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Automated optimal coordination of multiple-degree-of-freedom neuromuscular actions in feedforward neuroprostheses

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Abstract

This paper describes a new method for designing feedforward controllers for multiple-muscle, multiple-degree-of-freedom, motor system neural prostheses. The design process is based on experimental measurement of the forward input-output properties of the neuromechanical system and numerical optimization of stimulation patterns to meet muscle coactivation criteria, thus resolving the muscle redundancy (i.e., over-control) and the coupled degrees of freedom problems inherent in neuromechanical systems. We designed feedforward controllers to control the isometric forces at the tip of the thumb in two directions during stimulation of three thumb muscles as a model system. We tested the method experimentally in ten able-bodied individuals and one patient with spinal cord injury. Good control of isometric force in both degrees of freedom was observed, with RMS errors less than 10% of the force range in seven experiments and statistically significant correlations between the actual and target forces in all ten experiments. Systematic bias and slope errors were observed in a few experiments, likely due to neuromuscular fatigue. Overall, the tests demonstrated the ability of a general design approach to satisfy both control and coactivation criteria in multiple muscle, multiple axis neuromechanical systems, and which is applicable to a wide range of neuromechanical systems and stimulation electrodes.

Keywords

Artificial neural networks; Coupled degrees of freedom; Feedforward control; Neuroprostheses

I. Introduction

The actions of neuromechanical (i.e., neuro-musculo-skeletal) systems are planned and coordinated by the central nervous system and carried out by muscles acting on the skeleton. These muscles receive commands through motor pathways that travel from the brain to the muscles through the spinal cord. Damage to the pathways (e.g., through a spinal cord injury) can paralyze muscles below the level of injury. However, if there is no denervation, some neuromechanical function can be restored by electrically activating peripheral nerves innervating the paralyzed extremities [1–3]. To do so, electrical stimulation parameters (e.g., amplitude and pulsewidth) are mapped to external command signals by algorithms that produce feedforward control laws [4] to coordinate muscle actions for functional activities.

Many muscles cross multiple joints, producing moments that create mechanical interactions (i.e., coupled moments) at these joints. This complexity is increased by neuromechanical system redundancy (i.e., multiple muscles can act on the same joint to create synergistic moments and the same moment can be created with multiple levels of muscle cocontraction) [5]. The complexity introduced by mechanical coupling and redundancy has limited the mappings to a few operational modes [6] and current neuroprostheses do not provide independent control of coupled degrees of freedom, limiting the flexibility of restored function [7,8]. Analytical models that offer reasonably good approximations to complex musculoskeletal systems may not be feasible to implement at a reasonable cost [9–11], and model reduction simplifications may not provide the behavioral response needed to implement effective controllers. For this reason, there is a need for neuroprosthetic controllers that are capable of decoupling multiple degrees of freedom without using analytical systems.

Studies have demonstrated the ability of feedforward neural networks to model the non-linear relationship between muscle outputs and stimulus intensity [12] and to be used as neuroprosthetic controllers based on inverse models of neuromechanical systems [13–15]. However, these studies have been limited to single degree-of-freedom systems acted upon by a pair of antagonists. On the other hand, studies incorporating mechanical coupling between degrees of freedom have been performed in simulation only [16–18], have not attempted to provide independent control of the multiple DOF [19], or have been limited by the lengthy data collection processes and by the need for an experimental platform that allowed rapid controller implementation, which has been presented elsewhere [20]. Thus, our objective was to develop and test experimentally a feedforward controller capable of decoupling multiple degrees of freedom and automating the design of the controller using clinically-measured input-output data.

II. Methods

We chose to use the thumb as an experimental platform for testing the controller design and implementation processes. In this study, we control thumb-tip isometric forces in two degrees of freedom by stimulating three muscles that produce coupled forces along each axis.

