Unmatched muscle power: mapping physiological control to virtual world physics

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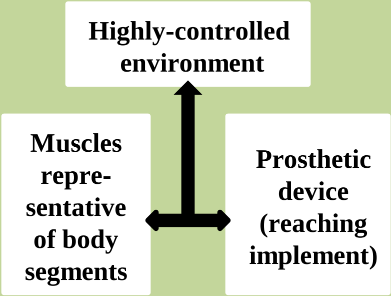
Introduction.

Unmatched muscle power is a theoretical and experimental technique intended to incorporate electrophysiological and adaptive properties of skeletal muscle into virtual environment control. In everyday settings where movement-related activities seem to be effortless, the production of muscle power is hypothesized to be perfectly matched to that activity.

The requirement of a mapping between the real and virtual worlds provides an opportunity to intentionally distort control parameters important to perception and action in a human-machine interface. By understanding the neural response to distorted feedback, better control strategies can be devised for applications relevant to rehabilitation technologies and non-standard populations.

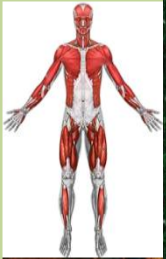
The amount of force output relative to that required for optimal control during a given physical activity can be under- or over-produced in cases of pathology or injury, or when the control imperative is poorly defined. In this submission, amplitude components of the EMG signal for selected arm muscles and object displacement in the virtual environment are used to parameterize aspects of this decoupling.

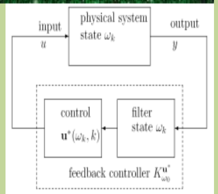


Basic idea behind unmatched muscle power experiments.

Experimental results utilizing various forms of force-feedback conditioning in a motion-controlled virtual environment will be briefly discussed. Using these findings and principles, biologically realistic control policies can be formulated to enhance purely statistical or symbolic descriptions of real-world activities.

Merging virtual worlds with physiological control.





Physiological control can play a role in the design of movement-based interfaces for rehabilitation and immersive simulation.

Control principles in such devices can be both linear (e.g. force-feedback) and nonlinear (dampening as a response to stimulus adaptation).

A design strategy which incorporates both kinematic and kinetic aspects of these relationships is needed.

Invariants, or scale-independent features of a system that most compactly define its complexity, can be used as statistical tools. Virtual environments can play a key role in identifying invariants by selectively decoupling environment and physiological function.

Rather than using deterministic models of natural phenomena (such as a programming description or machine learning approaches), we might be able to leverage key attributes of physical models to uncover key features of our coupled system.

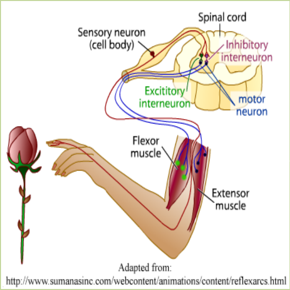
Neuromechanics: an emerging approach to brain, body, and behavior.

How do we touch, perceive, and interact with the physical world? An approach called neuromechanics [B] can provide insight into how we regulate movements in relation to mechanical stimuli.

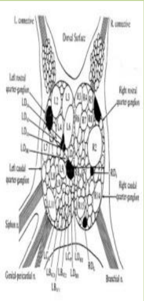
Neuromechanics is a means to integrate the function of brain, body, and environment in a way that treats each element in an explicit manner. The scope of inquiry may range from intentional movement behaviors in humans to the feeding mechanism in *Aplysia* [B].

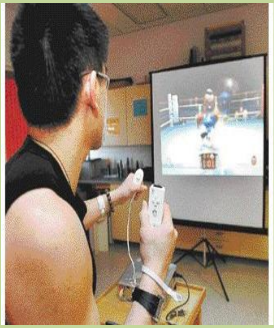
The benefit of a neuromechanical approach is that forces, torques, and friction [D] encountered by the body and experienced by the nervous system can be characterized as a key feature of behavior.

These physical bases of behavior are especially useful in the context of immersive virtual environments. This is traditionally known as



Scope of inquiry





haptic interaction [E].

