Naturally Supervised Learning in Manipulable Technologies
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ABSTRACT

Objective

It will be argued that haptic and proprioceptive sensory inputs serve a supervisory function in movement production related to the control of virtual environments and human-machine interfaces. To accomplish this, an approach new to human factors called neuromechanics will be used. This involves the introduction of novel techniques and analyses which demonstrate the multifaceted and regulatory role of adaptation in interactions between humans and motion and touch-based (e.g. manipulable) devices and interfaces.

Background

Neuromechanics is an approach that unifies the role of physiological function, motor performance, and environmental effects in determining human performance. In this paper, a neuromechanical perspective will be used to explain the supervisory role of environmental variation on human performance.

Method

Three experiments are presented using two different types of virtual environment that allowed for selective perturbation. Electromyography (EMG) and information related to kinematics were collected. Measures related to human performance dynamics were used to model the results.

Results and Conclusions

Results presented here provide a window into neuromechanical performance under a range of technologically-mediated conditions. Both descriptive and specialized analyses were conducted: peak amplitude analysis, loop trace analysis, and the analysis of unmatched muscle power. These analyses demonstrated that there are myriad consequences to force-related perturbations related to dynamic physiological regulation.

Applications

The findings presented here could be applied to the dynamical control of touch-based and movement-sensitive human-machine systems. In particular, the design of systems such as human-robotic systems, touch screen devices, and rehabilitative technologies could benefit from this research.

PREÇIS

This paper will explore the interface between physical performance and environmental variability. Virtual environments with physical intermediaries will be used to better understand the effects of force-based perturbations, both positive and negative. These findings, interpreted as naturally supervised learning mechanisms, may potentially inform the design of many manipulable technologies.

1.0 INTRODUCTION

In the last few years, there have been major advances in the commercial availability of touch-based and motion-driven devices. Devices such as the iPad, Nintendo Wii, Microsoft
Kinect, and other applications have required a new way of thinking about usability and ergonomic design. Parallel developments in the area of brain-computer interfaces (Wolpaw et al., 2002; Leeb et al., 2007), neurorehabilitation (Serruya & Kahana, 2008; Mussa-Ivaldi & Miller, 2003), and myoelectric control (Oskoei & Hu, 2007) may provide clues to this issue, but have not yet become a key component of human factors research. In this paper, I will demonstrate how an approach called neuromechanics (Enoka, 2001; Nishikawa et al., 2007) can be brought to bear on assessing the usability of such technologies. Neuromechanics is an approach that unifies the complexity of behavior with neurobiological outputs by looking at interactions between muscle activity and movement behavior. Examples include dynamical control strategies due to limb geometry (Yen & Chang, 2010) and neural mechanisms (Sutton et al., 2004), which can be characterized as morphological and neural control strategies, respectively.

1.1 Neuromechanical control as supervised learning

The human neuromechanical system can be understood as a complex control system which can adapt to environmental stimuli. Experiments in motor learning (Scheidt, Dingwell, and Mussa-Ivaldi, 2001) and computational neurobiology (Shadmehr & Wise, 2005) have demonstrated the role of perturbation in the learning of complex movements. In particular, the ability to recover from experimentally-induced perturbations serves as a buffering mechanism for dealing with changes in velocity and acceleration that occur during the execution of complex tasks. For example, the healthy movement system is generally robust to both incremental and nonlinear fluctuations in inertial and rotational forces when performing real-world tasks (Mosier et al., 2005; Chib et al., 2006). By introducing such force field distortions during a training period, the neuromechanical system undergoes a form of biological supervised learning (Houk, Adams, and Barto, 1994).
The concept of supervised learning is widely used in artificial intelligence (Sutton & Barto, 1998), particularly in the design of movement controllers for robots. While the biological analogues of this control strategy are not completely understood, we may utilize this conceptual model as a means to achieve improved performance in human-machine interaction. By using explicitly physical distortions of force in conjunction with the movement of simulated objects, an experimental session can be tightly controlled without losing the naturalistic aspects of this supervisory mechanism.

Unlike the top-down exemplars of categories typical in artificial supervised learning (Kotsiantis, 2007), the proposed natural supervisory mechanism involves the interactions of environmental structure and proprioception. While this does not provide a dominant bottom-up mechanism observed in self-organized behaviors (Gibson, 1979), the proposed supervised learning mechanism does allow for an overall more adaptable response that maximizes functionality of human-machine system.

1.2 Research Questions and Assumptions
This rationale for this work is related to previous work on human performance augmentation (Alicea, 2008), Brain-computer Interfaces (Wolpaw, 2007), and Augmented Cognition (Schmorrow, 2005). For the latter two applications in particular, tightly-integrated closed-loop control is essential for minimizing system error. While this work does not utilize a closed-loop system, the findings are relevant to maintaining closed-loop control. Therefore, this work fills a gap in the literature by way of addressing two questions. One question involves what physiological/cognitive responses and how much variability characterizes internal mechanisms that serve as responses to environmental stimuli. The other question involves the supervisory nature of environmental stimuli themselves, particularly when they are variable or switch-like. A related rationale involves working towards design principles for health-care and rehabilitative
applications. In these cases, this work should provide two useful outcomes: understanding the ability of clinical populations to recover from environmental perturbations, and how training mechanisms can be implemented in virtual environments.

To answer both questions and place it in the context of technological applications, the experimental investigations presented here featured the following: sets of environmental forces imposed on the upper limbs during reaching and active touch exploration, and presenting alternating sets of forces in sequences of variable length. This is similar to the learn-unlearn-relearn experimental approach derived from the motor learning (Mussa-Ivaldi, 1999) and aerospace medicine (Rafiq et al., 2006) communities.