A. Subject Population and Stimulation Systems

We modified a percutaneous stimulator [21] to stimulate the extensor pollicis longus (EPL), abductor pollicis brevis (AbPB), and adductor pollicis (AdP) muscles [22] of 10 able-bodied individuals with surface electrodes (Axelgaard, Fallbrook, CA.) at 50Hz. Cathode placements varied across subjects and were determined using a combination of motor point charts [23], previous experience, and observable muscle responses to stimulus probing using an active cathode (trial and error approach). The anodes were placed on the proximal forearm of all subjects. The skin was prepped with sterile alcohol pads (Tyco Healthcare Group, Mansfield, MA) to remove skin impurities. We applied Spectra® 360 conductive gel (Parker Laboratories, Inc., Fairfield, NJ) to reduce skin impedance. All surface electrodes were taped to the skin with Medipore (3M, St. Paul, MN) to reduce electrode displacement during muscle contractions. An individual with a C5 spinal cord injury (SCI) received stimulation at 16Hz with epimysial electrodes on the same set of muscles [24] that were part of a previously implanted hand grasp neuroprosthesis [25].

We used cathodic first, charge-balanced pulses [26,27] with maximum constant current as allowed by the stimulators (30 and 20 mA for surface stimulation and implanted neuroprosthesis, respectively) for input/output data collection as well as during controller testing. Prior to data collection, we stimulated all three muscles simultaneously (but with interlaced pulses) using the maximum pulsewidth allowed by the stimulator (i.e., 250 and 200 microseconds for surface stimulation and implanted neuroprosthesis, respectively) with two

four-second pulse trains, with ten second inter-train rest intervals to reduce the effects of muscle potentiation.

B. Experimental Setup

We measured isometric forces at the tip of the thumb for a single thumb posture (carpometacarpal joint approximately at 45 degrees of extension and 15 degrees of abduction; and metacarpophalangeal joint at 30 degrees of flexion). Experimental methods were the same for both subject populations unless indicated otherwise. We used a 3-axis force/moment transducer (JR3, Woodland, CA) to measure the forces at the tip of the thumb. The x-axis is orthogonal to the flexion/extension plane while the z-axis is orthogonal to the adduction/abduction plane (Figure 1). The long axis of the thumb indicates the y-axis. We cast the subject's hand and forearm to fix the carpometacarpal (CMC) joint in space and prevent wrist rotation. We cast the thumb phalanges to facilitate its attachment to the force transducer and to fix the interphalangeal (IP) joint in able-bodied individuals (the SCI individual had a surgically-fused IP joint [28]). Changes in elevation, as well as medial/lateral and anterior/posterior displacements of the forearm were prevented with industrial strength Velcro® (Velcro Industries B.V, Manchester, NH) attached to the cast and a platform that supported the arm. Wood plates lateral to the cast prevented pronation/supination of the hand/forearm.

C. Training Data

First, we estimated the stimulation range over which end-point forces could be modulated for each subject by systematically increasing/decreasing the pulsewidths (in 5 microsecond intervals) for each muscle between zero microseconds and the maximum pulsewidth allowed by the stimulator and estimating the activation and plateau/spillover pulsewidths. We defined activation threshold as the pulsewidth at which an end-point force was first detected by the force transducer, and spillover/plateau threshold as the pulsewidth at which the end-point force reached a plateau, antagonist activation was detected, stimulation became uncomfortable, or the maximum pulsewidth was reached.

Next we selected a number of equally-spaced pulsewidths covering this stimulation range to characterize the thumb-tip forces when muscles were stimulated individually and in combination. We selected six pulsewidths for the first muscle (typically EPL), four pulsewidths for the second muscle (typically AbPB), and six for the third (typically AdP). We assigned the lowest number of pulsewidths to the muscle with the least amount of force modulation (typically the AbPB). We randomized all possible pulsewidth combinations (i.e., 144) so the subjects could not detect stimulation patterns (which could result in biases in their muscle responses), and to distribute the effect of hysteresis, which we did not attempt to model, across the set of input/output data.

We stimulated the muscles at each randomized pulsewidth combination for two seconds, with ten seconds of rest between stimulus trains to reduce the effects of muscle fatigue. We measured the thumb-tip forces and averaged them over the last second of stimulation to generate steady-state input/output data to train a system model. We also averaged the force baselines for one second prior to the onset of each stimulus train. We subtracted these baselines from their respective force measurements so only active forces remained in the input/output data.

