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**Neural network control of functional neuromuscular stimulation
systems**

Abbas, James Joseph, Ph.D.

Case Western Reserve University, 1992

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***NEURAL NETWORK CONTROL OF
FUNCTIONAL NEUROMUSCULAR STIMULATION SYSTEMS***

by

JAMES JOSEPH ABBAS

Submitted in partial fulfillment of the requirements
for the Degree of Doctor of Philosophy

Thesis Advisor: Howard Jay Chizeck, Sc.D.

Department of Biomedical Engineering
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August 1992

CASE WESTERN RESERVE UNIVERSITY
GRADUATE STUDIES

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NEURAL NETWORK CONTROL OF FUNCTIONAL NEUROMUSCULAR STIMULATION SYSTEMS

ABSTRACT

by

JAMES JOSEPH ABBAS

A neural network control system has been designed for the purpose of controlling cyclic movements in Functional Neuromuscular Stimulation (FNS) systems. The design of the control system directly addresses three problems faced in the implementation of FNS control systems: customizing the control system parameters for a particular individual, adapting these parameters to account for changes in the musculoskeletal system, and resisting mechanical disturbances.

The control system is implemented by a two-stage neural network that utilizes adaptive feedforward and feedback control techniques. The first stage of the neural network, the Pattern Generator, generates a cyclic pattern of activity. The design of this stage is based upon neural models of vertebrate motor control systems. The signals from the Pattern Generator are adaptively filtered by the second stage, the Pattern Shaper. A learning algorithm that accounts for system dynamics and input time delays was developed for use in adapting the Pattern Shaper filtering properties.

Computer simulated models of electrically stimulated muscles acting on one- and two-segment skeletal systems were used to assess the potential utility of the neural network control system in FNS control. Results of the evaluation demonstrated that the control system can automatically customize stimulation parameters, adapt them on-line, and resist mechanical disturbances. The control system was also demonstrated to be capable of controlling movements of multi-joint systems and of utilizing biarticular muscle effectively. The success of the control system in this evaluation indicates that it may provide significant improvements to existing FNS control system technology and suggests that the technique should be investigated further.

These studies also indicate that this strategy may be appropriate for other applications in the control of dynamic, nonlinear systems with input time delays. The use of biologically motivated neural networks in the Pattern Generator provides this control system with unique features that are not readily available using existing control system techniques. The learning algorithm developed for use in the Pattern Shaper is particularly well-suited for use in engineering neural network control systems because it provides the ability to account for system dynamics and input time delays.

Dedication

To Ranu.

The mind stretched to a new idea never returns to its original dimension.

- Oliver Wendell Holmes

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Chapter 1. Introduction

Statement of the problem

In recent years, Functional Neuromuscular Stimulation (FNS) systems have been developed to assist people with neurological disorders such as those caused by spinal cord injury, stroke and head injury. These systems, which operate by electrically activating paralyzed muscles, are presently used primarily in experimental settings. Current research is directed at improving the various components of the FNS technology so that it can be used on a clinical basis. The work presented here is directed at improving the control component of the FNS system. Three major problems with FNS control systems are addressed by this work:

- ▶ *First, the stimulation parameters must be customized for each individual.* In order to generate a desired posture or movement, stimulation parameters must be specified for each muscle of each individual. Currently, a trial-and-error method is used which is time-consuming and unreliable.
- ▶ *Second, musculoskeletal system properties may change while the system is functioning.* Currently, stimulation parameters are fixed, and thus

performance will degrade as system properties change, *e.g.*, due to muscle fatigue.

- ▶ *Third, mechanical disturbances to the musculoskeletal system are always present.* Most current FNS systems do not use feedback information to determine stimulus parameters and thus do not perform well in the presence of disturbances.

Objectives

The long-term goal of this work is the development of lower extremity FNS systems which will be practical for everyday use by paraplegic individuals. The first objective of the work presented here was to design a control system to address each of the three major problems faced in the control of FNS systems that were stated above. The design of the control system was directed at providing:

- ▶ *automated customization* of control system parameters for a particular individual,
- ▶ *on-line adaptation* of control system parameters to account for changes in musculoskeletal system properties, and
- ▶ *disturbance resistance* to respond to mechanical perturbations.

The second objective of the work presented here was to evaluate the control system using computer simulated models of one-segment and two-segment musculoskeletal systems. The evaluation was directed at assessing the ability of the control system to provide each of the three features listed above.

Overview

A neural network control system has been designed for the purpose of controlling cyclic movements in lower extremity Functional Neuromuscular Stimulation systems. The design of the control system is based upon neural models of locomotor control and utilizes artificial neural network techniques. The control system was evaluated in a series of studies on computer simulated musculoskeletal models. These studies demonstrated that the control system addresses each of the three problems stated earlier by providing automated customization, on-line adaptation, and disturbance resistance. The success of the control system in this evaluation indicates that it may provide significant improvements to existing FNS control system technology and suggests that the technique should be investigated further.

The remaining chapters of this thesis document describe the work performed to achieve the stated objectives. Chapter 2 presents a review of the relevant literature and the rationale for the approach used to design and evaluate the control system.

Chapter 3 describes the design of the control system and Chapter 4 presents the evaluation of the control system on computer simulated musculoskeletal models. In Chapter 5, the implications of this work are discussed and proposals for future work are presented.

Chapter 2. Literature review and rationale

Literature review

Functional Neuromuscular Stimulation control systems

Functional Neuromuscular Stimulation (FNS) has been developed as a rehabilitative technology for people with neurological disorders such as those caused by spinal cord injury, stroke and head injury [26,31,39]. For people with disorders affecting the lower extremity, conventional treatment often utilizes long-leg braces to allow the patient to stand and to take steps. However, braces are rarely used regularly by patients [41] because they do not provide stable posture or efficient locomotion, they are difficult to use, and they are cosmetically unappealing. FNS has the potential to offer many advantages to bracing technology. In recent years there have been many significant developments in experimental FNS systems, but many of the components of these systems must be improved before they can be used clinically [12,31]. One such component is the FNS control system.

In FNS systems, a train of computer-controlled electrical pulses is used to activate paralyzed muscles. The pulse train is characterized by the pulse amplitude, pulse width, and pulse frequency. Modulating each of these parameters affects the

level of activation of a muscle, and hence the amount of force generated by it [13]. The function of the control system is to specify the parameters of the stimuli sent to the muscles. Many FNS systems fix two of the parameters and use either pulse width modulation, or pulse amplitude modulation to vary the level of muscle activation [13,26].

The FNS control system may include one, or several, of the components shown in the block diagram in Figure 1. As shown in the diagram, one possible component is a feedforward controller, which is used to provide an input sequence that has been predetermined. Feedback components can be used to supplement the signal from the feedforward controller or to trigger the feedforward controller. Adaptive components can be used to adjust parameters of the feedforward controller and/or the feedback controller. The sensor measurements can be used for two distinct purposes: either to influence the current operation of the control system via the feedback loop or to influence future (and current) operation of the control system via the adaptation loop.

Many FNS control systems operate in a feedforward or sensor-triggered feedforward manner in which the stimulation parameters are customized for each individual using a trial-and-error method [*e.g.* 31]. These systems have been successful in demonstrating the feasibility of using electrical stimulation to restore various functions. They have also demonstrated many of the shortcomings of this approach and have helped to identify areas in which improvements are needed before

FNS systems can be used extensively on a clinical basis [12,26]. Much of the previous work in FNS control system development has focused on providing the control system with three important features: 1) improved customization procedures for selecting the parameters of the feedforward or feedback controllers, 2) on-line adaptation of the parameters of the feedforward or feedback controllers, and 3) improved feedback control techniques.

Most efforts at improving the customization procedure have been aimed at the development of user-friendly software interfaces for the engineer/therapist [e.g. 32]. These efforts have provided some improvements, but the customization procedure still requires a substantial amount of effort from the engineer/therapist. There are no reports in the literature of automated customization procedures for feedforward controller parameters. A recent report describes an automated procedure for selecting feedback controller parameters [28]. This procedure significantly reduces the amount of time required for experimental evaluation of the feedback controller, but the procedure is not appropriate for clinical use.

There are also no reports in the literature of on-line adjustments to feedforward, or 'open-loop', controller parameters. Several groups, however, have investigated the use of adaptive closed-loop controllers which provide on-line adaptation of the parameters of a closed-loop controller [2,8]. One implementation of an adaptive closed-loop controller has been shown to provide good control of muscle force in a single-joint cat preparation [8,27]. One problem with this approach

is that proper adaptation can only occur under certain conditions, which cannot be assured in most FNS applications. A second problem is present in closed-loop controllers in general, and is described below.

Several types of closed-loop control have been investigated for use in FNS systems [e.g. 1,4,22,27]. They have been demonstrated to provide disturbance resistance and setpoint tracking capabilities under certain conditions. Their usefulness in FNS systems is limited by the availability and accuracy of sensor information and by the time delay inherent in muscle activation. The lack of accurate sensor information limits the choice of output variables to be controlled; the time delay limits the reaction time of the controller. Thus, a closed-loop control system which is completely driven by sensor information may be inadequate for many applications. A more practical approach may be to use a control system with both feedforward and feedback control system components. A recent study utilizing such an arrangement has provided promising results [46].

In summary, previous work in the development of FNS control systems has provided some insight into the requirements on the control system and into the feasibility of various approaches. From these studies, it can be concluded that:

- ▶ the control system should utilize feedback to provide disturbance resistance,
- ▶ the control system should also utilize feedforward control in order to minimize the role of the feedback controller. This will help to avoid

instabilities due to time delays in the response of the muscle and to reduce the dependence of the control system on sensor measurements that may be noisy,

- ▶ the control system should be adaptive to provide the ability to automatically customize stimulation parameters and to adjust them on-line to account for changes in musculoskeletal system properties, and
- ▶ the adaptation should occur in the feedforward component in order to avoid problems inherent in adaptive feedback techniques.

That is, a practical approach to FNS control system development would utilize an adaptive feedforward component which is supplemented by a feedback component.

Engineering techniques for implementing feedback controllers are well-developed and may be suitable for this application if used in conjunction with an adaptive feedforward controller. However, engineering techniques that would be suitable for adaptive feedforward control in this application are currently not available. Recent advances in the development of neurophysiological models of motor control and in the development of adaptive neural network techniques suggest that an adaptive neural network-based control system may be suitable for use in an adaptive feedforward controller.

Neurolocomotor control systems

Various neurobiological studies have provided an extensive, but still limited, understanding of the neural structures involved in the control of locomotion [19,20]. These studies have indicated that the basic structure of the locomotor control system might include supraspinal centers, a spinal pattern generator, and a spinal pattern shaper [5,9,16,20,48]. In this model of the hierarchical organization, the basis of the control system is the spinal pattern generator which is responsible for generating the oscillatory signals to drive the locomotor movement. The supraspinal centers provide signals to regulate and modify the activity of the spinal pattern generator. The spinal pattern shaper filters the signals from the pattern generator and supraspinal centers to provide signals to the muscles. Afferent signals are used at all levels in this hierarchy to assist in the regulation of movement [3,14,18,29,30,43].

Studies on the pattern generating circuitry of experimental animals have described some of the mechanisms utilized by the nervous system to generate oscillatory signals. The oscillatory behavior of some neuronal circuits is primarily driven by intrinsic oscillatory membrane properties of an individual neuron in the circuit. The oscillatory behavior of other neuronal circuits results primarily from the interactions amongst the individual neurons in the circuit [*e.g.* 15,17]. Most oscillatory neuronal circuits, including the examples cited above, probably use a combination of these two mechanisms [*e.g.* 25,33,42]. For the control of oscillatory movements of multi-segmented and multi-limbed bodies, some models [*e.g.*

7,11,19,40] have proposed the existence of several unit central pattern generators (uPGs), each responsible for generating oscillatory movements of a body segment.

Recently, models have been developed for several different pattern generator circuits. These efforts have demonstrated that neural models which incorporate details of the cellular and network structure of neurobiological systems can reproduce many features that are characteristic of neural control systems. For example, the use of detailed neural models can provide such features as stable endogenous rhythm generation, frequency modulation, phase-resetting, and phase-dependent reflexes [*e.g.* 7,10,17].