However, with the advent of brain-computer interfaces (BMIs) [E], both movement-based and physiological signals can be incorporated into virtual models of reality.

Invariants [B] identified during the interaction between physical and physiological systems can provide design principles for novel bioengineering devices.

Muscle Power in virtual environments.

Muscle power [C]: amount of muscle activity or limb movement required to produce a fixed amount of work.

The conventional physiological definition relies upon an entirely physical conceptualization of work.

In this poster, a virtual component representing an added control imperative will be introduced.

Muscle power in virtual environments must also take into account the mapping of muscle activity and movement to a computational model.

Unmatched muscle power: periods of time when muscle activity and movement behavior conspire to over- or under-perform relative to what is needed for the task at hand.

Environmental Switching: understanding and minimizing unmatched muscle power.

A number of experiments in systems as diverse as human upper-body movements, bacterial colonies, and artificial organisms [F] have suggested that alternating between environments can initiate adaptation and facilitate physiological regulatory mechanisms.

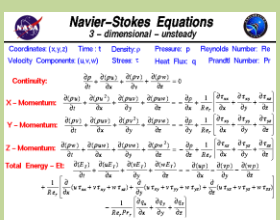
The process of switching between two alternating environments can have multiple effects. One is an immediate effect on performance after the environment is switched. The second is a delayed effect on performance that may not become evident until the environment has remained static for awhile.

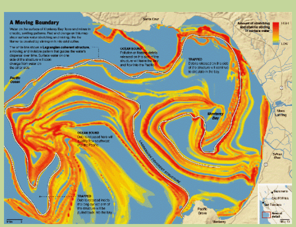
Application Domain: more complex virtual models of physical phenomena.

Interactive virtual environments that provide first-order movement control and haptic feedback require a computational model that balances completeness with compactness.

The simulation of fluid flows in a first-person canoeing simulation can be used to illustrate how the existence of unmatched muscle power depends on various representations of a physical phenomenon.

In some cases, models represent various features of the actual phenomenon at the expense of others. Physical features of the environment quantified using these frameworks have an effect on the magnitude of unmatched muscle power during interaction.





Fluid flows can be simulated using Navier-Stokes (left) and Lagrangian Coherent Structures (right).

In other cases, models might be used to exploit key features of neuromechanical function for purposes of rehabilitation [D] and performance enhancement. For future applications, the components of a virtual model might use representations such as Navier-Stokes and add specialized force-fields to optimize (or selectively perturb) performance.

Application Domain: prosthetic device design.

The term prosthetic device can refer to actual prosthetic and orthotic devices, which include artificial limbs, or wearable devices such as exoskeletons and sensor arrays [E]. Identifying instances of unmatched muscle power during continuous action might provide a way to map neuromechanical invariants to morphological structures.

Application Domain: BMI control.

Currently, BMI's use machine learning or signal processing techniques to find a well-characterized signal for control purposes [E]. Unmatched muscle power could be used as continuously-varying parameter to augment muscular control.

Future work.

There are several ways in which measurement of unmatched muscle power can be improved. Two of these possibilities are discussed here.

The loading chamber (see experimental setup section) could be modified to incorporate many different types of materials, from metal balls to sand to a highly viscous fluid. The effect would be to vary the inertial force component that determines the radius of gyration, and thus change the magnitude of a loaded perturbation.

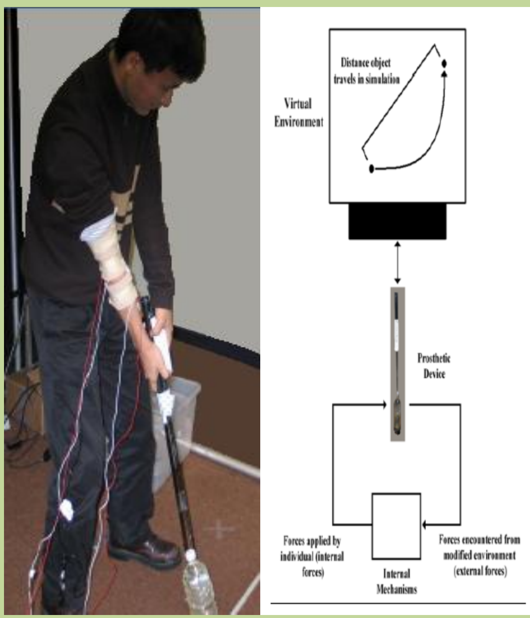
Additional experiments have been run using the Novint interface, which delivers a direct force-feedback stimulus at the hand. Switching between simulations of different surfaces in this environment showed an effect for contact forces due to differential surface properties.

