A Proportional Derivative Controller for Planar Arm Movement

Kathleen Jagodnik, M.S.[1,2]; Antonie van den Bogert, Ph.D.[2]; Michael Branicky, Ph.D.[3]; Philip Thomas, B.S.[3]; Robert Kirsch, Ph.D.[1]

1) Department of Biomedical Engineering, Case Western Reserve University
2) Department of Biomedical Engineering, Lerner Research Institute, Cleveland Clinic
3) Department of Electrical Engineering and Computer Science, Case Western Reserve University

INTRODUCTION

- Neurological movement disorders (e.g. stroke, spinal cord injury) can prevent voluntary limb control, while leaving intact nerves and muscles.
- Functional Electrical Stimulation (FES) can activate muscles and restore movement[1].
- Long term goal: to develop more sophisticated FES control methods that allow smooth, efficient and mechanically stable movement.
- Current FES control systems are less than ideal, particularly for gross motor tasks with a dynamic component; feedback has not been used clinically for Upper Extremity (UE) applications.
- Feedback is necessary to allow controller to adapt to changing conditions (e.g. muscle fatigue, environmental conditions).
- This project involves developing a feedback Proportional Derivative (PD) controller for a planar UE FES model, testing and optimizing its performance computationally, and implementing it in a human subject.
- We also begin to explore intelligent Reinforcement Learning control for FES systems in simulation.

PD CONTROLLER METHODS

Modeling

• Controller performance was evaluated using a biomechanical model for planar arm movement (Figure 1).

• The model had two segments and was driven by six muscles. Each muscle was modeled using a Hill-based approach.

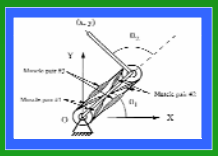
• Equations of motion were generated using SD/FAST (PTC, Needham, MA).

• A Proportional Derivative (PD) controller was used to control the arm model. Forward dynamic simulations were used to perform planar reaching tasks.

• The PD controller generates a response whose magnitude is proportional to the errors in joint angles and their time-derivatives. It determines stimulation value **u** for each muscle according to Equation 1:

$$u = G(s - s_0) \quad \text{(Eq. 1)}$$

where **u** is the matrix of muscle stimulation values, **G** is the 6 x 4 gain matrix, & **s** is a matrix of sensor values. For each optimization, G was determined to minimize the cost function, given by Equation 2:



$$f(G) = \sum_{i=1}^{2} \int \underbrace{(\theta_i - \theta_{i_target})^2}_{\text{error}} dt + W \sum_{j=1}^{6} \int \underbrace{(F_j)^2}_{\text{effort}} dt \quad \text{(Eq. 2)}$$

Figure 1: Biomechanical model[2]. Modeled muscles: anterior deltoid, posterior deltoid, brachialis, triceps short head, biceps, triceps long head.

• To determine optimal PD controller gains and to test various PD controller architectures, for each optimization, a set of 12 reaching tasks was used, with both elbow and shoulder initial and target joint angles varying from 20° to 80°.

• Generality and Robustness tests of the quasi-optimized PD controller were performed:

→ **Generality Test:** PD controller performed a set of 1,000 reaching tasks with randomly-generated initial & target arm positions

→ **Robustness Test:** All 6 muscles in model were randomly weakened, & the PD controller tested these systems on the 1,000 reaching tasks used in the Generality test.

Human Subject Experiments

• One FES human subject; 2-parameter PD controller was applied to elbow joint. Muscles stimulated were biceps and triceps long head.

• PD controller was implemented in Simulink.

• Simulink controller on host computer sends commands to target computer, which controls the Upper Extremity Control Unit (UECU) (Figure 2):

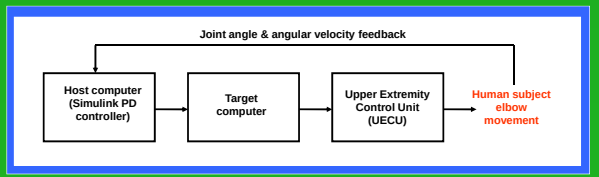


Figure 2. Block diagram of experimental setup of human subject FES elbow control.

• A variety of elbow reaching targets & PD controller gains was tested.