Some important principles underlying the neural control of locomotion include:

- ▶ pattern generators are usually involved in providing signals to motoneurons,
- ▶ typically, pattern-generating activity is initiated and/or influenced by other neural centers and afferent inputs,
- ▶ complex motions which involve several body segments may involve the interaction of many unit pattern generator elements for the generation of the overall pattern, and
- ▶ motoneurons generate output based upon the integration of inputs from pattern generators, afferent inputs, and other neural centers.

These general organizational principles help to provide neurolocomotor control systems with the ability to generate complex, coordinated, rhythmic movements in an uncertain environment. These same principles may be useful in the design of FNS control systems.

Adaptive artificial neural network technology

Computational algorithms which mimic some of the basic features of nervous systems have been under investigation for some time and have recently found widespread engineering applications [23,44]. Typically, a neural network consists of a highly structured array of interconnected neurons, each of which represents the most basic of the properties attributed to real neurons. Neural networks can 'learn' by adjusting weights on interconnections amongst the various neurons in the network [24]. The purpose of the learning is to adapt the properties of the network to serve a particular function. The learning algorithm consists of the 'update equation', which is the particular equation used to adjust the weights, and a learning 'paradigm', which is the particular selection of the signals to be used in the learning algorithm.

The most commonly used forms of artificial neural networks utilize a static model of a neuron, and therefore the output of the network is a static function of the input to it. Similarly, the update equation typically utilizes information from the present time step and thus is useful when the function served by the network is a static one. Most learning paradigms utilize a general measure of performance to

adjust all the weights in the network and are thus termed ‘global’ learning paradigms. These types of networks are useful tools for performing a nonlinear mapping from one multidimensional space to another and have seen many successful applications in pattern recognition problems [21,44]. One characteristic that makes these types of networks attractive for many applications is their versatility. That is, in different situations, the same architecture can be trained to learn very different nonlinear mappings. Little, if any, knowledge of the structure of the nonlinear mapping is required. However, there is a tradeoff in that the versatility is obtained at the cost of long learning times. In many applications, tens of thousands of iterations are required to achieve adequate learning [24,44].

In recent years, many investigators have sought to utilize neural networks for the control of dynamic systems [*e.g.* 6,35,36,37,38]. In general, there are two major problems faced in utilizing neural network techniques for this application: the system to be controlled has dynamics and lengthy training times may be impractical.

One approach to addressing the problem of system dynamics has been to present delayed versions of the system output variables as inputs to the neural network [*e.g.* 37,38]. In this configuration, the neural network acts as a nonlinear feedback controller; system output variables are used as the inputs to the network, and the outputs of the network provide the inputs to the system to be controlled. Since the network is supplied with present and past values of the system outputs, it often can learn the inverse dynamics of the system and thus can function successfully

[37,38]. There are two reports in which this type of an approach was utilized in control system configurations intended for FNS applications [45,47]. One design used a neural network in a feedback linearization scheme [45]. The other used a neural network to learn to map kinematic variables to normal EMG activity patterns with the eventual goal of using the kinematic data to generate FNS stimulation patterns [47]. However, both of these designs, and other designs which utilized this type of an approach, require thousands of iterations for training, and thus may not be suitable for on-line operation. In addition, each of these designs is heavily dependent on feedback control and thus would be of limited use in the control of systems with significant time delays.

To reduce the training times, several investigators have utilized learning paradigms that update only specific weights in the network [*e.g.* 34,36]. This type of paradigm is referred to here as ‘constrained’ in contrast with the ‘global’ learning paradigms described earlier. The tradeoff here is that much of the versatility obtained in a global learning paradigm may be lost by constraining some weights in the network. However, in applications in which the general characteristics of the system are known, constrained learning can be used to fine-tune the control. Two different control system designs that have used this approach for the control of robotic systems have been successful [34,36]. However, one design [36] is highly dependent on feedback information and thus would be of limited use in the control of systems with significant input time delays; the other design [34] is based upon an

inverse dynamic model of the system and thus would not be appropriate if reasonable inverse dynamic models are unavailable.

In summary, based upon reports in the literature, it can be concluded that:

- ▶ artificial neural network techniques can be used effectively as adaptive nonlinear filters,
- ▶ artificial neural networks can be trained to learn dynamic mappings, but most algorithms require lengthy training times,
- ▶ training times can be substantially reduced through the use of constrained learning paradigms,
- ▶ existing neural network control system designs are limited by lengthy adaptation times, heavy dependence on feedback control, or the need for inverse dynamic models.

Rationale

The chapters that follow describe the design and evaluation of a control system targeted for use in the control of cyclic movements using Functional Neuromuscular Stimulation. The overall structure of the control system consists of an adaptive feedforward component which is supplemented by a feedback component.

The specific implementation of the adaptive feedforward component consists of a two-stage neural network: the first stage is a pattern generator that is based upon models of neuromotor control systems and the second stage is an adaptive filter implemented using artificial neural network techniques. The specific implementation of the feedback component consists of a servo-controller which utilizes standard control systems engineering techniques.

The overall structure of the control system includes a feedback component in order to provide a mechanism for disturbance resistance. The effectiveness of a feedback controller is limited by the time delay inherent in muscle activation and the availability and accuracy of sensor information. In order to reduce the need for feedback controller action, this design has included a feedforward component. To be effective, a feedforward controller must be designed with detailed knowledge of the system or it must have adaptive properties. Since patient-specific models of musculoskeletal systems are not available, an adaptive feature was incorporated into the feedforward component. This adaptative feature provides a mechanism for automatically customizing the control system for a particular individual and adapting the control system on-line to account for changes in the musculoskeletal system.

The specific implementation of the adaptive feedforward component consists of a novel two-stage neural network structure. The decision to use a two-stage structure was based upon the notion that in applying an FNS control system on a varied population of individuals, for a given movement the basic activation pattern

would be the same but the details would be different. The two-stage structure takes advantage of this by utilizing the first stage to generate the basic pattern of activity, and the second stage to adjust the details of that pattern for the particular individual. Then, in implementing the control system on a population of individuals, the first stage would be the same for all, but the second would be customized for each individual. The implementation of the first stage is based upon a neural model of a motor control system. Neural models were used because recent modeling efforts have demonstrated that they can reproduce many of the characteristic features of neural control systems that would be desirable in an FNS system. In the two-stage structure of the adaptive feedforward component of the control system, the role of the second stage is that of an adaptive nonlinear filter. In the implementation of the second stage adaptive neural network techniques have been used because they have demonstrated to function effectively as adaptive nonlinear filters. However, existing artificial neural network techniques may not be appropriate for this application due to lengthy adaptation times and the inability account for system dynamics. Therefore, a new learning algorithm has been developed for use in this control system to overcome the shortcomings of existing techniques.

Figures

Figure 1. FNS control system components. This figure shows the various components of an FNS control system (unshaded boxes) and the musculoskeletal system to be controlled (shaded box). The FNS control system may include a feedforward controller and/or a feedback controller. Either of the two controllers may adapt their parameters, as shown by the adaptation loop. The feedback controller may provide input to supplement the feedforward controller signal and/or it may provide input to trigger feedforward controller sequences.

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Chapter 3. Control system design

Abstract

A neural network control system has been designed for the purpose of controlling cyclic movements in Functional Neuromuscular Stimulation (FNS) systems. The design of the control system directly addresses three of the major problems faced in the implementation of FNS control systems: customizing the control system parameters for a particular individual, adapting the control system to account for changes in the musculoskeletal system, and resisting mechanical disturbances. The control system is implemented by a two-stage neural network that utilizes a combination of adaptive feedforward and feedback control techniques. The first stage of the neural network, the Pattern Generator, generates a cyclic pattern of activity. The design of this stage is based upon physiological models of neural circuitry responsible for driving oscillatory movements in vertebrates. The signals from the Pattern Generator are adaptively filtered by the second stage of the neural network, the Pattern Shaper. A new learning algorithm was developed for use in the Pattern Shaper to provide it with adaptive filtering capabilities that could account for system dynamics and input time delays. The design of this adaptive feedforward control system is particularly well-suited for controlling rhythmic movements of

systems such as FNS systems, which are dynamic, nonlinear, and have significant input time delays.

Introduction

Functional Neuromuscular Stimulation (FNS) has been developed as a rehabilitative technology for people with neurological disorders such as those caused by spinal cord injury, stroke and head injury. FNS systems operate by providing computer-controlled electrical stimuli to paralyzed muscle via electrodes. In recent years there have been many significant developments in experimental systems, but many of the components of these systems must be improved before they can be used clinically [7,13,17,30]. This work is directed at improving one of the components: the control system. The function of the control system is to specify the parameters of the stimuli sent to the muscles.

Most FNS systems are primarily open-loop systems in which the pre-specified stimulation parameters are determined by trial-and-error [13,17]. These systems have been very successful in demonstrating the feasibility of using electrical stimulation to restore various functions and they have helped to identify three primary areas in which improvements are needed before FNS systems can be used on a clinical basis. *First, the stimulation parameters must be customized for each individual.* In order to generate a desired posture or movement, stimulation parameters must be specified

for each muscle of each individual. The trial-and-error method currently used is time-consuming and unreliable. *Second, musculoskeletal system properties may change while the system is functioning.* Currently, stimulation parameters are fixed, and thus performance will degrade as system properties change, *e.g.*, due to muscle fatigue. *Third, mechanical disturbances to the musculoskeletal system are always present.* Most current FNS systems do not use feedback information to determine stimulus parameters and thus do not perform well in the presence of disturbances.

In the literature, there are several examples of attempts to address each of these problems through the use of streamlined tuning procedures [*e.g.* 16,18], adaptive feedback control techniques [*e.g.* 2,4,11,15], and fixed-parameter feedback control techniques [*e.g.* 1,3,14]. The success of each of these attempts has been primarily limited by the inability to obtain accurate detailed models and the response time of the muscles. To overcome these limitations, the control system presented here is based upon an adaptive feedforward control component and also utilizes feedback.

The control system described in this chapter was designed for the purpose of controlling cyclic movements in FNS systems and directly addresses each of the three major problems in controlling FNS systems listed above. It is based upon a two-stage structure to provide adaptive feedforward control. The first stage, the Pattern Generator, produces a cyclic pattern of activation which is then adaptively filtered by the second stage, the Pattern Shaper. The design of the Pattern Generator is based

upon neurophysiological models of pattern generating circuitry and the design of the Pattern Shaper utilizes a neural network as an adaptive filter.

Neural network control system design

Control system design goals

The general design goals were to provide the control system with the features required to address each of the three problems in controlling FNS systems listed above. First, the control system should provide *automated customization* of the stimulation parameters to drive a given cyclic movement of a particular individual. It should be able to achieve this customization for movements over a wide range of movement frequencies and on multi-segmented systems. Second, the control system should provide *on-line adaptation* of the stimulation parameters to account for muscle fatigue. Third, the control system should provide *disturbance resistance* to respond to mechanical perturbations.

Two versions of the control system are presented here: the first was designed for controlling cyclic movements in planar one-segment musculoskeletal systems and the second was designed for controlling cyclic movements in planar two-segment musculoskeletal systems. The designs presented here are intended to form the basis for systems to control more complex musculoskeletal systems.

Design overview

The neural network control system described here utilizes the pattern generating capabilities of neurophysiological models and the adaptive properties of standard artificial neural network techniques. A diagram of the control system structure is shown in Figure 1. The *Pattern Generator*, (PG), uses a set of neurons in a physiologically-motivated architecture to generate a set of oscillatory signals that approximate those required for a given movement. The *Pattern Shaper*, (PS), uses a set of neurons in a simpler architecture and a learning algorithm to adaptively shape, or filter, the signals from the PG before they are sent to the muscles. The control system is referred to as the PG/PS control system.

In this design, the PG forms the basis of the feedforward control system. Its primary role is to generate a stable oscillatory rhythm. It also serves to provide a mechanism for phase-dependent reflex responses to mechanical disturbances. This stage of the control system was implemented using a neurophysiological model because such models have been demonstrated to exhibit these properties [5]. The parameters of the PG network were either drawn from the literature [5] or they were specified using an iterative trial and error procedure. All of these parameters remained fixed throughout the study, with two exceptions that are described in the text.

