# SIMULATIONS OF OPTIMAL REWEIGHTING OF MUSCLE COORDINATION REVEAL IMPORTANT BENEFITS OF MUSCLE REDUNDANCY

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## INTRODUCTION

For many decades, a dominant view in the motor control research community has been that the nervous system somehow needs to cope with the presumed computational challenge of selecting a muscle activation pattern from a seemingly infinite amount of patterns that give rise to the same endpoint forces [1]. Others have proposed that redundancy offers benefits, such as potentially enabling the preservation of muscle synergies under fatigue [2]. We, on the other hand, propose that instead of adhering to synergistic muscle activations, the central nervous system could take advantage of redundancy to explore the solution space: by dynamical reweighting of muscle activation patterns a (static force production in this case) task could be performed successfully for a longer period of time than by adhering to a same or synergistic pattern. However, the nature and benefits of such dynamical reweighting of muscle activation are not known.

## **METHODS**

We created a model of isometric three-finger grasps actuated by 21 muscles of the three fingers. The relationship  $\vec{f}(t) = J^{-T}RF_0(t)\vec{a}(t)$  describes the mapping from muscle activations to endpoint forces:  $\vec{a}(t)$  represents the time-varying vector of muscle activations, between 0 and 1, and  $\vec{f}(t)$  the 6dimensional grasp wrench (3 force and 3 moment components) applied to a grasped object. The matrix  $F_0(t)$  is diagonal and scales the muscle activations with respect to their maximal force generating capabilities. The matrix R maps the muscle forces to joint torques [4,5], while the transposed inverse Jacobian  $J^{-T}$ , which is posturedependent, maps the joint torques to the object wrench. To compute  $J^{-T}$ , we based the posture parameter values on [3], and described the fatigue

dynamics of the i-th muscle by:

Fatigue rate: 
$$\frac{df_{0_i}}{dt} = -\frac{1}{t_{fat}} a_i(t) f_{0_i}(t)$$

where the  $f_{0_i}(t)$  are the entries of the matrix  $F_0(t)$ . Hence, the fatigue dynamics directly affects the ability of muscles to generate force. Their fatigue rate is proportional to their activation level and a fatigue time constant  $t_{fat}$ . Because we focus on activity-dependent fatigue rates, recovery dynamics are not included at this point. We computed the optimal schedule of reweighting of muscle activation as minimizing the quadratic cost

$$Cost_{dynamic} = (F - F_0)^2$$

i.e., maintaining a constant sum of normal forces applied by the three fingers, while minimizing tangential components [3]. In [6] we describe how 20% MVC is a sufficiently low force magnitude such that no one muscle is necessary for the task. The initial coordination pattern  $\vec{a}(0)$ \* minimized the sum of squared muscle activations. This optimal coordination pattern was also the one adhered to when reweighting was not allowed. Its cost function

$$Cost_{proportion} = \left(\frac{\vec{a}(t)}{\sum_{i} a_{i}(t)} - \frac{\vec{a}(0)^{*}}{\sum_{i} a_{i}(0)^{*}}\right)^{2}$$

aims to keep constant the relative activation weights of muscles, i.e. the direction of the vector in activation space, while allowing an overall increase in activation in response to fatiguing. This was the conclusion in [3]. Lastly, we considered

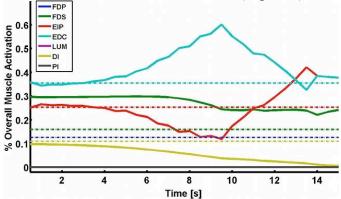
$$Cost_{proportion\& magnitude} = (\vec{a}(t) - \vec{a}(0)^*)^2$$

which in addition to the previous strategy, also aims to keep constant the activation vector magnitude. We used the GPOPS optimal control algorithm, in its MATLAB implementation, to find the optimal muscle activation schedule (i.e., time history of muscle activations) that optimizes each of the 3 cost

functions. Due to computational constraints, we set the fatigue time constant to 1 s and the time horizon to 15 s, and, for now, restricted ourselves to optimizing the activation schedule in the index finger only, assuming that the other 2 fingers produce the necessary force to meet the task conditions. Lastly, we compared the overall force reserves across the three strategies. This suffices for a rigorous initial comparison across these neural control strategies.

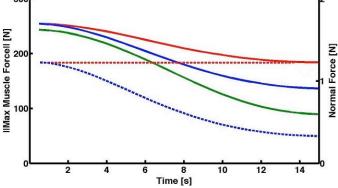
## RESULTS AND DISCUSSION

We tracked the relative contributions of individual muscles to overall muscle activation (Figure 1).



**Figure 1**: Index muscle activations as proportions of overall activation (solid lines: dynamic reweighting strategy, broken lines: rigid strategies). While several muscles hardly contribute, EDC takes over EIP's role initially, later they reverse.

Figure 2 quantifies the fatigue state of index finger musculature over time for all three strategies.



**Figure 2**: Force generating capability for three different muscle activation schedules (solid lines, left y-axis): dynamical (red), constant proportions (blue) and constant proportions and overall magnitude (green). Dashed lines show the index endpoint normal force (right y-axis) generated by each strategy. Note that the most rigid strategy fails quickly, while the other two (red dashed line) maintain the required normal force.

We see that, after 15 s, the dynamical reweighting strategy retains 25 % and 40 % greater force reserves, respectively, compared to the rigid approaches, the latter of which actually fails to produce the required endpoint force.

## **CONCLUSIONS**

While benefits have been attributed to muscle redundancy, to our knowledge this is the first work to show at the level of optimal coordination that dynamical reweighting provides greater specific functional benefits. Our results suggest that isometric force tasks, subject to very simple fatigue dynamics, can be executed with significantly less expenditure and possibly for a longer time, if the nervous system takes advantage of muscular redundancy by dynamically reweighting the activation magnitudes of muscles, thus traversing the solution space of activation patterns that fulfill the task. Importantly, we show that adhering to a specific, or even synergy-associated or synergyconstrained, activation pattern proves to be functionally detrimental in the presence of fatigue dynamics. Having the ability to dynamically change muscle activation patterns, while generating equivalent forces, possibly outweighs the presumed computational disadvantage of selecting muscle activation patterns.

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