D. System Model Training

We created a deterministic, time-invariant numerical forward model of the thumb neuromechanical system that maps the steady-state forward relationship between stimuli and end-point forces, which smoothed the data both temporally and spatially (Figure 2A). We implemented the system model with a two-layer feedforward ANN with sigmoidal [29] and linear [30] transfer functions in the hidden and output layers respectively. The system model

ANN had three inputs (EPL, AbPB, and AdP pulsewidths normalized to the activation and spillover/plateau thresholds), twenty hidden neurons, and two output neurons (forces at the tip of the thumb along both degrees of freedom: flexion/extension, abduction/adduction). The initial network weights and biases were selected at random. We trained the system model network with the Levenberg-Marquardt backpropagation algorithm [30] on 90% of the input-output data (selected at random) until the normalized fitting mean squared error was less than 1×10^{-5} N, until training reached 1000 epochs, or until the validation error began to increase with further training. We used the remaining 10% of the data as a validation set (i.e., to test the system model on data it was not trained on) to prevent over-fitting during training and to estimate generalization error.

We trained six ANNs with different random initial weights and biases. The ANN with the smallest validation RMS error was chosen for the system model.

E. Data Optimization and Unique Solution

We used the system model to create unique and optimal input/output data for subsequent training of an inverse feedforward controller. We generated 729 input-output data sets (nine pulsewidth levels for each muscle) with the trained system model. We found the set of pulsewidths corresponding to the forces in each of these sets, that minimized the summed squared muscle activation energies, subject to both force and activation energy constraints. We performed the constrained optimization using the Matlab® Optimization Toolbox *fmincon* function (The MathWorks Inc., Natick, MA).

The normalized activation [4,31] for muscle i is estimated by $a(i)$.

$$a(i) = \frac{PW(i) - PW_{min}(i)}{PW_{max}(i) - PW_{min}(i)}, \quad (1)$$

where $PW(i)$ is the stimulus pulsewidth applied, $PW_{min}(i)$ is the activation threshold, and $PW_{max}(i)$ is the spillover/plateau threshold. The objective function calculated the total

activation energy $\sum_i a_i^2$ with a 1×10^{-8} tolerance. Note that the activation energy is dimensionless when calculated with normalized activations.

The constraint function specified both force and activation energy constraints. The force constraint (2) is an equality constraint requiring the force components of each data set to remain the same during the optimization process, ensuring that the force domain is well covered. The force constraint is described by

$$(F_{x_{initial}} - F_{x_{optimal}})^2 + (F_{z_{initial}} - F_{z_{optimal}})^2 = 0, \quad (2)$$

where $F_{initial}$ and $F_{optimal}$ are the forces prior to and following optimization, respectively. The activation energy constraint (3) is an inequality constraint that prevents the activation energy from decreasing below a set minimum (a_{min}), enabling specification of a minimum level of coactivation.

$$3(a_{\min})^2 \leq \sum_i a_i^2, \quad (3)$$

where $a_{\min} = 0.2$ (i.e., 20%) to achieve a reasonable amount of muscle coactivation but avoiding high levels that might fatigue the muscles (unless these are required to generate the desired force).

The tolerance for violation of both constraint equations was set to 1×10^{-4} . The maximum number of iterations and function evaluations were set to 500. The rest of the `fmincon` parameters were set to their default values. The initial condition for the optimization was a scaled version of the original set of pulsewidths (scaling factor, $s=0.8$). We also constrained the lower and upper bounds of the activations (4) to prevent the system model from working at the periphery of its training domain.

$$a_{\text{low}} + 0.05 \leq a \leq a_{\text{high}} - 0.05, \quad (4)$$

where a_{low} and a_{high} represent the low and high boundaries of the activations in the training data set.

F. Inverse Controller

We created an ANN-based deterministic inverse model of the neuromechanical system from the optimal data. This inverse model was used as a feedforward controller for the electrically stimulated thumb (Figure 2B). We implemented this inverse controller using a two-layer feedforward ANN with two inputs (thumb-tip forces along both degrees of freedom), twenty sigmoidal hidden neurons, and three linear outputs (normalized pulsewidths for the EPL, AbPB, and AdP muscles). We selected the initial weights and biases at random. Similarly to the system model, we trained the controller using the Levenberg-Marquardt backpropagation algorithm on 90% of the optimal data (selected at random) and used the remaining 10% to perform validation tests and prevent over-training. We terminated training when the normalized fitting MSE was less than 1×10^{-5} N, when training reached 1000 epochs, or when the validation error increased with further training.