The PS provides the adaptive capabilities and thus directly addresses the problems of customizing the control system for a particular individual and adapting

the control system to account for changes in the musculoskeletal system parameters. Some of the parameters of the PS are adapted using an on-line training procedure to provide it with adaptive capabilities. Most of the parameters, however, were pre-specified or pre-trained using an off-line training procedure. Servo-control supplements to the Pattern Shaper also contribute to the disturbance resistance capability of the control system. The parameters of the servo-controller were not adapted in order to avoid instability problems that can arise with the use of adaptive feedback control.

Computer simulations were used in the design, development and testing of the neural network control system. These simulations were performed on a SUN Microsystems Sparcstation™ using software that was developed as a part of this project. The Euler integration method with a time-step of .001 seconds was used to integrate the dynamic equations of the neuron model.

Pattern Generator

The oscillatory behavior of some neuronal circuits is primarily driven by intrinsic oscillatory membrane properties of an individual neuron in the circuit. The oscillatory behavior of other neuronal circuits results primarily from the interactions amongst the individual neurons in the circuit. Most oscillatory neuronal circuits probably use a combination of these two mechanisms [*e.g.* 9,19,27]. In some

neuronal circuits it has been shown that the first mechanism is dominant at certain frequencies and the second mechanism is dominant at other frequencies [*e.g.* 9].

The pattern generator structure used here is based upon the model of Lamprey swimming circuitry [8,9]. In this vertebrate fish, it has been shown that pacemaker properties of individual neurons and the network interactions amongst the neurons both contribute towards the generation of stable, coordinated oscillatory activity [9]. This model was chosen as the basis of the control system for several reasons. First, the cellular and network mechanisms responsible for generating the stable oscillatory rhythms are well-documented [9]. Second, models of the neural circuitry have demonstrated many properties which would be desirable in an FNS control system, such as: oscillations over a wide range of frequencies [9], incorporation of sensory signals [24,28,29], and intersegmental coordination [9]. Third, although the neural circuitry is responsible for controlling movements of a fish, it has been suggested that a relatively straightforward extension of the basic structure might be utilized by legged animals [10]. Fourth, a control system based on this model could be designed which is not extraordinarily complex, either conceptually or computationally.

In the control system described here, the function of the Pattern Generator network is to produce oscillatory signals that approximate those required for a given movement. The PG network consists of a set of coupled unit pattern generators (uPGs), one pair for each joint movement to be controlled. Each uPG consists of a set of three neurons, each of which plays a specific role in generating the pattern.

The overall pattern of activity is determined by the properties of the individual neurons, the properties of the individual uPGs, the interactions amongst them, and afferent input provided to them.

Neuron model

Each neuron in the PG network is described by the following set of equations:

$$\frac{dV_{m_i}(t)}{dt} = (I_{syn_i}(V, t) + I_{PM_i}(V, t) + I_{inj_i} - \frac{V_{m_i}}{R_{m_i}}) / C_{m_i} \quad (1)$$

$$y_i(t) = 1 / (1 + e^{-2 * m_i * (V_i(t) - V_o)}) \quad (2)$$

where $V_m(t)$, R_m , and C_m , are the membrane voltage, resistance, and capacitance; I_{syn} is the synaptic current input; I_{PM} is the pacemaker current; I_{inj} are externally injected currents; $y(t)$ is the output; m is the output function gain; V_o is the offset membrane voltage for the output function.

The synaptic current flowing into a neuron is given by:

$$I_{syn_i}(V, t) = \sum y_j(t) * g_{syn_{ij}} * (E_{syn_{ij}} - V_{m_i}(t)) \quad (3)$$

where V_{m_i} is the membrane voltage of neuron i , y_j is the activity of pre-synaptic neuron j , $g_{syn_{ij}}$ and $E_{syn_{ij}}$ are the conductance and the equilibrium potential for synapse between neuron j and neuron i . In this model, the time-varying properties of neuronal synaptic conductances have not been included, and thus the synaptic

conductance is a constant value. Note that the synaptic current flowing into neuron i is dependent upon the membrane voltage of the post-synaptic neuron as well as the activity of the pre-synaptic neuron.

The set of pacemaker currents (I_{PM}) provides a single neuron in isolation with the ability to generate oscillatory behavior. The model used for the pacemaker currents is similar to that described by Brodin *et.al.* [5] and is described by the following set of equations:

$$I_{PM_i}(V,t) = I_{NMDA_i}(V,t) + I_{KCa_i}(V,t) \quad (4)$$

$$I_{NMDA_i}(V,t) = K_{NMDA_i} * g_{NMDA_i} * p_i(t) * (E_{NMDA_i} - V_{m_i}(t)) \quad (5)$$

$$\frac{dp_i(V,t)}{dt} = A_{\alpha_i} e^{(V_{m_i} - E_r)/C_{\alpha_i}} (1 - p_i(t)) - A_{\beta_i} e^{(E_r - V_{m_i})/C_{\beta_i}} p_i(t) \quad (6)$$

$$I_{KCa_i}(V,t) = g_{KCa_i} * [Ca_{NMDA_i}] * (E_{KCa_i} - V_{m_i}(t)) \quad (7)$$

$$\frac{d[Ca_{NMDA_i}]}{dt} = p_i(t) * \rho_{NMDA_i} * K_{NMDA_i} * (E_{CaNMDA_i} - V_{m_i}(t)) - \delta_{NMDA_i} [Ca_{NMDA_i}] \quad (8)$$

where I_{NMDA} is the current through n-Methyl-D-aspartic acid (NMDA) receptor channels; I_{KCa} is a calcium-dependent potassium current; g_{NMDA} , and g_{KCa} are the conductances of the NMDA receptor channels and calcium-dependent potassium channels, respectively, which are constant values; E_{NMDA} , E_{CaNMDA} , E_{KCa} are the equilibrium potential for the NMDA receptor channels, the NMDA receptor channels

for calcium, and the calcium-dependent potassium channels, respectively; K_{NMDA} is a scaling factor; p is the fraction of NMDA channels open; A_α , A_β , C_α , and C_β are constants regulating the opening and closing of NMDA channels; E_r is the resting potential, $[Ca_{NMDA}]$ is the calcium concentration due to currents through the NMDA channels; ρ_{NMDA} and δ_{NMDA} are rate constants for calcium accumulation and depletion.

There are two components to the pacemaker currents described by Eq. 4-8 above: one which raises the membrane potential (I_{NMDA}) and one which lowers the membrane potential (I_{KCa}). The NMDA-receptor-mediated current provides the driving force for the excitatory burst in the pacemaker neurons. It is a phasic current due to the voltage- and time-dependent processes which are responsible for opening and closing the NMDA channels. Eq. 6 describes the rate of change in the fraction of NMDA channels which are open. Note that there are two terms in this equation, one for opening channels and one for closing them. As these channels open, current flows into the neuron, thus raising the membrane potential.

There are several mechanisms which contribute to the termination of the excitatory burst in the pacemaker neurons. The first mechanism is the closing of the NMDA channels which is regulated by the second term in eq. 6. The second mechanism is the calcium-dependent potassium current, I_{KCa} , which lowers the membrane potential. Ca^{++} flows through the NMDA channels and as it accumulates inside the cell it opens K^+ channels which are sensitive to the local Ca^{++} concentration. The rate of change of Ca^{++} concentration is given by eq. 8, and the

Ca^{++} concentration determines the I_{KCa} as given in eq. 7. The third mechanism for excitatory burst termination results from the network interconnections and is described in the Network structure section that follows.

Although this neuron model is based on one from the literature [5], several modifications have been made. In this work, a non-spiking neuron model is used, the neuronal activity is modelled as a sigmoidal function of the membrane voltage (eq. 2), and synaptic interactions are included (eq. 1).

Network structure

The architecture of the PG network is based upon the model of the neuronal circuitry responsible for generating locomotion in the Lamprey which consists of a set of coupled unit Pattern Generators (uPG) [9]. In this control system, one pair of uPGs is used for each degree-of-freedom at each joint. Each uPG is a set of three interconnected neurons. The network architecture and the signs of the synaptic interactions are shown for one pair of uPGs in Figure 2. Each neuron in the uPG serves a specific function in the generation of the oscillatory activity. The excitatory neuron, E_s , provides the excitatory drive; the inhibitor of synergists, I_s , provides recurrent inhibition to contribute to the termination of the excitatory burst; and the inhibitor of the antagonists, I_a , provides inhibition of the opposite uPG to ensure that the oscillation of the two uPGs is out of phase. These three neurons correspond to EIN, LIN and CCIN neurons, respectively, as presented in [9]. The parameters of

the model used for each of the neurons are given in Table 1. The activity patterns for each of the neurons in the pair of uPGs are shown in Figure 3. This oscillatory pattern of activity at 1 Hz is the basic pattern used in the phase resetting studies described below and provides the basis of the feedforward controller input in most of the studies described in Chapter 4.

Frequency adjustments

In an FNS control system, it would certainly be desirable to have the capability of varying the frequency at which an oscillatory movement is executed. Neural systems that control oscillatory behavior usually have the ability to vary the frequency of oscillation over a wide range. In the Lamprey, it has been shown that there are at least two mechanisms that can be used to regulate the frequency of oscillation. First, increasing (decreasing) the maximum number of NMDA channels available, presumably by the release of excitatory amino acids, will raise (lower) the frequency of oscillation. Second, increasing (decreasing) the tonic level of excitatory input to uPG neurons will raise (lower) the frequency of oscillation. This second mechanism has been incorporated into the PG structure, as shown in Figure 4. The t_2 neuron provides tonic excitatory inputs to neurons in each of the pair of uPGs. Decreasing the level of tonic excitation results in a lower oscillation frequency (Figure 5) and increasing the tonic excitation results in a higher oscillation frequency

(Figure 6). As the level of activity of the t_2 neuron is varied, the oscillation frequency changes as shown in Figure 7.

The data in Figure 7 demonstrate that, although there are many nonlinear properties of individual neurons and their interactions, there is a monotonic and almost linear relationship between one parameter in the network and one characteristic of the output of the network. This relationship suggests that the network can be trained to oscillate at a given frequency by making adjustments to the level of t_2 activity. This training was implemented by adding the t_1 neuron which is maximally active and provides a tonic drive to the t_2 neuron. The t_2 neuron receives no other synaptic inputs and thus its activity level is entirely determined by the strength of the synaptic input from t_1 . Thus, by adjusting the conductance of $t_1 \rightarrow t_2$ synapse, the activity level of the t_2 neuron is modified, which then causes a change in the frequency of oscillation of the PG network. The conductance of the synapse ($g_{syn\ t1 \rightarrow t2}$) was adjusted using the following learning rule:

$$\Delta g_{syn\ t1 \rightarrow t2}(t) = \eta * (T - T_{des}) \quad (9)$$

where η is the learning rate, T is the actual period of oscillation, and T_{des} is the desired period of oscillation. This learning algorithm was used to train the network to oscillate at frequencies of 1 Hz, 0.5 Hz and 1.5 Hz as shown in Figures 3, 5, and 6, respectively. Although this learning algorithm may not be suitable for on-line

operation, it does provide an automated procedure for setting the oscillation frequency by specifying a single control system parameter.

Phase resetting

Phase resetting is a type of reflex exhibited by many neural systems controlling oscillatory behavior. It can be described as follows: if one cycle of activity finishes early, the next cycle should start immediately and should be of normal length. Figure 8 describes phase resetting in more detail. In normal neural control systems, phase resetting serves an important function by providing a mechanism for using sensory information to make adjustments to the timing of oscillatory control signals. This type of timing adjustment is important in the control of FNS systems, and therefore a phase resetting mechanism has been incorporated into the PG. In addition, this type of reflex is often phase-dependent, *i.e.* the response of the system to an input may depend on the phase at which the input arrived. This characteristic of the reflex mechanism also plays an important functional role and therefore has been included as part of the phase resetting mechanism.

To provide a phase resetting mechanism to the PG, two neurons, r_1 and r_2 , were added to each pair of uPGs as shown in Figure 9 (only r_1 is shown in the diagram). Each of these neurons receives inputs from neurons in the uPG and inputs from sensors measuring musculoskeletal system outputs. Each of the neurons

provides excitatory input to one uPG and inhibitory input to the other. Figure 10 shows the changes in PG activity resulting from a pulse input provided to the r_1 neuron. Note that the input results in one short PG cycle then the PG returns to its normal cycle length, thus the phase of the PG has been reset. The effect of this input to the r_1 neuron depends upon the phase of PG activity at which the input arrived, as shown in Figure 11. The r_1 , r_2 neurons thus provide the PG with the capability of a phase-dependent phase-resetting reflex.

