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An optimized proportional-derivative controller for the human upper extremity with gravity

Kathleen M. Jagodnik [a,b,c,*], Dimitra Blana [d], Antonie J. van den Bogert [a,e,f], Robert F. Kirsch [a,g,h,i]

[a] Department of Biomedical Engineering, Case Western Reserve University, Cleveland, OH, United States
[b] Fluid Physics and Transport Processes Branch, NASA Glenn Research Center, Cleveland, OH, United States
[c] Center for Space Medicine, Baylor College of Medicine, Houston, TX, United States
[d] Institute for Science and Technology in Medicine, Keele University, UK
[e] Department of Mechanical Engineering, Fenn College of Engineering, Cleveland State University, Cleveland, OH, United States
[f] Orchard Kinetics, LLC, Cleveland, OH, United States
[g] Cleveland Functional Electrical Stimulation (FES) Center, Cleveland, OH, United States
[h] Louis Stokes Cleveland Veterans Administration Medical Center, Cleveland, OH, United States
[i] MetroHealth Medical Center, Cleveland, OH, United States

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ABSTRACT

When Functional Electrical Stimulation (FES) is used to restore movement in subjects with spinal cord injury (SCI), muscle stimulation patterns should be selected to generate accurate and efficient movements. Ideally, the controller for such a neuroprosthesis will have the simplest architecture possible, to facilitate translation into a clinical setting. In this study, we used the simulated annealing algorithm to optimize two proportional-derivative (PD) feedback controller gain sets for a 3-dimensional arm model that includes musculoskeletal dynamics and has 5 degrees of freedom and 22 muscles, performing goal-oriented reaching movements. Controller gains were optimized by minimizing a weighted sum of position errors, orientation errors, and muscle activations. After optimization, gain performance was evaluated on the basis of accuracy and efficiency of reaching movements, along with three other benchmark gain sets not optimized for our system, on a large set of dynamic reaching movements for which the controllers had not been optimized, to test ability to generalize. Robustness in the presence of weakened muscles was also tested. The two optimized gain sets were found to have very similar performance to each other on all metrics, and to exhibit significantly better accuracy, compared with the three standard gain sets. All gain sets investigated used physiologically acceptable amounts of muscular activation. It was concluded that optimization can yield significant improvements in controller performance while still maintaining muscular efficiency, and that optimization should be considered as a strategy for future neuroprosthesis controller design.

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1. Introduction

Spinal cord injury (SCI) impairs movement and sensation below the level of injury. High-level SCI, which affects the cervical C1–C4 levels, compromises voluntary motor function below the neck. Although communication between the brain and peripheral neuromuscular system is impaired, muscle function remains intact. Functional Electrical Stimulation (FES) is a technology that uses electrical current to activate peripheral nerves that otherwise would be inactive due to injury (Crago et al., 1996) to restore useful muscular movement. FES neuroprostheses have been applied to numerous physiological systems, including upper extremity function, which is addressed in the present study.

Feedforward control is the form most commonly used for clinical FES applications (Peckham and Knutson, 2005; Lynch and Popovic, 2008). It entails calculating and applying muscle stimulation patterns using available information about the system, without the use of feedback signals. It is simple to implement and does not require sensors; however, this absence of sensors also makes the success of the movements generated heavily dependent on accurate models of the controlled system and environment.

* Correspondence to: NASA Glenn Research Center, 21000 Brookpark Rd., MS 110-3, Cleveland, OH 44135, United States. Fax: +1 216 368 4969.
E-mail addresses: kathleen.jagodnik@nasa.gov, kmjagodnik@gmail.com (K.M. Jagodnik).

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Feedback control requires the use of sensors, which detect arm properties and allow the controller to correct its actions if they deviate from the desired behavior. Upper extremity (UE) FES applications of feedback control have included shoulder function (Yu et al., 2001), elbow extension (Giuffrida and Crago, 2001; Memberg et al., 2003), hand grasp (Kilgore et al., 1989), and wrist stabilization (Lemay and Crago, 1997).

Additionally, more advanced upper extremity FES controllers have been investigated. These can involve the combination of feedforward and feedback control (Abbas and Chizeck, 1995; Blana et al., 2009), reinforcement learning (Izawa et al., 2004; Thomas, 2009; Jagodnik, 2014), and artificial neural networks (Giuffrida and Crago, 2005; Hincapie and Kirsch, 2009).

Many projects that develop advanced controllers compare their new control method to more basic feedback control, e.g. proportional-derivative (PD) or proportional-integral-derivative (PID), to demonstrate the superiority of the newly-developed advanced controller. However, there is often minimal effort invested in adequately tuning the feedback controllers intended for comparison, and we hypothesize that these feedback controllers may often perform worse than they would have, had they been properly tuned. PID controller tuning algorithms include the Ziegler–Nichols method (Ziegler and Nichols, 1942; Astrom and Hagglund, 2004) and the Chien, Hrones, and Reswick method (Chien et al., 1952). However, these tuning methods can often result in poor performance (Astrom and Hagglund, 2001), particularly for nonlinear systems such as FES control. For example, when using Ziegler–Nichols tuning, overshoot is common for nonlinear systems (Dey and Mudi, 2009). Such tuning algorithms cannot be considered optimized. Because these simpler feedback controllers have not been given the same care in tuning as the more advanced controllers to which they are being compared, it is likely that inaccurate conclusions may be drawn when comparing these two classes of control algorithms.

