Task-Based Methods for Evaluating Electrically Stimulated Antagonist Muscle Controllers

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Abstract—Single-joint motor neural prosthesis control algorithms were tested in a novel animal model. The model consisted of a human subject who provided joystick inputs to a controller. The controller output determined the stimulus activation levels of two antagonist muscles which manipulated the ankle joint of an intact, anesthetized cat. Using visual feedback, the subject manipulated the system to perform positioning tasks which simulated normal activity of an intact limb.

Three controllers were evaluated, open-loop reciprocal control, P-D closed-loop reciprocal control, and open-loop cocontraction control. The results demonstrated that in the presence of visual feedback, open-loop cocontraction control compared favorably in performance to a P-D closed loop controller. This has a practical value for the implementation of clinical neural prostheses since it suggests that in some cases, feedback transducers may not be required for fine control.

I. INTRODUCTION

Electrical stimulation of paralyzed muscles is a promising rehabilitation technique to restore limb function to spinal cord injured persons [8], [14], [15], [25], [26]. Widespread clinical implementation of neural prostheses will require solutions to problems such as implanted device biocompatibility, electrode lead breakage, and premature muscle fatigue but will also require the design of controllers which enable users to perform useful tasks with their electrically mobilized limbs. The research reported here was addressed specifically to the problem of designing neural prosthetic controllers.

There were two objectives of this work. The first was to develop and use a novel experimental animal model for evaluating controllers. The intent of the model was to create a realistic simulation of a simplified neural motor prosthesis system while retaining the ability to closely control experimental parameters. The second objective was to use the model to evaluate simple forms of open- and closed-loop controllers which used a pair of antagonist muscles acting on a single joint. A particular issue was to explore the implications of allowing cocontraction versus reciprocal activation of the antagonist muscle pair.

This paper describes the animal model and reports the results of comparing the antagonist muscle controllers. A preliminary version appeared in [11] and the work is fully described in [10].

II. HARDWARE EMULATOR

Features

Neural prosthetic controllers were evaluated using a "hardware emulator" model which placed a human operator in the control loop for a set of electrically stimulated animal muscles (Fig. 1). The core of this model was the ankle joint of an anesthetized cat acted on by two electrically stimulated antagonist muscles, the medial gastrocnemius, and the tibialis anterior. A torque motor coupled to the ankle joint provided loads to simulate an environment. The model was operated by an able-bodied human subject who manipulated a joystick to perform a task while watching the results of his joystick input on a display screen. Automatic control of the stimulated muscle system resided in a computer which measured position, velocity, and torque of the ankle and position of the joystick, and from this information calculated appropriate muscle activation levels. Control algorithms could be easily changed in the computer, making comparisons among control strategies straightforward.

One feature of the emulator was its inclusion of the complex hardware elements which cannot be accurately represented by mathematical models, namely, electrically stimulated muscles and human operators. This should be contrasted with designing neural prosthetic controllers by computer model simulations, by traditional animal model nerve–muscle preparation experiments, or by experimentation on disabled human subjects, all of which have contributed to this field. Mathematical simulations are valuable during the initial phases of controller design but fail to capture crucial nonlinear and time varying muscle behaviors such as complex recruitment curves or fatigue. Both simulations and traditional nerve–muscle preparations neglect or simplify the man–machine interface between the human operator and the neural prosthesis. Stimulating human subjects provides all of the real hardware but adds extraneous complications such as difficulty in transducing desired feedback signals, unpredictable coupling between surface stimulation and the underlying muscle response (which can be improved with implanted or subcutaneous electrodes but at the cost of a surgical procedure), and psychological effects such as the subject’s motivation and desire for the project to succeed. Although these factors are important components of a working neural prosthesis, they can confound studies which are concerned solely with control algorithms.