When being used on a musculoskeletal system, the PG/PS control system will be attempting to track a desired joint movement trajectory. The oscillation of the desired trajectory must be synchronized with the oscillation of the outputs of the PG, $x(t)$, in order to provide the appropriate signals for generating the movement. This synchronization has been implemented by adding the s_1 and s_2 neurons to the uPG circuit as shown in Figure 12 (only s_1 is shown in the diagram). This neuron receives input from the E_s neuron and is used as a trigger for the desired joint movement trajectory signal, θ_{des} . When the activity of the s_1 neuron exceeds a threshold, the phase of θ_{des} is reset. Since the s_1 neuron receives its input from the PG, this neuron provides a mechanism for synchronizing θ_{des} with the signals from the PG. By adjusting the conductance of the synapse onto the s_1 neuron, the relative phase shift between $x(t)$ and θ_{des} can be regulated in a manner similar to that described above for regulating the frequency of oscillation.

Two-segment movements

The basic PG structure described above for driving oscillatory movements of a one-segment system was modified for driving a two-segment system. The PG structure for the two-segment consists of two of the PGs used for one-segment systems, as shown in Figure 13. The movement for which this PG is designed is a swinging movement of a two-segment leg in which the angle trajectories are similar to those of normal walking.

The PG consists of a pair of uPGs for each joint, in this case, one pair for hip flexion-extension and one pair for knee flexion-extension. The uPGs are coupled via synaptic interconnections such that the knee uPGs are entrained by the hip uPGs. These interconnections have been set in order to generate PG output signal, $x(t)$, that approximates the muscle activation signals required for the specified movement. The large excitatory input from the hip flexion uPG causes the knee uPGs to go through their entire flexion-extension phase during one-half of the hip cycle. The inhibitory input from the hip extension uPG causes the knee uPGs to be silent during the second half of the hip cycle.

Pattern Shaper

The Pattern Shaper takes its input from the Pattern Generator and provides stimulation to the muscles. This stage uses modifications to established artificial neural network techniques. The purpose of the pattern shaper is to map the nominal

trajectories provided by the pattern generator circuit to the stimulation that is actually sent to the muscle. That is, it filters the signals provided by the PG. The learning algorithm adjusts parameters in the network in an attempt to produce an appropriate set of muscle activation trajectories for the desired movements.

Neuron model and network structure

The PS consists of several *PS units*, each of which filters the signal sent to one stimulation channel (Figure 14). Each PS unit consists of a vector of 16 interconnected neurons. Each neuron in the vector is described by the following pair of equations:

$$\frac{dV_{m_{kj}}(t)}{dt} = (w_{x_k} * x_k(t) + \sum_i (w_{lat_{ki}} * y_{ki}(t)) - \frac{V_{m_{kj}}(t)}{R_{m_{kj}}}) / C_{m_{kj}} \quad (10)$$

$$y_{kj}(t) = 1 / (1 + e^{-2 * m_{kj} * (V_{kj}(t) - V_{o_{kj}})}) \quad (11)$$

where $V_m(t)$, R_m , and C_m , are the membrane voltage, resistance, and capacitance; $x(t)$ is the signal from the PG; w_x , w_{lat} , and w_y are the input, lateral and output weights, respectively; $y(t)$ is the output of a neuron; m is the output function gain; V_o is the offset membrane voltage for the output function; k is the index of the PS unit, j is the index of the neuron within a PS unit, and i is the index of a synapse on the neuron. Note that each neuron receives weighted inputs from the PG and from the other neurons in the PS unit. These *input weights* and *lateral weights* are set such that the

input from the PG produces a chain of activation through the vector of neurons, as described in Figure 15. These weights are not adapted in the course of operation. The output of the PS unit is the weighted sum of the activities of all neurons in the unit and the feedback controller input:

$$z_k(t) = \sum_j w_{y_{kj}} * y_{kj}(t) + z_{FB_k}(t) \quad (12)$$

where $z_k(t)$ is the output of the PS unit, $w_{y_{kj}}$ is the output weight, $y_{kj}(t)$ is the output of a neuron; $z_{FB_k}(t)$ is feedback controller input; k is the index of the PS unit, and j is the index of the neuron within a PS unit. These output weights, $(w_{y_{kj}})$ are adapted by the learning algorithm described below. Thus, the PS unit is an adaptive, nonlinear, dynamic filter of the signal from the PG.

Learning algorithm

In artificial neural network techniques, the learning algorithm consists of an ‘update equation’, which is the equation used to adjust the weights, and a learning ‘paradigm’, which is the particular selection of the signals to be used in the update equation. Learning algorithms commonly used in artificial neural networks may not be suitable for application in an FNS control system because they usually require several thousand presentations of the data for sufficient training to occur [e.g. 22,23]. This is primarily due to the fact that they use ‘global’ learning paradigms in which all synaptic weights are adjusted based upon a general measure of performance.

Some learning algorithms converge more quickly by using ‘constrained’ learning in which specific synaptic weights are adjusted based upon specific characteristics of network performance [e.g. 20,21]. These algorithms cannot directly account for the system dynamics and input time delays, and thus may also be unsuitable for application in FNS control systems.

The demands of the FNS control system application require that training should take place rapidly (*i.e.* over several cycles of movement) and it should directly account for the system dynamics and input time delays. To meet these demands, a new learning algorithm was developed for use in this control system. This algorithm, termed ‘*time-averaged learning*’, uses a moving average of past neural activation values in the update equation and thus it can directly account for system dynamics and input time delays. It also uses a constrained learning algorithm that provides it with the ability to rapidly adapt the properties of the network.

Time-averaged learning is a form of a heterosynaptic hebbian learning algorithm. In classical hebbian learning [6], the change in the synaptic weight is proportional to the product of the activation levels of the presynaptic and postsynaptic neurons:

$$\Delta w(t) = \eta * y_{post}(t) * y_{pre}(t) \quad (13)$$

where w is the synaptic weight, η is the learning rate, and y_{pre}, y_{post} are the pre- and post-synaptic activation levels. In a heterosynaptic hebbian algorithm, the change in

the synaptic weight is proportional to the product of the presynaptic activity and the activity of an auxiliary neuron:

$$\Delta w(t) = \eta * y_a(t) * y_{pre}(t) \quad (14)$$

where y_a is the activation level of the auxiliary neuron. In the implementation used here, the error signal, $e_k(t)$, is used in place of the activity level of the auxiliary neuron. This learning updates the weight based upon the current value of the error signal and the current presynaptic activation level. However, due to the dynamic response of the system and the substantial time delays in the response of the muscles, the current value of the error is related to previous activation levels, not the current one. Therefore the '*time-averaged learning*' algorithm used in this control system is given by:

$$\Delta w_{y_k}(t) = \eta * e_k(t) * \sum_n a_n * y_k(t - n * SP) \quad (15)$$

where $\Delta w_{y_k}(t)$ is the change in output weight j of PS unit k , η is the learning rate, $e_k(t)$ is the error signal for PS unit k , $y_k(t)$ is the output of the neuron j of PS unit k , a_n are filter coefficients, n is the filter order, and SP is the muscle stimulus period.

There are several features in the PS design which are well-suited for controlling rhythmic movements in FNS systems. Some specific problems faced in this application which are directly addressed by the PS design include: nonlinear muscle recruitment, muscle input/output hysteresis, muscle input delay, and muscle

contraction/relaxation dynamics. The signal sent to the muscle is a weighted, linear combination of the trajectories as shown in Figure 15, and the learning algorithm determines the weight on each trajectory. Since the set of trajectories is sequential in time, there is a unique combination of activation levels at each stimulation time step, and thus the learning algorithm can account for nonlinear muscle recruitment. The use of previous activation terms in this learning algorithm is an important feature which enables the control system to learn to control dynamic systems with an input time delay.

Discussion

Neurobiological basis of the control system design

Many aspects of the design of this control system are based upon an understanding of the operation of neurobiological motor control systems. One reason for taking this approach is that the types of problems faced in the control of FNS systems have not been adequately addressed by traditional control system techniques. FNS systems are nonlinear, multi-dimensional dynamic systems with significant input time delays. Although there are many techniques available for the control of nonlinear dynamic systems, none of them are particularly well-suited for FNS control due to the fact that the system to be controlled is not well understood, it varies from subject to subject, and there are no good quantitative subject-specific models of the

system. A second reason for taking this approach is that recently developed models of the neural control of movement have demonstrated how various cellular and network properties can result in many of the characteristic features of neural control systems. Since the goal of this control system is to replace function lost due to injury to nervous system, it would be desirable to mimic these characteristic features of neural control systems. A control systems which is based upon a neural model of motor control may be able to restore many of these aspects of the lost function.

The overall structure of the control system is based upon the hierarchical organization of the locomotor control system [10] which includes supraspinal centers, a spinal pattern generator, and a spinal pattern shaper.

The supraspinal centers include the motor cortex, the cerebellum, and various structures in the brainstem. Models of these centers have not been explicitly included in the design of this control system, but many of the functions they serve have been incorporated. For example, the tonic drive to regulate movement frequency in the control system serves the function mediated by reticulospinal inputs in the vertebrate system, and the synaptic learning algorithm of the pattern shaper serves the adaptive function which may be mediated by the cerebellum. Future developments to enhance the functionality of this control system could explicitly include models of these supraspinal inputs to the pattern generator.

The pattern generator plays an important role in the control system by providing the basic timing mechanism for driving the oscillatory movement.

Although it has not been conclusively demonstrated that a spinal pattern generator exists in humans, there is strong evidence of it in limbed vertebrates [12]. While this question of the existence of a spinal pattern generator is an interesting one, it is of little relevance to this work. The use of a pattern generator is justified by the fact that it provides the control system with the many desirable features such as stable endogenous rhythm generation, frequency modulation, phase-resetting, and phase-dependent reflexes. These features of the control system are attributable to the combination of the capacitive neuron membrane, the intrinsic pacemaker currents, and the highly structured network architecture.

The pattern shaper acts to filter the signals from the pattern generator in this control system. In the spinal cord, there is a complex network of neurons (motoneurons, Renshaw Cells, Ia interneurons, etc.) which are involved in processing signals provided by other spinal centers and by supraspinal centers. It has been shown that these neurons are not part of a spinal pattern generator [25], but they do play an important role in determining the signals provided to the muscles. Explicit models of these neurons have not been used in the control system designed here, but the filtering function they serve has been incorporated into the design of the pattern shaper network. Future developments of this control system could include models of the specific neural elements of the spinal circuitry involved in shaping the signals being provided to the muscles.

Control of dynamic systems

There are three aspects of this design that are important developments in the area of control systems engineering: the use of neurobiological models in control system design, the development of a new learning algorithm, and the characteristics of the learning paradigm used. Here, the word ‘algorithm’ refers to the equation used to update neuron properties and the word ‘paradigm’ refers to the specific selection of the training signal and the neuron properties to be updated.

First, as discussed earlier, this work has demonstrated some of the potential advantages of using neurobiological models in the design of control systems. Neural control systems exhibit many features that are often desirable in engineering control systems. This work has demonstrated how many of these desirable features can be achieved by using models of the cellular processes and network architecture of neural systems.

Second, the *time-averaged learning* algorithm developed here for use in the PS provides a mechanism for adaption in neural network control of nonlinear dynamic systems with input time delays. Standard neural network learning algorithms have been very successful at performing nonlinear mappings. The *time-averaged learning* algorithm uses a modification to these standard neural network learning algorithms that specifically addresses the problems presented by the dynamics of the system and the input time delays. The following chapter presents an example of an application of this learning algorithm in the control of a model of

an FNS system. The algorithm may be useful in other neural network control system applications as well as in neural network systems for processing sequential images of time-dependent processes.

Third, the use of a constrained learning paradigm in both the PG and the PS provides an example of how artificial neural network learning algorithms can be used to provide rapid adaptation in engineering control systems. Global learning paradigms can provide the neural network with versatility, but at the cost of long training times. For many applications this tradeoff is an acceptable one, but for many applications of control systems long training times are not acceptable. The evaluation of the PG/PS control system described in Chapter 4 provides an example of how a constrained learning paradigm can be used to provide rapid adaptation in an engineering control system application.