Experimental Setup.

Taking inspiration from the motor control and systems biology literature, an experimental approach was used that involved transitioning (or switching) between two different force fields. A reaching implement was used as a stand-in for a prosthetic device.

Using a motion controller and reaching implement (a repurposed golf club), two conditions were explored. The "loaded" condition involved weighting the end of the implement with a chamber filled with either a liquid or solid. The "unloaded" condition involved using only the motion controller. The Nintendo Wii was used (WiiSports), which requires mimicry of movements associated with a given activity.

The result of the loaded condition was to increase the radius of gyration (R_o) and perturb movement. Additional perturbation was introduced by interlacing loaded and unloaded conditions, which introduced unknown lag and gain when the controller was used by itself to control action in the virtual environment.



Perturbation definition: a series of trials that differ from the previous or subsequent block.

Figure 1.
Experimental apparatus. Left: subject swinging the loaded version of the device in the virtual environment (turned off).

Right: relationship between the virtual environment, technological devices, and the physiological system.

Work from performance.

Unmatched muscle power can be thought of in terms of power production and work using the following equations.

$$P = \frac{W}{t} \qquad [1.0]$$

$$W = F(d), \qquad F = \frac{W}{d} \qquad [2.0, 2.1]$$

where P is power, W is work, F is force exerted, t is time, and d is displacement of object. In this case, a heuristic for work (W) is our EMG amplitude, and our heuristic of displacement (d) is mapped physiological output.

When the amount of power produced is large, more work is required over a finite time period for a specified displacement of the object. This results in a greater degree of mismatch as proposed by theory. In these analyses, time (t) was kept constant. However, if t is treated as a variable, unmatched muscle power becomes a second-order derivative of the relationship between EMG amplitude and movement performance as shown in equ. 3.0.

$$\frac{d^2F}{dt} = F(d) \qquad [3.0]$$

Performance Measurements.

Actual movement behavior relative to force exerted was characterized by mapped physiological output

$$MPO_t = \frac{|D_{req} - D_{moved}|}{D_{req}} \qquad [4.0]$$

where D_{req} is the distance an object is to be moved in the virtual environment, and D_{moved} is the distance the object actually travels in simulation (see Figure 1, right frame).

The radius of gyration for the reaching implement was held constant, and is defined by

$$R_o = \frac{\frac{\pi r_4}{4}}{A} \qquad [5.0]$$

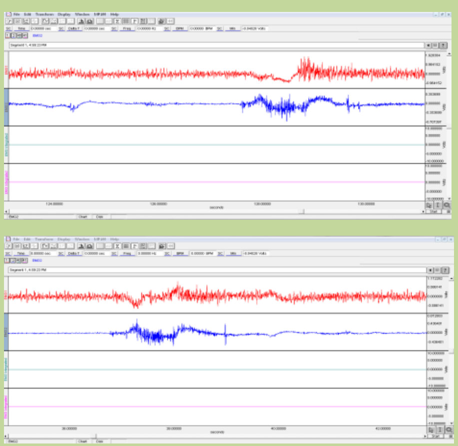
where the numerator is the moment of inertia and A is the cross-sectional area of the reaching implement.

Unmatched muscle power can be characterized by Equ. 6.0, which is the proportion of raw signal peak (RP) to mapped physiological output (MPO) over a finite time interval.