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The hardware emulator was closely related to a neural prosthesis system. The human operator modulated real control signals, drove real muscles with physiologic dynamic and fatigue characteristics, and received visual feedback of task performance from the system. This is important if one wants to compare control algorithms using real tasks since there is no definitive relationship between performance on traditional engineering tests such as step and frequency responses to performance of a task such as holding a cup. In contrast to clinical systems, however, with the emulator one can surgically manipulate the animal model to isolate muscles of interest and to place electrodes and feedback transducers.

Limitations

The emulator is a single degree-of-freedom system which limits the choice of tasks to evaluate. Fortunately, many common tasks, such as grasping and pointing, are also single degree-of-freedom and can be simulated directly. A disadvantage of the emulator, however, is that in the case of simulated grasping tasks, the mass and inertia of the grasped object is not reflected to the proximal limbs of the operator as it would be in the case of quadriplegic grasping.

Another limitation of the model is that cat and human muscle are not identical [1]. These differences in fiber types affect the quantitative results presented in this paper but are not significant enough to alter the main conclusions. Stimulated muscle fatigue also influence the ability of the subjects to perform the tasks, but in the same manner as it would in a working neural prostheses.

III. Equipment

Muscle Interface

Fig. 2 illustrates the experiment layout of the hardware emulator. The left hindlimb of an anesthetized cat was fixed to an experiment table by clamps at the hip, knee, and ankle. The foot was amputated and the tendons to the tibialis anterior (TA) and medial gastrocnemius (MG) were isolated and attached to cables which wrapped around a stepped pulley connected through an in-line torque transducer to the shaft of a dc servomotor. The tendon clamp was a 10–12 gauge uninsulated crimp butt connector (2C10, Thomas and Betts, Elizabeth, NJ) which was easy to apply and, if properly crimped, secure. The pulley acted as a substitute ankle joint transmitting the muscle torque to the motor and allowing the motor to ex-
ert a loading torque back on the muscles. The pulley radius was 1.42 cm for the MG cable and 1.75 cm for the TA cable. The maximum pulley rotation was ±22.5°, resulting in a total muscle stretch of 14 mm for TA and 11 mm for MG, somewhat less than the excursion they undergo in normal walking [13]. Muscle rest tensions (which defined the muscle rest lengths) were set to match the in vivo muscle tensions with the cat ankle and knee joints at 90° and ranged from 25 to 50 g for TA and from 200 to 250 g for MG. The horizontal layout eliminated the influence of gravity.

TA and MG were chosen for the antagonist pair because both have been studied extensively and because both contain a mix of fast and slow muscle fibers [2], [9], [19]. Their dynamic properties approximately match but MG has a larger peak force. MG was chosen over the fatigue resistant soleus to preserve this dynamic similarity.

**Stimulating Electrodes**

The muscles were activated by two stimulation electrodes which wrapped around the peroneal and tibial nerves. Tripolar cuff electrodes were used, fabricated from a 0.5 in length of clear silastic tubing with three circumferential 36 g stranded stainless steel wires (BWR-3.48, Bergen Cable Technologies, Lodi, NJ) spaced at 0.125 in intervals. The cuffs fit loosely around the nerves and the tripolar contact arrangement confined the current within the cuff, preventing crosstalk between the two stimulation channels [23].

**Stimulator**

A computer controlled, two-channel nerve stimulator was designed and built for these experiments. It provided isolated, charge-balanced, biphasic current pulses with a waveform consisting of a negative rectangular pulse followed by a 50 µs delay and then a positive rectangular pulse for charge balancing. The stimulator had a pulse amplitude range from 0 to 1.5 mA, pulse width from 0 to 100 µs in steps of 100 ns, and interpulse-interval from 0 to 13 s in steps of 200 µs. For these experiments, interpulse interval was held fixed at 25 ms (40 Hz) and pulse amplitude was manually adjusted during the calibration procedure for each muscle and typically set near 1.0 mA. The computer actively controlled muscle activation by pulse width modulation (PWM). Since the full dynamic range of muscle force was typically recruited over a relatively narrow range of pulse widths, the 100 µs PWM resolution was necessary to ensure sufficient control resolution.