Summary

A neural network control system has been designed for the purpose of controlling cyclic movements in Functional Neuromuscular Stimulation systems. The control system consists of an adaptive feedforward controller which is implemented by a two-stage neural network. The first stage of the neural network, the pattern generator, generates a cyclic pattern of activity. This stage is based upon neural models of locomotor control and displays many properties of normal locomotor

control systems that are desirable in an FNS system. The signals from the pattern generator are adaptively filtered by the second stage of the neural network, the pattern shaper. This stage uses a new learning algorithm that provides it with the ability to rapidly adapt its filter properties and to account for the system dynamics and input time delays. The design of the control system presented here is suitable for the control of one- and two-segment systems, and is intended to form the basic structure for the control of multi-segmented, multi-limbed systems. An evaluation of this control system on one- and two-segment computer simulated musculoskeletal models is presented in Chapter 4.

Tables

<i>name</i>	R_m (M)	C_m (pF)	V_o (mV)	m	<i>pre-syn. neuron</i>	g_{syn} (μS)	E_{syn} (mV)
Es_1	60	.045	25	.04	Ia_2	2.0	-30
					Is_1	2.0	-30
					t_2	0.5	60
					r_1	3.0	60
					r_2	2.5	-30
Is_1	50	.02	25	.2	Es_1	0.05	40
					Ia_2	0.10	-40
					t_2	0.12	40
					r_1	4.00	10
					r_2	2.00	35
Ia_1	10	.02	10	.3	Es_1	0.20	20
					Is_1	0.10	-20
					Ia_2	0.10	-20
					r_1	0.05	20
					r_2	0.20	-20
r_1	1	.1	0	2	Es_1	1.0	-60
					Is_1	4.0	-60
s_1	1	.1	0	1	Es_1	0.2	-50

Table 1. Pattern Generator neuron parameters. This table presents the parameters of the neurons in the pattern generator network used in this study. All parameters in the table were selected using a trial-and-error method to obtain the desired oscillatory characteristics. Each row presents the parameters of one neuron: name, membrane resistance, membrane capacitance, output function voltage offset, output function gain, presynaptic neurons, synaptic conductances, and equilibrium potentials for the synapses. The network is symmetric (except t_1, t_2) and therefore parameters are given for only one side. The parameters used for the t_1, t_2 neurons were: $R_m = 1, 1$; $C_m = 1, 0.1$; $V_o = 10, 50$; and $m = 100, .1$. The neurons Es_1, Es_2 included the intrinsic pacemaker currents described in the text. The parameters used in both neurons for these variables were: $g_{NMDA} = 0.5 \mu S$, $g_{KCa} = 0.04 \mu S$, $E_{NMDA} = 70 mV$, $E_{CaNMDA} = 90 mV$, $E_{KCa} = -10 mV$, $K_{NMDA} = 10$, $A_\alpha = 1400$, $A_\beta = 10.08$, $C_\alpha = 17$, and $C_\beta = 19$, $\rho_{NMDA} = 0.5$, and $\delta_{NMDA} = 2$. All of these parameters for the pacemaker currents were obtained from [5], except A_α and K_{NMDA} , which were modified to adjust the range of oscillation frequencies.

Figures

Figure 1. Neural network control system block diagram. This figure shows the various components of the neural network control system (unshaded boxes) and of the musculoskeletal system to be controlled (shaded boxes). The pattern generator, PG, provides a set of oscillatory signals to the pattern shaper, PS. The PS filters, or shapes, these signals to provide the activation signals to the muscle. Both the PG and the PS can utilize feedback and adaptation.

Figure 2. Pattern generator diagram. A six neuron network based upon the model of Grillner [8] was used to generate an oscillatory pattern of activity. Bars indicate excitatory synapses and circles indicate inhibitory synapses. The network consists of two unit pattern generators (uPGs), each of which has three neurons that serve specific functions in generating the oscillatory rhythm. The excitatory neuron, E_s , provides the excitatory drive; the inhibitor of synergists, I_s , provides recurrent inhibition to contribute to the termination of the excitatory burst; and the inhibitor of the antagonists, I_a , provides inhibition of the opposite uPG to ensure that the oscillation of the two uPGs is out of phase.

Figure 3. Activity pattern of PG neurons. These plots show time traces of the outputs of the six PG neurons oscillating at a frequency of 1 Hz. Solid lines show the outputs of the neurons in one uPG, and dashed lines show the outputs of the other uPG.

Figure 4. PG with tonic drive regulating oscillation frequency. This diagram shows the basic PG circuitry with the addition of the t_1 and t_2 neurons to provide a tonic input to regulate the oscillation frequency. The t_2 neuron provides excitatory input to the E_i neuron and to the I_i neuron on each side of the PG. The t_2 neuron is tonically active and its activity level is entirely determined by the weight of the $t_1 \rightarrow t_2$ synapse. The t_1 neuron is maximally active, *i.e.* $y_{t1}(t) = 1$ for all t . The arrow crossing the $t_1 \rightarrow t_2$ synapse indicates that this weight can be adjusted. The learning rule for this adjustment is described in the text.

Figure 5. PG neuron output traces at 0.5 Hz. These plots show time traces of the outputs of the six PG neurons oscillating at a frequency of 0.5 Hz. Solid lines show the outputs of the neurons in one uPG, and dashed lines show the outputs of the other uPG. Note that at this frequency, the I_s neuron is barely activated and thus does not contribute significantly to the termination of the E_s burst. Therefore, the termination of the burst is almost entirely due to the intrinsic cellular properties of the E_s neuron.

Figure 6. PG neuron output traces at 1.5 Hz. These plots show time traces of the outputs of the six PG neurons oscillating at a frequency of 1.5 Hz. Solid lines show the outputs of the neurons in one uPG, and dashed lines show the outputs of the other uPG. Note that at this frequency, the activity of the I_s neuron is more pronounced than at lower frequencies and thus it contributes to the termination of the E_s burst.

Figure 7. Varying the PG oscillation frequency. This plot demonstrates that the activity level of the t_2 neuron determines the frequency of PG oscillation. The horizontal axis indicates the activity level, $y_2(t)$, of the t_2 neuron. The vertical axis indicates the frequency at which the PG circuitry oscillates for a given value of $y_2(t)$. Note the monotonic relationship between the two variables which demonstrates that oscillation frequency can be regulated by adjustments to the activity level of the t_2 neuron.

Figure 8. Explanation of phase resetting. This diagram illustrates the concept of phase resetting. The set of three traces at the top show the "on" (line present) and "off" (no line present) phases of cyclic activity. The top trace shows the normal rhythm of the "on"- "off" cyclic activity. The middle trace shows the result of an input (shown by the arrow) which results in early termination of a cycle when there is no phase resetting. Here, after the one short cycle, there is one long cycle and then it returns to the normal cycle length. Subsequent cycles are in phase with the original cyclic pattern. The bottom trace shows the result of the same input when there is phase resetting. Here, immediately after the one short cycle it returns to the normal cycle length. In this case, the subsequent cycles are out of phase with the original cyclic pattern, *i.e.* the phase has been reset. The set of three traces at the bottom show plots of the cycle period vs. time which correspond to the three traces at the top.

Figure 9. PG diagram with phase resetting. This diagram shows the basic PG circuitry (2 uPGs, 3 neurons in each uPG) with the addition of neurons which provide resetting inputs to the PG. Two neurons, r_1 and r_2 , were added to the circuit. The r_2 (neuron is not shown in the diagram) is symmetric with the r_1 neuron and provides excitation to the neurons in uPG₁ and inhibition to the neurons in uPG₂. Each of the resetting neurons provides excitation to one uPG and inhibition to the other.

Figure 10. PG phase resetting. Time traces of some of the PG variables demonstrate the effect of an input to the r_1 neuron on PG function. A current pulse (ampl. = 30 nA, width = 100 msec) was supplied to the r_1 neuron at time $t = 2.2$ seconds, as indicated by the dark arrow. The bottom plot shows the membrane voltage of the r_1 neuron; the second plot shows the output of the r_1 neuron. Note that the membrane voltage of the r_1 neuron oscillates at a level that is below threshold until the externally applied input causes it to exceed threshold. The third plot shows the outputs of the two E_s neurons; the top plot shows the period of the oscillation of the E_s neurons. Note that the pulse input from the r_1 neuron to the PG results in phase resetting of the PG, *i.e.* it results in the early termination of one cycle, but then the PG returns immediately to its normal rhythm.

Figure 11. PG phase-dependent reflexes. This plot shows the composite results from several trials in which a pulse was applied to the r_1 neuron at different points in the oscillatory cycle. The horizontal axis indicates the percent of cycle at which the input was applied; the vertical axis indicates the cycle period. The solid triangles indicate the period of the cycle during which the pulse was applied, *i.e.* the cycle that was reset. The solid circles indicate the period of the subsequent cycle, *i.e.* that which followed the reset cycle. The nominal oscillatory period for the PG was 1 second. A value of 1 for the reset cycle indicates that the input had no effect on the PG, a value < 1 indicates that it resulted in early termination of the cycle. These data demonstrate the phenomenon of the phase-dependent reflex, in which the effect of an input to the PG will depend upon the phase at which it arrived. For trials in which there was early termination of the cycle, a value of 1 for the cycle after reset indicates that the phase had been reset.

Figure 12. PG diagram with synchronization of the desired trajectory. This diagram shows the basic PG circuitry (2 uPGs, 3 neurons in each uPG) with the addition of two neurons which are used to synchronize the oscillations of the desired trajectory with the oscillations of the PG. The s_1 neuron receives input from the E_{s1} neuron that causes its membrane voltage to oscillate. The output of this neuron is used to reset the oscillation of the desired trajectory, which is generated by the box labelled DT in the diagram. The synaptic weight determines the relative phase difference between the s_1 and the E_{s1} , and therefore also between the desired trajectory and the PG. The network is symmetric, and includes a neuron, s_2 (not shown in the diagram), that receives input from the E_{s2} neuron.

Figure 13. PG diagram for two-segment system. This diagram illustrates the architecture of the PG for generating movements in a two-segment system. In this case, the interconnections have been set such that the outputs of the pattern generator provide signals for generating the two-segment movement described in Chapter 4. The pair of uPGs at the top provide signals to the muscles acting at the hip; the pair of uPGs at the bottom provide signals to the muscles acting at the knee. With these interconnections, the pair of uPGs at the knee are entrained by the pair at the hip. The knee trajectory goes through its full flexion-extension phase during one-half of the hip cycle due to the large excitatory input from the hip flexion uPG. The knee angle is relatively constant during the second half of the hip cycle due to the inhibitory input from the hip extension uPG.

Figure 14. PS unit. Each unit of the pattern shaper consists of a vector of 16 interconnected neurons. Each neuron receives weighted input from the pattern generator and from other neurons in the vector and generates an output, y_{kj} . The output of the PS unit, z_k , is the weighted summation of the outputs of the neurons in the vector and the feedback controller signal, z_{FBk} . Note that there are three sets of weights: the weights on the inputs from the PG ($w_{x kj}$), the weights on the lateral interconnections amongst the neurons in the vector ($w_{lat kji}$), and the weights on the output summation ($w_{y kj}$). The 'k' indicates the PS unit number, 'j' indicates the number of neuron in the PS unit, and 'i' indicates the number of the presynaptic neuron for the lateral interconnections.

Figure 15. Outputs of neurons within one PS unit. This plot shows the time trajectories of the outputs of 8 neurons (the even numbered of the 16 neurons in the network) in the PS unit when provided input from the PG oscillating at 1 Hz. Note that the temporal pattern activity across the neurons consists of a chain of activation travelling through the neurons in the vector. The output of the unit at any one time, thus consists of the weighted summation of a limited number of neurons, since most will have zero output. For all neurons in the network, the parameters were set as follows: $R_m = 0.5 \text{ M}$, $m = 0.8$, $C_m = (0.1 + 0.01*j) \text{ pF}$, $V_o = (2.5 + 0.5*j) \text{ mV}$, where j is the index of the neuron in the vector. The input weights (w_x) and the lateral weights (w_{lar}) were pretrained using the learning algorithm described in the text to generate the activity pattern shown above. After this off-line pre-training, these weights remained fixed throughout all of the studies described in the text.