While it may appear that perturbations at different points in the learning sequence is a confounding variable, it is also worth noting that from a naturalistic standpoint, the phenomena of stimulus presentation order and timing of perturbation are not independent. Because we do not always associate a perturbation with either learning or unlearning provides us with a series of internal controls through which we can investigate contextual effects. In fact, sequence of presentation is perhaps the most important factor for uncovering the effects of perturbation and function of the hypothesized internal mechanisms. The driving force behind the expected changes involve switching between different force fields, which is approximated in these experiments by physically loading the hand and/or arm with different types of forces.

1.3 Manipulations and Measures

In these experiments, environmental structure is introduced using a virtual simulation with limited force feedback. In two of the three experiments, perturbation is introduced using a tool with a variable weight on its distal end. This provides an unstable radius of gyration for an otherwise deterministic task. In the third experiment, perturbation is introduced by the virtual
environment itself though variable resistance during the free exploration of different surface types. This provides an unstable elasticity for an otherwise deterministic task.

In this paper, inertial and/or rotational forces will be used to perturb haptic (e.g. the sense of touch) or truly proprioceptive (e.g. the sensation of joint and limb movement) sensory inputs in semi-natural contexts. The contributions of haptic/proprioceptive sensation and learning to natural supervised learning can be measured indirectly using the mapped physiological output (MPO) and unmatched muscle power (UMP) variables. These are dependent on two interrelated environmental parameters: inertial feedback and the strength of perturbation, which contribute to dynamic responses exhibited by the human-machine system.

There is also a relationship between environmental forces that serve as sensory input and muscle power that serves as physiological and behavioral output. The concept of muscle power (see Enoka, 2004; Josephson, 1999) can be used to understand the role of unmatched muscle power. Traditionally, a measure of muscle power involves assessing the role of muscle length, particularly the shortening velocity of a particular muscle during movement, to produce a force output. Muscle power can be thought of as energy per unit of object movement. When a discrepancy between electrophysiological amplitude and the movements of objects in a virtual environment exists, then we may observe unmatched muscle power. Observing changes in unmatched muscle power, particularly across conditions, is particularly informative for therapeutic applications.

2.0 METHODS

2.1 Participants.
Thirty-seven participants were used in the swinging device switching experiment (Experiment #1). Thirty-two subjects were used in the extended swinging device switching experiment (Experiment #2). Fifteen subjects were used in the tactile surface switching
experiment (Experiment #3). Participants gave their informed consent before participating in the study. The study was approved by the local ethics committee and performed in accordance with local ethics committee standards. Participants gave their informed consent before participating in the study. The study was approved by the local ethics committee and performed in accordance with local ethics committee standards.

2.2 Design for Experiment #1: Swinging Device Switching Experiment

An experiment called the swinging device switching experiment was conducted to better understand the immediate effects of haptic/proprionceptive perturbation on a short-term training regimen. A 2 (swinging device) x 3 (learning blocks) x 4 (perturbation type) x 16 (trials) mixed experimental design was used. The between subjects factors are swinging device and perturbation, while the within subjects factors are learning blocks and trials. Swinging device setting has two levels: unloaded controller and loaded controller. Perturbation type has two levels: perturbation and non-perturbation. Learning type has three levels, learning, unlearning, and relearning. Table 1 shows the specifics of the 2x3x4x16 design.

<table>
<thead>
<tr>
<th>Sequence Presentation</th>
<th>L, U, L</th>
<th>U, L, U</th>
<th>L, U, U</th>
<th>U, L, L</th>
</tr>
</thead>
<tbody>
<tr>
<td>Learning Block 1</td>
<td>16 trials</td>
<td>16 trials</td>
<td>16 trials</td>
<td>16 trials</td>
</tr>
<tr>
<td>Learning Block 2</td>
<td>16 trials</td>
<td>16 trials</td>
<td>16 trials</td>
<td>16 trials</td>
</tr>
<tr>
<td>Learning Block 3</td>
<td>16 trials</td>
<td>16 trials</td>
<td>16 trials</td>
<td>16 trials</td>
</tr>
</tbody>
</table>

2.3 Design for Experiment #2: Extended Swinging Device Switching Experiment

The extended swinging device switching experiment was conducted to better understand the extended effects of haptic/proprionceptive perturbation on a short-term training regimen. A 2 (swinging device) x 4 (perturbation type) x 5 (learning blocks) x 16 (trials) mixed experimental design was used. The between subjects factors are swinging device and perturbation, while the
within subjects factors are learning blocks and trials. Swinging device setting has two levels: unloaded controller and loaded controller. Perturbation type has four levels: interleaved, early, late, and none (control). Learning type has five levels, learning, unlearning, secondary learning, secondary unlearning, and tertiary learning. Table 2 shows the specifics of the 2x4x5x16 design.

Table 2. Experiment #2: 2x4x5x16 factorial design for the extended prosthetic device switching experiment. All perturbations (P) are delivered using the prosthetic device (loaded condition).

<table>
<thead>
<tr>
<th></th>
<th>Alternate* condition</th>
<th>Early condition</th>
<th>Late condition</th>
<th>None (control) condition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Learning</td>
<td>16 trials</td>
<td>16 trials</td>
<td>16 trials</td>
<td>16 trials</td>
</tr>
<tr>
<td>Unlearning</td>
<td>16 trials</td>
<td>16 trials</td>
<td>16 trials</td>
<td>16 trials</td>
</tr>
<tr>
<td>Secondary Learning</td>
<td>16 trials</td>
<td>16 trials</td>
<td>16 trials</td>
<td>16 trials</td>
</tr>
<tr>
<td>Secondary Unlearning</td>
<td>16 trials</td>
<td>16 trials</td>
<td>16 trials</td>
<td>16 trials</td>
</tr>
<tr>
<td>Tertiary Learning</td>
<td>16 trials</td>
<td>16 trials</td>
<td>16 trials</td>
<td>16 trials</td>
</tr>
</tbody>
</table>

* alternate = perturbation during learning, secondary learning, and tertiary learning (blocks 1, 3, and 5).

