Simple EMG-Driven Musculoskeletal Model Enables Consistent Control Performance During Path Tracing Tasks

Dustin Crouch and He Huang, *Senior Member, IEEE*

Abstract— **Consistent, robust performance is critical for the utility and user-acceptance of neurally-controlled powered upper limb prostheses. We preliminarily evaluated the performance consistency of an electromyography (EMG)-driven controller based on a two degree-of-freedom musculoskeletal hand model, whose simplified structure is more practical for real-time prosthesis control than existing, complex models. Parameters of four virtual muscles were computed by numerical optimization from an able-bodied subject's kinematic and EMG data collected during wrist and metacarpophalangeal (MCP) flexion/extension movements. The subject attempted to trace a series of paths of different complexity (straight and curved) with the fingertip of a virtual hand displayed on a computer screen; the straight-path tracing tasks were repeated on a second test day to evaluate performance consistency over time. The subject's tracing accuracy during the tasks was consistent both between tasks of varying complexity (i.e. straight vs curved) and between test days when tracing the straight paths. Additionally, task duration, straightness, and smoothness did not significantly differ between the two straight-path test days. The consistent performance between days was achieved even with a very short (~15 seconds) calibration period to re-normalize EMG. The subject also coordinated movements of the wrist and MCP joints simultaneously during the task, much like with healthy, intact limb movement. Our promising results suggest that a musculoskeletal model-based controller may provide consistent and effective performance across a range of operating conditions, making it potentially practical for prosthesis control. Further research is needed to determine whether musculoskeletal model-based control (1) is effective for executing real-world tasks, and (2) can be extended to populations with neuromuscular impairment (e.g. amputation).**

I. Introduction

Enabling reliable and intuitive neural control of powered upper limb prostheses remains an elusive challenge. Many upper limb amputees abandon even the most advanced prosthetic devices, in part, for lack of a satisfactory user interface [1]. The most popular and convenient source of neuromotor information for prosthesis control has been electromyography (EMG) signals from residual limb muscles. However, EMG measurements can vary substantially due to both intrinsic (movement dynamics, limb posture change, fatigue) and extrinsic (electrode shift) factors. Interpretations of a user's movement intent from EMG can become less accurate under these conditions that generate high EMG variability [2]. Unfortunately, many such conditions, including electrode shift or displacement with prosthesis donning, doffing, and daily use [3], are typical. Some approaches used to account for EMG variability associated with electrode shift require additional sensors, increasing the burden of prosthesis use [4]. More practical and comprehensive solutions are needed to make neurally-controlled powered prostheses more robust to EMG variability.

One reason that EMG-driven controllers are confounded by signal variation may be their naïve process for mapping neural commands (i.e. EMG) to intended movements. Current control algorithms use a "black-box" approach to associate individual or groups of EMG signals with discrete movement directions *without accounting for the underlying musculoskeletal structure and dynamics*. Conversely, humans control a redundant, non-linear neuromuscular system in which the mechanical contributions each muscle, whose force can vary independently from one another, are combined across muscles to move one or more joints. Each unique multi-joint movement stems from a unique combination of muscle forces elicited from non-discrete patterns of neural commands. Accounting for individual muscle contributions in a prosthesis controller would permit continuous multi-joint movement predictions and, when confronted by EMG variability, may predict movement intent that controllers based on discrete movements and EMG patterns would fail to recognize.

