost [18], [19] and the effect of noise [20].

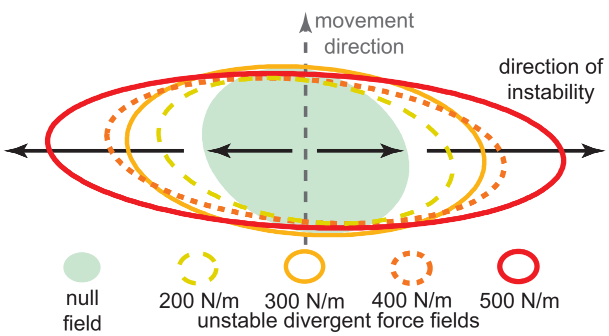

Figure 1. Endpoint stiffness of the arm after adaptation to instability in the horizontal direction. Mean stiffness across subjects obtained by [18]. The stiffness increased primarily in the direction of instability, scaling with the size of the external instability. There was no increase of stiffness in the direction of movement demonstrating that stiffness was tuned.

Although this clearly demonstrates that the sensorimotor control system can change endpoint stiffness, musculoskeletal mechanics may limit the degree of tuning of the stiffness that can be achieved [21]. For example, in a simple two degree-of-freedom limb, there are only three sets of muscles that can tune the stiffness ellipse (single joint elbow, single joint shoulder, and biarticular muscles). Therefore, to investigate the degree to which the endpoint stiffness ellipse can be tuned directly, subjects adapted to a series of unstable environments, each with different directions of instability [22]. After learning, subjects had adapted the endpoint stiffness so that it was primarily increased in the direction of instability [22]. Moreover, the muscle activity associated with each instability direction demonstrated that the tuning of endpoint stiffness was achieved partially through selective co-activation of different muscles, each contributing to increased stiffness in different directions.

III. Learning Impedance Control

Adaptation to novel dynamics induces both an initial increase in co-contraction and a change in the predictive force compensation [23]-[27]. If the environment is stable, this increased co-contraction is gradually reduced to the original level in the null field. However, during movements in unstable environments, this co-contraction continually increases until the movements are fully stabilized. Then, only gradually, does the co-contraction reduce until the final activity selectively controls the endpoint stiffness in the appropriate directions [24]. Thus it appears that the final tuning of the stiffness may result not only from signalled increases in the activation of perturbed muscles but also through selective tuning during the minimization (or decay) of co-contraction.

Many studies have suggested that dynamic adaptation occurs through trial-by-trial adaptation of the internal representation of forces or joint torques (i.e. iterative learning [28]). However, this approach cannot explain adaptation to unstable environments [2] where impedance control is required. Instead an approach was proposed whereby optimization results from a trade-off of accuracy, stability, and energy minimization [29]. The algorithm itself suggests that the update of muscle activation occurs as a function of the time-varying error sequence from the last movement. During each movement, the current joint angle is contrasted with the desired joint angle to provide a time-varying (or a state-varying) sequence of errors. Each error measure is used by a V-shaped update rule to determine the change in muscle activation, which is shifted forward in time on the subsequent movement to compensate for neural delays. The V-shaped learning rule has a different slope for each muscle depending on whether the muscle is too stretched or shortened at each point in time (Fig. 2). Unlike many learning algorithms, a large error will generate an increase in the activation of both the agonist and antagonist muscles, whereas a small error (or even no error) induces a small decrease in muscle activation. As each muscle has different slopes depending on the direction of the error, this leads to an appropriate change in reciprocal muscle activation driving compensatory changes in joint torques. However large errors increase co-contraction directly increasing the joint stiffness and decreasing effects of noise and unpredictability, while small errors lead to a reduction in co-contraction, allowing the algorithm to minimize the muscle activation. Together this algorithm trades-off stability, metabolic cost and accuracy while ensuring task completion [29].