2.4 Design for Experiment #3: Tactile Surface Switching Experiment

The tactile surface switching experiment was conducted to assess whether or not effects similar to those observed in Experiments #1 and #2 were also observed specifically in the context of touch. Experiments #1 and #2 involved introducing and removing surface reaction forces typical of a swinging device with fixed physical parameters. An alteration between loading and unloading the arm with rotational forces resulted in an effect on task performance. It was therefore suspected that variable inertial forces from different surfaces would demonstrate various types of effects demonstrated by the swinging device switching experiment. As a result, a 3(perturbation type) x 3(block) mixed experimental design was conducted to investigate the effects of free exploration of different surface types on muscle activity. To more directly address the effect of differential loading, the perturbation is introduced at a uniform point in the sequence. The between-subject factor was perturbation type. Perturbation had three levels: hard
perturbation, weak perturbation, and reverse perturbation. Block had three levels: surface learning block 1, surface learning block 2, and surface learning block 3. Table 3 shows the specifics of this 3x3 design.

**Table 3. Experiment #2: 3x3 factorial design for the tactile surface switching experiment. All surface names are defined as they are in the Novint tutorial program.**

<table>
<thead>
<tr>
<th>Perturbation Type</th>
<th>Surface Exploration Block 1</th>
<th>Surface Exploration Block 2*</th>
<th>Surface Exploration Block 3</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Hard</strong></td>
<td>Magnetic (3 minutes)</td>
<td>Honey (3 minutes)</td>
<td>Ice (3 minutes)</td>
</tr>
<tr>
<td><strong>Weak</strong></td>
<td>Bumpy (3 minutes)</td>
<td>Rubber (3 minutes)</td>
<td>Sandpaper (3 minutes)</td>
</tr>
<tr>
<td><strong>Reverse</strong></td>
<td>Honey (3 minutes)</td>
<td>Bumpy (3 minutes)</td>
<td>Sand (3 minutes)</td>
</tr>
</tbody>
</table>

* perturbation introduced.

2.4 Apparatus Protocol

This section describes various features of the apparatus used in these experiments. This includes the instrumentation used to produce measures and manipulate performance.

2.4.1 Apparatus for Experiments #1 and #2. The simulation portion of both swinging device switching experiments will be conducted using the Nintendo® Wii gaming platform (Nintendo Corporation, Kyoto, Japan) using the simulation *Wii Sports Golf* (Figure 1). The Nintendo® Wii uses several simulation simulation-specific parameters and a motion controller to produce computer-generated simulation action. All simulation-specific parameters, such as wind speed and club surface type, will be held constant.

2.4.3 Apparatus for Experiment #3. The simulation portion of the tactile surface switching experiment will be conducted using the Novint Falcon (Novint Corporation, Albuquerque, NM) 6 degree-of-freedom force-feedback device (Figure 2). This input/output controller was used to manipulate a virtual sphere tiled with various surfaces (Figure 2). During the experiment, the subject manipulated a knob which moved the arms of the controller. These movements were
mapped to a cursor in the virtual environment, with which each simulated surface was freely explored.

Figure 1. Images of the experimental setup and apparatus for both swinging device switching experiments. Left: image of an individual standing in front of the CAVE-like virtual environment wearing electrodes during an example of the loaded experimental condition. Right: a screenshot of the experimental task, a Wii Sports putting simulation.

2.5 Experimental Perturbation

Perturbation will be achieved using two mechanisms: a distortion of forces during a commonly encountered repetitive task that subjects were allowed to informally practice on beforehand, and a quick, drastic changes in the forces being explored for 3 minute intervals.

2.5.1 Perturbations for Experiments #1 and #2. For both swinging device switching experiments, the purpose of the swinging device is to simulate a set of environmental conditions that perturb upper-arm morphology and the current physiological state. For both loaded and unloaded conditions, the Wiimote motion controller uses a gyroscope to translate actions produced by the human into a virtual analogue of physical movement. Besides the Wii, the Segway uses a similar mechanism to map user input to continuous motion. While this produces gyroscopic forces of limited scope which act as a source of inertial feedback, the gravity and velocity effects of the simulation physics should be consistent within each condition. In the loaded conditions, the
addition of the swinging device forces participants to perform the putting task in the context of a distorted pendulum.

2.5.2 Unloaded vs. loaded conditions. The unloaded controller conditions will involve using the controller that is standard with the Wii system. In unloaded conditions, participants manipulate action in the virtual environment with a motion controller alone, mimicking the motions of the reaching activity without any of the feedback from the swinging device (i.e. motion coupling between the swinging device and counterweight).

![Experimental setup and apparatus](image)

**Figure 2.** Images of experimental setup and apparatus for the tactile surface switching experiment. Top: image of an individual seated in front of the Novint simulation environment wearing electrodes and engaging the Novint force-feedback device with their right hand. Bottom: three examples of surfaces presented in the Novint environment (from left: rubber, magnetic, and honey). Participants touch a sphere with these properties using a virtual hand (cursor-like object in front of the rubber and magnetic spheres).

The loaded controlled consists of a Wiimote motion controller strapped to a customized swinging device. In this experiment, the swinging device consists of two golf clubs bound together at the shaft with a dynamic counterweight (a bottle filled with a liquid of specific density) attached at the base of the shafts. The swinging device was designed this way to ensure
that previous experience with golf clubs or other swinging tools was minimized and that a perturbation due to loading could be systematically introduced.

