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New control strategies for neuroprosthetic systems

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Abstract—The availability of techniques to artificially excite paralyzed muscles opens enormous potential for restoring both upper and lower extremity movements with neuroprostheses. Neuroprostheses must stimulate muscle, and control and regulate the artificial movements produced. Control methods to accomplish these tasks include feedforward (open-loop), feedback, and adaptive control. Feedforward control requires a great deal of information about the biomechanical behavior of the limb. For the upper extremity, an artificial motor program was developed to provide such movement program input to a neuroprosthesis. In lower extremity control, one group achieved their best results by attempting to meet naturally perceived gait objectives rather than to follow an exact joint angle trajectory. Adaptive feedforward control, as implemented in the cycle-to-cycle controller, gave good compensation for the gradual decrease in performance observed with open-loop control. A neural network controller was able to control its system to customize stimulation parameters in order to generate a desired output trajectory in a given individual and to maintain tracking performance in the presence of muscle fatigue. The authors believe that practical FNS control systems must exhibit many of these features of neurophysiological systems.

Key words: *adaptive control, closed-loop, feedback, feedforward, FES, FNS, open-loop.*

INTRODUCTION

The availability of techniques to artificially excite paralyzed muscles opens up enormous potential for restoring both upper extremity and lower extremity movements with neuroprostheses. In addition to stimulating the muscle, the neuroprosthesis must take on other tasks normally performed by the nervous system to both control and regulate the artificial movements. The control task refers to specification of the temporal patterns of muscle stimulation to produce the desired movements; and the regulation task is the modification of these patterns during use to correct for unanticipated changes (disturbances) in the stimulated muscles or in the environment.

The purpose of this paper is to review recent developments in the control and regulation of movements produced by neuroprostheses. The topics were chosen not because they are current clinical practice, but because they represent significant recent advances and are representative of the diverse control approaches that are likely to be required in future neuroprostheses. This introduction will define some basic control concepts (feedforward, feedback, and adaptive control, see **Figure 1**) that are used in the subsequent sections. These concepts are not unique to engineering; examples can be found throughout physiology. A good fundamental description of the concepts with specific reference to

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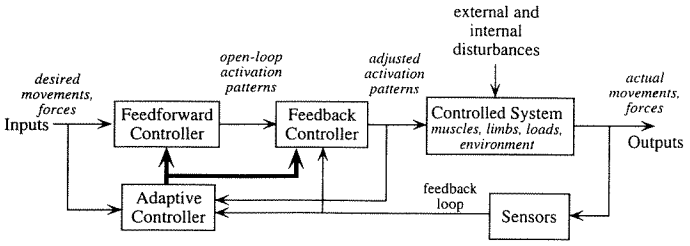

Figure 1.
Generic block diagram illustrating concepts of feedforward (open-loop) control, feedback control, and adaptive control. In feedforward control, the desired movements and forces are used to generate the muscle activation patterns that should produce the movement. In feedback control, sensors are used to monitor the actual movements and forces, and a feedback controller modifies the activation patterns to correct for differences between the desired and actual outputs. In adaptive control, the inputs and outputs are monitored and the feedforward and/or feedback controllers are modified to optimize performance.

physiological systems can be found in Houk's writing (1).

The temporal specification of stimulation patterns (control) for both upper and lower extremity neuroprostheses is difficult because of the complexity of the musculoskeletal systems. Specification of the patterns must account for the nonlinear and dynamic relationships between stimulus parameters and muscle output, and between muscle output and limb output, as well as the varying load encountered as the user interacts with the environment. In some systems, only the steady-state (static) input-output properties are considered; however, in most systems, both static and dynamic properties are important. For example, in the hand grasp neuroprosthesis developed at Case Western Reserve University and the Cleveland VA Medical Center (CWRU/VAMC), the stimulus parameters for seven muscles are altered on the basis of a single continuously graded command signal to open and close the grasp and to modulate the force applied to objects being grasped (2). Grasp control is synthesized by specifying constant relationships (pulse width maps) between the single command signal that is graded by the user and the pulse width applied to each muscle. Synthesis is carried out either by following simple qualitative rules (3) or with a quantitative automated process (4). Grasp synthesis accounts for nonlinear relationships between the stimulus parameters and the grasp output, but does not take into account the dynamic properties of the system being controlled, since the dynamic properties are not very significant for grasp-release tasks.

Grasp control in the CWRU/VAMC system does not require a command signal to be generated by the neuroprosthesis, since it is under voluntary control by the user. In contrast, a neuroprosthesis controller for locomotion, while allowing stimulation to be started and stopped voluntarily by the user, must generate commands to create the basic walking pattern. Furthermore, the synthesis process must take into account the dynamic properties of the muscles and the limb.

In current neuroprosthetic implementations, locomotion is synthesized by iteratively modifying a basic time-varying stimulation pattern to improve the gait of each subject (5). Stimulus magnitudes and timing are altered on the basis of walking performance, as assessed visually or by quantitative motion analysis. The iterative modification rules are based on the experience of experts, and compensate for both system nonlinearities and dynamic properties. The dynamic properties that are most important are the inertia of limb segments and the time between when a muscle is stimulated and when it actually generates force to accelerate or decelerate the limb. Because of the dynamic system properties, a single pattern is not suitable for all walking speeds.

The control systems described above can be classified as feedforward control systems, since they specify the stimulus parameters (musculoskeletal system inputs) that are expected to be needed to produce the desired movement (system outputs). Feedforward control systems do not make corrections if the actual movement deviates from the desired movement. Deviations are common in neuroprostheses because properties of stimulated muscle vary with time (e.g., fatigue) and because the user operates in a constantly changing environment (e.g., changes in the slope of the walking surface).

A broad category of control systems that correct for a changing system or environment is feedback control. In a feedback control system, sensors monitor the output and corrections are made if the output does not behave as desired. The corrections are made on the basis of a control law, which is a mathematical prescription for how to change the input to reduce the difference (error) between the desired output and the actual output. Much of the work done in automatic control of stimulated muscle in the last 20 years has focused on feedback controllers. The objectives have been assessing how well feedback control can regulate motor activities, and identifying the best control law for the system being controlled and for the type of behavior desired (6). Feedback control has been successful in

regulating hand grasp (7) and standing posture (8), but it appears that another strategy, adaptive feedforward control, is likely to be required for dynamic activities such as locomotion.

Adaptation refers to the ability of a control system to change how it responds to inputs or disturbances, based on changes in the properties of the controlled system or the environment. In movement control, the musculoskeletal system properties are monitored by measuring the inputs (commands, stimulus parameters) and the actual outputs (movements, forces) during neuroprosthesis operation. From the inputs and outputs, the feedforward controller and/or the feedback control law are altered to improve performance according to a predetermined optimization criterion. For example, in locomotion control, the quadriceps stimulation intensity might be progressively increased in amplitude to compensate for fatigue that would cause the knee to buckle during standing.

There are tradeoffs in the choice of control system for a neuroprosthesis. Even extremely simple feedback control laws can improve performance greatly and can compensate for any source of disturbance, but they also have drawbacks. Feedback control requires output sensors, and compensation is generally slower than in feedforward control since an output error must be present to generate a controller response. Thus, feedback control might be best used for slow movements, and for maintaining a steady posture (e.g., hand grasp). On the other hand, feedforward control requires much more detailed internal information about how the system behaves in order to generate a stimulus pattern that will produce an accurate movement, and it may produce poor movements if the system properties change. The most significant advantages of feedforward control are that it can be used for rapid movements such as the swing phase of gait, and it does not require sensors. Adaptation requires sensors to monitor output, and can be used to improve the performance of either feedback or feedforward control. The neuroprosthetic systems described below use a mix of the three types of control system, and all employ some type of machine intelligence. The technologies that have been investigated include optimization, rule bases, neural networks, adaptive logic networks, and fuzzy logic.