The performance of each controller was estimated via the generalization (i.e., prediction) error calculated with the validation test. We trained six ANNs using the same architecture and data but with different random initial weights and chose the ANN with the smallest validation RMS error as the inverse controller.

G. Controller Evaluation

We evaluated the ability of the controller to provide independent force control in the adduction/abduction and flexion/extension directions by manually selecting forty target vectors spread across the subject's force domain (ensuring the target forces were not part of the training data) and using the optimally-trained inverse controller to predict the stimulation pulsewidths required to achieve those forces. The EPL, AbPB and AdP muscles were stimulated with the predicted pulsewidth sets (two seconds per set followed by ten seconds of rest) while the subjects were still in the experimental setup (Figure 1) and the resulting end-point forces (i.e., actual forces) were measured. The subjects were blinded to the target forces and stimulation parameters to avoid volitional contractions that could potentially bias the results.

We considered the controllers successful when, for both degrees of freedom, the RMS errors between the target and actual forces were less than 2N [32,33] and the correlations between target and actual force components were statistically significant ($\alpha = 0.05$). In addition, we performed a regression analysis of the actual/target forces to test for systematic offset/slope errors.

We separated both the target and actual force sets into two subsets (indicated by subscripts 1 and 2) of 20 vectors each ($F_{t1}, F_{t2}, F_{a1}, F_{a2}$) by choosing every other force vector in each force set. Set number one served as a control and we removed any bias (5) from the actual forces in set two by subtracting the difference between the average target forces $\bar{F}_t$ and the average actual forces $\bar{F}_a$

$$bias = \bar{F}_t - \bar{F}_a, \quad (5)$$

RMS errors were calculated for both data sets in the form of total (set one) and residual (set two) variability. We defined total variability S_t as the RMS error between the target (F_t) actual forces (F_{a1}) for each degree of freedom in the control set, and residual variability S_r as the RMS error between the target and actual forces in the set after the bias was removed.

The correlations between the targets and actual forces were calculated using Pearson's correlation. A least-squares regression analysis of the dependencies of the actual forces on the target forces was performed using Minitab (Minitab Inc., State College, PA.) to estimate systematic slope/offset differences.

III. Results

Data from only ten experiments are presented here due to a failure of the force transducer during one able-bodied experiment.

A. Physiological and System Model Behavior

Stimulation of the three muscles resulted in a range of force components in the abduction-adduction (x-axis), flexion/extension (z-axis) plane (see Figure 3 and Table I). In most cases, the maximum adduction force exceeded the maximum abduction force. The forces were more balanced in the flexion and extension directions. The full force ranges varied from about 5 to 20 N across subjects and directions.

Table I summarizes the system model fitting and generalization errors. The trained system models replicated the behavior of the neuromechanical systems (i.e., learned the input-output relationships of the training data) with fitting RMS errors under 8% of the neuromechanical system's force range for both degrees of freedom in all experiments except abduction/adduction in experiment 18, in which the RMS error was just below 11%. The system models in seven of the ten experiments (12, 13, 15, 16, 17, 19, and 21) predicted the behavior of the neuromechanical system for data not used in the training with generalization RMS errors under 11% of the force range for both degrees of freedom (Table I). The generalization errors ranged up to 20% in the remaining experiments (14, 18 and 20).

The forces produced by individual muscles added nonlinearly when the muscles were stimulated simultaneously. This can be seen by the example in Figure 3A, where there are several force points in the extension/abduction direction that cannot be achieved by summing the force vectors produced by the individual muscles. The system model captured this

characteristic successfully, as illustrated in Figure 3B, which compares four experimental and model-predicted force vectors in a region of nonlinear summation.

The degree of nonlinear summation was quantified as the difference between the force vector obtained when all muscles were activated ($\vec{F}(U_{ept}, U_{abpb}, U_{adp})$ with different combinations of (pulsewidths) and the summed force vector resulting when each muscle was activated individually using the same pulsewidths ($\vec{F}(U_{ept}, 0, 0) + \vec{F}(0, U_{abpb}, 0) + \vec{F}(0, 0, U_{adp})$). The degree of nonlinear summation (for each experiment) was estimated as the average distance between 20 force vector pairs selected randomly. The average distances ranged from 1.4 to 7.8N, and were all significantly different from zero ($p=0$). The SCI experiment (21) had a significantly smaller ($p=0$) amount of non-linear summation than all able-bodied individuals. The degrees of nonlinear summation were equal for the musculoskeletal system and for the system model ($p>0.05$) for all experiments except 18, for which the system model showed a larger amount of non-linear summation than the neuromechanical system ($p=0$).