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Chapter 4. Control system evaluation

Abstract

The evaluation of a neural network control system that was designed for the purpose of controlling cyclic movements in Functional Neuromuscular Stimulation (FNS) systems is described in this chapter. The control system, which was described in Chapter 3, was implemented by a two-stage neural network that utilized a combination of adaptive feedforward and feedback control techniques. The first stage of the neural network, the Pattern Generator, generates a cyclic pattern of activity. The signals from the Pattern Generator are adaptively filtered by the second stage of the neural network, the Pattern Shaper. The control system is referred to as the PG/PS control system.

The PG/PS control system was evaluated on computer simulated musculoskeletal models. The model of electrically stimulated muscle used in the study included nonlinear recruitment, linear dynamics, and multiplicative nonlinear torque-angle and torque-velocity scaling factors. Both one- and two-segment planar models that included passive constraints on joint movement were used in the

evaluation. Results of the evaluation have demonstrated that the control system can provide automated customization of the feedforward controller parameters for a given musculoskeletal system, it can account for changes in the musculoskeletal system by adapting the feedforward controller parameters on-line, and it can provide resistance to mechanical disturbances. In addition, the control system is capable of controlling movements of multi-joint systems and of utilizing biarticular muscle effectively. These results indicate that this adaptive control strategy may be suitable for application in the control of FNS systems. The ability of the control system to rapidly adapt and to account for system dynamics and input time delays indicates that this strategy may also be appropriate for other applications in the control of dynamic systems.

Introduction

The design of a neural network control system targeted for use in the control of cyclic movements in lower extremity Functional Neuromuscular Stimulation (FNS) systems was described in Chapter 3. Briefly, the control system (Figure 1) consists of an adaptive feedforward controller, which is implemented by a two-stage neural network, and a fixed-parameter feedback controller, which uses a proportional-derivative algorithm. The first stage of the neural network, the pattern generator (PG), generates a cyclic pattern of activity. The signals from the PG are adaptively

filtered by the second stage of the neural network, the pattern shaper (PS). The filtering properties of this stage are adapted using *time-averaged learning*, which is a modified version of standard artificial neural network learning algorithms. The two-stage control system is referred to as the PG/PS control system.

This chapter describes an evaluation of the PG/PS control system using computer simulated musculoskeletal models. Three major problems faced in FNS control are: 1) the stimulation parameters must be customized for each individual, 2) musculoskeletal system properties may change while the system is functioning, and 3) mechanical disturbances to the musculoskeletal system are always present. In order to address these problems, the control system was designed to provide *automated customization*, *on-line adaptation*, and *disturbance rejection*. The goal of the evaluation described below was to assess the efficacy of each of these features of the control system.

Methods

Muscle model

The muscle model used in the evaluations captures many of the characteristic features of electrically stimulated muscle that cause problems for the control system. The model includes nonlinear recruitment, contraction dynamics, force-length

dependence and force-velocity dependence. Components of various muscle models have been drawn from the literature to develop the model used in this study.

Uniarticular muscle model

The equations describing the muscle model are given in Table 1; a block diagram of the model is shown in Figure 2. When an electrical pulse is provided to a muscle it activates, or recruits, a certain number of muscle fibers. As the pulse width (or pulse amplitude) is varied, the number of fibers recruited varies, as does the amount of force generated by the muscle. The relationship between the pulse width and the steady-state force generated by a muscle [6], expressed as a fraction of the maximum steady-state force, is termed the recruitment curve. The recruitment curve thus is the steady-state input-output relationship for the muscle. It is typically nonlinear, and displays a deadband and saturation. A third-order polynomial with a deadband and saturation [4] (Table 1., eq. 5) was used to model the recruitment curve.

As a muscle fiber is activated, force is generated by a dynamic process. A second-order auto-regressive, moving average (ARMA) model with first order input and an input delay [2] (Table 1. eq. 2) was used to model the muscle dynamics.

The amount of force, or torque, generated by a muscle depends upon its length and its velocity. Several models have used multiplicative scaling factors to describe these dependencies [14,19]. Here, a modified version of the multiplicative

model described in [14] was used (Table 1, eq. 1). In the original model, a linear approximation to the torque-angle relationship and a bilinear approximation to the torque-velocity relationship were used. Here, the torque-angle relationship was approximated by the quadratic equation given in Table 1, eq. 3, and the torque-velocity relationship [8] was approximated by the equation given in Table 1, eq. 4. The torque was calculated at each stimulation period and was held constant throughout the duration of the stimulation period.

Biarticular muscle model

The uniarticular model was modified to represent the behavior of biarticular muscle (Figure 3, Tables 1,2). Modifications were made to capture two important aspects of biarticular muscle actions: first, biarticular muscles exert torques at two joints; and second, the torque exerted at one joint depends upon the angle and angular velocity of the second joint. As in the uniarticular muscle model, the torque exerted by the biarticular muscle model at each joint was the product of three terms, as in Table 1, eq. 1. The same recruitment curve and muscle dynamics terms were used at both joints. The secondary joint (arbitrarily labelled as secondary) had additional scaling factor, K_b , to account for differences in the peak torque levels at the two joints. The same torque-velocity factor was used in the torque calculation at both joints, and was based upon the sum of the angular velocities at the two joints (Table 2, eq. 3). Two different curves are used to determine the torque-angle factors at the

two joints, but the angle used in the calculation is the sum of the two angles with each angle being offset by its reference angle (Table 2, eq. 1,2).

Model of muscle fatigue

Reports in the literature indicate that in electrically stimulated muscle, fatigue can cause a drop in peak muscle torque (approx. 50% reduction over 100 seconds) [3,10] and that it may also cause a shift in the recruitment deadband. In this work, two different models of muscle fatigue were used: one model of fatigue consisted of an asymptotic drop in muscle input gain to 50% of its original value over 100 seconds, the second model consisted of an asymptotic vertical shift of 50% in the recruitment curve over 100 seconds. That is, muscle fatigue was simulated by varying muscle input gain (b_0), or muscle recruitment offset (γ_0), over the course of the simulation trial as described by the following equations:

$$b_0(t) = b_0(t - SP) + k_f * (b_{0f} - b_0(t - SP)) \quad (1)$$

$$\gamma_0(t) = \gamma_0(t - SP) + k_f * (\gamma_{0f} - \gamma_0(t - SP)) \quad (2)$$

where b_{0f} and γ_{0f} are the final values of b_0 and γ_0 , respectively, k_f is the fatigue rate factor, and SP is the stimulus period. The change in b_0 results in a change in the input gain of the linear muscle dynamics (Table 1, eq. 2). The change in γ_0 results in a shift of the nonlinear recruitment curve (Table 1, eq. 5), which has the compound effect of an increase in deadband with a drop in muscle input gain.

Skeletal model

Three different skeletal models were used in this study. Most of the simulations were performed on a planar model of a single skeletal segment in swinging pendulum configuration with one degree-of-freedom (Figure 4, Table 3). The model includes linear stiffness and damping which act to resist movement at the joint. The skeletal segment is acted upon by an agonist-antagonist pair of muscles across the joint. Studies were also performed on a planar inverted pendulum model (Figure 4) that was identical to the swinging pendulum model except that the direction of gravity was reversed. The studies on two-segment systems utilized the planar model which is shown in Figure 4 and which is described in Table 4. In this two-segment model, nonlinear constraints on joint movement [1] were also included (Table 4). In the two-segment studies that involved only uniarticular muscles, there was an agonist-antagonist pair of muscles acting at each joint. In the study using biarticular muscles, two muscles which spanned both joints were added.

Model parameter selection

The set of parameters for the muscle model (listed in Table 5,6) were drawn from several sources in the literature. Muscle recruitment parameters ($\gamma_{1,2,3}$) and muscle dynamics parameters (a_1, a_2) were drawn from studies using electrical stimulation of paralyzed quadriceps muscles [4]. Peak steady-state muscle torque values (τ_{ss}) were drawn from models of the muscle actions of the human lower

extremity [9]. Due to the fact that electrically stimulated paralyzed muscles rarely have the torque-generating capacity of muscles with intact innervation, peak muscle torques of 50% of the published values [9] were used in these studies. The b_0 parameter of the muscle model was determined by the following equation:

$$b_0 = 50\% * \tau_{ss} * (1 - a_1 - a_2) \quad (3)$$

Torque-angle scaling parameters (θ_o , θ_w) were estimated from models of the human lower extremity in which peak steady-state torque exhibited an angle dependence [9]. Torque-velocity scaling parameters (k_w , ω_{max}) were drawn from studies on human muscle with intact innervation [12,15]. Parameters of the model of muscle fatigue ($k_f = 0.002$, $b_{of} = 50\% b_o$, $\gamma_{of} = -0.5$) were estimated from published data of the fatigue rates of electrically stimulated paralyzed muscle [3,10]. These parameters were selected such that the peak steady-state muscle torque decayed to 50% of its original value over the course of a 100 second simulation run.

The set of parameters for the skeletal model (listed in Table 5,6) were also drawn from various sources in the literature. Body segment parameters (m , l , I) for the thigh and shank were drawn from studies on human cadavers [5]. Passive joint constraints (K_S , K_B , $k_{min,max}$, $m_{min,max}$, $\theta_{min,max}$) for the hip and knee were drawn from models of the passive joint structures of the human lower extremity [1,11,18].

In the studies on the one-segment system, the peak steady-state muscle torque parameters and the muscle torque-angle scaling parameters were selected to be

representative of the combined hip flexors and the combined hip extensors [9]. The skeletal model parameters of the thigh segment (hip joint) were used [18]. In the studies on the two-segment system, the peak steady-state muscle torque parameters and the muscle torque-angle scaling parameters were selected to be those of individual muscles (iliopsoas, gluteus maximus, the three vasti of quadriceps, the short head of biceps femoris, rectus femoris, and the hamstrings) [9]. The skeletal model parameters of the thigh and shank (hip and knee joints) were used in the two-segment model [1,11,18].

Control system performance specifications

For studies on the one-segment system (see Figure 6), the desired angle trajectory for tracking was specified to be:

$$\theta_{des} = \theta_o + A * \sin(2 * \pi * f * t - \phi) \quad (4)$$

where θ_o is the angle offset (0°), A is the amplitude (20°), f is the frequency (1 Hz for most studies), ϕ is the phase shift (0°), and t is time.

For studies on the two-segment system, the desired angle trajectories were selected to be similar to those of normal walking [17]. Since these studies involved movement of an unloaded swinging limb, however, the knee flexion that occurs during stance phase of normal walking was not included in the specification of the

desired trajectory. The desired angle trajectory for the hip joint on the two-segment system (see Figure 15) is given by:

$$\theta_{h_{des}} = \theta_{h_o} + A_h * \sin(2 * \pi * f * t - \phi_h) \quad (5)$$

where θ_{h_o} is the angle offset for the hip (5°), A_h is the amplitude for the hip (15°), f is the movement frequency (1 Hz), ϕ_h is the phase shift for the hip (0°), and t is time. The desired angle trajectory for the knee joint on the two-segment system consists of a linear portion and a cosine portion:

$$\begin{aligned} \theta_{k_{des}} &= \theta_{k_o} + 0.2 * A_k * (t - (\phi_k / 2 * \pi * f)) / t_1 & t \leq t_2 \\ &\theta_{k_o} + 0.5 * A_k * (1 - \cos(2 * \pi * (f / .6) * (t - t_1) - \phi_k)) & t > t_2 \end{aligned} \quad (6)$$

where θ_{k_o} is the angle offset for the knee (-5°), A_k is the amplitude for the knee (50°), f is the movement frequency (1 Hz), ϕ_k is the phase shift for the knee (30°), $t_1 = 0.4/f$, t_2 is the time at which the cosine curve exceeds the linear curve, and t is time.

In all studies, the root-mean-square (rms) value of the tracking error was used as the primary measure of control system performance. Studies on single-segment movements using FNS [7,13,16] and on locomotion control in normals [17] indicate that an rms tracking error of $< 2^\circ$ would provide significant improvements in FNS control and would be adequate for the control of locomotion. Therefore, in these studies, rms tracking errors of $< 2^\circ$ were considered acceptable. In addition to the tracking measures, the amount of applied muscle torque used to generate a given

movement was also considered. Lower values of muscle torque were assumed to result in lower rates of muscle fatigue, and thus were rated higher in the evaluation.

