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Using the Intact Human Hand to Benchmark Real-Time Myoelectric Control Performance for Robotic Interfaces

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***Abstract*— The objective of our study was to demonstrate how the intact human hand can be used as a benchmark for electromyogram (EMG)-based myoelectric control of robotic interfaces (e.g., myoelectric prostheses). Using the intact human hand as a gold standard for control algorithms is attractive because able-bodied participants are widely available, have stereotypical movements, and possess highly refined motor control. We compared within-subjects performance of a real-time virtual posture-matching task between a musculoskeletal model-based EMG controller (model trials) and the human hand (goniometer trials). Goniometer trials had lower (i.e., better) normalized path length (2.0±1.6) and task duration (3.3±3.4 sec) than model trials (4.1±4.3 and 12.3±10.7 sec, respectively; p<0.0001). Though, qualitatively, actual (measured by goniometers) and virtual joint angles assumed similar relative postures during model trials, there was a constant offset between them. Additionally, joint angles were more variable during model trials than goniometer trials. The results quantified the extent to which task performance and movement characteristics were not as good with the EMG controller (in this case, the musculoskeletal model-based controller) as with the gold-standard intact human hand. How EMG controllers compare with intact human hand control can drive and inform controller advancements.**

***Clinical Relevance*— The gold-standard intact human hand provides an objective way to decide which EMG control algorithms to translate to clinical robotic interfaces.**

I. Introduction

Researchers have developed numerous control algorithms that interpret users' movement intent from electromyograms (EMG) for robotic interfaces, such as myoelectric prostheses [e.g., 1, 2]. Ideally, the best-performing algorithms would be translated for clinical use on commercially available prostheses. However, objectively determining the relative real-time performance of myoelectric control algorithms is an open challenge. Currently, relative performance is determined by comparing algorithms directly to one another in individual studies [3-5]. This is problematic because each study can, practically, only evaluate and compare a small number of algorithms. Comparing among studies is problematic because of inter-study differences in performance metrics, algorithm parameters, and study design.

Current limitations in ranking myoelectric control algorithms could be addressed by determining their absolute real-time control performance with respect to some gold standard. Clinical interfaces such as myoelectric prostheses are intended to replace as much of the missing limb's function as possible; therefore, a reasonable gold standard is the control performance of the intact human hand. Such a gold standard is attractive because able-bodied participants are widely available and healthy human movements, such as reaching and grasping [6, 7], are stereotypical across the population. Besides facilitating comparison, an added benefit of the proposed gold standard is that it would provide abundant data of human motor control to inform and improve existing and emergent control algorithms.

To clarify, using the intact human hand as a gold standard does not simply mean using able-bodied subjects to test control algorithms, which is very common [1, 5, 8]. Rather, intact hand kinematics would be used to directly control the movements of the interface. Doing so permits the most intuitive control while also accounting for any effect of the interface itself on task performance. Tracking hand motion in real time is common for many virtual reality applications [9-11] but not, to our knowledge, for comparison to myoelectric control algorithms.

The objective of our study was to demonstrate use of the intact human hand as a benchmark for EMG-based myoelectric control of robotic interfaces. The algorithm we selected for the demonstration was based on a lumped-parameter musculoskeletal model of the wrist and hand [2, 12]. During a previously developed virtual posture-matching task [12], subjects controlled a virtual hand using either the model-based controller or joint angles measured directly from their hand using electrogoniometers. Because able-bodied subjects were used for both control modes (algorithm and intact hand), we evaluated both virtual task performance and wrist/hand kinematics. We expected that able-bodied subjects would have better task performance and smoother wrist/hand kinematics with goniometer-based control than with model-based control.

II. Methods

A. Musculoskeletal Model-Based Controller

We used an existing planar (i.e., two-dimensional) dynamic musculoskeletal model of the wrist and hand; the model was implemented for real-time forward dynamics simulation in MATLAB (Mathworks, Inc., MA, USA) to permit real-time control of a virtual hand on a computer screen [2, 12]. The model had two degrees of freedom: wrist

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flexion/extension and metacarpophalangeal (MCP) flexion/extension. Additionally, there were four virtual, lumped-parameter, Hill-type muscles [13, 14] that did not have series elastic elements (i.e. tendons). The virtual muscles were grouped as agonist-antagonist pairs, one pair crossing the wrist only and the other crossing both the wrist and MCP joints, to mimic the arrangement of muscles with respect to joints in the biological limb. The model's parameters were defined from a previously reported generic model whose parameters were averaged across customized models of 10 healthy young adult subjects [15].