B. Optimization

We obtained a single set of pulsewidths for each experiment that reduced the activation energy necessary to achieve each of the required force targets across the force domain (Figure 4) subject to the activation constraints. We quantified the overall reduction by summing the activation energies across all 729 points. The summed energy was reduced by at least 50% in six of ten experiments (Table I), 36% in three experiments, and 7% in the remaining experiment. Optimization always created a region of the force domain where the activation energy was equal to the minimum level of muscle coactivation (i.e., $a = a_{min} = 0.2$).

The reductions in energy and activation achieved by optimization are illustrated in Figure 5 for experiment 20, by applying a rotating unit force vector to the inputs of two inverse controllers – one that was trained on the non-optimized input-output data and a second that was trained on the optimized data. There were substantial reductions in total activation energy in most force directions. Individual muscle activations were reduced in most directions as well, but there are also directions where activation was increased in one muscle, but decreased in others.

C. Controller Performance

Actual and target forces from four experiments are shown in Figure 6. The actual forces matched the target forces with a total variability (i.e., RMS error) of less than 2N along both degrees of freedom in seven of ten experiments. The remaining three experiments had errors smaller than 2N for one of the degrees of freedom. Nine of ten experiments showed residual variability (i.e., after bias removal) under 2N.

The actual and target forces were highly and significantly correlated ($R^2>0.5$, $p=0$) in all ten experiments (Table I). Regression analyses showed linear dependence of actual force on target force in all ten experiments ($p<0.001$). Low adjusted R^2 (<0.7) helped identify bias errors in both degrees of freedom for one experiment, and in one degree of freedom for four experiments. Slopes significantly different from 1 (e.g., greater than 2 and lower than 0.6) suggested scale differences in two out of ten experiments, but only for one degree of freedom. The slope coefficient was significant ($p<0.05$) for all ten experiments. The intercept coefficient was significant ($p<0.05$) for six of ten experiments.

IV. Discussion

Although inverse controllers have been created for neuromuscular systems with multiple DOF [19], these studies failed to address coupling between these DOF and neglected the redundancy

associated with muscle coactivation, and as such, controller errors prevent them from being successfully used clinically.

We developed an inverse-model feedforward controller for neuroprostheses capable of decoupling multiple degrees of freedom in coupled musculoskeletal systems. We implemented the controller with ANNs because not only can these model both static and dynamic nonlinear systems [34–36], but they can generalize from noisy experimental input/output data [37–39].

We used a similar approach to an earlier simulation study of wrist angle and hand grasp control [16,40]. Briefly, we collected input-output data from a neuromuscular system, reversed the inputs and outputs, and trained an ANN based controller to invert the relationship. This, however, did not work adequately in experimental tests [20]. Subsequent simulation studies (unpublished) demonstrated that the inverse controller did not always select predictable patterns of coactivation because the training data contained redundant input-output data. Thus, in this study, we eliminated redundant input-output data and choose data sets that optimized a coactivation criterion. The mechanical characteristics of the thumb, which include redundancy and coupled degrees of freedom, allowed us to use the CMC joint of the thumb as an experimental model. The system model mapped the static forward relationship between electric stimuli and the steady-state end-point forces. It provided a numerical model of the input/output properties and simultaneously smoothed the data, both temporally and spatially, but did not remove redundancies introduced by multiple muscles.

Computer simulations using ANNs with two layers and up to 50 hidden neurons trained on experimental data (not shown in the results) showed smaller actual/target force training and validation RMS errors (17 to 20N) when twenty hidden neurons were used for both the system model and inverse controller.