**Torque Motor Loading**

A dc torque motor (JR16M4CH, PMI Motors, Syosset, NY) rated at a continuous stall torque of 3.52 N·m and matching servoamplifier (SSA-54-10-30, PMI Motors) were used for muscle loading. The maximum force exerted by the MG muscle could be as high as 10 kg but with the 1.42 cm pulley radius, resulted in torques of 1.4 N·m, well within the capabilities of the torque motor. The lightweight pancake armature minimized motor inertial load effects. The motor contained an integral tachometer to measure velocity and incremental optical encoder to measure position of the load pulley. An in-line torque transducer was fabricated and inserted between the motor shaft and the load pulley to measure net muscle torque.

Real-time computer control enabled the motor to present a variety of loading environments to the muscles. By feeding back position, velocity, and acceleration (the acceleration state was estimated by digitally differentiating the tachometer velocity signal), the motor could be controlled to simulate any load with second-order dynamics, that is any combination of a spring, mass, and dashpot as is described in [4]. In our controller, positive torque feedback was used to partially cancel inherent motor friction and inertia, resulting in an improved load simulation, particularly when the muscles were being asked to pull against no load. Although not used in the experiments reported here, additional motor control laws were developed to simulate compliant loads such as would be experienced in grasping tasks.

**Display**

The purpose of the display was to provide visual feedback to the human subject performing a stimulated task. The hardware consisted of a Tektronix 603 x, y CRT monitor controlled by the computer through two 8-bit D/A converters. A real-time graphic animation software package was written to control the display. Although limb motions are rotary systems, in some simulations, cartesian animation pictures were used to reduce the graphics computation burden. The display resolution was 256 × 256 pixels and was placed at a distance where the user could resolve one pixel differences in animation motion.

**Joysticks**

The command input of the human subject was through one of two joysticks. The displacement joystick was a commercial x, y unit (Model 521, Measurement Systems, Norwalk, CN) with one axis locked and the return springs disconnected. The maximum command range for this joystick was ±30°. The isometric squeeze joystick contained two upright cantilever beams, each instrumented with a full-bridge strain gage set at its base. The maximum command range for this joystick was ±2.1 kgf. The joystick signals were sampled with 11 bits of A/D conversion providing 0.05 percent full scale resolution.

**Computers and Control**

All experiments were controlled by computers. A DEC LSI-11/23 with attached floating point coprocessor supervised the experiments, acquired data, communicated with satellite processors, and controlled the torque motor. All real-time control loops ran at 200 Hz. Two satellite single-board computers (FRC68000, Force Computers, Santa
Clara, CA) each with a Motorola 68000 CPU, were connected to the host over 38.5 K baud serial lines. One satellite controlled the nerve stimulator while the other performed graphic computations and drove the graphics display. Software was written in Fortran, C, and Assembly language.

IV. TASKS AND CONTROLLERS

Subject Tasks

Controllers were tested while the subjects performed two tasks, pointing and suspension, using the hardware emulator. These two tasks were chosen because they embody essential capabilities which will be required by even simple neural prostheses and because they were relatively simple to implement.

The pointing task [Fig. 3(a)] tested the ability of the subject to track a randomly moving target by using the joystick to manipulate the position of the stimulated cat muscle system. The crosshair target cursor moved along the line following a 0.5 Hz band-limited white noise signal generated by the computer. The display scale was set so that a full excursion across screen corresponded to \(\pm 45^\circ\) of load pulley rotation \((-22.5^\circ \text{ to } +22.5^\circ)\). As explained above, this resulted in TA and MG excursions which were somewhat less than what they undergo during normal walking. During the pointing task, the torque motor was controlled to present no load to the muscles to simulate pointing in an environment with no kinematic constraints. This was achieved by closing a positive torque feedback loop around the motor to partially cancel its internal friction and inertia.