This learning algorithm is able to predict the time-varying pattern of muscle activity for each muscle during each movement throughout adaptation, and can adapt to both stable and unstable dynamics [29]. Moreover, this algorithm [30] was able to reproduce both the scaling of the stiffness ellipse with the magnitude of instability [18] and the change in orientation of the stiffness ellipse with the directional change in instability [22]. Furthermore, if the external dynamics requires both a change in net-force and increased stability [31], the algorithm learns to produce both to achieve the desired movement [30]. However, the sensorimotor control system generalizes learning from many learned movements to form a single model of any one environment. The learning algorithm was therefore extended to multiple movements by generalization the model over the state space using a radial basis neural network mapping [32]. This extended model was able to replicate adaptation [33] and generalization [34] to a variety of stable dynamics as well as adapt simultaneously to instability in two different directions of movement [35]. This computational model of adaptation, relying on a simple update rule is able to explain and predict the changes in endpoint stiffness, force and muscle activation, learning to coordinate control of redundant muscles to perform a task while minimizing instability, energy and systematic error.

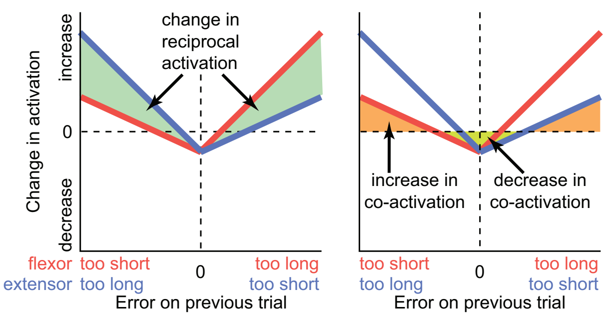

Figure 2. Illustration of V-shaped learning algorithm of [29]. The change in muscle activation for both the flexor (red) and extensor (blue) are plotted as a function of the kinematic error on the previous trial. These functions specify changes in reciprocal activation (joint torque), co-activation (stiffness) and reductions in muscle activation (metabolic cost). Further details can be found in [1], [3], [29].

IV. FEEDBACK MODULATION OF IMPEDANCE

Muscular co-contraction increases joint stiffness, thereby producing an instantaneous response to any disturbance. However, this co-contraction requires energy to maintain, thereby increasing stability at the expense of metabolic cost. Another technique that the sensorimotor control system can exploit to maintain stability is to increase feedback gains, which act to increase the muscle stiffness at a delay [13]. Although there are conditions in which the delayed feedback responses would be unable to maintain the stability, many studies have shown increased feedback gains for postural tasks both in the upper and lower limbs [36]-[39]. These conditions of postural control often have allowable timescales for correction which are longer than those for object manipulation [40]. As this allowable time for correction decreases, feedback mechanisms for controlling impedance become less useful and direct co-contraction more necessary. However, several studies have provided evidence that the sensorimotor control system regulates feedback gains for impedance control even under conditions of unstable force field interaction [22], [41], albeit along with increased co-contraction.

Modulation of feedback gains may have important functions that cannot be achieved by co-contraction alone. For example, in the two degree of freedom limb, the endpoint stiffness can only be modulated independently in three directions [22] and is governed to a large degree by the mechanical properties of the musculoskeletal system [21]. However, feedback responses are not limited by the properties of the muscles, as stretch of one muscle can be used to increase force in a different muscle through heteronymous reflex responses. Thus feedback gains can provide compensation for complex patterns of instability, for example increasing the anti-symmetric (rotational) stiffness of the arm [22] or contributing to responses in another limb [42], [43]. Moreover, feedback gains are not limited to stretch reflex responses, but can also respond to visual errors [44], which can enhance the endpoint stiffness of the limb at even longer delays [45]. Furthermore, recent studies have shown that feedback gains are not simply excited or inhibited but can be modulated independently for different perturbation directions [46] or updated according to task goals [47], [48].

V. CONCLUSION

The extensive ability of feedback gains to modulate and tune the stiffness of the limbs to the environment opens up new questions into the mechanisms of adaptation. Specifically, it is important to understand the manner in which the sensorimotor control system learns and tunes the feedback responses to the external environment. Several papers have already demonstrated that these feedback gains are modulated as part of the adaptation process [26], [49], but as of yet we have little understanding about the process by which the adaptation occurs or what specific factors drive increases or decreases in feedback gains. Understanding the mechanism of feedback gain learning is critical if we wish to understand how humans are able to learn complex manipulation tasks.

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