One goal of the control system design process was to provide the PG/PS control system with the ability to automatically customize itself for controlling a particular musculoskeletal system. For the purposes of a clinical system, it would be desirable to achieve adequate customization within several minutes. In these studies, the customization procedure was performed over 20 second trials because the models used here are considerably simpler than an actual implementation of an FNS system.

For studies evaluating the phase resetting mechanism of the Pattern Generator, a ‘resetting index’ was defined as:

$$RI = 100 \% * (T_{reset} - T_o) / T_o \quad (7)$$

where T_o is the normal oscillation period and T_{reset} is the period of the cycle after the reset. Note that the objective of the phase resetting mechanism is that the cycle after reset should be of normal length (*i.e.* $T_{reset} = T_o$), and therefore perfect resetting would result in $RI = 0$. In these studies, RI values $< 5\%$ were considered acceptable.

In controlling oscillatory movements, it would be desirable to have the ability to vary the oscillatory frequency of movement without significant changes in the control system. In this work, a cycle frequency of 1 Hz was used in most of the

studies. The ability of the control system to generate movements over a range of frequencies (0.5 - 1.5 Hz) was also evaluated.

Control system implementation

The neural network control system and the musculoskeletal model were both implemented on a SUN Microsystems Sparcstation™ using software which was developed on-site. The software provides facilities for simulating the neural network control system, simulating the musculoskeletal model, and on-line graphical display and file I/O of neural and musculoskeletal variables. The Runge-Kutta integration method with a timestep of .001 seconds was used to integrate the differential equations of the skeletal model. The Euler integration method with a timestep of .01 seconds was used to integrate the differential equations of the neuron model. The Euler method was also used for the PG neuron model except that a time step of .001 seconds was required due to the dynamics of pacemaker currents. The parameters of the PG used throughout the study are as listed in Chapter 3, Table 1 and the activation trajectories of each of the PG neurons are shown in Chapter 3, Figure 3. All parameters of the PS were fixed, with the exception of the output weights, w_y , which were adapted using the *time averaged learning* algorithm described in Chapter 3.

Simulation studies

The evaluation of the neural network control system consisted of a series of studies performed on computer simulations of the musculoskeletal models described above. These studies were designed to assess the ability of the control system to provide *automated customization*, *on-line adaptation*, and *disturbance resistance*. Throughout the series of studies, four different control system configurations (Figure 5) were used: feedforward (FF), feedforward with feedback (FF/FB), adaptive feedforward (FF/AD), and adaptive feedforward with feedback (FF/AD/FB).

Automated customization

The first, and most important, control system design goal was to provide the PG/PS control system with the ability to automatically customize its properties for controlling a given movement in a particular musculoskeletal system. The series of studies described below were directed at assessing the ability of the control system to achieve automated customization, with particular emphasis on the adaptive properties of the PS.

Customization for individuals of a varied population

The objective of this study was to determine if the automated customization procedure of the PG/PS control system could make the appropriate adjustments to control each of several different musculoskeletal systems from a varied population. The same set of PG parameters was used for each musculoskeletal system, but the PS parameters (only the output weights) were customized for each system. Therefore, the adjustments to the feedforward controller performance were entirely due to changes in the output weights of the PS.

The one-segment musculoskeletal system in the swinging pendulum configuration was used in this study. A population of musculoskeletal systems was generated by varying the system parameters from the original set listed in Table 5. Each of seven different musculoskeletal system parameters were varied one at a time $\pm 50\%$ in increments of 10% . The following parameters were varied: muscle input gain (b_0), muscle torque-velocity slope factor (k_w), muscle maximum shortening velocity (ω_{max}), muscle torque angle curve width (θ_w), segment mass (m), joint stiffness (K_s), and joint damping (K_B). Thus, a population of 71 different systems with a wide range of system properties was used for evaluating the automated customization procedure of the control system. The FF/AD/FB control system was then used in a simulation run consisting of 20 cycles of movement (20 sec.) during which the PS weights were adapted, or equivalently, the feedforward controller was customized. The evaluation phase consisted of a 10 second simulation run in which

the feedback controller and the adaptation algorithm were disabled, *i.e.* the FF control system configuration was used. The root-mean-square (rms) value of the tracking error calculated over the last second of the 10 second trial was used as the evaluation criterion for the customized FF controller.

Each of these musculoskeletal systems was used in a two-phase experiment which included a training phase and an evaluation phase. In the training phase, the PS output weights were initialized to zero and the feedback controller and adaptation algorithm were enabled. For use in the learning algorithm during the training phase the error signals for the PS units of the two muscles were calculated as

$$\begin{bmatrix} e_f \\ e_e \end{bmatrix} = \begin{bmatrix} +1 \\ -1 \end{bmatrix} \begin{bmatrix} \theta_{des} \\ -\theta \end{bmatrix} \quad (8)$$

where e_f , e_e are the error signals for the PS units of the flexor and extensor, respectively; θ_{des} is the desired joint angle and θ is the actual joint angle. Therefore the error signals for the agonist/antagonist pair of muscles have the same absolute value, but differ in sign.

The control system was customized for each of the 71 musculoskeletal systems in the population described above and then evaluated. Time traces of various control system and musculoskeletal system outputs during one training session are shown in Figure 6. The musculoskeletal system parameters in this trial were those listed in Table 5. In the training phase the output weights (w_y) of the PS are initially zero,

and therefore there is no feedforward control signal. As adaptation occurs, the feedforward component of the stimulation signal increases and therefore less is required of the feedback controller. By the end of the 20 second training session, the feedforward controller has been customized and is providing virtually all of the signal sent to the muscle. The setpoint tracking improves as the training phase progresses. Time traces of control system and musculoskeletal system outputs during the subsequent evaluation phase are shown in Figure 7. In this evaluation phase, the rms value of the tracking error for the customized feedforward controller was calculated to be 0.3° .

Figure 8 shows the composite results of the customization for each of the 71 different musculoskeletal systems. Note that for each of the systems, the rms tracking error for the customized feedforward controller was approximately 0.5° , which is about 1% of the peak-to-peak amplitude of the desired angle trajectory. These results demonstrate that the adaptive properties of the PS provide the PG/PS control system with the ability to automatically customize the parameters of the feedforward control system for each of a wide variety of musculoskeletal systems.

Effects of mechanical disturbances

This study was designed to characterize the effects of mechanical disturbances on the customization procedure. The one-segment musculoskeletal system in the swinging pendulum configuration (parameters listed in Table 5) was used in this

study. Mechanical disturbances were simulated in this series of simulation trials by applying uniformly distributed torque noise at the joint. In each run, the mean value of the torque noise was set to 0 and the range was set to a value that was varied from 1-10 Nm. The maximum range value was selected to be approximately 50% of the peak-to-peak torque required to drive the system in the disturbance-free case. The two-phase experiment described earlier was repeated 10 times (one experiment at each noise level) except that mechanical disturbances were applied during the training phase. No disturbances were applied during the evaluation phase.

Figure 9 demonstrates the effect of mechanical disturbances on the customization procedure. This figure shows that applying higher levels of noise during the training phase degrades the performance of the customized feedforward controller. Note, however, that even at levels of disturbance torques of 8 Nm, the rms error is approximately 2° (or 5% of the peak-to-peak amplitude of the desired angle trajectory). These results indicate that the customization procedure is less effective in the presence of disturbance torques, but that its performance is still acceptable even with high levels of disturbance torques.

Effects of measurement noise

This study was designed to characterize the effects of measurement noise on the customization procedure. The one-segment musculoskeletal system in the swinging pendulum configuration (parameters listed in Table 5) was used here. In

this series of experiments uniformly distributed measurement noise was added to the joint angle signal used by the adaptation procedure and the feedback controller. The measurement noise added to the joint angle was a uniformly distributed signal with mean = 0, range = $1-8^{\circ}$. The maximum range value was selected to be 20% of the peak-to-peak amplitude of the desired signal trajectory. The two-phase experiment described earlier was repeated 8 times (one experiment at each noise level) except that measurement noise was applied during the training phase.

Figure 10 demonstrates the effect of sensor measurement noise on the customization procedure. Note that even high levels of measurement noise levels applied during the training phase have little effect on the customization procedure. For all noise levels, the rms errors of the customized feedforward controller tracking were less than 2° (less than 5% of the peak-to-peak amplitude of the desired angle trajectory). These results indicate that the customization procedure can still be effective in the presence of measurement noise.

Control of movement over a range of frequencies

The purpose of this study was to determine the ability of the PG/PS control system to customize itself for controlling movements at different frequencies. In this series of experiments, the one-segment musculoskeletal system in the swinging pendulum configuration (parameters listed in Table 5) was used. The two-phase experiment described earlier was repeated 10 times, with a different frequency of

movement in each experiment. The parameters of the PG network were the same in each experiment, with the exception of the $t_1 \rightarrow t_2$ synaptic weight, which was specified using the procedure described in Chapter 3.

The triangles in Figure 11 show the rms error of the feedforward control system after customization at a given movement frequency. Over most of the frequency range tested, the rms value of the tracking error was less than 2° . At a movement frequency of 1.5 Hz, however, the rms value of the tracking error is approximately 5° . This high value of the tracking error is primarily due to the fact that as movement frequency increases, the phase-shift between the input signal and the desired angle trajectory decreases. The adaptive properties of the PS are able to account for this shift over much of the frequency range, but not at 1.5 Hz.

In the description of the PG in Chapter 3, the mechanism for synchronizing the desired trajectory with the PG oscillation was described (Chapter 3, Figure 13). The relative phase between these two signals can be regulated by adjusting the weight of the $E_s \rightarrow tr$ synapse using the training algorithm for the PG that was described in Chapter 3. The set of 10 experiments at different frequencies was repeated, except that training of both the PG and the PS was utilized. The PG training used here consisted of adjusting only the $E_s \rightarrow tr$ weights, based upon the phase difference between the desired and actual trajectories. The results of this set of experiments are indicated by the circles in Figure 11. The improved tracking obtained here at higher movement frequencies is due to the fact that training of the synaptic weights in the

PG circuitry adjusted the phase shift between the PG outputs and the desired angle trajectory.

Control of an inverted pendulum

The purpose of this study was to determine if the customization procedure could be used to determine feedforward controller parameters for the control of an inherently unstable system. The inverted pendulum configuration of the one-segment musculoskeletal system with the parameters listed in Table 5 was used in this study. The parameters used for the PG were those listed in Chapter 3, Table 1. and thus the PG was identical to that used for controlling the swinging pendulum. The two-phase experiment described above was repeated on this inverted pendulum system.

Time traces of various control system and musculoskeletal system outputs during the training session are shown in Figure 12. Note that tracking improves over the course of the training session to the point where almost perfect tracking is achieved. Time traces of control system and musculoskeletal system outputs during the subsequent evaluation phase are shown in Figure 13. In this evaluation phase, the feedback controller and the adaptation are both disabled, and therefore the results indicate the quality of the customized feedforward controller tracking. In this trial the rms value of the tracking error was calculated to be 1.6° . These results demonstrate the ability of the customization procedure to determine appropriate parameters for feedforward control of an inherently unstable system.

Control of a two-segment system

This study was designed to evaluate the ability of the customization procedure to account for the dynamic coupling amongst the segments of a multi-segmented body. The two-segment skeletal system with a pair of uniarticular muscles acting at each joint (Figure 4, parameters listed in Table 6) was used in this study. The desired trajectories for the hip and knee joints are shown in Figure 15, 16. The parameters used for the PG are listed in Chapter 3, Table 1. The protocol used in this study consisted of three phases. First, the PS parameters for the muscles acting at each joint were customized to generate the desired movement of a single-segment system using the training protocol described above. That is, the PS parameters of the muscles acting at the hip (iliopsoas and gluteus maximus) were customized for generating movement of the thigh which was not coupled to the shank. Similarly, the PS parameters of the muscles acting at the knee (vasti and short head of biceps) were customized for generating movement of the shank which was not coupled to the thigh. Second, these PS parameters were used in feedforward control of the two-segment system using the evaluation protocol. If the coupling between the segments is not significant for this movement, this feedforward control system should perform well. Third, the PS parameters were retrained for generating movement of the two-segment system. In this training, adjustments to the PS parameters of muscles acting at a joint (hip or knee) were based upon the tracking error at that joint (Figure 14). That is, the error signal for each of the muscles was calculated as

$$\begin{bmatrix} e_v \\ e_b \\ e_i \\ e_g \end{bmatrix} = \begin{bmatrix} -1 & 0 \\ +1 & 0 \\ 0 & +1 \\ 0 & -1 \end{bmatrix} \begin{bmatrix} \theta_{hdes} & -\theta_h \\ \theta_{kdes} & -\theta_k \end{bmatrix} \quad (9)$$

where e_v , e_b , e_i , and e_g are the error signals used for the PS units of the vasti, biceps, iliopsoas, and gluteus respectively. θ_h and θ_k are the hip and knee angles, and θ_{hdes} , θ_{kdes} are the desired hip and knee angles. Finally, the retrained set of PS parameters were used in feedforward control of the two-segment system using the evaluation protocol.