The suspension task [Fig. 3(b)] tested the ability of the system to stabilize an inverted pendulum in a gravity field. This is analogous to controlling the position of the ankle joint during quiet standing with the hip and knees locked. Although the command input for a neural prosthesis which controlled balance would not be under voluntary control, this simulated task was useful because it tested the ability of a subject to control a stimulated muscle system working against an unstable load. The display for the suspension task presented an inverted pendulum whose angular position was proportional to the position of the load pulley \(90^\circ\) on the display equalled 22.5\(^\circ\) on the load pulley. The subject’s goal was to keep the pendulum upright using the stabilizing torque provided by the cat muscles despite the presence of a destabilizing, simulated gravity field provided by the torque motor which attempted to pull the pendulum off center. Although the tangential force of gravity on an inverted pendulum acts as a nonlinear, negative spring, it was implemented in the simulation as a linear spring with a constant of \(-62.8 \text{ g } \cdot \text{cm}/^\circ\). When the pulley was at its extreme position of 22.5\(^\circ\), this resulted in a motor torque of 1.413 kg \cdot cm. The simulated inertia was small because differentiating velocity to provide an acceleration feedback signal added noise and caused motor stability problems when attempting to simulate large inertias. (This will be solved by adding an accelerometer to the system.) The simulated load, therefore, was analogous to a large mass at the top of a short shaft. To statically stabilize the load, the controlled muscle system was required to provide a stiffness greater than \(+62.8 \text{ g } \cdot \text{cm}/^\circ\). Peak forces in the stimulated muscles ranged from 2.8 to 3.5 kg for TA and 5.0 to 9.2 kg for MG which translates into peak torques at the load pulley of 4.9 kg \cdot cm to 6.1 kg \cdot cm for TA, and 7.1 kg \cdot cm to 20.1 kg \cdot cm for MG. Either muscle could overcome the maximum simulated load torque and could easily pull the pendulum upright from its toppled position.

Muscle Control Strategies

Three simple algorithms for controlling electrically stimulated muscles were tested. One should remember that for all three controllers, the human subjects were closing a supervisory visual feedback loop by watching the results of their actions on the display.

Under single-input, open-loop control (OL), the position of the subject’s displacement joystick dictated the stimulated muscle activation levels with maximum joystick position generating maximum muscle force [Fig. 4(a)]. The muscles were reciprocally activated with no cocontraction and the subject was required to close the loop using visual feedback from the display.

Closed-loop position control (CL) used a proportional position loop with rate feedback to enhance stability [Fig. 4(b)]. The position of the subject’s displacement joystick provided the reference command signal to the system. Controller gains were selected by trial and error tuning at the start of each experiment. The tuning procedure was to enter a set of gains and then to perform a set of position step responses for three input step levels as well as running a brief pointing task. With experience, this iterative procedure rapidly converged on a set of gains which gave
acceptable performance over the entire operating region. Typical step response performance was 10–90 percent rise time of less than 100 ms and less than 11 percent overshoot. The tuning was checked periodically during an experiment and readjusted when necessary. A more formal procedure of choosing gains would incorporate mathematical models of the stimulated muscle system. Because muscle models are imperfect, however, final gain tuning on the animal model would always be required. Since single-input, single-output P-D controllers are simple to tune by trial and error, the simulation stage was omitted. An integral term was not added to form a complete P-I-D controller. Integral action would drive the steady-state position error to zero but comes at a cost of reducing system stability. Since the subject was always watching the task and providing a command input, steady-state errors could be manually corrected. This would not be the case for an autonomous controller where the reference position is provided internally.