During the real-time forward dynamics simulation, EMG data were processed as previously described [12]. Briefly, EMG signals were smoothed, rectified, enveloped, and normalized by the maximum values of processed EMG recorded during pre-experiment maximum voluntary contractions. Muscle activations ranged from zero (inactive) to one (maximally active). Muscle activations were used to compute muscle forces that depended on muscle length and velocity according to the Hill-type muscle model [14, 16]. To execute the real-time forward dynamics simulation, the muscle forces were applied to the model, and the equations of motion were integrated forward in time in small timesteps (Δt=0.001 sec) to estimate joint angles.

B. Posture-Matching Task

The real-time posture-matching task, implemented in MATLAB, required subjects to align the virtual hand with four target postures [12] (Figure 3). The virtual hand was as a 2-degree-of-freedom (wrist and metacarpophalangeal (MCP) flexion/extension) planar stick-figure. A resting posture was defined to approximate the human hand's posture when relaxed. The four target postures were selected to be within the virtual hand's range of motion but with different combinations of wrist and MCP joint angles.

In each trial, subjects were shown the four target postures sequentially and in a randomized order. For each target posture, the subject first had to align the virtual hand first with the resting posture, then with the target posture. The resting and target postures were achieved when each of the virtual hand's joint angles were within ±10° and ±5°, respectively, of the postures for 0.5 consecutive seconds. If the subject failed to achieve a target posture within 60 seconds, the software automatically advanced to the next target posture. The subjects were instructed to complete each trial as quickly as possible.

C. Experiment Set-Up

All procedures were approved by the University of Tennessee Institutional Review Board (IRB). We recruited 10 able-bodied subjects (5 female). All sensors were placed on each subject's dominant hand. Four bipolar EMG surface electrodes (Norotrode 20, Myotronics, Inc., Kent, WA) were placed on the skin over four muscles, each corresponding to one of the four virtual muscles according to their arrangement with respect to the joints: extensor carpi radialis longus (wrist and MCP extension), extensor digitorum (wrist extension), flexor digitorum (wrist and MCP flexion), and flexor carpi radialis (writst flexion) muscles. The electrodes recorded the EMG signals used to drive the musculoskeletal model-based controller. We placed two electrogoniometers (SG65, Biometrics LTD, Newport, UK) to measure MCP and wrist flexion/extension angles (Figure 1); the goniometers were chosen because their output voltage could be efficiently converted to joint angles for real-time control. EMG and goniometer data were recorded synchronously at 3000 Hz (TeleMyo 2400T, Noraxon, Scottsdale, AZ)

D. Musculoskeletal Model-Based Controller Tuning

Before the experiment, we tuned the musculoskeletal model for each subject in two steps. First, we adjusted each joint angle of the virtual hand by a constant value so that, when the subject's hand was relaxed, the virtual hand approximated the resting posture. Second, we defined the values of four linear gains that scaled the magnitudes of the muscle activations of the four virtual muscles (one gain value per muscle). The purpose of the gains was to adjust the sensitivity of the virtual hand's movements based on verbal feedback from the subjects while they attempted to align the virtual hand with the target postures.

E. Experiment Trials

The subjects were seated with their dominant elbow placed on an arm rest; the elbow was flexed to 90° and the forearm was in neutral pronation/supination. During the experiment, the subjects controlled the virtual hand with either the goniometers or the musculoskeletal model-based controller, hereafter referred to as goniometer trials and model trials, respectively. Subjects completed 6 blocks (3 goniometer, 3 model) of 5 trials with the order of blocks randomized. In model trials, the virtual hand's joint angles were set equal to the angles predicted by the musculoskeletal model and offset by a constant value according to the tuning procedure described above. In goniometer trials, the virtual hand joint angles were set equal to those measured by the gonimoeters.

F. Data and Statistical Analysis

The data measured in every trial were (1) EMG from four muscles, (2) goniometer-measured wrist and MCP joint angles, and (3) virtual hand joint angles. Note that goniometer-measured and virtual hand joint angles were equal for goniometer trials. The goniometer-measured joint angle data contained low-amplitude, high-frequency noise, typical of analog sensors; to reduce the noise content and for consistency, both actual (i.e. measured from the goniometer) and virtual wrist and MCP joint angles were smoothed in MATLAB using a 4^{th}-order zero-phase digital Butterworth low-pass filter with a 4-Hz cutoff frequency. From the smoothed joint angle data, we computed two performance measures: normalized path length and task duration [12]. Normalized path length was the trajectory length (in joint space) divided by the minimum possible trajectory length. Task duration was the time elapsed between achieving the base posture and achieving the target posture.