For this reason, we propose to mathematically optimize a proportional-derivative (PD) controller gain set for a 3-dimensional human shoulder and arm system, and to compare its performance on dynamic reaching tasks to PD controller gain sets tuned using standard algorithms. We hypothesize that optimization will yield significantly improved performance when compared with standard, non-optimal, tuning methods. PD control was selected because it represents a basic feedback control architecture, and because goal-directed reaching movements with a single endpoint specified per task are being performed (Heaviside step function with no explicit trajectory specified); such a task specification could result in compromised performance should an integral control component be added, as in a PID controller. Additionally, PD control is consistent with the Equilibrium Point hypothesis, which effectively explains certain features of motor control (Bizzi et al., 1992; Feldman et al., 1998).

We have previously determined for a planar arm system that using simulated annealing to optimize PD control can yield excellent performance (Jagodnik and van den Bogert, 2010). To extend our previous work, we optimize a PD controller to perform goal-oriented reaching movements, using a 3-dimensional biomechanical model of a human arm that has 5 degrees of freedom (DOF). We explore two PD controller architectures: one with 2 gains, and another with 10. The optimized controller gain sets are applied to a large variety of point-to-point reaching tasks, and tested for their ability to generalize to tasks for which they had not been optimized, and for their ability to withstand muscular fatigue. The performance of our optimized controller gain sets is compared with that of three other PD controller gain sets that have not been optimized for this system, and conclusions are drawn about the utility of optimization for neuroprosthesis controller development.

2. Methods

2.1. Biomechanical model

For all experiments described, a 3-dimensional (3D) computational musculoskeletal model of the human arm was used that has 5 degrees of freedom (DOF) (Table 1) and 102 muscle elements grouped into 22 muscles (Table 2) (Chadwick et al., 2009). The model includes gravity and uses a fixed scapula as the base of the model. All joints are modeled as hinges, with the glenohumeral joint consisting of three such hinges (Chadwick et al., 2009); this joint is modeled according to the Y–Z′–Y″ convention (Fig. 1). Rotations and displacements are defined according to Wu et al. (2005). Muscles are modeled as a Hill structure (Zajac, 1988) with activation dynamics and contraction dynamics. Passive muscle force was not included because the difficulty in correctly estimating the L_{slack} value for the parallel elastic element (Chadwick et al., 2009) for all muscle elements was found to negatively impact model performance. The model was implemented for forward dynamic muscle-driven simulation.

2.2. Controller design and optimization

The PD controller calculates muscle stimulation values proportional to joint angle errors and angular velocities (Eq. (1)). The sign of the moment arm is also included in this equation, to ensure production of movement in the proper direction, given that each muscle can potentially affect multiple DOFs. The PD controller initially calculates 102 outputs, one for each muscle element. For each of the 22 muscles, the calculated stimulation values of its N elements were averaged, and this mean value was applied to all elements of the muscle, resulting in a total of 22 unique muscle stimulation values applied per iteration (Fig. 2). This grouping constrained the system to a more realistic approximation of an FES system, in which an electrode would stimulate discrete muscles or muscle groups, rather than individual muscle elements.

The PD controller equation is as follows:

$$u_i(t) = \sum_{j=1}^{5} -sign(R_{ij}(\theta))\left[(Kp_j{*}(\theta_{actual} - \theta_{target}) + Kd_j{*}(\dot{\theta}_{actual} - \dot{\theta}_{target}) \right] \quad (1)$$

where

$$\mathrm{sign}(R_{ij}(\theta)) = \begin{cases} 1, \text{ if} R(\theta) \geq 0.5 \text{ mm} \\ 0, \text{ if} |R(\theta)| < 0.5 \text{ mm} \\ -1, \text{ if} R(\theta) \leq -0.5 \text{ mm} \end{cases} \quad (2)$$

and $R_{ij}(\theta)$ is moment arm, index i represents the muscle, index j represents degree of freedom, Kp_j is the proportional gain matrix about degree of freedom j, Kd_j is the derivative gain matrix about degree of freedom j, θ is joint angle, and $\dot{\theta}$ is joint angular velocity. We assume that we do not need to know the actual moment arm, which will vary between people and when comparing human

Table 1
Angular limits for 3D arm model degrees of freedom.

Degree of freedom	Min angle (deg)	Max angle (deg)
Plane of elevation	−10	90
Angle of elevation	5	90
Internal rotation	−55	70
Elbow flexion	5	140
Forearm pronation	5	160