The third controller, open-loop cocontraction control (CC), was implemented by having the subject manipulate the 2° of freedom, isometric joystick [Fig. 4(c)]. Pushing with the thumb on one side of the joystick activated the agonist muscle, pushing with the finger on the other side of the joystick activated the antagonist muscle, and squeezing both sides caused cocontraction. Full activation of the joystick (2.1 kgf) resulted in maximal stimulated muscle force. Since designing wearable feedback transducers presents a difficult challenge to the development of practical closed-loop neural prostheses, this controller was chosen in part to determine how well an open-loop, operator controlled neural prosthesis would perform. It was hypothesized that a controller which gave the subject independent control over the antagonist muscle pair and which included the possibility of simultaneous activation of the muscles to modulate joint stiffness, would result in performance that was significantly improved over a single input open-loop controller which restricted the muscles to reciprocal activation. For these experiments, this was indeed the case. Theoretical aspects of cocontraction controllers have been explored by Hogan who showed that a wide variety of natural movements can be implemented by manipulating stiffness in one or two joint muscles [16] and who also showed (using optimization techniques to find minimum energy solutions) that elbow muscles cocontract when given the task of holding a heavy weight upright in the hand [17]. Also, the value of single and antagonist pair muscle stiffness controllers has been experimentally demonstrated by Crago et al. [7] and Lan et al. [18].
To improve control of the muscle, an inverse recruitment map was placed in the forward path of all three controllers. This map linearized the relation between input command and isometric force output, a technique which has been used successfully by other groups [5], [22], [24]. The map was calculated by isometrically stimulating each muscle at approximately 25, 50, 75, and 100 percent of maximal isometric force for 1.0 s and the force measured as the average over the last 0.5 s of stimulation. The resulting force as a function of stimulus strength curve was then inverted and stored in a look-up table for use by the digital controllers. The inverse map computed using just four measured data points was shown to compare favorably to that computed from 11 data points in linearizing the muscle response. The linearization was checked periodically during the experiments and recalibrated as needed. Note that the inverse map was computed with the muscles in their neutral positions with no accounting for the length-tension characteristics of stimulated muscle.

V. METHODS

Surgical Preparation

Adult cats were anesthetized by intramuscular Ketamine (20 mg/kg) followed by intravenous sodium pentobarbital (32 mg/kg). The animals were maintained in a surgical plane of anesthesia during surgery and in a lighter plane during the data sessions.

The tendons to the tibialis anterior (TA) and medial gastrocnemious (MG) were exposed, cut as far distally as possible, and clamped to 0.044 in. diam. wire rope. To prevent abnormal tearing, no attempt was made to separate the MG-LG tendon so in these experiments, the passive length tension curve of the MG also contained the LG component. The foot was then amputated and skin flaps closed around the exposed distal ends of the tendon. A midline incision was made in the popliteal fossa and the sciatic nerve exposed by blunt dissection. One electrode cuff was placed around the tibial nerve and the second around the peroneal nerve. All tibial nerve branches except those to MG were cut, and the sciatic nerve sectioned proximally to disable reflex paths. The skin wound was then closed, allowing the electrode leads to move freely.

The cat was placed on its right side and the left hindlimb rigidly clamped at the hip, knee, and ankle joints. The TA and MG tendons were stretched to their rest tensions (defined as the passive muscle tension with the ankle and knee joints at 90°), and the cables attached to the load pulley. The cat’s body temperature was maintained by a heating pad and the short lengths of exposed tendon were periodically dripped with mineral oil to prevent drying. Although muscle properties are sensitive to temperature [3], [21], a better temperature control system was not necessary because the muscles were under the skin and presumably at their normal physiologic temperature.

Experiment Design

Experiments were performed on 12 acute cat preparations using eight human subjects who operated the hardware emulator. In each experiment, all six combinations of the three controllers and two tasks were tested. For each of the six task-controller combinations, there were four 30 s trials with a 5 min muscle recovery period between each trial. A rest period of longer than 5 min was desired but would have extended the duration of a data session beyond what a human subject could comfortably tolerate. Isometric force was measured before and after each trial to check for muscle fatigue. Before each set of four trials, muscle calibration was checked and, if necessary, a new inverse map calculated or new CL gains found. Prior to each task-controller combination, subjects were trained on the hardware emulator with a mathematical muscle model substituting for the stimulated cat muscles. The objective of these training sessions was to minimize contamination of the results by learning effects.