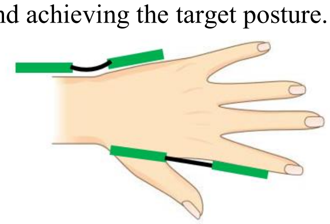

Figure 1. Placement of the two goniometers. One spanned the metacarpophalangeal (MCP) joint on the radial side of the hand, and the other spanned the wrist joint on the ulnar side of the hand.

We performed a statistical analysis to determine the effect of control mode (goniometer vs model), target (1, 2, 3, 4), and the test by target interaction on task performance and movement smoothness. We used a mixed-effects ANOVA model with two random blocking factors: individual “subjects” and “experiment block” conditions. The raw experimental data had a skewed right distribution, so the data were log-transformed to meet the normality assumption for the ANOVA analysis. Least square means were computed and separated with the Tukey HSD correction method. A Levene's test was used to assess the equal variances for the residuals. A Shapiro-Wilk W and QQ normality plots were used to evaluate the normality of ANOVA residuals. Finally, we computed the pair-wise Pearson’s correlation coefficient, r, for each pair of task performance measures. JMP, version 15.1 was used for the analysis (SAS institute, NC, USA). Differences and correlations were considered significant for $p<0.05$.

III. Results

Task performance was better in goniometer trials than in model trials based on the log-transformed task duration and nomralzed path length data (Figure 2). Goniometer trials had lower task duration (3.3±3.4 sec, median=2.4 sec) than model trials (12.3±10.7 sec, median=8.7 sec, $p<0.0001$). Moreover, for task duration, there was a significant interaction between test and target ($p=0.0057$); during model trials, target 3 was significantly different from targets 4 and 1. Goniometer trials had lower normalized path length (2.0±1.6, median=1.6) than model trials (4.1±4.3, median=2.4, $p<0.0001$). For normalized path length, there was a significant effect of ‘target’; target 3 was significantly different from targets 4 and 1. Log-transformed normalized path length was weakly but significantly correlated with log-transformed task duration ($r=0.410$, $p<0.0001$).

Since we also recorded goniometer data during model trials, we compared subjects' actual and virtual hand movements during model trials. Qualitatively, actual and virtual joints assumed similar relative postures (Figure 3); for example, for targets 3 and 4, the MCP joint was flexed (i.e. negative angle) while the wrist joint was extended (i.e. positive angle) for both actual and virtual hands. However, on average, the virtual joints were more flexed (i.e. more positive) than the actual joints.

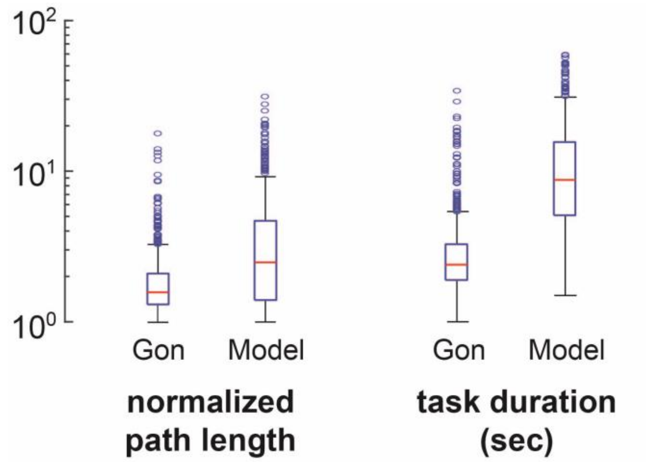

Figure 2. Box plot comparison of task performance between goniometer (Gon) and model trials (across subjects, trials, and targets) based on measurements of normalized path length and task duration. Plotted on a log scale since the data were skewed. Circles show trial outcomes that were >1.5X the interquartile range.

IV. Discussion

Unsurprisingly, our results supported the initial hypothesis that performance of the virtual task would be better with the intact human hand (via electrogoniometers) than with the musculoskeletal model-based controller. Controlling the virtual hand with goniometers was very intuitive for subjects. It was also not surprising that the two task performance measures were correlated with one another, though weakly so. For example, a trial could be expected to have a higher task duration, on average, when the virtual hand had a greater total