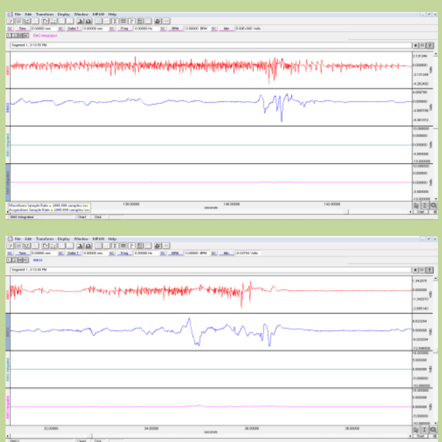
$$UMP = \frac{RP_i}{MPO_i} \qquad [6.0]$$

$$RP_i = \frac{S_{max}}{T_i} \qquad [7.0]$$

In equ. 7.0, *RP* is the raw signal peak over a finite time interval, S_{max} is the EMG signal across the duration of that time interval, and T_i is the duration of a single trial. For each of these windows, the signal was rectified and peak signal amplitude was calculated.



Raw EMG signal, loaded (top two windows)



Raw EMG signal, unloaded (top two windows)

Discovery of unmatched muscle power characteristics.

To discover the patterns underlying the unmatched muscle power phenomenon, a series of plots were produced that characterize the complex function *f(UMP)* under a series of conditions.

These plots include components of the UMP measurement considered seperately, the UMP measurement as a function of each type of experimental condition, and the raw EMG signal under loaded and unloaded conditions.

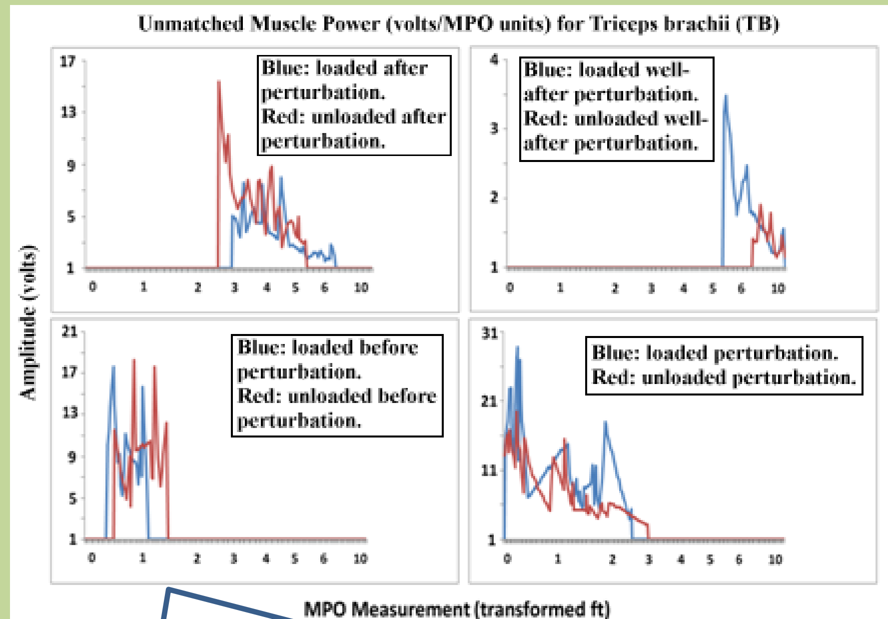


Figure 2. Unmatched muscle power for Triceps brachii (TB). Counterclockwise: upper left, comparison of loaded after perturbation and unloaded after perturbation; lower left, comparison of loaded before perturbation and unloaded before perturbation; lower right, comparison of loaded perturbation and unloaded perturbation; upper right, comparison of loaded well-after perturbation and unloaded well-after perturbation.