The feedforward controllers designed from experimentally-measured input/output data provided independent control of coupled degrees of freedom, as shown by the significant correlations and the low RMS errors between the actual and target force components. Additionally, the stimulation met optimization criteria specified to minimize coactivation. Since the method makes minimal *a priori* assumptions about the structure of the system being controlled, we have successfully demonstrated a general method of designing inverse feedforward controllers that is applicable to a wide range of electrode types and different neuromechanical systems, and which can be rapidly implemented, tested, and deployed using a high-level software platform. It should be noted that the method presented here is independent of the type of electrode (surface, epimysial, intramuscular, or nerve-cuff) used. It does not depend on electrode selectivity and is not affected by spillover.

For applications in hand grasp, we chose a 2N RMS criterion because it represents approximately 10% of the mean pinch force magnitude for SCI individuals after surgical reconstruction of the hand [32,33]. This criterion, however, may be too stringent for weaker subjects. Therefore, the criteria and assessment tools (e.g., statistical tests, error metrics, etc.) should depend on the functional objectives. Such criteria could be rapidly tested using software environments that allow rapid prototyping of different mathematical models [41] and controllers [20] appropriate for these objectives.

Regardless of their internal structure, feedforward controllers that are designed to invert the properties of the system being controlled require excellent knowledge of those system properties whether that knowledge is based on analytical models or experimental data. The approach taken in this study was to rely entirely on input-output data that can be measured experimentally to design the controller. This approach can be extended directly to other neuromechanical systems and is subject-specific.

Since neuromechanical systems are highly nonlinear and interactive [42], the training data must adequately sample the operating domain to adequately characterize the system properties. Assuming uniform sampling over each input range and testing of all input combinations, the amount of input-output data needed increases exponentially with the number of inputs controlling a single joint. This places significant practical limitations on applying blindly this technique or any other systems identification technique in controller design. With more inputs, it will be beneficial to take into account *a priori* knowledge of the system (e.g., independence of some inputs or degrees of freedom) to reduce the data collection demands. Analytical models based on particular neuromechanical system structures offer a potential advantage in controller design, since the model structure includes known interactions and nonlinearities. However, structurally based analytical models [43] must be parameterized for individual patients, a process which can also require extensive experimental data. Furthermore, all parameters may not be identifiable from input-output data alone, requiring customization of the model [9,11].

The system models provided a numerical model of the input-output properties of the neuromechanical system, and generated forces that matched those of the neuromechanical system with low fitting and validation errors even in regions of low spatial sampling, in regions of high coactivation levels, and in the presence of nonlinear summation.

The nonlinear summation evident in all of the experiments reported (Figure 3B) is a characteristic of electrical stimulation that can occur if selectivity is not perfect. It is particularly common with surface electrodes, with proximal nerve cuff electrodes, at high stimulation levels with nearly any type of electrode, and when there are changes in nerve-electrode geometry due to movement elicited by the stimulation [44–46]. The non-linear summation in these experiments was likely generated by two mechanisms. The first mechanism was activation of multiple muscles due to spillover from the use of surface electrodes in the nine experiments in able-bodied subjects. The SCI experiment had a significantly smaller amount of non-linear summation than the able-bodied individuals. The second mechanism was changes in electrode-nerve geometry due to hand movements, indicated by the fact that non-linear summation was present even when implanted electrodes were used. Since the same degree of non-linear summation is evident in both the neuromechanical system and the system model, it does not affect the interpretation of our results.

Thus, by using system models, we were able to replicate the nonlinearities and interactions of the neuromechanical system (Figure 3A) and smooth some of the spatial and temporal variability in the training data. Since the system model interpolated between data points, we were able to increase the amount of training data for the inverse controllers from 144 to 729 data sets, interpolating in regions of the force domain where few experimental data were measured due to experimental time limitations or less-than-optimal sampling.

The design method is adaptable to different control optimization criteria [47,48]. One could alternatively synthesize a controller where force and coactivation were co-modulated or controlled by separate inputs, by formulating appropriate optimization objective functions. We successfully trained controllers using data optimized with an activation energy minimization criterion. The inverse controllers trained on the unique optimal solutions were able to predict the stimulus inputs (Figures 1B,4C–E) required to achieve target force outputs along the abduction/adduction and flexion/extension axes within the force domain of each subject (Figure 5A) using less coactivation than would have resulted if we had not optimized the training data (Figure 5B). However, the direction of these forces upon single-muscle stimulation cannot be compared to forces obtained with kinematic models of the thumb [11, 49,50] or under different experimental conditions [22,51] because surface electrode and transducer positioning (different for each experiment to accommodate for different hand sizes) result in different end-point forces. Furthermore, our goal to control forces within the functional