Computational musculoskeletal modeling and dynamic movement simulation potentially provide an ideal platform for incorporating neuromuscular elements in prosthesis control, but have rarely been used to do so. For one, many existing models include several muscles to accurately represent anatomy, requiring EMG to be recorded (cumbersome and impractical) or estimated (potential source of error) for each muscle to accurately predict movement. Simulating upper limb movement in real-time with such complex models, though previously demonstrated for some models [5, 6], can be computationally intensive. Lumped-parameter models that include fewer muscle elements simplify simulations and require fewer control inputs [7]. However, estimating parameters for such models is not straightforward since they are typically defined using anatomical or physiological measurements [8]. The challenges of estimating parameters are manifold in amputees whose residual muscles may have altered and unobservable perceived biomechanical roles at the missing (imagined) hand, evidenced by distorted phantom limb sensations [9]. We previously reported a novel approach for estimating model parameters, using a subject's own EMG and kinematic data, to account for intra-subject variability in the (perceived) biomechanical action of (residual) muscles

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D Crouch and H. Huang are with the NCSU/UNC Department of Biomedical Engineering, NC State University, Raleigh, NC, 27695-7115; University of North Carolina at Chapel Hill, Chapel Hill, NC 27599*

Corresponding author: Dustin Crouch (E-mail: dlcrouch@ncsu.edu, Phone number: 919-515-4412)

[10]. The model's offline predictions of movement direction matched measured able-bodied kinematics for >80% of timepoints. However, it is unclear whether such a customized, simplified model can enable consistent and effective real-time control for performing goal-oriented tasks.

The purpose of this pilot study was to demonstrate the online control performance consistency of a two degree-of-freedom (DOF) EMG-driven musculoskeletal model. We evaluated the ability of an able-bodied subject to perform a series of virtual path tracing tasks of varying complexity (i.e. straight and curved paths). Outcomes of the tracing tasks would preliminarily demonstrate whether musculoskeletal model-based controller could enable (1) effective control during a high-precision tracing task; (2) consistent day-to-day performance with minimal recalibration; and (3) simultaneous multi-joint movements. The results of this study may lead to the development of a new and robust biologically-inspired controller powered upper limb prostheses.

II. Methods

A. Data Collection and Parameter Optimization

One able-bodied right-handed male subject (age 31, height=178cm, weight=66kg) with no reported history of neuromuscular impairment (e.g. stroke) participated in the study. Kinematic and EMG data were recorded synchronously while the subject performed 5 sets of movements: 1) alternating wrist flexion/extension at 0.25 Hz, 2) alternating MCP flexion/extension at 0.25 Hz, 3) random wrist flexion/extension, 4) random MCP flexion/extension, and 5) random simultaneous wrist and MCP flexion/extension. The subject performed two trials in each set, and data were recorded for approximately 30 seconds for each trial. During trials, the subject maintained a static posture with the arm and forearm in neutral and the elbow flexed to 90°. Retroreflective marker positions were recorded at 120 Hz using an infrared motion capture system (Vicon Motion Systems Ltd., UK) and low-pass filtered at 6 Hz. EMG were recorded at 960 Hz (Biometrics Ltd, UK) from four forearm muscles based on their known biomechanical contribution to wrist and MCP joint movement in the intact limb: extensor carpi radialis longus (ECRL), extensor digitorum (ED), flexor carpi radialis (FCR) and palmaris longus (PL). EMG data were high-pass filtered (4th order Butterworth filter, 40 Hz cutoff frequency), rectified, and low-pass filtered (4th order Butterworth filter, 10 Hz cutoff frequency). To estimate muscle contraction magnitude during trials, processed EMG data were normalized to the maximum processed EMG values recorded during maximum voluntary contractions (MVCs).

Using a previously developed constrained numerical optimization procedure, we computed 24 muscle parameters, 6 for each of 4 hill-type muscles, for a planar two DOF (wrist and MCP flexion/extension) musculoskeletal model [10]. A series elastic element (i.e. tendon) was not included.