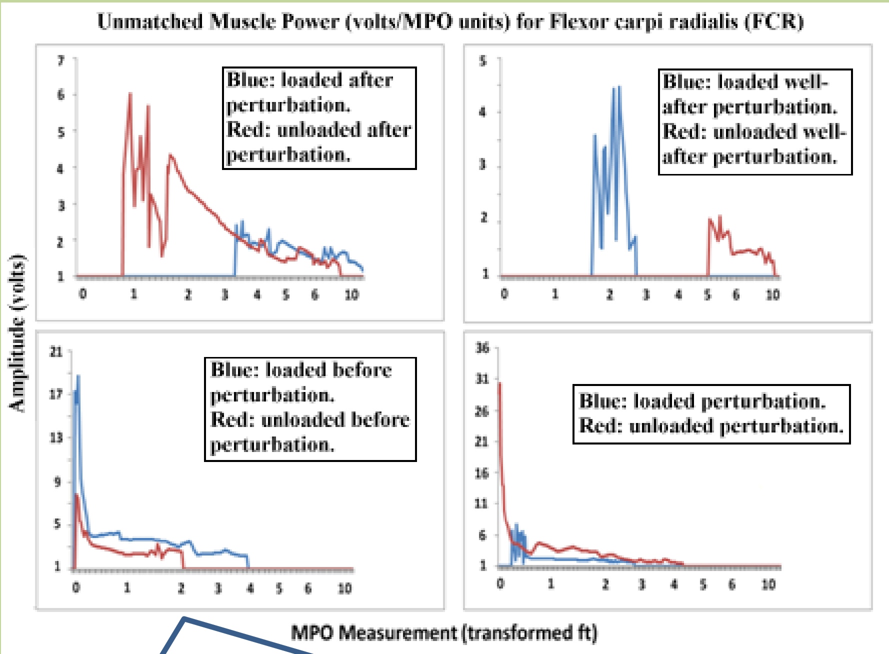


Figure 3. Unmatched muscle power for Flexor carpi radialis (FCR). Counterclockwise: upper left, comparison of loaded after perturbation and unloaded after perturbation; lower left, comparison of loaded before perturbation and unloaded before perturbation; lower right, comparison of loaded perturbation and unloaded perturbation; upper right, comparison of loaded well-after perturbation and unloaded well-after perturbation.

Unmatched muscle power can be characterized as a complex function which is variable for specific conditions. In Figure 2 and 3, a comparison between loaded and unloaded conditions are made for four different conditions.

Significant jaggedness characterize the amplitude of the waveform above a baseline of 1. The most basic result is that patterns of unmatched muscle power are variable between representative humeral (TB) and forearm (FCR) muscles.

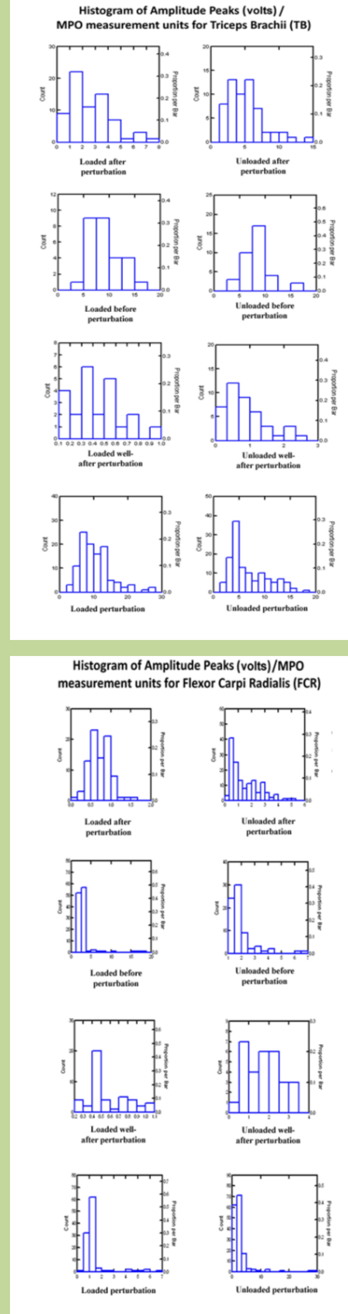


Figure 4. Histogram for ratio of Amplitude Peaks for Triceps brachii (TB - top) and Flexor carpi radalis (FCR - bottom to MPO measurement for all trials in an experimental block (i.e. Unmatched Muscle Power). For purposes of analysis, the data were sorted into classes representing intervals of the UMP measurement.

The other obvious result is a lack of unmatched muscle power for small MPO values after a perturbation has been encountered. This may be due to a clearer control imperative for smaller distances to the target.

If we consider MPO as an error measurement, trials in which accuracy is greater for goal distances of any length results in less matching and thus less raw EMG amplitude.