region of each musculoskeletal system does not depend on the relative orientation of the force components with respect to a global coordinate frame, but with respect to the spread of the training data. An inherent limitation of feedforward controllers is their dependence on the repeatability of neuromechanical system properties. The high correlations between the actual and target forces along both degrees of freedom showed the controllers were capable of providing independent control even in the presence of systematic bias and slope errors that were likely due to neuromuscular fatigue. For those cases patients may still be able to adjust and control force production by altering their command signal because of the one-to-one relationship between the target and actual forces.

Additional work is needed to extend the application of these controllers to clinical applications, many of which require kinematic control or a combination of kinematic and kinetic control. This study focused on force (kinetic) control, since it is a fundamental prerequisite for eventual application to kinematic control. The ability to control endpoint force demonstrates the ability to control muscle activation, using force as a surrogate metric. Kinematics result from the interactions of muscle forces, the skeleton and soft tissues, and external loads. If the loads are compliant and reproducible (i.e., no external perturbations), then kinematics can be measured as the outputs and can serve as surrogate measures of muscle activations, in the same manner that force did in the current experiments. Thus, there is strong reason to believe that the same design process will be directly extendable to kinematic or kinetic/kinematic control.

Feedforward control is only one strategy for controlling neuromechanical systems, and is limited by an inability to compensate for unpredictable internal or external perturbations. In cases where compensation for perturbations is essential, feedforward control can serve as an important adjunct to a closed-loop feedback control system, providing a faster response time by reducing the errors that must be corrected by feedback and providing an intrinsic coordination framework for those corrections [4,14].

The current study was also limited to steady-state control, which is satisfactory for some applications where velocities and accelerations are low, such as in hand grasp. However, the design method could also be extended to dynamic control (e.g., upper extremity reach, postural balance, or locomotion) by collecting dynamic input-output data, constructing a dynamic system model, and employing dynamic optimization techniques.

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Figure 1.

Experimental setup showing the force/moment transducer as well as the thumb and hand/forearm casts. The thumb was inserted into the thumb cast and the hand/forearm cast was secured to the table with Velcro straps and side-mounted restraints (not shown) to prevent undesired movement of the arm, wrist, and hand. Coordinates are fixed with respect to the transducer, and the x-axis measured the abduction/adduction forces while the z-axis measured the flexion/extension forces.

Figure 2.

Schematic representation of the system model (A) and inverse controller (B). U_{EPL} , U_{AbPB} , and U_{AdP} represent the individual muscle activations for the EPL, AbPB, and AdP muscles respectively. F_x and F_z represent the x (abduction/adduction) and z (flexion/extension) components of the end-point forces.

Figure 3.

Individual muscle responses overlaid on the thumb tip force domain (dots). The force domain (A, B) was obtained by stimulating all three muscles with different combinations of pulsewidths (experiment 3). (A) The broken lines connect measured forces where only a single muscle was stimulated with increasing pulsewidth. The solid lines connect the forces predicted by the system model for the same pulsewidths. Curvatures in the muscle responses resulted from small posture variations (e.g., forearm shift, wrist rotation, etc.). (B) Actual raw force components measured during data collection (dots) and system model force components (diamonds) in a region of the force domain that cannot be attained by linear summation of the forces shown in panel A. The lines connect raw forces to system model forces (diamonds) resulting from stimulation with the same pulsewidths.

Figure 4.

Magnitude of the original and optimized energies (indicated in gray scale according to the bar on the right) obtained from normalized muscle activations as a function of the forces along both degrees of freedom (experiment 9). The energy (dimensionless) of the optimized data across the force domain is lower than the energy of the original data.

Figure 5.

(A) Force domain (gray dots) and target forces (dark circle) used to test an optimized and a non-optimized inverse controller (experiment 9). The test forces were selected by rotating a 0.5N target force vector around the origin. The test forces were the same for the optimized and non-optimized controllers. (B) Activation energies (dimensionless) of two identical controllers trained on optimized (darker lines) and not-optimized (lighter lines) data. The radius represents the energy amplitude. (C, D, E) Controller-predicted activations for the EPL, AbPB, and AdP muscles, respectively. The radii represent normalized muscle activation. The energy and individual muscle activations of the optimized controller are generally lower than those of the not-optimized controller in most force directions. Thus, muscle fatigue onset will be slower, for a given set of target forces, when the optimized controller is used.