B. Implement Musculoskeletal Model for Real-time Control

The model with the subject's customized parameters was implemented in MATLAB for real-time control of a two-dimensional, two DOF virtual hand displayed on a computer monitor (Fig 1). Two additional joints, whose angles were equal to the MCP joint angle, were added distal to the MCP joint increase the fingertip workspace. Raw EMG signals were acquired at 1000 Hz using a 16-channel EMG system (Motion Lab Systems, Inc), high-pass filtered (3rd order Butterworth filter, 70 Hz cutoff frequency), rectified, low-pass filtered (3rd order Butterworth filter, 5 Hz cutoff frequency), and normalized to maximal EMG values during MVCs performed at the beginning of each testing session. The processed EMG data were downsampled to 200 Hz (each point the average of 5 consecutive processed EMG timepoints) and input directly to the muscles in the model during a forward dynamic simulation. Though not explicitly modeled in the real-time controller, the electromechnical delay between neural excitation and muscle activation was implicitly accounted for by delays introduced by EMG signal processing and dynamic simulation. The position of the virtual hand was computed at 200 Hz and updated on the computer monitor display at 20 Hz.

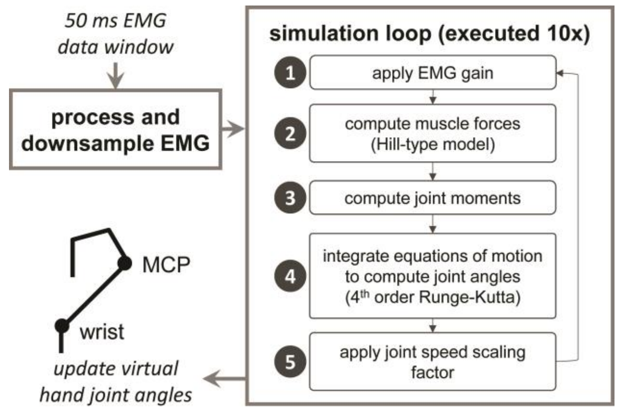

Fig. 1. Real-time control steps. EMG were downsampled to 10 timepoints for each 50 ms EMG data window, and each timepoint was the control input for one iteration of the simulation loop. The virtual hand joint angles were updated after each 10 simulation iterations.

C. Virtual Path Tracing Task

To preliminarily evaluate the performance and consistency of a model-based control system, we quantified the subject's ability to trace straight and curved paths with the fingertip of the virtual hand. Three test sessions (2 straight-path and 1 curved-path) were performed on separate days to assess control performance over time. Before the first straight path and curved path tracing sessions, the controller was tuned iteratively until the subject and experimenter were satisfied with the virtual hand movement. Between straight-path test days 1 and 2, the surface EMG electrodes were replaced, potentially introducing electrode shift. Additional EMG data during MVCs were collected for approximately 15 seconds (i.e. no parameter tuning).

We defined ten straight paths whose locations and orientations varied within the virtual hand's reachable workspace (Fig 2). Distinct start and end points were specified to vary the fingertip movement direction required to trace the paths. The start and end points, a straight line between them, and the subject's fingertip trajectory after reaching the start point were displayed on the screen during each trial. The subject attempted to trace each path 3 times; each attempt (trial) began when the subject exited the start point and ended when the subject reached the end point. At the beginning of the test session, the subject was instructed to move the fingertip of the virtual hand from the start point to the end point while following the path as closely as possible.

Two curved paths were defined within the virtual hand's reachable workspace (Fig 3). The paths' start and end points were defined such that the overall motion of the fingertip was either in a clockwise or counterclockwise direction with respect to the wrist. The subject was given the same verbal instructions as for the straight-path tracing task. Given the higher complexity of the task compared to tracing a straight path, the subject could attempt to trace each path approximately 20 to 30 times.

B. Data Analysis

As a measure of tracing accuracy, we computed the mean perpendicular distance (MPD) between the fingertip and path over each trial as a percentage of the total hand length (palm+finger segments). For each *straight* path, the trial with the lowest MPD was selected for further analysis to highlight the potential performance of the model across paths. Task duration was the time required to move the fingertip from the start to end point. We also computed the straightness (the ratio of the fingertip trajectory length to path length [11]) and smoothness (a non-dimensionalized measure of the spectral arc length [12]) of the fingertip trajectories. The mean and standard deviation of each fingertip trajectory metric were computed across trials for each of the two test days. Two-tailed paired Student's t-tests were performed to compare performance between test days. Differences for which $p<0.05$ were considered significant.