The loaded condition provides a perturbation along two axes of movement input to the virtual environment (see Rabin et al., 1999), and provides a distortion of haptic/proprioceptive information that complements the absence of such information as presented by the unloaded controller. During both the unloaded and loaded blocks, the operator will make sixteen reaches with respect to the Wii sports simulation. As the task takes place on a virtual putting green, the goal of each trial will be to get the ball in the hole as often as possible. When successful, this will minimize the variance of the mapped physiological output measurement for a single trial.

2.5.3 Perturbation for Experiment #3. For the tactile surface switching experiments, perturbations were embedded in three types of sequences: hard, weak, and reverse. In all cases, the switch to the surface corresponding to the perturbation type coincided with the second (unlearning) block. All simulated surfaces were presented as the edges of a sphere. A hard perturbation was defined by a honey surface in between surfaces simulating a magnet and ice. A weak perturbation was defined by a rubber surface in between surfaces simulating a series of bumps and sandpaper. The honey surface was referred to as a “hard” perturbation because honey has a higher surface resistance than rubber (which was defined as the soft perturbation). In the reverse perturbation, a really hard surface (the series of bumps) was presented in between honey and sand, which already have a relatively high surface resistance.

2.6 Electromyography

Surface electromyography (EMG) was collected using the Biopac MP150 amplifier. Hardware filtering was done to remove ambient noise, while an infinite-impulse response (IIR) filter was used to remove potential ECG artifacts. EMG-related activity was collected from two points on the dominant arm corresponding with two muscles: the triceps brachii (TB) and flexor
carpi radialis (FCR). The triceps brachii corresponds to the humerus, while the flexor carpi radialis corresponds to the forearm. The loop trace graphs for all experiments were produced using a filtered raw signal. Filtering was done in two steps. First, a low-pass infinite-impulse filter (IIR) of 40Hz has used to clean the raw signal. A 50-element long running average algorithm was then applied recursively across each time series. This down-sampled the raw signal to 30Hz. To measure spikiness in the tactile surface switching experiment, the rectified EMG signal for each 3 minute long experimental block was recursively partitioned into non-overlapping windows 10-seconds in duration using the peak detector function in AcqKnowledge 3.8.1 (Biopac Corporation, Goleta, CA). This algorithm produced a signal that represented all of the peaks for each window in the time-series.

2.6.1 Preparations for EMG surface electrodes. EMG measurements were collected using skin surface electrodes using the following protocol. An impedance check was run using a Checktrode MK-III (UFI, Morro Bay, CA) unit on the preparation before each set of trials to ensure calibration of the instrument. The skin was cleaned and abraded using a mixture of 70% isopropyl alcohol (C3H8O), 30% water (H30), and electrode gel (Biopac Model GEL-1). Adhesive surface Ag-Ag-Cl electrodes (Biopac Model EL-503) were attached to appropriate places on the skin. Surface recording sites for each individual were determined using a standard skeletal muscle atlas, palpation, and measurement. The surface sites and portions of the electrode lead were then secured in place with athletic tape; athletic tape was wrapped several times around the body segment in question. Both of these procedures were done minimize shifting of the electrode and lead wires and to maintain impedance between the skin surface and the electrode.

3.0 MEASURES AND EQUATIONS
3.1 Perturbation definition

Perturbation can be defined mathematically as

\[ P = \frac{D_{\text{end}} - D_{\text{begin}}}{t} \]  

where \( P \) is the degree of perturbation, \( D_{\text{end}} \) is the magnitude of perturbation at the end of perturbation, \( D_{\text{begin}} \) is the magnitude of perturbation at the end of perturbation, and \( t \) is the duration of perturbation. This is similar to a traditional rate equation.

3.3 Inertial Feedback

The effects of the forcing chamber on the operator were kept constant by filling it with water at room temperature. This medium has a specific density of 1, which can be defined as

\[ P \propto d_S, \quad d_S = \frac{W}{v_{\text{ol}}} \]  

where \( P \) is degree of perturbation, where \( d_S \) is specific density, \( W \) is weight, and \( v_{\text{ol}} \) is volume.

3.3 Mapped Physiological Output Measure

Mapped physiological output (MPO) is measured using the following equation

\[ \text{MPO}_t = \frac{|D_{\text{req}} - D_{\text{moved}}|}{D_{\text{req}}} \]  

where \( D_{\text{req}} \) is the fixed distance a virtual object needs to be moved over a given trial, \( D_{\text{moved}} \) is distance the virtual object is actually moved resulting from muscle force production captured by the input device, and \( \text{MPO}_t \) is mapped physiological output for a single reach related to the presented task.

3.4 Unmatched Muscle Power Measure

Unmatched muscle power (UMP) is defined by the following equation

\[ \text{UMP} = \frac{R_{PI}}{\text{MPO}_i} \]  

where \( \text{UMP} \) is unmatched muscle power, \( RP \) is raw signal peak over a finite time interval corresponding with the duration of an experimental trial, and \( \text{MPO}_i \) is mapped physiological output for the trial corresponding to the \( RP \) window. When the UMP measurement equals 0,
there is an absolute match between how much a given muscle is stretched during movement and the amount of resulting force mapped into the virtual environment by mechanical motion of the arm about the rotational axis of the controller. UMP measurement exceeding 0 but is less than 1 result in underpowered movement. Digital translation of force, being only tangentially related to the biological kinematics, resulted in object movement that fell well short of the goal. UMP measurements exceeding 1 represents overpowered movement. In these cases, too much force was translated from the muscle through the controller, resulting in object movements that went beyond the goal. A unit was defined as energy expended per meter of mapped physiological output, while energy was defined as the maximal amplitude of the EMG signal within a variable but finite time window. Note that this differs from the energy of a power spectrum, which is calculated for various frequency bands in the signal.