Control of Upper Extremity Motor Tasks with Functional Neuromuscular Stimulation (FNS)

Control of the upper extremity involves transporting the hand to a desired position in space and providing postural stability for the arm while manipulating objects. In people with C4–C6 spinal cord injury (SCI), the muscles that control these functions may be partially or completely paralyzed. The goal of FNS is to restore some degree of the lost function even with limited channels of stimulation and simple control strategies (9). An important and distinctive characteristic of most upper extremity movements is that they are goal directed rather than cyclic. The amplitude, speed and direction of arm motions vary from one movement to the next. Thus, a generator of movement patterns must be capable of providing a rich variety of patterns. This contrasts significantly with the needs of a pattern generator for locomotion, which is repetitive and requires relatively few patterns.

Structure of a Perturbation Controller

Earlier studies focused on developing feedback control strategies for FNS motor task control. One strategy was to regulate the stiffness of the limb by combining position feedback and force feedback. Stiffness is an inherent property of muscles that is an important determinant of limb stiffness (10–12). Stiffness regulation, as opposed to pure position or pure force regulation, is advantageous because it can operate under both isometric and/or unloaded conditions to provide regulation of interaction force and/or movements. Stiffness regulation has been demonstrated in hand grasp tasks (7), and can be implemented with a variety of feedback controllers (13). Feedback stiffness control has also been demonstrated in an animal model for two-joint movement control or end-point force control (14).

In arm movements, the inertias and interactions between joints play significant roles in determining movement trajectories (15). Feedback control cannot compensate accurately for these effects. With feedforward (open-loop) control, compensation is often made in advance. It is based on the mechanics of the system to ensure consistent performance under changing conditions.

Control of arm movement by FNS entails specification of a stimulation pattern for a set of redundant muscles, which are highly nonlinear and time-varying actuators. To account for the biomechanics of the limb and the muscles, and to adapt to system changes such as muscle fatigue, Lan has proposed a combined strategy that includes both open-loop and closed-loop controls to achieve the needed diversity of task control (16). The controller, shown in **Figure 2**, is called a perturbation

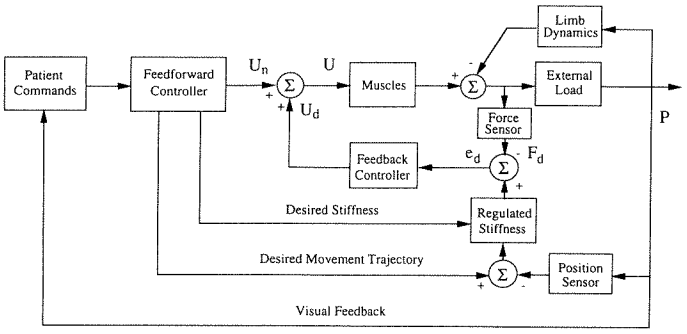

Figure 2.
A perturbation control structure for controlling arm movements and regulating the stiffness at the end point of the arm. In this case, the feedforward controller specifies the nominal muscle activation patterns (Un), and in addition specifies the desired movement trajectory and the desired endpoint stiffness. Sensors monitor the endpoint position and force so that a feedback controller can make adjustments (Ud) to the activation patterns. The controlled system consists of the muscles, external load, and limb dynamics.

controller. In this system, the user initiates a task by instructing the controller with specific commands. The feedforward controller interprets the instructions and generates a pattern of stimulation commands to the muscles. Theoretically, if all dynamic and nonlinear properties are taken into consideration, the feedforward rules should be able to drive the limb to perform the movement satisfactorily. In practice, necessary simplifications in the specification of stimulation pattern by the feedforward controller result in errors in performance. In addition, muscle fatigue will also cause deviation from the desired movements. Therefore, a feedback controller is incorporated to eliminate the performance errors due to these disturbances, which are viewed as perturbations to the system.

An Artificial Motor Program for Multijoint Movements

Currently, Lan is focusing on the feedforward controller, and developing an artificial motor program (AMP) that can generate muscle stimulation patterns for a class of movements of various directions, speeds, and distances (17,18). The goals for the AMP are 1) to produce normal looking movements; 2) to generate a whole class of movements rather than just a single movement; 3) to be tunable to suit different users and different muscles; and 4) to be able to minimize muscle stimulation (i.e., limit fatigue). This is illustrated for the simplest case of multijoint movement control, a two-joint system controlled by at least three pairs of muscles. One pair of muscles controls the elbow joint, a second pair controls the shoulder joint, and a third pair (biarticular muscles) controls both the elbow and the shoulder. The number of muscles is greater than the number of mechanical degrees of freedom, making the system redundant. In such systems, there is no unique solution to the kinematic control problem, and more than one set of muscle inputs can produce nearly identical trajectories.

The human brain has solved the problem of controlling arm movement through a hierarchical neural control structure. Although we do not fully understand how the nervous system achieves the solution, we still can use the normal motor system as a template for potentially useful strategies of FNS movement control. In this way, Lan established a method of generating an AMP guided by the hierarchical structure of the human motor control system. He created a three-level model structure: a bottom level consisting of a two-joint musculoskeletal system with three pairs of muscles, a middle level analogous to reflex control, and a top level that minimizes effort of movement (19). The input to this model consists of three parameters that specify a movement: P0 is the initial position of the arm, Pf is the final position of the arm, and Ph constrains the maximal level of an excitation signal (ranging from 0 to 1) for each pair of muscles. The AMP puts out a vector of control signals; each element contains two components: one for flexor control and one for extensor control.

The bottom level of the model includes nonlinear two-joint dynamics of the arm, a proportionality between muscle force and stiffness, linear muscle activation dynamics and a nonlinear joint viscosity. The middle level contains a neural circuit of reciprocal inhibition, and linear neural excitation dynamics. The neural circuit integrates the efferent and afferent signals to produce muscle activation signals. This function is believed to be accomplished in the normal spinal cord through interneurons (20). The top level calculates two descending commands, equilibrium points for each joint and excitation signals for each pair of antagonist muscles. These are continuous functions of time.

The model has constraints due to its global inputs: movement has to start at the initial position and finish at the final position, and there is an upper bound on the excitation signal which delineates the maximal level of muscle force that can be recruited. Also, there is a constrained range of joint movement and a constrained

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range of muscle inputs. The upper bound of excitation is the parameter that is tuned to adjust the kinematic characteristics of the movement.

Analysis of the AMP

The input parameters specifying the movement do not completely specify the input signals to the muscles. The complete set of muscle input signals is found by a dynamic optimization technique that analyzes the behavior of the AMP for two-joint planar arm movements (17,18). The optimization criterion was to minimize the effort, as defined by Hasan (19), which tends also to minimize joint stiffness. With this criterion, the co-contraction of antagonistic muscles is at a minimum level, and thus muscle fatigue can be reduced during FNS movement control.

An example of a reaching movement is shown in **Figure 3**. Hand movement is illustrated in **Figure 3a**. A nearly straight movement with a bell-shaped velocity profile is obtained. The movement in the Y direction, particularly, is very similar to what would be observed in a single joint movement. The joint movements are illustrated in **Figure 3b**. These movements are also very similar to a single joint movement. The joint stiffnesses are dynamically modulated. Muscle activation patterns are illustrated in **Figure 3c**. A triphasic and biphasic pattern of muscle activation is produced.