III. Results & Discussion

The subject completed all 10 straight-path (Fig 2) and 2 curved-path (Fig 3) tracing tasks, keeping the fingertip relatively close to each path while moving the fingertip from the start to end point. Qualitatively, tracing accuracy was consistent across all paths, regardless of their complexity (straight vs curved), location, orientation, and direction of fingertip movement. As measured by MPD, accuracy was consistent across all trials. The MPD was 3.5% (SD=2.5%) and 5.5% (SD=3.5%) for curved paths 1 and 2 (Fig 3), respectively, compared to a mean of 4.8% (SD=2.4%) and 4.3% (SD=2.5%) across trials during straight path test days 1 and 2, respectively.

Performance while tracing straight paths was consistent between test days, even without tuning parameters between days. Accuracy (MPD), task duration, and fingertip trajectory straightness and smoothness did not significantly differ between test days 1 and 2 (Fig 4). The consistency of the model's performance following a simple EMG calibration (15-second EMG measurement during MVCs) is promising since a quick calibration procedure would be convenient daily prosthesis use.

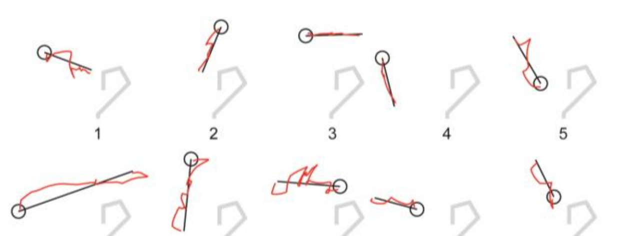

Fig. 2. Straight paths (black line) and fingertip trajectories (red line) during the first straight-path tracing test day. Black circles indicate the start point for each path. The grey lines indicate the size and location of the virtual hand with respect to the paths. The subject was able to keep the fingertip reasonably close to each path regardless of its location, orientation, and direction of fingertip movement.

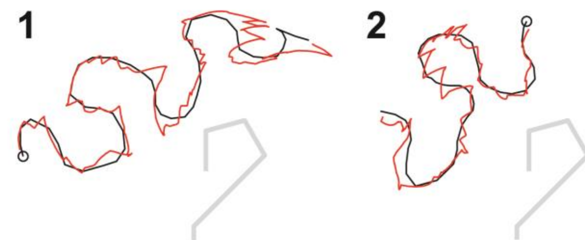

Fig. 3. Curved paths (black line) and fingertip trajectories (red line). Overall fingertip motion was in a (1) clockwise or (2) counterclockwise direction. Black circles indicate the start point for each path. The grey lines indicate the size and location of the virtual hand with respect to the paths. The subject was able to keep the fingertip reasonably close to each path.

A key feature our musculoskeletal model-based control is that multiple joints can be moved simultaneously, as in the intact limb. The paths that the subject traced were oriented in such a way as to encourage simultaneous, coordinated wrist and MCP joint movements to trace them. In turn, the subject effectively coordinated motion between the two joints to varying degrees during the tracing tasks (Fig 5). Multi-joint coordination may be more efficient than moving one joint at a time, as in existing prosthesis control schemes, because the limb can be moved to a desired posture or endpoint location more directly. Additionally, simultaneous multi-joint control may be more intuitive to use since it is a hallmark feature of human motor control.