3.5 Muscle Peak Amplitude Measure

The peak amplitude is calculated using the following equation

$$RP_i = \frac{SIGNAL_{max}}{TRIAL_i}$$  \[5\]

where \(RP\) is the raw signal peak over a finite time interval, \(SIGNAL\) is the EMG signal across the duration of that time interval, and \(TRIAL\) is the duration of a single trial. For each of these windows, the signal was rectified and peak signal amplitude was calculated.

3.6 Spikiness

Spikiness is generally defined by the parameter \(z\) (Krishna et al., 2006), described as

$$z = \frac{MAX_i - MIN_i}{MEAN_i}$$  \[6\]

where \(MAX_i\) is the maximum value over interval \(i\), \(MIN_i\) is the minimum value over interval \(i\), and \(MEAN_i\) is the mean value over interval \(i\).

4.0 RESULTS
Basic descriptive evaluations and parametric statistical tests were conducted on the tactile surface switching experiment and extended swinging device switching experiment results. Figure 3 is a graph labeled with significant results from a Bonferroni corrected paired t-test (see Table 4 for result of all tests) for both muscles over all conditions of the tactile surface switching experiment. Significant and near-significant results between block pairs are shown using red and black brackets, respectively. Of note is the relatively greater number of significant results for a muscle representing involvement of the forearm (FCR). This suggests that active touch exploration shows direct effects in the forearm, which is evidence that activity type can influence the type of mechanism used to deal with the perturbation (e.g. morphological vs. physiological control).

Table 4. Selected paired t-test results on TB and FCR muscles for tactile resistance switching experiment. All p-values < .05 level (Bonferroni corrected).

<table>
<thead>
<tr>
<th></th>
<th>TB</th>
<th>FCR</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Weak</td>
<td>Hard</td>
</tr>
<tr>
<td>Learning vs. Unlearning</td>
<td>p &gt; .07 *</td>
<td>p &gt; .38</td>
</tr>
<tr>
<td>Unlearning vs. Relearning</td>
<td>p &gt; .27</td>
<td>p &gt; .18</td>
</tr>
<tr>
<td>Learning vs. Relearning</td>
<td>p &gt; .33</td>
<td>p &gt; .19</td>
</tr>
<tr>
<td><strong>FCR</strong></td>
<td><strong>Weak</strong></td>
<td><strong>Hard</strong></td>
</tr>
<tr>
<td>Learning vs. Unlearning</td>
<td>p &lt; .01</td>
<td>p &gt; .07*</td>
</tr>
<tr>
<td>Unlearning vs. Relearning</td>
<td>p &gt; .11</td>
<td>p &lt; .03</td>
</tr>
<tr>
<td>Learning vs. Relearning</td>
<td>p &lt; .02</td>
<td>p &gt; .14</td>
</tr>
</tbody>
</table>

* near-significance.

In Figure 4, the p-values for the UMP measurement were also calculated using a paired t-test for both the triceps brachii and flexor carpi radialis muscles using data from Experiment #3. For the experimental control, or presentation of the unloaded condition during all blocks, UMP (TB) exhibits statistical significance at the .05 level when comparing blocks 2, 3, 4, and 5. The
UMP measurement for flexor carpi radialis (UMP-FCR) when compared between blocks 2 and 3 are significant p < .04.

Figure 3. Paired t-tests and significant results for the tactile resistance switching experiment (see also Table 4). Red brackets = significant results (shown). Black brackets = ** near significance

For the UMP (TB) measurement in the late condition, comparisons flanking the transition event between non-perturbation and perturbation are significant, p < .03 and p < .03, while a comparison of blocks immediately before and after a switching point in the condition is not significant, p > .40. For the interleaved condition, the third switching event (from unloaded to loaded) is significant for UMP (TB), p < .04, and nearly significant, p < .09 for UMP (FCR).

The proportional UMP measurements for TB and FCR (Figure 5) reveal finer detail regarding the effects of perturbation on the neuromechanical system. For UMP (TB), there were three distinct effects. For the interleaved condition, perturbation results in an immediate increase in UMP, and appears to be sustained in the tertiary learning block. The early condition shows that the removal of a perturbation suppresses UMP in an immediate fashion in that the effect
wears off in the next block. The late condition shows that UMP is also suppressed after a double dose of perturbation is presented.

The UMP (FCR) measurement shows different effects for the same condition. In the interleaved condition, UMP is stable across all blocks but is consistently lower than the control condition in all cases. For the early condition, there is a slight decrease in the response to a double dose of perturbation. In addition, there may also be a delayed response to the switching of forces. Finally, the late condition demonstrates that there is a slight decrease in UMP until the perturbation is introduced. Interestingly, secondary learning and tertiary learning have similar UMP values, which may demonstrate a transitory effect of introducing a perturbation late in the sequence.

Figure 4. Bar Charts for Unmatched Muscle Power (UMP) for Triceps Brachii and Flexor Carpi Radialis). UMP is measured in volts per meter (V · m*(0.3048)).

4.1 Peak Amplitude Analysis
To better understand how the muscle activity showed variability with respect to the different experimental conditions, I conducted a peak amplitude analysis. This analysis was
conducted to answer the question of how much muscles are being activated relative to the amount of activation required. The first step was to extract the raw EMG signal recorded for each muscle. For each block, the raw signal was partitioned into 16 windows, each corresponding to a particular experimental trial. These data were averaged across all individuals who were administered a particular condition.

Figure 5. Unmatched muscle power (Left: Triceps Brachii (TB). Right: Flexor Carpi Radialis (FCR)) by mean across blocks of trials and as a percentage of baseline (in every instance, baseline for block is 100 and represented by black horizontal lines). UMP is measured in volts per meter (V·m$^\circ(0.3048)$).