In summary, the optimized AMP displayed four distinct features:

1. The movement produced was smooth with a bell-shaped path-velocity profile, giving it the grace of a natural movement.
2. The AMP could generate movements in different directions, across different distances, and at different speeds. Therefore, it had sufficient diversity for controlling a class of movements.
3. The AMP could be tuned to accommodate different inertial loads of the limb. Thus, it could be used in people with different limb sizes.
4. The AMP produced triphasic burst activities in muscle stimulation patterns in both moderate and fast speed movements. The normal EMG patterns observed during voluntary movements have similar triphasic burst features (21). This characteristic may be seen as the result of minimizing muscle activation.

Muscle stimulation patterns and movement kinematics obtained by the AMP are consistent with experimental data on both single joint and multijoint arm movements. Thus, it appears that this AMP can be used as a starting point for implementing a feedforward controller for arm movements, or even for the swing phase of gait. Further computer simulation and experimental studies will be required to realize and test this AMP with the combined feedforward/feedback controller design (22).

Control Strategies for FNS-Assisted Ambulation

Two important functional goals for lower extremity FNS are standing and locomotion. Standing and maintaining a balanced posture are required to perform many activities, and feedback control of standing posture has been an important area of investigation. Feedback control is especially appropriate for postural regulation during standing because adequate time is available for feedback corrections. Restoring gait is considered to be more challenging because of 1) the high inertia of the limbs during swing and the body during stance, 2) the low muscle torques generated by electrical stimulation, 3) the slow response of muscles to control inputs compared to the duration of the movement, and 4) the interaction of the endpoint of the limb with a changing terrain. Two approaches to gait control were tested. First were attempts to control and regulate the swing phase of gait, which is particularly difficult because of the high inertia and the short duration. The second study investigates the use of artificial neural networks for pattern generation of the cyclic behavior required for gait.

Four Strategies for Controlling and Regulating the Swing Phase of Gait

The goal was to optimize stimulation patterns in order to obtain well coordinated cyclical movement, in a way that would compensate for muscle fatigue and external disturbances. In controlling cyclical movement, such as ambulation, one can try to follow pre-set (i.e., reference) joint angle trajectories. However, in the swing phase of gait, following exact trajectories is unimportant and inefficient, leading to fatigue due to the large forces that must be exerted to precisely control the high inertia body segments. For these reasons, control of movements was based on natural gait objectives such as step length, foot clearance, or balance.

A group at the University of Twente in The Netherlands examined the swing of the lower leg generated by stimulation of quadriceps in a controlled setup. The objective was to reach a reference maximal knee angle at each cycle. Successful performance was

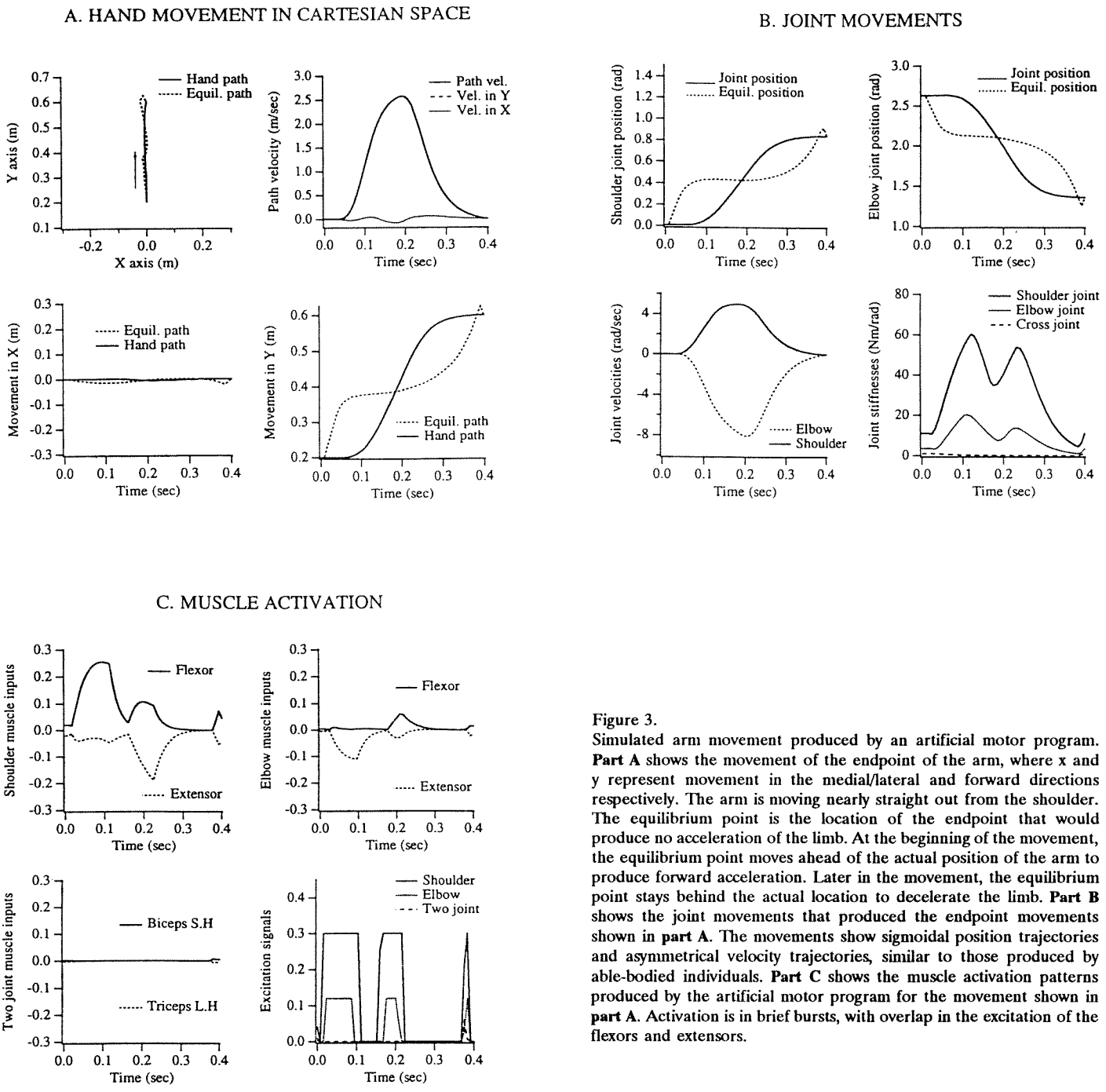

Figure 3.
Simulated arm movement produced by an artificial motor program. **Part A** shows the movement of the endpoint of the arm, where x and y represent movement in the medial/lateral and forward directions respectively. The arm is moving nearly straight out from the shoulder. The equilibrium point is the location of the endpoint that would produce no acceleration of the limb. At the beginning of the movement, the equilibrium point moves ahead of the actual position of the arm to produce forward acceleration. Later in the movement, the equilibrium point stays behind the actual location to decelerate the limb. **Part B** shows the joint movements that produced the endpoint movements shown in **part A**. The movements show sigmoidal position trajectories and asymmetrical velocity trajectories, similar to those produced by able-bodied individuals. **Part C** shows the muscle activation patterns produced by the artificial motor program for the movement shown in **part A**. Activation is in brief bursts, with overlap in the excitation of the flexors and extensors.

judged by accuracy of the angle reached, degree of compensation for fatigue, degree of compensation for disturbances, and ability to minimize stimulation. Four control strategies were compared: 1) open-loop (i.e., feedforward control with an optimized pre-set stimulation pattern); 2) feedback control to follow pre-set reference trajectories; 3) cycle-to-cycle control (open-loop during each cycle, comparison with objective and adjustment of the stimulation pattern for the next cycle); and 4) model-based predictive control (23). In model-based predictive control, adjustment for disturbances is attempted during the same cycle. This is only possible if one can estimate (predict) at each point during the cycle whether or not the objective (in this case, the knee joint

angle) will be reached. Such a prediction requires a model of the system, and therefore the first objective of this study was to develop such a model.