ADF analysis for different orders of stimuli.

An Amplitude Distribution Function (ADF) can provide informationn w.r.t. peaks and other important information in the raw signal [A].

Figure 4 provides a series of histograms characterizing the unmatched muscle power measurement for each unique condition presented.

For the muscle representing the humerus (Triceps brachii), the histogram exhibits a broader distribution during perturbation for both stimulus conditions. Likewise, a perturbation moves a given histogram distribution leftward (lower) after perturbation.

For the muscle representing the forearm (Flexor carpi radialis), the UMP distribution is low before perturbation. In the unloaded stimulus condition, this does not change after perturbation. In the loaded stimulus condition, this distribution moves rightward (higher) after perturbation.

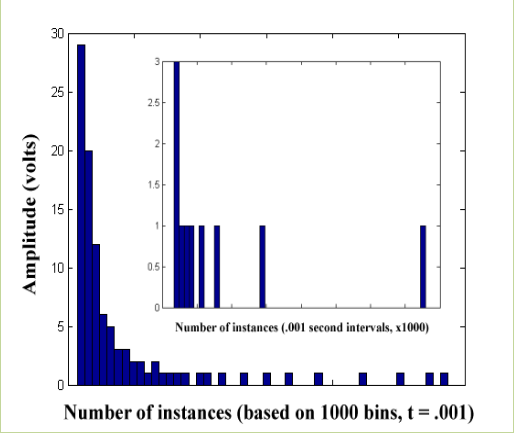
General ADF analysis for loaded vs. unloaded stimuli.

Since Triceps brachii and Flexor carpi radialis are not antagonistic muscles, their activity can provide a window into different phases of neuromuscular regulation due to a common set of imposed forces and inertial movements (see Figure 5).

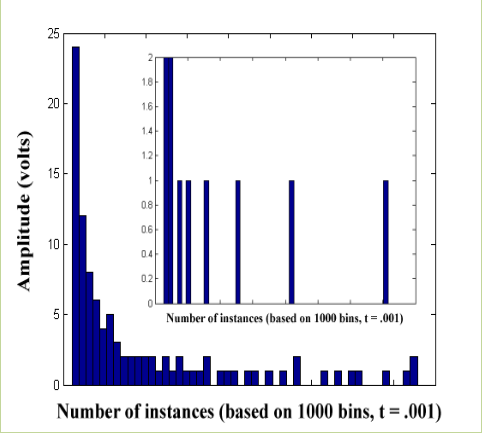
From this result, it appears that loading the arm results in enhanced modulation of activity at the humerus, but little effect at the forearm. In the case of the humerus, there were more instances covering a broader range of amplitude values in response to the loaded stimulus.

By looking at the course-grained analysis (see Inset), it appears that the loaded stimulus has an pronounced effect on both muscles, albeit differential.

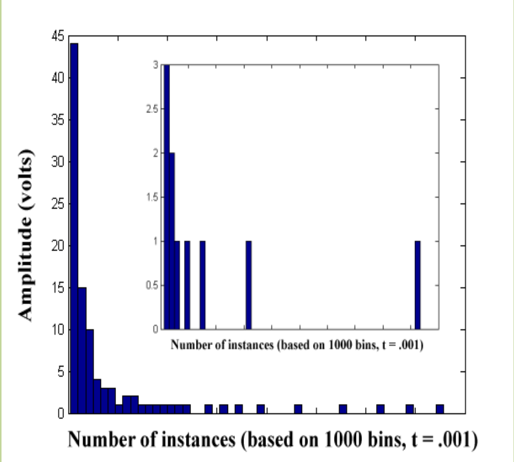
The loaded condition in the representative forearm muscle in particularly interesting in that more modulation is apparent in cases when the unloaded stimulus is present.