4.1.1 Relating peak amplitude to mapped physiological output. The next step involved comparing these peak data with the MPO measurement for each trial. This was done using the UMP measurement. Figures 1 and 3 demonstrate the relationship between these two variables for each muscle recorded. As demonstrated in Figures 3 and 4, the activity of TB and FCR is affected by both the experimental conditions of a particular block and the conditions of previous blocks. For example, the before and after perturbation blocks for TB (Figure 6), activity is within the same range for both unloaded and loaded blocks. For this muscle, activity increases for larger
values of MPO and decreases for smaller values of MPO. When comparing the before and after perturbation blocks for FCR (Figure 7), there appears to be a reduction in unmatched muscle power for the unloaded blocks but an overall increase in the loaded blocks. Furthermore, there appears to be greater activity for smaller MPO values.

Figure 6. Components of unmatched muscle power for Triceps Brachii (TB). Counterclockwise: upper left, comparison of loaded after perturbation and unloaded after perturbation; lower left, comparison of loaded before perturbation and unloaded before perturbation; lower right, comparison of loaded perturbation and unloaded perturbation; upper right, comparison of unloaded well-after perturbation and loaded well-after perturbation.

4.3 Analysis of unmatched muscle power (UMP)

The next step is to discover the relative proportion of unmatched muscle power for several classes of UMP values characterized by each experimental block. This analysis was conducted to demonstrate the mismatch between perturbations in forces, typical response to encountered forces, and response to perturbed forces. Figures 8 and 9 show the results of Figures 6 and 7 in histogram form. Peaks in the histogram show the relative abundance of UMP
measurements for a certain value. It was found that across both muscles, the loaded technological device resulted in a raw signal with greater amplitude before and during perturbation, and a greater degree of unmatched muscle power produced after and well-after perturbation. This result was reversed somewhat for the FCR muscle during perturbation, which may involve the predominance of muscular control in this context. This may suggest that a combination of perturbation and previous experience will result in a particular neuromuscular response.

4.3.1 Differential effect of perturbation type. For the flexor carpi radialis (FCR, Figure 8), the results can be divided into the effects of the loaded and unloaded perturbations. Before the loaded perturbation was introduced, 90% of the UMP values were between 3 and 4, while a very small proportion of values up to 30 were represented. After the loaded perturbation was

![Figure 7. Components of unmatched muscle power for Flexor Carpi Radialis (FCR). Counterclockwise: upper left, comparison of loaded after perturbation and unloaded after perturbation; lower left, comparison of loaded before perturbation and unloaded before perturbation; lower right, comparison of loaded perturbation and unloaded perturbation; upper right, comparison of unloaded well-after perturbation and loaded well-after perturbation.](image)
introduced, the majority of UMP values were under 1, while a small proportion of values were either 0 or between 1 and 1.5. This means that the loaded perturbation created a situation where muscle power was being produced in such a way that reduced the amount of force translated into the virtual environment by the controller.

\[ \text{Figure 8. Histogram for ratio of Amplitude Peaks for Flexor Carpi Radialis (FCR) to MPO measurement for all trials in an experimental block (a.k.a Unmatched Muscle Power). For purposes of analysis, the data were sorted into classes representing intervals of the UMP measurement.} \]
In the case of the unloaded perturbation, 75% the UMP values were concentrated between 1 and 3.5 before perturbation, while after perturbation a little more than half of the values were distributed between 0 and 1, while there was a broader distribution of values between 1 and 6. Again, the production of muscle power was being shifted after the perturbation blocks so in a way that was biased towards the underproduction of force.

Overall, the triceps brachii (TB - Figure 9) demonstrated similar effects for both the loaded and unloaded perturbations. While the TB and FCR are part of the same mechanical system that results in a physiological output, they are on different segments of the dominant arm, which makes comparisons of their contribution to force output important. After each perturbation type, there was a downward shift in the values of the UMP value exhibited in this population. Both before and after perturbation, the majority of UMP values were above 1. This means force production was overpowered both before and after perturbation, but less so after the perturbation was introduced.

4.3.3 Direct effects of perturbation. The direct effects of loaded and unloaded perturbation can also be compared between the two muscles (TB and FCR). This is the effect on force output and unmatched power during the perturbation itself. The loaded perturbation resulted in a much lower UMP measurement for the FCR than for the TB. In the case of TB, between 75-80% of the UMP values were between 6 and 14, while none of the values were between 0 and 3. By contrast, 90% of the UMP values generated by the FCR were between 0.5 and 1.5. This may mean that TB contributes much more towards overpowered movement during the loaded perturbation, and activity in this muscle may need to be regulated to a greater extent by internal mechanisms after perturbation. A similar but much less pronounced pattern of TB overcompensation is seen in the case of an unloaded perturbation. In addition, UMP
measurements using the FCR indicate that an unloaded perturbation results in unpowered movements of the forearm, while UMP measurements using the TB indicate overpowered movements of the humerus.

Figure 9. Histogram for ratio of Amplitude Peaks for Triceps Brachii (TB) to MPO measurement for all trials in an experimental block (a.k.a Unmatched Muscle Power). For purposes of analysis, the data were sorted into classes representing intervals of the UMP measurement.

4.3.3 Effects well-after initial perturbation. Finally, it was asked what occurs to the UMP measurement well-after perturbation, or two blocks removed from the original perturbation. In both muscles and for both perturbations, it appears that the UMP measurement increases across
the spectrum, with both smaller and larger UMP values being equally represented in the population. This may indicate that changes induced by the perturbation introduced over the course of a single block may not have a lasting effect, at least as it pertains to the matching of required force production to muscle peak amplitude and actual force production.