Identification of a Model for Control

An important need in adaptive control is a model that can be used to adjust the stimulation pattern on the basis of recent system behavior. In the case of the swinging shank, the controlled system includes a passive component (the shank and knee) which can be modelled as a pendulum with an angle dependence, gravity, stiffness, damping, and an inertia. The second active component consists of the stimulated muscle. The muscle models that were considered included activation dynamics with a delay, angular velocity dependence, and angle dependence. Thus, the combined passive and active model components would allow prediction of the angle trajectory that would be achieved by a series of stimulation pulses.

The Dutch researchers identified a model of the stimulation controlled shank in a series of experiments in which the quadriceps was stimulated in a random way such that the whole range of combinations of angle and angular velocity was covered. Knee joint angle, angular velocity and acceleration were measured during the stimulation, as shown in **Figure 4a, b,** and **c**. The subject was seated with the lower leg free to move (24,25).

The slow-varying part of the angular accelerations (**Figure 4c**) are due to the passive dynamics of the swinging leg and the effects of gravity. The sharp peaks are the result of the stimulation. Peak heights vary with angle and angular velocity due to muscle length-tension and force-velocity properties. In order to estimate the accelerations due to muscle stimulation alone, Franken and colleagues at Twente used the slowly varying components to model the behavior of the leg between the pulses (24). The passive model was then used to subtract the passive contributions from the total acceleration. The remaining active muscle contribution is plotted as the acceleration due to the muscle stimulation in **Figure 4d**.

The muscle model selected was the simplest among four that were evaluated (25). It involved only a gain and a delay and did as well as the model with activation dynamics in predicting joint angle trajectory. Prediction results for 100 ms and 1000 ms ahead are shown in **Figure 5**. Since muscle fatigue would be apparent in the muscle gain, it was estimated adaptively.

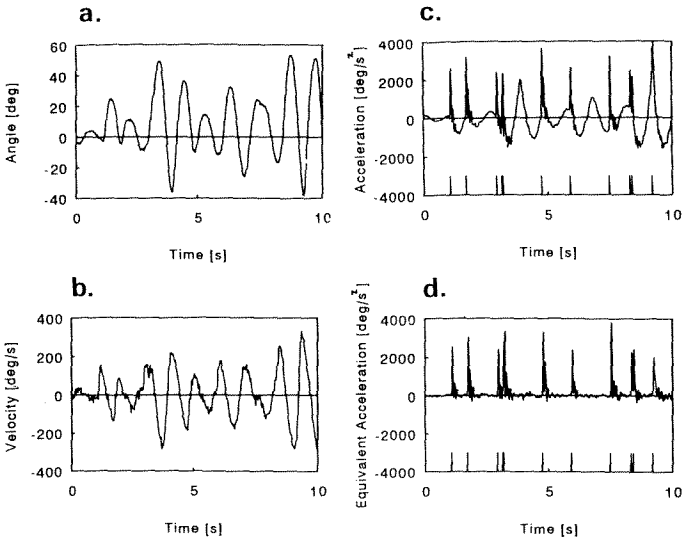

Figure 4.
Measured and estimated signals of the freely swinging shank system. The quadriceps were stimulated with a pseudorandom interpulse interval (IPI) stimulation sequence at maximal recruitment. a. the measured knee angle. b. knee angular velocity estimated from the angle signal. c. the measured angular acceleration and applied stimulation pulses. d. the estimated equivalent acceleration M/I due to quadriceps stimulation. M/I was obtained by subtracting the contribution of the passive system from the measured angular acceleration. Each sample of M/I resulted from substitution of measured knee angle, angular velocity, and accleration in the identified model for the passive system. The stimulation pulses are also shown. Reprinted with permission from Franken HM, Veltink PH, Tijsmans R, Nijmeijer H, Boom HBK. Identification of quadriceps-shank dynamics using randomized interpulse interval stimulation: IEEE Trans Rehab Eng 1995:3:182–92, © 1995 IEEE.

Experimental Comparison of the Four Control Strategies

Three types of tests were used to evaluate the four control strategies: open-loop, trajectory-following, cycle-to-cycle, and predictive control. All four were tested for control and regulation of knee extension in sitting subjects. In addition, cycle-to-cycle control was compared to open-loop control in tests with subjects standing and walking.

In tests of all four strategies, subjects sat with their shanks free to swing forward under control of the stimulated quadriceps (see **Figure 6**). Every 3 sec a new movement was initiated from a resting position. For some trials a freely hanging basketball obstructed the motion. In these comparisons, the cycle-to-cycle and model-based predictive controllers performed better than the open-loop and trajectory-following controllers with respect to accuracy after disturbance of the swing

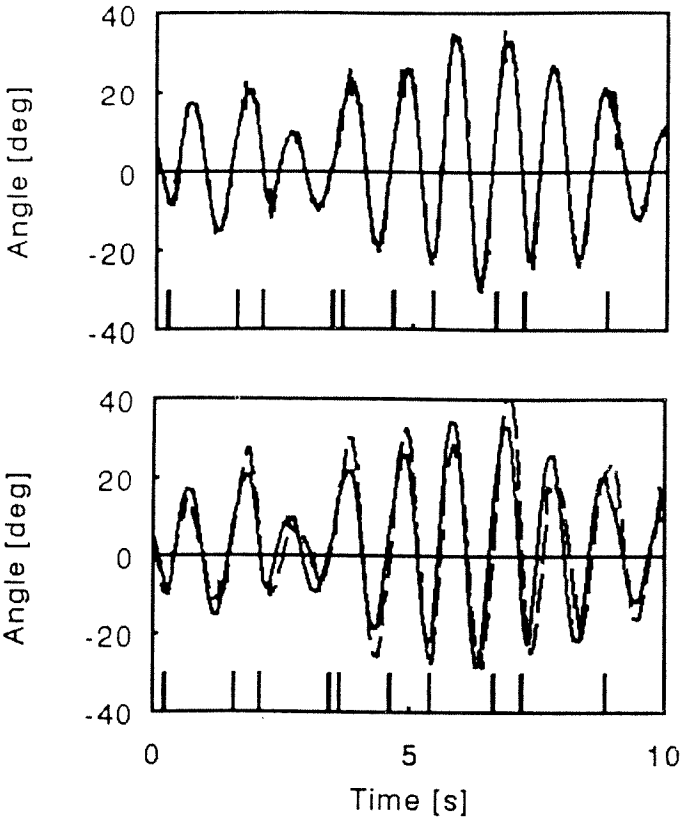

Figure 5.
Actual (solid) and estimated (dashed) knee angle in subject JM-left, using the simplest muscle model. Each point in the graph for the estimated knee angle followed from a prediction ahead for a period of 100 ms (top) or 1000 ms (bottom). Adapted from Franken HM, Veltink PH, Tijsmans R, Nijmeijer H, Boom HBK. Identification of quadriceps-shank dynamics using randomized interpulse interval stimulation: IEEE Trans Rehab Eng 1995:3:182–92, © 1995 IEEE.