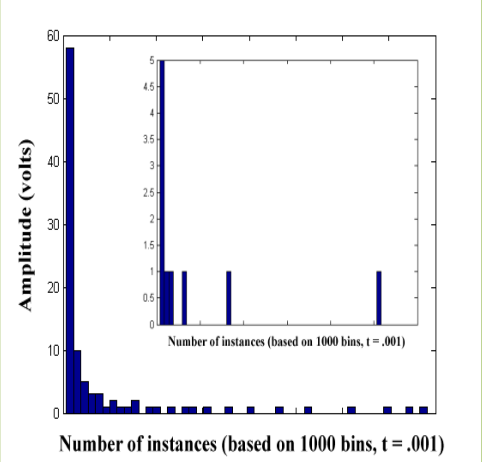
Unloaded Stimulus: representative humeral muscle (Triceps brachii)



Loaded Stimulus: representative humeral muscle (Triceps brachii)



Unloaded Stimulus: representative forearm muscle (Flexor carpi radialis)



Loaded Stimulus: representative forearm muscle (Flexor carpi radialis)

Figure 5. Amplitude distribution functions for two stimulus conditions (left vs. right) and two representative muscles (top vs. bottom) in the arm. Inset for each graph is a course-grained analysis of same data. NOTE: only first ten items for x-axis are shown.

References

A) Amplitude Distribution Function (ADF):

Irene, E.A. Surfaces, interfaces, and thin films for microelectronics. Wiley, New York (2008).

Hagberg, M. The amplitude distribution of surface EMG in static and intermittent static muscular performance. European J. of Applied Physiology and Occupational Physiology, 40(4), 265-272 (1979).

B) General theoretical concepts:

Schmidt, M. and Lipson, H. Distilling Free-Form Natural Laws from Experimental Data. Science, 324(5923), 81-85 (2009).

Computational Neurobiology. Shadmehr, R. and Wise, R. Computational Biology of Reaching and Pointing. MIT Press, Cambridge, MA (2005).

Neuromechanics. Holmes, P., et.al The dynamics of legged locomotion: Models, analyses and challenges. SIAM Review 48:207-304 (2006).

Full, R.J. and Koditschek, D.E. Templates and anchors: Neuromechanical hypotheses of legged locomotion on land. J. of Experimental Biology 202:3325-3332 (1999).

Beer, R.D. Intelligence as Adaptive Behavior: An Experiment in Computational Neuroethology. Academic Press (1990).

C) Muscle power:

Enoka, R. Neuromechanics of Human Movement. Human Kinetics, Champaign, IL (2002).

Josephson, R.K. Dissecting Muscle Power Output. J. of Experimental Biology, 202, 3369-3375 (1999).

Bejan, A. and Marden, J.H. Unifying constructal theory for scale effects in running, swimming, and flying. Journal of Experimental Biology 209, 238-248 (2006).

D) Muscle rehabilitation and mechanics:

Aisen et..al The effect of mechanical damping loads on disabling action tremor. Neurology. 43(7):1346-50 (1993).

Barbeau, H. Locomotor Training in Neurorehabilitation: Emerging Rehabilitation Concepts. Neurorehabilitation and Neural Repair, 17(3), 3-11 (2003).

Clarke et.al The Effects of Repeated Rehabilitation “Tune-Ups” on Functional Recovery After Focal Ischemia in Rats. Neurorehabilitation and Neural Repair, 23(9), 886-894 (2009).

E) Physical models and physiological interfaces:

Brewer, B.R et.al Feedback Distortion to Overcome Learned Nonuse: a system overview. Proc. of the IEEE EMBC, 1613-1616 (2003).

Durand, D.M. Neural interfacing: not just BCI or BMI! Journal of Neural Engineering, 4, doi:10.1088/1741-2560/4/3/E01 (2007).

Nicolelis, M.A. Brain-machine interfaces to restore motor function and probe neural circuits. Nature Reviews Neuroscience, 4, 417-422 (2003).

Pentland, A. Looking at People: Sensing for Ubiquitous and Wearable Computing. IEEE Transactions on Pattern Analysis and Machine Intelligence, 22(1), 107-109 (2000).

F) Environmental switching:

Kashtan, N. et.al Varying environments can speed up evolution. PNAS USA, 104, 13711-13716 (2007).

Scheidt, R.A., Dingwell, J.B., and Mussa-Ivaldi, F.A. Learning to move amid uncertainty. J. of Neurophysiology, 86, 971-985 (2001).