4.3 Work Loop Trace Analysis

This analysis was conducted to answer the question of how selected muscles work together to regulate movement. Figures 10, 11, and 13 shows a loop trace of the Triceps Brachii (TB) and Flexor Carpi Radialis muscles for Experiments #1, #2, and #3, respectively. In each graph, the co-contraction of both muscles before, during, and after perturbation is represented. The loop trace is derived from the raw signal, and is a way of demonstrating how the muscle work together functionally across a time-series. Using a graphical representation, we may assess the contributions of two different muscles as they perform work simultaneously. In cases where muscles act synergistically, the EMG trace forms an elliptical trajectory orbiting an attractor point (0,0). Perturbations in the experimental setting will immediately change the loop trace shape, and long-term effects will result in hysteresis (e.g. traces that do not return to its original shape).

4.3.1 Work loop trace for Experiment #1. An example from Experiment #1 is shown in Figure 10. For condition 1, when the loaded perturbation is introduced during the learning block 3, the forearm muscle (FCR) temporarily exhibits less amplitude during perturbation. This does not necessarily mean that individuals are compensating by shifting some of the work to the humerus, because there is no corresponding change in the shape of the loop trace. This suggests that internal robustness mechanisms are at work in this case. In condition 3, when the unloaded perturbation is introduced during the learning block 3, the forearm muscle (FCR) exhibits a greater range of amplitude during perturbation. This is in contrast to condition 1, the humeral
muscle (TB) contributes to a slight shift in the loop trace pattern. This may reflect a contribution of morphological control during this set of conditions.

Figure 10. Loop trace for the prosthetic device switching experiment. The raw signal for the triceps brachii (TB - measured in volts) is plotted against the raw signal for the flexor carpi radialis (FCR – measured in volts). The x-axis represents values attained by the TB muscle, while the y-axis represents values attained by the FCR muscle. Data are arranged in the following manner: each row represents a specific condition, and each column represents a particular set of blocks in the experiment.
In condition 3, when the loaded perturbation is introduced during the learning block, the extent of the loop trace pattern is limited by the range of the recording equipment. However, the work loop trace shifts inward from these lower and upper bounds in blocks subsequent to the perturbation. This may suggest an interaction between morphological control and internal mechanisms under these conditions. For condition 4, when the unloaded perturbation is introduced during the learning block, the loop trace changes its shape post-perturbation that correspond with changes in amplitude for the humeral muscle (TB). This may suggest a role for internal adaptive mechanisms are at work under these conditions.

4.3.3 Work loop trace for Experiment #2. Results for the work loop trace analysis is shown in Figure 11 and Table 5. The lesson of the loop trace from the extended swinging device switching experiment is that control and interleaved conditions result in small but largely insignificant changes in the loop trace. A correlation analysis conducted on the horizontal-vertical, vertical-diagonal, and horizontal-vertical components of loop trace skew revealed that these changes demonstrated similar trends. \( H_s \)-\( V_s \) and \( V_s \)-\( D_s \) values exhibit weak correlations (c-values between .30 and -.30), \( V_s \)-\( D_s \) values exhibit strong negative correlation (c-values below -.65). In the interleaved condition, it appears that loading has an effect on \( H_s \) and \( V_s \) values independent of changes in \( D_s \) values. Beyond the finding that uniform (alternating) perturbation and uniform force field conditions yield a similar result, broader relevance of this finding to adaptability and the ability to absorb and learn from the changes in loading remains to be understood.

Table 5. Percentage of datapoints in each quadrant* of the work loop trace plot for the extended swinging device switching experiment, by block and condition. Global skew of data points in three directions: horizontally (\( H_s \) value), vertically (\( V_s \) value), and diagonally (\( D_s \) value). Global skew = arbitrary units.

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* quadrants of the work loop trace are defined by values along the x- and y-axis in the following way: N, P = negative, positive; P, P = positive, positive; P, N = positive, negative; N, N = negative, negative.

By contrast, conditions that embody early and late loading show changes related to loading, but also changes due to staying in one force field state over three experimental blocks. Using the $D_s$ (diagonal skew) values as a criterion, it appears that the early and late loading conditions exhibit instability within loading perturbations and between loaded and unloaded
blocks. However, the control condition shows larger values of $D_s$ in both the first (learning) and final (tertiary learning) block when compared to the third (secondary learning) block. In these cases, a correlation analysis conducted on the horizontal-vertical, vertical-diagonal, and horizontal-vertical components of loop trace skew showed that for the early loading condition, $H_s$, $V_s$, $H_s$, $D_s$, and $V_s$, $D_s$ all have a $c$-values of above .60 (positive correlation). For the late loading condition, $H_s$, $V_s$ has a $c$-value of .45 (moderately positive correlation) and $H_s$, $D_s$ has a $c$-value of -.46 (moderately negative correlation). Changes in the $H_s$ and $V_s$ values between learning and tertiary learning suggests that there is more to be learned with regard to variation in muscle activity during selective perturbation.

4.3.3 Work loop trace for Experiment #3. An example from the tactile surface switching experiment is shown in Figure 12. For the reverse perturbation condition, there is a change in the loop trace shape both during and after the perturbation. Changes in both the humeral (TB) and forearm muscle (FCR) seem to be independent of each other, although there appears to be a shift in the amplitude of the humeral muscle (TB). This may suggest that slight adjustments are made to muscular control of the humerus during active touch exploration not made during a controlled reaching movement.

For the hard perturbation condition, there is relatively little change in the loop trace shape across the experiment. After perturbation, the amplitude of the forearm muscle (FCR) increases. This is a result similar to the first condition of Experiment 1, and suggests that the same internal regulatory mechanisms are at work. This can be contrasted with the weak perturbation condition, where the loop trace pattern gradually shifts rightward as the amplitude of the humeral muscle (TB) changes. This change occurs during and after perturbation, which suggests either an
internal adaptive mechanism or an interaction between internal adaptive mechanisms and morphological control.

Figure 11. Work loop trace for the extended prosthetic device switching experiment. The raw signal for the triceps brachii (TB - measured in volts) is plotted against the raw signal for the flexor carpi radialis (FCR – measured in volts). The x-axis represents values attained by the TB muscle, while the y-axis represents values attained by the FCR muscle.