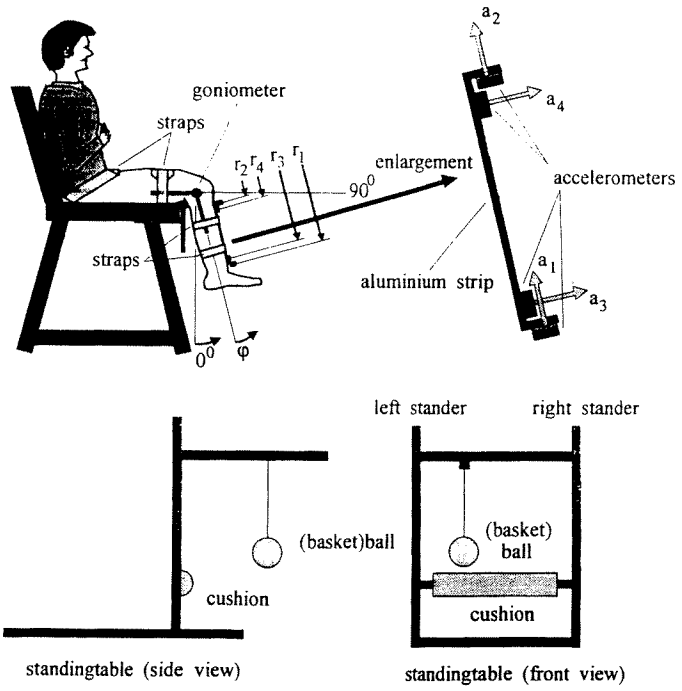

Figure 6.
Experimental setup for testing control strategies of lower leg swing with paraplegic subject seated.

and adaptation to fatigue. Model-based control was the only strategy that corrected for disturbances during a cycle; this occurred when the disturbance was early in the cycle, but not in all instances.

In the next set of comparisons, attempts were made to generate stepping-like movements from stance. The subject wore a reciprocating gait orthosis (RGO), and stood in a standing table, as shown in **Figure 7** (26). Surface stimulation at 50 Hz was applied to hamstrings, quadriceps, and hip flexors. The cycle-to-cycle control strategy was compared to the open-loop strategy. In the cycle-to-cycle strategy, movement parameters at the end of each cycle were compared to the gait objectives, and the stimulation for the next cycle was adjusted on the basis of the error in the preceding cycle. This test was restricted to adjustment of hip flexor stimulation. Objectives were constant hip angle range (equivalent to constant step length), foot clearance, and knee extension at the end of the swing phase. For open-loop control, an optimized stimulation pattern was developed to yield these objectives, as shown in **Figure 8**. Each cycle began with stimulation of the hamstrings (for foot clearance), followed by the hip flexors (to swing the leg forward), and finally the quadriceps (to extend the knee).

Open-loop control produced a large overshoot in the hip angle range at the start. Over the next few hundred cycles, the range decreased below the target level as the muscles fatigued. In comparison, with cycle-to-cycle control the overshoot was shorter, with the angle well regulated at the target level.

Finally, some of these control elements were incorporated into the stimulation system. In complete T5–6 level SCI subjects, Franken and colleagues used a hybrid system to provide surface stimulation to the quadriceps, hamstrings, and hip flexors, together with an RGO (27). While not an optimal neuroprosthetic system, it was adequate to allow testing of these control methods. A high level control allowed the user to initiate each step. This was a finite state system similar to ones reported by others (28). Sensors (a hip goniometer and a crutch force sensor) allowed the user to start each step without having to operate a hand switch. Addition of the cycle-to-cycle controller suc-

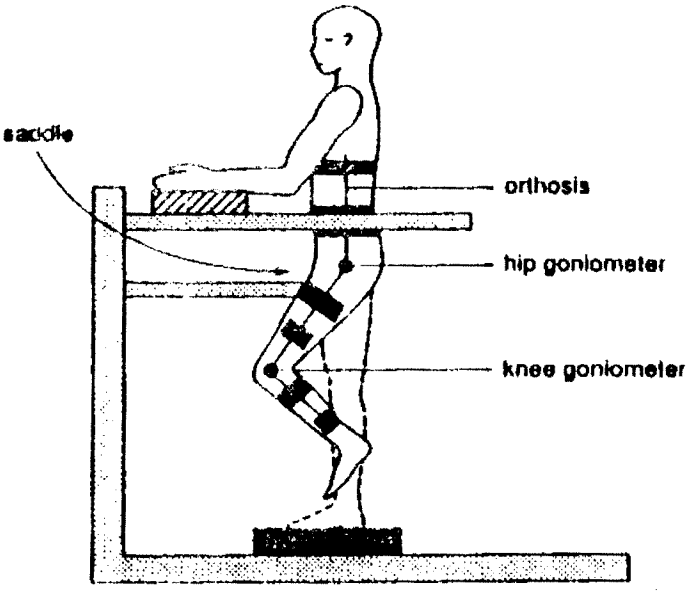

Figure 7.
Experimental setup for testing control strategies of leg swing while paraplegic subject was standing. Subject wore a self-fitting modular orthosis that restricted motion of the freely swing-leg to the sagittal plan with a locked ankle joint. Hip, knee, and ankle of the supporting leg were locked; the standing leg was elevated by a block; a bicycle saddle provided additional support. Trunk and pelvis movements in the sagittal and frontal plane were prevented by the setup. Hip and knee angles of the freely swinging leg were measured by externally mounted goniometers. Reprinted with permission (26).

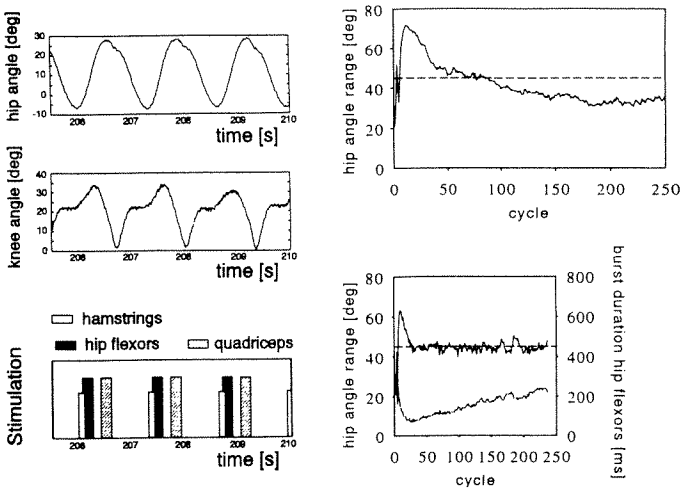

Figure 8.
Results of stimulation trials. Left: hip and knee angle and stimulation onset and duration during the open-loop stimulation trial in subject A with optimised stimulation for the three muscle groups: hip flexors, quadriceps, and hamstrings. Stimulation sequences were applied without adaptation. Upper right: hip angle range per swing cycle obtained in the open-loop controlled stimulation trial with optimized stimulation timing for the three muscle groups in subject A. The desired value for each swing phase objective is indicated by the dotted line. Lower right: hip angle range (solid) and hip flexor burst duraton (dash-dot) per swing cycle obtained in a cycle-to-cycle controlled stimulation trial in subject A. Hip flexor stimulaton burst duration was adapted from cycle-to-cycle with the onset remaining unchanged. Stimulation onset and burst duration for hamstrings and quadriceps were identical to the open-loop experiment settings. Reprinted with permission (26).

cessfully adjusted stimulation bursts on the two sides to make the gait symmetrical. Effectiveness of the controller was limited by the limited range of electrically activated hip torques that could be generated and by the movement limitations imposed by the RGO.