Data Analysis

Position, velocity, net muscle torque, and joystick commands were digitized and stored at 50 Hz for each of the 30 s trials. Performance on both tasks was measured by computing the mean square tracking error (MSTE) during the 30 s trial. This measurement excluded data from the first and last 2.5 s of a trial to avoid contamination by start and stop transients. For the pointing task, the tracking error was between the target and the subject-controlled cursor, while for the suspension task it was the angular distance of the pendulum away from the upright position. In both cases, a high score indicated poor performance. Scheffe multiple comparisons were used to determine the significance of differences between the three controllers and analysis of variance tests indicated whether effects of testing order or of differing experimental animals and human subjects contaminated the results [27].

Because avoiding muscle fatigue is an important criterion for neural prostheses, mean muscle use required by each controller was also measured during the tasks. Muscle use was estimated by integrating the input commands (excluding the first and last 2.5 s of the 30 s trial) to each muscle generated by the controller algorithm, the same indicator used by Oguztoreli and Stein to measure muscle input costs [20] and by Hogan to measure muscle energy [17]. Muscle energy indicators which use mechanical power as a parameter could not be used because the torque transducer only indicated net torque rather than individual muscle torques. Fatigue indicators were also not used because of their erratic nature and requirements for long recovery periods.

VI. RESULTS

Subject Trials

Typical 30 s suspension time trials for OL, CL, and CC controllers are illustrated in Fig. 5. Note that the system was set to an initial position of 2.3° before the start of each trial. The task of stabilizing the pendulum was impossible when the subject was using OL, but simple when using CL or CC. The primary difference between the latter two controllers was that the subjects needed more time...
within a trial to overcome the start-up transient using CC which accounts for the longer transient period seen for CC in Fig. 5. The upright position was an unstable equilibrium and there were enough internal disturbances that the system would topple if the subjects let go of the command joysticks when using either OL or CC.

Fig. 6 shows typical pointing task trials with the three controllers. Here, the differences between controllers are not as marked although the pointing task was more difficult when using OL.

The MSTE performance scores were averaged over all experiments and all subjects (a total of 48 records) and Scheffe multiple comparisons were used to determine statistical comparisons among the controllers. The results are presented graphically in Fig. 7 where the marker denotes the mean score (large scores imply poor perfor-
Fig. 7. Comparisons among controller performance scores for pointing and suspension tasks. The MSTE score is the mean square tracking error over all but the first and last 2.5 s of the 30 s trial (see text for details). The data are pooled across all experiments with the dot indicating mean score, the vertical bars indicating standard deviation, and the boxes indicating 95 percent simultaneous confidence intervals. A high score indicates poor performance.

Fig. 8. Comparisons of muscle use by the three controllers for pointing and suspension tasks. The muscle use indicator is the average command to each muscle taken over the length of the trial. The plot indicates results pooled across all experiments with the dots denoting the mean and the bars denoting the standard deviation. Each point on the plot is the average of the TA and MG muscle use indicators. The vertical axis units are muscle command where 1000 = maximal activity of the muscle. The CC controller uses both muscles more than either the OL or the CL controller.

In terms of performance, the vertical bars indicate standard deviation and the boxes indicate 95 percent simultaneous confidence intervals for the mean. If the mean for one controller fell within the 95 percent confidence interval box of another, the two controllers were not statistically discernible.

The figure demonstrates that for both tasks, using OL resulted in significantly poorer performance than when using either CL or CC. Performance scores when using CC, however, were the same as those achieved using CL. Two-way ANOVA tests confirmed that these results were not contaminated by using different animals and subjects for each experiment, nor by the order in which the controllers were presented to the subject. In addition, with the exception of CC, short-term learning was not a factor in these experiments since, on average, subjects did no better than on the fourth trial of a particular task-controller combination than they did on the first. For the CC controller, however, there was a slight performance increase on the pointing task over the four replications.

Learning also occurred during the training trials where the subject was manipulating the muscle model simulation rather than the actual stimulated muscle system.

Fig. 8, showing the muscle use indicator, summarizes how much the muscles were used by each controller and clearly illustrates that CC, which permits cocontraction, leads to more muscle use than either OL or CL. The same
result was reached when comparing trials across controllers which had similar kinematic performance scores. In those cases, trials using CC required more muscle use for equivalent performance than when using OL or CL.