5.0 DISCUSSION

One interesting result of these experiments was that a perturbation, whether it was of a different type or at a different position in the condition, has a different effect on physiological
output and muscle activity. This can be explained theoretically by further considering the mechanisms of internal, morphological, and environmental regulation and how they relate to the capacity for adapting to changes in the environment. In addition, the results show that there may be two separate regulatory mechanisms: one governing the retention of temporal information about the perturbation, and another that exploits information inherent in the haptic/proprrioceptive environment.

5.1 Learning and Physiological Adaptation as Regulatory Mechanisms

One way to connect theoretical concerns to applications is by considering the relationship between learning and physiological regulation (Dworkin, 1993). In this case, “regulation” involves how haptic/proprrioceptive sensory information is processed, selected upon, and represented in both the peripheral and central nervous systems (Wolfe et al., 1995). When presented with an environmental challenge, a participant will respond in one of two ways. The first way is to exhibit performance decrements characterized by work loop trace skew and large amounts of unmatched muscle power. This represents a failure to adapt. The second way is to be robust or become increasingly so to perturbations over time. This is a much more subtle response, and most likely involves some components of procedural and/or motor learning (Mussa-Ivaldi, 1999; Shadmehr & Wise, 2005).

5.1.1 Components of the adaptive response. The adaptive response itself has two components: innate and acquired. The innate response is related to physiological state, and is related to abilities involving motor coordination and muscle strength. Related work on this same dataset (Alicea, 2008a; Alicea, 2008b) and the literature on prosthetics design (Herr, Huang, & McMahon, 2002) suggest that limb size and shape may contribute to differences in performance. Based on work using virtual reality to restore balance and enable movement rehabilitation (Jeka et al., 1997; Holden & Dyar, 2002), it is also predicted that potential applications to clinical
populations will have to be context- and patient-specific. On the other hand, while the learning response may also be stratified by physical ability, the juxtaposition of differential forces may allow for invariant features in both sets to be more readily extracted and applied to future contexts (Mussa-Ivaldi, Giszter, & Bizzi, 1995). This is a form of skill transfer that acts to supervise the adaptive capacity of nervous system mechanisms responsible for the processing of touch/proprioceptive information. The extraction of these common features by the nervous system should be highly similar across individuals. They are driven by the structure of haptic/proprioceptive sensory information, thus comprising an important component of any potential application.

5.2 Affordances and the Physiology of Everyday Things

To make this work relevant to applications such as translational medicine and ergonomic design, we must consider how the switching between different environments might emphasize how the invariant features of different but related force fields may serve as affordances (Gibson, 1979; Norman, 1999). In particular, the right sequence of perturbations may act to reinforce components of the environment that contain information.

5.2.1 Usability in physiological context. Norman (1988) has discussed how usability is best characterized by a mapping between cognitive processing and product design. In the case of these experiments, it has become apparent that a mapping between human physiological responses and product design is also important. In the physiological context, the concepts of homeostasis and allostatic drive (Sterling & Eyer, 1988) may ultimately be critical to understanding how technologies, from touch-driven interfaces to motion-driven virtual environments, interact with the user and elicit a particular response. It is worth noting that the consensus in brain-computer interface (BCI) design (Mason & Birch, 2003; Wolpaw, 2010) does
not directly address this issue. Whether the “physiology of everyday things” is context-specific or related to a specific set of muscles and brain regions remains to be seen.

Figure 12. Loop trace for the tactile surface resistance switching experiment. The raw signal for the triceps brachii (TB - measured in volts) is plotted against the raw signal for the flexor carpi radialis (FCR – measured in volts). The x-axis represents values attained by the TB muscle, while the y-axis represents values attained by the FCR muscle.
5.3 Applications to Manipulable Technologies

Manipulable technologies, or information technologies that you can touch, move, and otherwise physically control, can play a role in both medical and non-medical applications. In the realm of medicine, customizable manipulable interfaces may aid people who suffer from movement disorders and aging-related muscle weakness. Manipulable interfaces can function as both training devices for rehabilitation and as aids for making otherwise hard-to-manipulate devices more usable. For non-medical applications, the work presented in this paper might be adapted to training people of various anthropometric dimensions to use touch screens of different sizes and degrees of capacitance. The goal for future medical and non-medical applications alike should revolve around optimizing which extremes and patterns that define certain sets of forces (e.g. pendular-like reaching movements or ballistic exploratory movements) are most helpful in the recovery of function and maintenance of performance, respectively.

KEY POINTS

* emerging manipulable technologies (e.g. touch- and motion-based interfaces) will ultimately feature a number of non-uniform forces and sequences of stimuli that can be simulated using virtual environments with physical intermediaries.

* the dynamics and complex relationships between simulation, the physical world, and human physiology can be better understood through the lens of neuromechanics, an approach that unifies biomechanics, neuroscience, embodied perspectives, and systems engineering.

* it was found that selective perturbation, in relation to a staggered training protocol can uncover various differences in performance, which remain to be formally classified but are suggestive of underlying cognitive and morphological regulatory mechanisms.

* these findings can be integrated with existing mobile and virtual technologies to provide a versatile, programmable tool for rehabilitative and non-medical applications.

6.0 REFERENCES


**SHORT BIOGRAPHY**

Bradly Alicea is currently a researcher in the Cellular Reprogramming Lab at Michigan State University. Bradly was formerly (2004-2009) a member of the MIND Lab at Michigan State University. He has published, attained degrees, and attended conferences in a number of academic fields ranging from evolutionary and cell biology to computational science. His interests lie at the frontiers and intersections of fields of systems biology, high-performance computing, measurement techniques, virtual environments, intelligent systems, neurobiology, and biophysics/biomechanics.