In summary, the best control was achieved by attempting to meet naturally perceived gait objectives rather than following an exact joint angle trajectory. Adaptive feedforward control, as implemented in the cycle-to-cycle controller, gave good compensation for the gradual decrease in performance observed with open-loop control. Disturbances during a cycle may be adjusted for with a model-based predictive control strategy. The model does not need to include the activation dynamics of muscle, since in this case performance is limited by the inertia of the limb segment being controlled.

Neural Network Algorithms in Locomotion Control

Neural networks have been applied in a wide variety of engineering problems that involve pattern recognition, pattern classification, adaptive filtering, and control. In an engineering block diagram, a neural network is a block that receives inputs, performs some calculations, and generates outputs. It is called a neural network because the algorithm used in its internal processing is based on models of nervous system function. The underlying idea is that each neuron generates output based on the inputs that it receives from other neurons. The pattern of interconnections among neurons determines the network architecture. Neurons may receive inputs from or send outputs to other system components. The interconnection strengths among neurons are often adapted using a learning algorithm to modify the input-output properties of the network. The capability of learning complex nonlinear input-output mappings is often the characteristic that makes neural networks an attractive option in engineering design.

The development of new algorithms and architectures and the application of existing algorithms are both

active areas of research. In one approach, new neural networks incorporate more complex biological features such as the capacity to generate complex oscillatory patterns. The authors believe that a practical FNS control system must exhibit many features of neurophysiological systems. Neural network techniques, when used in conjunction with other engineering control system and signal processing techniques, may be a viable approach to achieving this goal.

The nonlinear processing capabilities of neural networks make them attractive for use in many biomedical problems. Also, their adaptive capabilities make neural networks particularly attractive for use in rehabilitation applications where the engineering system must often be customized for a particular individual. Several researchers have previously used neural networks in FNS systems. Veltink et al. used neural networks to generate stimulation patterns by learning the mappings between biomechanical output variables and EMG signals from normal subjects (29). Lan et al. used neural networks to generate muscle stimulation patterns for the control of arm movements (30). Kostov et al. used adaptive logic networks (which are similar to neural networks) to provide switching signals to a multistate FNS controller (31). The successes of these studies, along with the results reported here, indicate that neural networks may be useful in many components of a variety of FNS control systems.

This section describes a neural network (both the architecture and learning algorithm) that was developed by Abbas and colleagues for the purpose of controlling cyclic movements in an FNS system (32–34). The long-term objective of this work is the development of control systems for FNS locomotion. In such an FNS control system, the major problems to be addressed are: 1) each patient is different in terms of strength, recruitment properties, weight, height, and so forth; 2) muscle response properties change due to fatigue; and 3) the external environment is uncertain. Here, our focus is on the first problem, intersubject variability, which arises on a practical level when an FNS system is tuned for a particular user. Automatically customizing the control system addresses the first problem and may also be able to address the problem of muscle fatigue, provided the customization can be performed on-line and rapidly. The problem of the uncertain environment, which is not addressed here, may require the use of controllers that exploit the inherent stiffness properties of muscle and/or those that use feedback or predictive control as described above.

Abbas and colleagues developed a control system that utilizes one neural network as a pattern generator and a second neural network as an adaptive filter. They conducted experiments on simple, one-segment systems, constituting the first stages of the evaluation of the control system. The first set of experiments was performed on computer-simulated models of a single-segment skeletal system; the second set of experiments was performed on seated human subjects. Results indicate that the control system performs well on these simpler systems; thus, further evaluation on more complex systems is warranted.

Design of Neural Network Controller

The control system builds on a general model of the neurophysiological control system for locomotion, which consists of three components: a spinal pattern generator, which is responsible for generating the basic locomotor rhythms; the spinal segmental circuits, which filter the signals from the pattern generator and send outputs to the muscles; and supraspinal centers, which influence both the spinal pattern generator and the spinal segmental circuitry. Paralleling their best understanding of this natural system, Abbas and Chizeck have built a control system that has a pattern generator (PG) and a pattern shaper (PS), see **Figure 9** (32,34). This control system does not yet include the supraspinal centers. The PG generates the basic rhythm for control

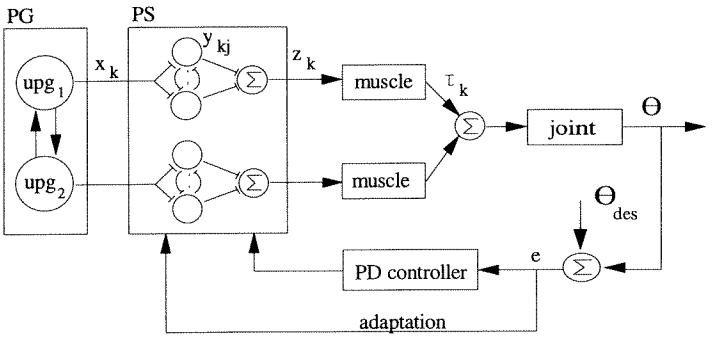

Figure 9.
PG/PS Control System Block Diagram. The control system consists of two components: the pattern generator (PG) and the pattern shaper (PS). Outputs from the PG are adaptively filtered by the PS before being sent to the muscles. The objective of the control system was to track the desired joint angle trajectory in the simulation studies and to track a desired torque trajectory in the experiments on human subjects. The feedback controller was active in some of the simulation runs but it was inactive in all experiments on human subjects.

ling a given movement. The PS adaptively filters those signals and sends its output to the muscles. The adaptive properties of the PS provide the control system with the ability to customize stimulation parameters for a particular individual and to adjust them on-line to account for fatigue. In some of the computer simulation experiments reported below, a proportional-derivative feedback controller was also active.

The PG is a set of coupled neural oscillators, based on a model of neural circuitry (35). In this work, the PG was chosen to generate two outputs: one to drive the flexor muscle and one to drive the extensor muscles. Each output from the PG first passes through a PS unit, which adaptively filters the signal before it is sent to the muscle. Each PS unit consists of a set of 16 neurons. The output of the PS unit is the weighted summation of the outputs of the neurons in the unit. The learning algorithm uses a tracking error signal to adjust the weights on this summation (34). A novel feature of the learning developed for use in this controller is the manner in which past stimulation values are related to tracking errors at the current time. This allows the learning algorithm to account for the delay and the dynamics of the musculoskeletal system response. It is important to note that the adaptation of the controller parameters does not require an explicit model of the system being controlled. It only assumes the direction in which a muscle will act (i.e., more stimulation to the flexor will produce more flexion) and that tracking errors at the current time can be attributed to stimulation values over the past several time steps. In summary, the operation of the PG/PS controller can be described as follows: the PG provides the basic pattern of activation for each of the muscles for a particular movement and the PS provides fine tuning of that pattern for a particular individual.

Evaluation of Neural Network Controller in Simulation

Computer simulation studies were used in the development and evaluation of the control system. These studies (34) used a model of a single skeletal segment in a swinging pendulum and in an inverted pendulum configuration that included linear stiffness and damping. The skeletal segment was acted upon by an agonist/antagonist pair of muscles. For each muscle, the torque generated was modeled as the product of three terms: an activation term (that included nonlinear recruitment and linear dynamics), a torque-angular velocity term (to account for the length-tension properties of muscle), and a torque-angle term (to account for the force-velocity properties of muscle).