Simultaneous activation of both muscles was enabled only with cocontraction control. One might expect task performance, particularly for the suspension task, to improve as the subject commanded more cocontraction since this increases system stiffness and improves disturbance rejection. The results for the suspension task, however, showed no relation between performance and levels of cocontraction which indicated that a second factor, learning, was also occurring, a factor reinforced by the instructions given to subjects for using the squeeze joystick. Each person was directed to pick the minimum squeezing which did not sacrifice performance. As subjects became familiar with the task, they cocontracted less while maintaining the same performance level. This is demonstrated in the CC suspension trial shown in Fig. 9. During the first 5 s, the subject was unable to keep the pendulum upright. The subject then squeezed the joystick to cocontract the muscles and the system stabilized. From 11 s, cocontraction was gradually reduced until at 17 s the system toppled again. The subject re-established by increasing cocontraction and then gradually eased off from 22 s to the end of the trial.

Nonlinear Behavior Caused by Length-Tension Properties

The behavior of the closed-loop controller in step response tests without the human subject clearly demonstrated the importance of muscle nonlinearities. Fig. 10 shows the CL position response to step inputs of two different amplitudes when an intentionally large position feedback gain was set in the CL controller. For a step input command of $R = 22^\circ$ the system was stable, while for an input command of $R = 9^\circ$ it was not. A second example of this nonlinear behavior is illustrated in Fig. 11 which shows the same system's closed-loop, position response to a low-frequency, stochastic input. The circles indicate regions where the system broke into magnitude dependent oscillations. Similar behavior was seen for a wide range of position feedback gains. It was possible to lower the gains for stable behavior over all input step commands (which was done for the human subject testing), but at the cost of a large steady-state error.

Inverse Recruitment Map

Placing the inverse recruitment map in the forward path of each controller improved the linearity of the muscle's static command input to isometric force output. Without the map, the linearity ranged from 25 to 38 percent (maximum deviation from a straight line reported as percent full scale). With the map, the linearity was 6 to 16 percent with the best performance occurring immediately following a map calibration. The map was most effective in correcting the recruitment curve deadzone which occurs at stimulus activation levels which are too small to excite motor unit axons in the nerve.

VII. DISCUSSION

Controller Comparisons

The emulator enabled a direct performance comparison between open-loop, PD closed-loop, and cocontraction
controllers for positioning tasks with the controller input under the control of a human operator and with visual feedback. The results demonstrate that single-input open-loop control (OL) is a poor choice for the tasks tested in this paper. The subjects found the joystick sensitive near the center region making it difficult to control either the cart or the pendulum. Reducing the sensitivity by lowering the joystick gain was not a solution since the subject then lost control over the whole muscle range.

Using closed-loop position control (CL) or open-loop cocontraction control (CC) led to improved performance. Subjects performed best with CL and found it the easiest to use. Because of the muscle nonlinear, time-varying behavior, however, one must exercise caution before clos-
ing the loop. In these experiments, to prevent instabilities, feedback gains were kept low resulting in a system with large steady-state errors and poor disturbance rejection. The subject, however, was continually monitoring the results of his actions using visual feedback and steady-state errors could be corrected easily. The primary function of CL, therefore, was to partially linearize the system and give the subject a more predictable response.

The results for open-loop cocontraction control were of particular interest. After training, most subjects felt comfortable with the isometric joystick and were able to perform almost as well using CC as when using CL. One explanation for this improved open-loop performance is that CC is the only one of the three controllers to permit cocontraction. In these experiments, limiting controllers to reciprocal activation of muscles precluded good tracking performance, particularly near the neutral position where both tendons were slack because, as will be discussed below, the system was attempting to use unloaded muscle force generators to control position, an impossible task. The good results obtained with the CC controller were encouraging because they imply that it might be possible to design open-loop neural prosthetic controllers whose performance in the presence of visual feedback is as good as some closed-loop designs.