INVESTIGATIONS: PROCEDURES & RESULTS

(1) Generality & Robustness Tests of PD Controller

• Performance was similar among all 3 controllers (Tables 1 & 2).

• Good ability to generalize to non-optimized movements (Table 1).

• Controllers showed robustness after muscles had been weakened (Table 2).

• Weakened muscles resulted in slower and less accurate movements (compare Tables 1 & 2), but performance was still acceptable.

Table 1. Generality Test results

Performance Measure	PD controller (# of parameters) 2	16	24
Avg. Error (°)	5.50	5.32	5.29
Avg. Effort (N)	25.10	23.26	22.18
Avg. Speed (sec) (time to reach 5° from target)	0.25	0.22	0.23

Table 2. Robustness Test results

Performance Measure	PD controller (# of paramters) 2	16	24
# of Failures (for 5° threshold)	15	16	15
Avg. Error (°)	7.44	7.24	7.13
Avg. Effort (N)	17.43	16.08	15.75
Avg. Speed (sec) (time to reach 5° from target)	0.36	0.34	0.37

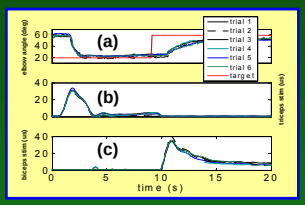


Figure 3. Human elbow extension task followed by elbow flexion task. (a) elbow angle. (b) triceps stimulation. (c) biceps stimulation.

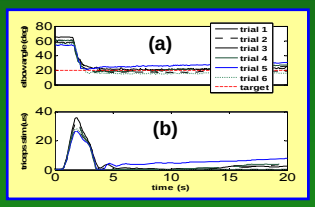


Figure 4. 6 human trials of the same elbow extension task using optimized PD controller gains. (a) elbow angle. (b) triceps stimulation.

(2) PD Controller Human Subject Experiments

• Single-extension (Figure 3) and extension-flexion (Figure 4) elbow reaching tasks were tested.

• Repeatability of performance between trials was variable (e.g. Trial 5 in Figure 4); spasticity, fatigue can affect performance.

• Sub-maximal muscle stimulations were required to achieve movements (Figures 3(b), 3(c), 4(b)).

• PD controller achieved good, but variable, performance, if it was tuned correctly.

(3) Reinforcement Learning Control in Simulation Experiments

1. **Differences between subjects' arms (functional muscles, atrophy and spasticity) require parameter-tweaking in closed-loop controllers.**
2. **Reinforcement Learning controller automates this process by learning to minimize the joint angle error and muscle forces over time.**
3. **Continuous Actor-Critic architecture[3] was used in arm simulation tests.**
4. **Adaptive ability was tested by adding a baseline 20% biceps stimulation, simulating muscle spasticity.**
5. **Performance was evaluated by integrating reward function over time for 256 fixed, 2-second arm movements.**
6. **Before learning, Actor-Critic was pretrained to mimic PD controller.**

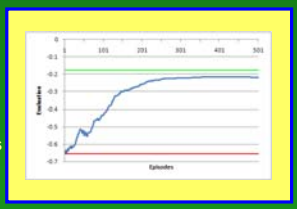


Figure 5. Plot of Actor-Critic evaluation (blue line) on arm simulation over 2-sec episodes. The red line is the PD controller's performance on this test, and the green line is the evaluation of the PD controller on the unmodified arm.

Result: The Actor-Critic architecture is able to adapt to changing arm dynamics in simulation and should be considered for human subject experiments.

DISCUSSION & CONCLUSIONS

Modeling

• All versions of the PD controller achieved good performance (distinguished by a smooth approach to target joint angles and absence of oscillation in the steady state), provided that the cost function used by the optimization algorithm was properly specified.

• All 3 PD controllers showed good robustness & ability to generalize.

• RL controller is able to adapt to changing conditions, and shows promise for FES arm control.

Human Subject Experiments

• Controller performance was generally good, if controller was tuned properly.

• Subject's muscular spasticity and fatigue create an unpredictable system; PD controller could have problems adapting to significant changes.

FUTURE WORK

• Implement PD controller for shoulder joint in human subject

• Enable PD controller to receive real-time instructions from human user

• Develop PD controller for a system that includes gravity

• Continue investigating Reinforcement Learning as a promising method of adaptable FES control.

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