One component of the evaluation sought to characterize the controller's ability to automatically determine an appropriate set of stimulation parameters to generate a specified movement in a given individual. Here, the pattern generator was configured to provide an oscillatory signal at a frequency of 1 Hz, and the pattern shaper output weights were initialized to 0 (therefore without adaptation, no stimulation would be sent). The desired joint angle trajectory was specified to be a 1 Hz sinusoid with an amplitude of 20°. The network was trained for 20 cycles with the feedback controller active. **Figure 10** demonstrates that good tracking was achieved after only a few cycles and that the tracking performance was maintained (RMS tracking error is less than 0.5°) after the feedback controller had been inactivated, thus indicating that the PS had adapted so than an appropriate feedforward stimulation pattern was delivered to the muscles.

In order to determine if the PS could adapt to generate the same movement on different individuals, several trials were conducted with the same computer simulation experiment described above on the same system model, but the parameters of the model were varied from trial to trial. Seven system parameters (muscle gain, torque-angle width, torque-velocity slope, maximum shortening velocity, segment mass, joint stiffness, and joint damping) were varied over a range of ±50 percent in increments of 10 percent to generate 71 different systems on which to test the adaptation algorithm. In each of these trials, the RMS error of the feedforward controller was approximately 0.5°, which is about 1 percent of peak-to-peak amplitude of the signal being tracked. These results indicate that the network was able to customize the stimulation parameters for each of the 71 model variations.

Similar tests on an inverted pendulum have indicated that the network was able to customize the stimulation parameters to generate the desired movement of this inherently unstable system and thus achieve very good tracking without the use of feedback control. Other tests using computer simulations were performed in order to determine the effects of measurement noise and disturbances on both the adaptation and the feedforward tracking performance. These tests indicated that the performance of the network was degraded, but still within acceptable limits, for large values of measurement noise and mechanical disturbances (34).

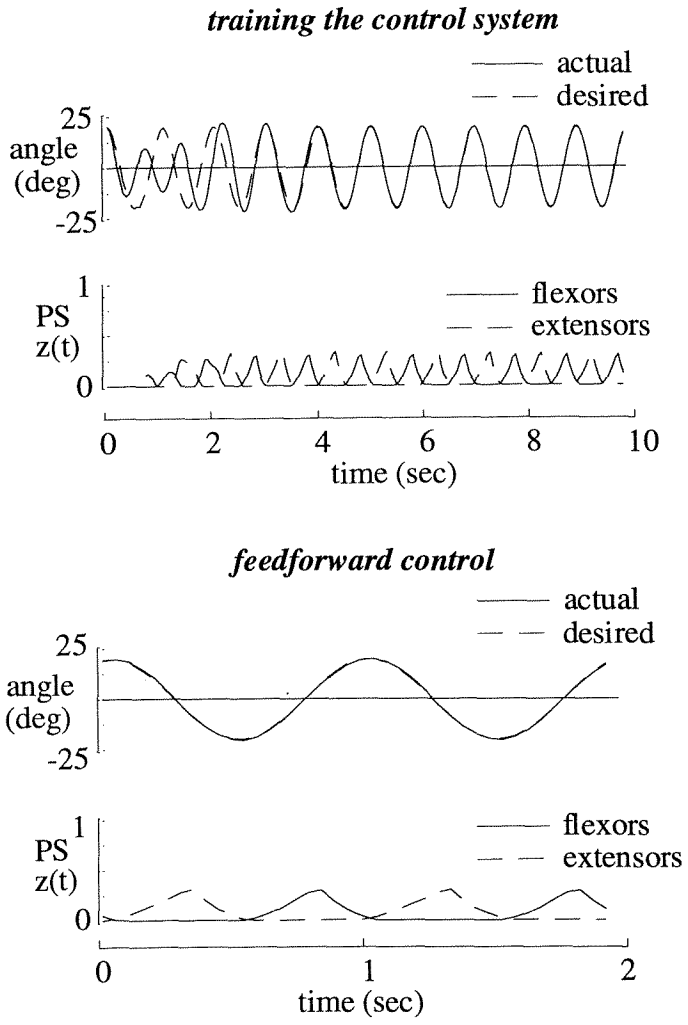

Figure 10.
Simulation results demonstrating that rapid training achieved by the control system (top) and that excellent tracking is achieved by the feedforward controller after adaptation was complete (bottom). The actual and desired traces virtually overlap.

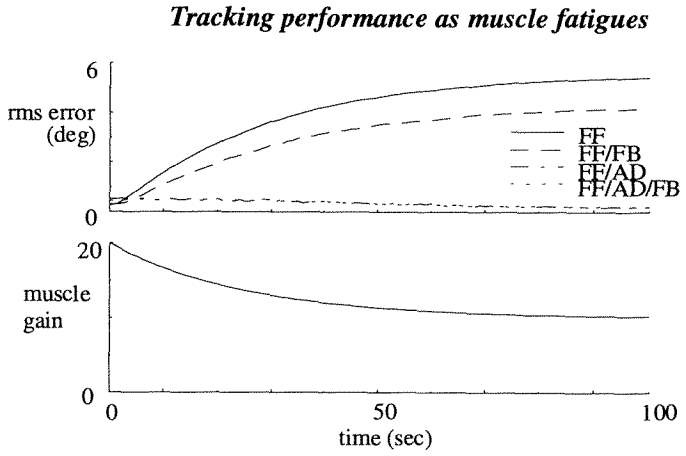

Figure 11.
Simulation results demonstrating that tracking performance is maintained as muscle fatigues if adaptation is enabled. The bottom trace shows the drop in muscle gain through the course of the trial, the top set of traces shows the tracking performance (RMS value of the tracking error) of each of the controller configurations tested. The performance of the non-adaptive controllers (FF, FF/FB) degrades as fatigue sets in, but the adaptive controllers (FF/AD and FF/AD/FB) maintain very good tracking performance throughout the trial (note that these two traces virtually overlap).

In another stage of the evaluation, Abbas sought to characterize the performance of the controller under conditions of muscle fatigue. In these sets of experiments, he first trained the controller on a system that was not fatiguing for 20 cycles of movement; then he introduced muscle fatigue by producing an asymptotic decay of muscle gain to 50 percent of its original value, as shown in **Figure 11**. He examined the performance of four controllers: the feedforward controller that already had been trained, feedforward with feedback, feedforward with adaptation, and feedforward with both adaptation and feedback. The results shown in **Figure 11** indicate that performance degrades with fatigue for the feedforward or the feedforward with feedback control configurations and that performance is maintained when the adaptation is enabled. Thus, the adaptive properties of the PS provide the controller with the ability to compensate for muscle fatigue.

To summarize this section, computer simulation studies have been used to characterize the performance of the PG/PS neural network control system. It is capable of customizing the stimulation parameters to generate a given movement in a variety of simulated systems and it is able to adjust those parameters on-line in order to account for simulated muscle fatigue.

Evaluation of Neural Network Controller in Experiments on Human Subjects

Although computer simulations are a useful tool for iterative development of FNS control systems, experimentation on human subjects is still required to assess the performance of the control system. In the first evaluation of this control system in humans, the task of the controller was to control isometric muscle torque in

seated subjects (33). The main objective here was to determine if the control system could customize stimulation parameters in order to generate a cyclic torque trajectory signal that included ramp-up, ramp-down, and rest periods (desired torque trajectory is shown in **Figure 12**). A second objective was to determine whether it could adapt stimulation parameters to maintain tracking performance in the presence of muscle fatigue.