Figure 6.

Target and actual forces along the abduction/adduction (x-axis; A, C) and flexion/extension (z-axis; B, D) axes for experiments 10 (A, B) and 3 (C, D). Small RMS errors indicate good force control over both degrees of freedom.

TABLE I

Exp num	Initial Energy	Optim.Energy	Inv.ctrl Energy	Degree of Freedom	Fitting RMS error (N)	Val.RMS error (N)	Min F (N)	Max F (N)	F Range (N)	Data R ²	Regr R ²	Slope	Offset (N)
1	2412	1209	1120	abd/add	1.3	1.1	-14.3	4.0	18.3	0.91	0.89	2.2	6.3*
				flex/ext	1.0	1.4	-5.6	7.1	12.7	0.82	0.62	0.6	-0.0
2	1982	1243	1111	abd/add	0.6	0.8	-10.2	1.5	11.6	0.93	0.77	1.4	0.4*
				flex/ext	0.5	0.8	-7.3	5.8	13.1	0.86	0.87	0.8	-0.9
3	2644	1013	954	abd/add	1.0	2.1	-10.8	6.8	17.6	0.89	0.82	0.7	-0.6
				flex/ext	1.2	3.0	-9.3	9.8	19.1	0.83	0.63	0.9	0.3*
4	2121	1290	1111	abd/add	0.8	1.0	-12.8	0.9	13.7	0.88	0.85	1.2	0.2*
				flex/ext	0.6	0.8	-3.8	4.0	7.9	0.73	0.49	0.6	-0.0*
5	2844	1794	1770	abd/add	0.7	0.9	-8.7	1.7	10.3	0.52	0.23	0.5	-0.2*
				flex/ext	0.6	0.6	-4.1	6.0	10.1	0.90	0.73	0.6	1.0
6	1535	1416	1270	abd/add	0.9	1.2	-11.3	0.8	12.1	0.85	0.64	0.6	-1.6
				flex/ext	0.7	0.8	-3.0	5.6	8.6	0.83	0.57	1.0	-1.8
7	1920	942	849	abd/add	1.5	2.2	-10.8	3.4	13.4	0.84	0.71	0.9	-2.7
				flex/ext	1.1	1.4	-12.5	3.6	16.1	0.98	0.92	1.0	-0.5
8	1988	928	746	abd/add	0.4	0.8	-1.8	5.9	7.7	0.78	0.71	0.6	0.7
				flex/ext	1.1	1.8	-11.2	9.1	20.4	0.91	0.89	1.0	-0.9
9	3071	1398	1174	abd/add	0.8	1.7	-3.2	6.3	9.4	0.54	0.25	1.4	2.4
				flex/ext	0.4	0.5	-5.2	3.9	9.1	0.92	0.82	1.2	-0.3
10	2146	939	667	abd/add	0.3	0.3	-3.8	0.9	4.7	0.77	0.64	0.7	-0.5
				flex/ext	0.4	0.6	-5.5	5.1	10.6	0.79	0.71	0.8	-0.3

Initial energy represents the summed squared energy of the redundant data that was collected (prior to optimization). Optimal energy is the summed squared energy of the optimal solution found (used to train the inverse controller). Inverse controller energy is the summed squared energy of the pulsewidths predicted by the inverse controller in response to the set of optimal target forces. Energies are dimensionless because they were calculated from normalized activations. Low system model fitting and validation RMS errors (<10% of the force range) suggest the system model was capable of learning the nonlinearities of the musculoskeletal system and provided a good representation of the real musculoskeletal system, even for those regions of the force domain not included in the training (validation data). Data R² indicates the correlation between the actual and target force components along each axis. Regression R² indicates the amount of variability in the actual/target force data explained by the regression model. The slope (dimensionless) and offset are the coefficients of the regression analysis model with their respective p-values. All correlations and regression coefficients were significant (p = 0). Offset coefficients marked with * were not significant (p > 0.05).