Our results demonstrated that the real-time endpoint control enabled by the musculoskeletal model was consistent and functional over a large workspace and for tasks of varying complexity. However, more work is needed to determine how performance during the virtual tasks may translate to real-world conditions and functional tasks. For example, we evaluated task performance with the subject's limb in a single

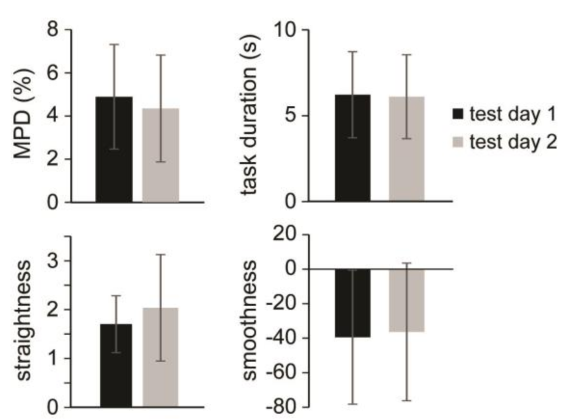

Fig. 4. Accuracy (MPD), task duration, straightness, and smoothness of fingertip trajectories during straight-path tracing tasks, averaged across trials for each test day. Task performance was consistent between days.

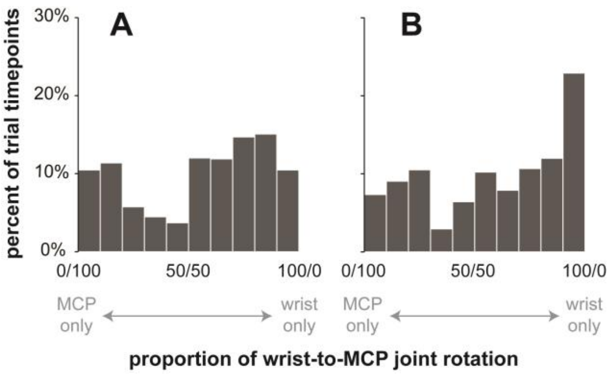

Fig. 5. Histogram of the proportion of wrist-to-MCP angular rotation when tracing (A) straight path 6 (see Fig 1) and (B) curved path 1 (see Fig 2). Each bar represents the percentage of timepoints for a given 10% range of wrist-to-MCP rotation. The approximate even distribution among ranges indicates that the subject coordinated wrist and MCP movements to varying degrees throughout each trial.

posture; it is unclear whether model predictions are robust to EMG variation across other functional upper limb postures, which challenges movement prediction accuracy in other controllers [13]. Extending the model to clinical applications, such as prosthesis control, introduces other challenges. The number of EMG sources may be more limited in amputees, and the effects of neural plasticity following injury may affect the biomechanical intent of the neural command [9]. Additionally, EMG response to external loads, as when bearing a prosthesis' weight or holding an object at the hand, may adversely affect the model's control output. In future work, we plan to assess the robustness of our model-based control against these potential sources of EMG-variation and, when appropriate, develop techniques to account for them.

There were several limitations of our study. First, 24 muscle parameters in the model were defined by numerical optimization. Given the large number of parameters and ranges of possible parameter values, it is likely that the optimized parameter set represents a local, rather than global, minimum. Other optimization algorithms (e.g. simulated annealing), approaches, and computing resources may be needed to more fully explore the parameter space and identify a global minimum. Second, we chose one of several reported methods for computing each of the accuracy, straightness, and smoothness measures, as a means to comprehensively compare performance of the straight-path tracing tasks between two test days. The values of these outcome measures are task-dependent and may not be comparable to those reported for other tasks. Finally, we did not evaluate task performance with other widely used EMG-driven control schemes (e.g. pattern recognition, direct myoelectric control) that have demonstrated simultaneous multi-joint control [14, 15]. Because the control dynamics vary drastically among the model and these other control techniques, it would be useful in future studies to quantify their relative performance and identify tasks and test conditions for which each control is best suited.

IV. Conclusion

Our EMG-driven musculoskeletal model enabled consistent and effective real-time, simultaneous multi-joint control of a virtual hand between tasks and test days. The possible applications of our biologically-inspired controller extend beyond upper limb prosthesis control to include lower limb prostheses, orthoses, and exoskeletons, other HMI and teleoperation systems, rehabilitation, and basic research in human movement science and motor control. While our results are promising, more work is needed to determine whether performance extends to real-world functional tasks and to clinical populations.

Acknowledgment

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