Cocontraction control requires two input channels per joint, a disadvantage since control sites are scarce on an SCI person. The isometric joystick used in these experiments would not be feasible for a practical neural prosthesis, but was an appealing means of testing the cocontraction control strategy. When subjects squeezed to cocontract, the stiffness of both the stimulated muscles and the subject's hand muscles increased so that the control action felt natural. A second disadvantage of cocontraction control is that the ability to cocontract could result in premature fatigue of the stimulated muscles. A control which uses cocontraction must make the appropriate choice of system stiffness to give acceptable performance without rapid fatigue.

Nonlinear Effects

There are two explanations for the poor performance with open-loop reciprocal control and for the closed-loop magnitude dependent oscillations seen in Figs. 10 and 11. One is that the controller performs well when modulating a single muscle but fails when rapidly switching between two muscles which occurs in the region near the zero position. Referring to Fig. 10, for $R = 22^\circ$, the system had no overshoot and only one muscle was active. For $R = 9^\circ$, the system had an initial overshoot which required turning on the antagonist muscle to pull the system back. Another overshoot in the opposite direction turned the agonist back on to sustain the oscillations.

A second explanation is based on the nonlinearity of passive muscle length-tension curves. Fig. 12 illustrates a hypothetical set of active length-tension curves for an agonist muscle and the passive length-tension curve for its antagonist where equilibrium positions are dictated by the intersections of the active and passive curves. These curves are similar to experimentally measured curves and have the important characteristic of a passive antagonist curve. The joint position will be dictated by the intersection of the appropriate active agonist curve with the passive antagonist curve. In the center region, small changes in agonist muscle activation $u$ cause large changes in position. Near the left edge, however, the antagonist curve is stiffer and small changes in agonist $u$ only cause small changes in position. The system therefore is easier to control at the extremes than near the center.
don the restriction of reciprocal muscle activation and allow cocontraction of the muscles near the zero position, analogous to biasing the output stage of a push-pull transistor amplifier to eliminate dead zone effects. Cocontracting the muscles would then provide a continuous load for the active muscle to work against and would eliminate the dead zone problems inherent to reciprocally activated systems. A disadvantage of this strategy is that the muscles would contract more which may cause premature fatigue. Control strategies which incorporate cocontraction when operating in regions of low muscle activation (independent of position) have been successfully tested by Crago et al. [6] and Lan et al. [18].

Limits of Study

The limits of these experiments should be recognized. Only three, single-joint controllers were tested and evaluations were based on only two tasks, both calling for position regulation. No evaluations were made of disturbance rejection or of performance in an environment containing obstacles. It is likely that high performance controllers for neural prostheses will be task dependent. Clearly this is the case for a delicate grasping activity which calls for both good position tracking when approaching the object and good force tracking to achieve a successful grasp. For example, a stiffness controller [6], [7], [18], which combines both of these objectives, has been proven in grasping applications but because of poor disturbance rejection in its position control mode, might be unsuited for gait applications.

VIII. Conclusions

The objective of this work was to develop and use an experimental, task-based emulator to evaluate open and closed-loop controllers for neural prostheses. The results support the following conclusions:

1) The good performance of open-loop cocontraction control shows that one can devise open-loop controllers which, in the presence of visual feedback, allow performance of positioning tasks which compare favorably to performance with closed-loop controllers. This result demonstrates the value of cocontraction for position control tasks in neural prostheses. The disadvantage of cocontraction control is that it requires more than one input command channel per degree-of-freedom of motion and may cause premature muscle fatigue.

2) Closed-loop P-D position controllers partially linearized muscle response leading to a more predictable system behavior. Because of calibration drift, feedback gains remained low, resulting in systems with large steady-state positioning errors.

3) The nonlinear length-tension behavior of muscles can cause magnitude-dependent oscillations in a fixed-gain, closed-loop position controller. Simple muscle models which neglect these effects may lead to unsatisfactory controller designs.

4) Stimulated muscles need loads to work against. These loads may be supplied externally by the environment or internally by the active and passive spring properties of antagonist muscles.

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