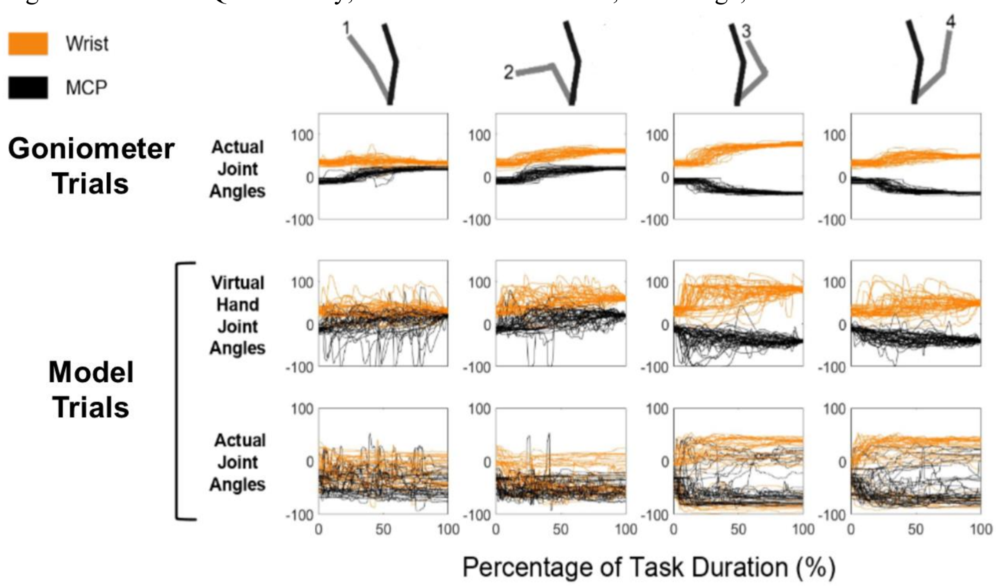

Figure 3. Example of one subject’s joint angles (in degrees) during the target acquisition task for each target over the percentage task duration. The top row represents healthy hand movement as measured by the goniometers during the goniometer-driven test. The middle row represents the joint angles of the virtual hand using the EMG-driven controller. The bottom row represents the actual joint angles of the subject’s hand during the EMG-driven test. All trials across all blocks are included in each target plot. The target postures (grey numbered) relative to the neutral posture (black) are shown above the data plots.

displacement (i.e., higher normalized path length).

We evaluated subjects' real-time control performance of a planar virtual posture-matching task. Other types of virtual tasks, such as moving the fingertip along a virtual path, could be used [12]. The evaluation could also be extended to three-dimensional virtual and physical environments, which have more ecological validity. Other measures have also been used to evaluate performance of similar target-based tasks for human-machine interfaces [e.g., 17]. It is preferable that any two task performance measures are less correlated so that they provide unique, rather than redundant, information about performance.

Our within-subjects comparison of the two control modes was possible because we included only able-bodied subjects. One potential way to adapt the proposed method for unilateral amputees is to have subjects complete the task while attempting bilateral mirrored movements; the data needed for goniometer and model trials would be measured from the sound and residual limbs, respectively (e.g.[2]). A limitation of this approach is that it assumes that the sound-limb kinematics are perfectly aligned with the movement intent of the residual limb, which is unlikely based on the bilateral wrist and hand movements of able-bodied subjects [18].

There were two limitations of the tuning procedure that should be addressed in future studies. First, the current tuning procedure was subjective and based on (1) the individual experience and approach of the tuner and (2) verbal feedback from the subject during a tuning session. An automated tuning procedure should be developed to make it more objective and consistent. Second, the tuning procedure was based on the select goal of enabling subjects to easily move the virtual hand to each of the target postures. It is not clear if different or more tuning goals would yield better control performance.

There were other study limitations. Surface EMG is more convenient than intramuscular EMG but includes more noise and crosstalk from other muscles, which can degrade control performance. Due to inter-subject variation in musculoskeletal anatomy, electrode placement may not have been consistent among subjects. Potential errors in goniometer measurements, due to calibration errors or variation in goniometer placement among subjects, may have caused some mismatch between the virtual and biological hands. Other (e.g., marker-based) motion capture methods may measure wrist/hand kinematics more accurately.

V. Conclusion

Our study demonstrated a new paradigm for using the intact human hand as a gold standard for benchmarking the performance of EMG control algorithms for myoelectric prostheses and other neural-machine interfaces. Such a gold standard would permit a more valid comparison of control algorithms among different studies to reliably determine their relative performance. Determining the relative performance of control algorithms will help more rapidly translate high-performing algorithms to clinical applications and advance the state of the art. Next steps toward broad adoption of the proposed method include (1) defining a set of standardized tasks, experiment methods, and outcome measures, and (2) establishing an online repository for the exchange of data for the intact human hand.

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