Four SCI subjects with intramuscular electrodes implanted bilaterally in the quadriceps muscle group were included in the study. Subjects were seated in a dynamometer with their knee angles fixed at 20°. Quadriceps were stimulated at 20 Hz with the controller determining the pulsewidth. In these studies, the feedback controller was not active and thus the results presented demonstrate tracking performance of an adaptive feedforward controller.

Sample traces from one experimental trial that lasted 300 sec (120 cycles) are shown in **Figure 12**. These data demonstrate that the control system adapted within a few cycles to generate the desired torque trajectory with this muscle and that the tracking performance was still maintained at the end of the trial. Note that the stimulation values sent towards the end of the trial were much higher than those at the beginning of the trial. This indicates that the muscle had apparently fatigued: the controller was using higher stimulation values to generate the same torque trajectory. This is demonstrated again in **Figure 13**, where the maximum pulsewidth in each cycle was plotted along with the RMS value of the tracking error in each cycle for the same muscle on three days of experiments. On each day, the controller maintained tracking performance by adapting the stimulation parameters during the course of the experimental trial.

Similar results were obtained in experiments with the other muscles tested on the same four subjects (33). These results demonstrate the ability of the control system to customize stimulation parameters in order to generate a desired output trajectory in a given individual and to maintain tracking performance in the presence of muscle fatigue. Future work will use both computer simulation and experiments on human subjects to evaluate the ability of this neural network control system to generate single-joint and multijoint movements.

DISCUSSION

The primary emphasis of the control systems presented above is feedforward control. One aspect of this approach is the generation of stimulus patterns to produce coordinated movements. We have shown that a motor program for a novel movement does not have to be generated in an ad hoc experimental manner, but can

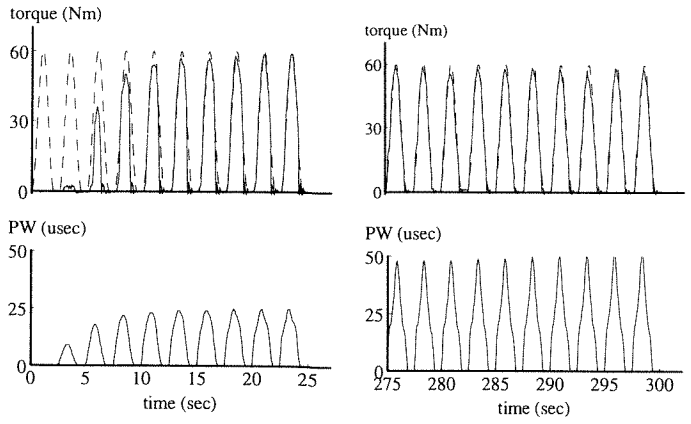

Figure 12.
Experimental results demonstrating that good tracking is achieved rapidly and maintained at the end of the trial. The two left panels show the stimulation pulsewidth (PW) trajectory and the actual (solid) and desired (dashed) torque traces for the first ten cycles of an experimental trial. The two right panels show the same variables for the last ten cycles of a trial that consisted of 120 cycles with each cycle lasting 2.5 seconds.

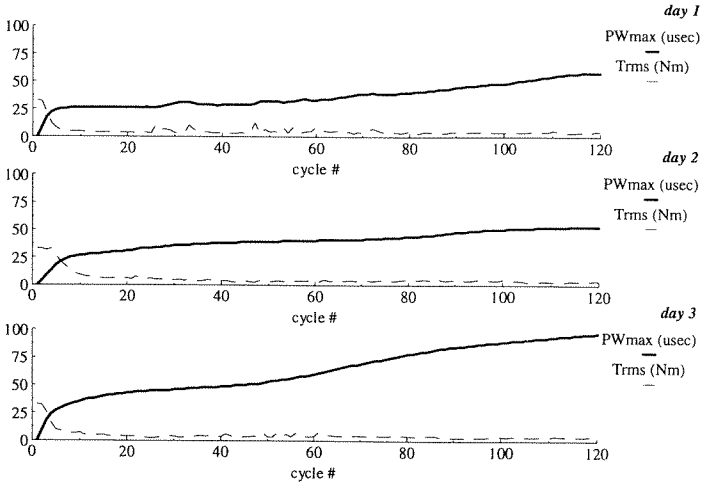

Figure 13.
Experimental results demonstrating that good tracking performance is maintained throughout the trial but that the stimulation required to achieve the good tracking increases steadily throughout the trial. The three panels show the RMS value of the torque tracking error (dashed lines) and the peak value of the pulsewidth within a given cycle (solid lines) on each of three different experiment days.

be generated computationally by application of simple principles. Another aspect of fundamental importance in feedforward control is adaptation when the details of the controlled system are unknown to begin with, and are subject to temporal variations. The two systems for lower extremity control described above showed rapid adaptation to meet the needs for individual subjects and to compensate for fatigue.

All the results presented were obtained under limited, well controlled conditions or in computer simulation. This is appropriate since the objective was to show the feasibility of novel control approaches to meet the needs of the more complex clinical problem. It is likely that many different approaches will have to be combined to implement automatic control in clinical systems. Different phases of motor tasks will require different solutions. For example, rapid arm movements or the swing phase of gait may require adaptive feedforward control such as demonstrated above. A method of implementing such control clinically for control of gait is under development at the Cleveland VA Medical Center. The adaptive function is effected by a gait evaluator that incorporates rules developed from expert knowledge of the system[1]. In contrast to the gait cycle, the stance phase of gait, quiet standing, or maintenance of a stable arm posture may benefit from feedback control in addition to feedforward control and adaptation.

Several lower extremity motor neuroprostheses incorporate orthoses which reduce the number of degrees of freedom to be controlled, provide support and assist balance, and offer mounting sites for mechanical sensors (36–39). While these orthoses may decrease the number of muscles that need to be stimulated to produce stepping or walking, in their present form, they interfere with the full range of electrically-activated motions[2]. Another element that demands consideration in designing control methods is the neuroprosthesis user's residual voluntary function.

Many difficulties still lie ahead for integrating automatic control techniques into motor system neuroprostheses. One of these difficulties is sensors. By necessity, anything other than pure feedforward control relies on sensors to measure the movement outcomes. Sensors must 1) identify the phase or state of a movement task to determine what controls are to be enforced at a given time, and 2) provide information about the performance of the stimulated limb to be used for feedback corrections, feedforward commands, or adaptation to changing conditions (40).

While most of the variables to be measured are routine for conventional engineering systems, they present formidable challenges in neuroprosthetic applications. The challenges include 1) development of sensors of small size, 2) mounting the sensors on (or in) the person in an unobtrusive and cosmetically acceptable manner, 3) providing communication of power and information to and from the sensor and the point of control processing, and 4) developing sensor signal processing methods. The use of natural sensors (as described by Hoffer et al. in this issue) may solve the first two problems, but greatly increases the difficulties of signal acquisition and processing.

The difficulties outlined above are likely to limit the rate at which advanced control techniques are integrated into motor system neuroprostheses. However, the significant increase in performance achieved makes such an approach highly attractive, and in many cases mandatory.

[1] H. Chizeck, personal communication, July 1994.

[2] D. Popovic, personal communication, July 1994.

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