Time traces of various control system and musculoskeletal system outputs during the evaluation using PS parameters trained on the one-segment systems are shown in Figure 15. Note that tracking performance is very poor due to the coupling between the segments that has not been accounted for in the customization on the uncoupled one-segment systems. Figure 16 shows time traces of various control system and musculoskeletal system outputs during the evaluation using PS parameters that had been retrained on the two-segment system. Note the improved tracking performance of this feedforward control system after customization on the coupled two-segment system. These results demonstrate the ability of the automated customization procedure to account for the dynamic coupling amongst skeletal segments in determining appropriate feedforward control system parameters.

Using biarticular muscles

The purpose of this study was to determine if the automated customization procedure could learn to utilize biarticular muscles appropriately in the control of a multi-segmented body. The musculoskeletal system was the same as used in the previous study, except that two biarticular muscles (rectus femoris and hamstrings) were also added. The desired trajectories, the parameters used for the PG, and the protocol were the same as those in the previous study. The training algorithm used in this study was identical to that of the previous study, except that the training signal provided to the biarticular muscles was the sum of the errors at the two joints crossed by the muscle (Figure 17). That is , the error signal for each of the muscles was calculated as:

$$\begin{bmatrix} e_v \\ e_b \\ e_h \\ e_r \\ e_i \\ e_s \end{bmatrix} = \begin{bmatrix} -1 & 0 \\ +1 & 0 \\ +1 & -1 \\ -1 & +1 \\ 0 & +1 \\ 0 & -1 \end{bmatrix} \begin{bmatrix} \theta_{hdes} & -\theta_h \\ \theta_{kdes} & -\theta_k \end{bmatrix} \quad (10)$$

where e_v , e_b , e_h , e_r , e_i , and e_g are the error signals used for the PS units of the vasti, biceps, hamstrings, rectus, iliopsoas, and gluteus respectively. θ_h and θ_k are the hip and knee angles, and θ_{hdes} , θ_{kdes} are the desired hip and knee angles. Figure 18 shows time traces of various control system and musculoskeletal system outputs during the evaluation using PS parameters that had been trained for 20 seconds on the two-segment system using biarticular muscles. Note that tracking performance is comparable to that of the feedforward controller utilizing only uniarticular muscles. Figure 19 shows the tracking performance of the feedforward controller after 200 seconds of training. Note that tracking has improved slightly over the longer training trial and that the various phases of the muscle activation patterns are more clearly delineated. Here, rectus femoris has one phase of activation at the point where knee extension is initiated and the hip is flexing. Hamstrings has two phases of activation in the cycle: the primary phase of activation occurs at the point where hip extension is initiated and the knee extension is terminated, the secondary phase occurs towards the end of the hip extension and at the initiation of knee flexion. The activity patterns of these muscles are consistent with their muscle actions and indicate that they are being used appropriately. These results demonstrate that the PG/PS control system can learn to use biarticular muscles effectively for the control of multi-segmented systems.

On-line adaptation

The second goal of the control system design process was to provide the ability to adapt in order to account for changes in musculoskeletal system properties that might occur while the system is operating. One cause for such changes in the musculoskeletal system properties is that electrical activation of paralyzed muscles can result in rapid muscle fatigue. The occurrence of this fatigue is primarily due to two factors: the muscles are often poorly conditioned and the mechanism for electrical activation of the muscle usually recruits the less fatigue-resistant fibers first. Muscle fatigue can cause problems for the FNS control system because it can result in a drop in peak muscle torque and changes in the recruitment properties of the muscle.

This set of experiments was designed to determine if the adaptive properties of the PG/PS control system could account for on-line changes in musculoskeletal system properties, such as those caused by muscle fatigue. The swinging pendulum configuration of the one-segment musculoskeletal system with parameters listed in Table 5 was used in this study. The PG parameters used were those listed in Chapter 3, Table 1, and the initial PS parameters were those resulting from the 20 second training trial on the musculoskeletal system without fatigue. Thus, at the initiation of the trials described below, the control system had already been customized for the musculoskeletal system in its non-fatigued state.

This evaluation consisted of several different simulation runs, in which muscle fatigue was simulated by varying either muscle input gain, (b_0), or muscle recruitment offset, (γ_0). The simulation run lasted 100 seconds, during which one of the musculoskeletal system parameters was varied in time from its original value (see Figures 20,21), as described earlier in the Methods section. For each of the two muscle parameters that were varied, simulation runs were performed using four different control system configurations: FF, FF/FB, FF/AD, and FF/AD/FB.

Figure 20 shows the results of the four simulation runs in which muscle input gain was varied. The performances of the fixed-parameter control systems (FF and FF/FB) degrade significantly as the musculoskeletal system properties change. The FF/FB control system performed better than the FF control system but, despite the action of the feedback controller the rms error gradually increased. However, the adaptive capability of the FF/AD and FF/AD/FB systems allowed these systems to maintain good tracking performance despite changes in the musculoskeletal system. Similar results were obtained from the set of studies using the model of muscle fatigue which involved a shift in the recruitment curve (Figure 21). These results (Figures 20,21) demonstrate the ability of the adaptive properties of the PG/PS control system to account for on-line changes in musculoskeletal system properties.

Disturbance resistance

The third goal of the control system design process was to provide the PG/PS control system with the capability of resisting mechanical disturbances that might occur in the course of operation of the FNS system. Such disturbances may be caused by internal spastic muscle contractions or external loading of the limb. Two mechanisms have been incorporated into the design of the PG/PS control system to account for such disturbances. The first is a *servo-control* mechanism that is used to supplement the signal from the PS. The second is a *phase-resetting* mechanism that is used to reset the phase of the PG activity.

Servo-control

This study was designed to investigate the ability of the servo-control mechanism to resist mechanical disturbances. The inverted pendulum configuration of the musculoskeletal system (parameters listed in Table 5) was used in this series of simulation runs in which uniformly distributed torque noise was applied at the joint. In each run, the mean value of the torque noise was set to 0 and the range was set to one of 5 different levels (0-5 Nm). The parameters of the PG/PS control system were those resulting from the 20 second training trial on the inverted pendulum system described above. Twelve simulation runs were conducted: one at each of 6 different noise levels on the FF control system configuration and on the FF/FB control system configuration.

Composite results from this set of simulations are shown in Figure 22. Note that the performances of both the FF and FF/FB control systems were degraded by the addition of mechanical disturbances to the system, but that performance is better if the feedback controller is active. These results indicate that supplementing the feedforward signal of the PG/PS control system with a servo-control input can substantially improve tracking performance in the presence of mechanical disturbances.

Phase-resetting

This study was designed to investigate the role of the phase-resetting mechanism in responding to applied mechanical disturbances. The swinging pendulum configuration of the musculoskeletal system (parameters listed in Table 5) was used in this series of simulation runs in which pulse disturbance torques were applied at the joint (ampl. = 2 Nm, width = 50 msec). The parameters of the PG/PS control system were those resulting from the 20 second training trial on the swinging pendulum system described earlier. This study consisted of two sets of 10 simulation runs in which the pulse disturbance was applied at different phases of the movement cycle. The phase-resetting mechanism was inactive in one set of simulation runs, and active in the other. In all simulations the servo-control mechanism was active, and the adaptation was turned off.

Example traces from a simulation in which the phase-resetting mechanism was not active are shown in Figure 23. The application of the disturbance pushes the system away from its desired trajectory, but the combined action of the feedforward and the servo-control mechanisms quickly restore the movement to track its desired trajectory. However, a large amount of muscle torque (approximately 3 times the amount required for unperturbed movement) is required to restore the tracking performance. Example traces from a simulation in which the phase-resetting mechanism was active are shown in Figure 24. Once again, the application of the disturbance pushes the system away from its desired trajectory. In this case, however, the signal to the PG causes a reset in its cyclic activity and a reset of the desired trajectory (due to the synchronization of the desired trajectory with the PG as described in Chapter 3). Once again, tracking is restored rather quickly, but here, the large peak in applied muscle torque is absent. The PG reset mechanism recognizes the early termination of the cycle and resets the PG and the desired trajectory. This makes the tracking problem easier for the servo-controller and thus less muscle torque is required. The data from these two trials indicate that the phase-resetting mechanism provides a 61 % reduction in peak muscle torque and an 18 % reduction in rms muscle torque. Composite results from the series of experiments in which the disturbances were applied at different phases of the movement cycle are presented in Figure 25. The phase-resetting mechanism exhibited phase-dependent properties, and it resulted in a substantial reduction in the amount of muscle torque

used to drive the movement. These results indicate that the phase-resetting mechanism can play an important role in an FNS control system by reducing the amount of torque required from the set of muscles.

Discussion

Neurobiological basis of the control system design

Several aspects of the design of this control system are based upon an understanding of the operation of neurobiological motor control systems. The most important of these design features are the two-stage structure of the control system and the neuron model and network architecture of the Pattern Generator. The evaluation of the control system presented here illustrates many of the advantages of incorporating these features into the design.

The two-stage design of the control system provides the basic structure within which the adaptive algorithms can function effectively and rapidly. This control system uses the Pattern Generator to provide the basic oscillatory rhythm. The PG functions primarily, but not entirely, in a fixed-parameter, open-loop mode. The adaptive features of the control system are almost entirely provided by the adaptive filtering characteristics of the Pattern Shaper. One direct consequence of this two-stage structure is that the customization procedure does not start with a blank slate. The basic pattern of activation of the muscles has already been specified, and

therefore the customization procedure is only required to fine-tune that pattern. Without this structure, the adaptation would be much slower and potentially less stable. The type of approach is used by the nervous system where evolution has determined the basic structure, but the details are continuously fine-tuned by adaptive processes.

The characteristics of the neuron model and network architecture of the PG provide it with the ability to generate oscillatory patterns that exhibit features such as stable endogenous rhythm generation, frequency modulation, phase-resetting, and phase-dependent reflexes. The characteristics of the neuron model and of the network architecture of the PG have been exploited in this design to provide features desirable in the control of FNS systems. This work has thus provided an example of how neurobiologically-based neuron models and network architectures can be effectively used in engineering design. There is great potential for the use of neurobiologically-based neural networks in the design of control systems as well as many other engineering applications.

Use of the control system in FNS applications

With regards to FNS applications, one of the most important aspects of this work may be the development of a procedure for automatically customizing the control system for a particular individual in a short time. The problem of 'fitting' an FNS system to a patient could certainly hinder, if not completely block, the

eventual clinical application of FNS technology. This work promises to provide significant improvements to procedures currently used in experimental FNS systems.

The unpredictability of the environment in FNS applications (both internal and external) most likely necessitates the use of feedback control techniques, but the time delays inherent in the response of the system can cause severe problems for the feedback controller. Hence, feedforward control techniques have to be used. Furthermore, the inability to obtain quantitative patient-specific models of the system to be controlled may necessitate the use of some form of adaptive control. The PG/PS control system is particularly well-suited for an FNS application because it uses a combination of adaptive feedforward and feedback control techniques.

One feature of the PG/PS control system that could cause substantial problems in a clinical application is that the adaptive procedures and the feedback control techniques are both dependent upon sensor measurements of musculoskeletal system variables. For many FNS applications, sensor measurements may be highly inaccurate or entirely unavailable. The results of one study presented here indicated that the customization procedure maintained adequate performance in the presence of uniformly distributed noise. Other noise models might also be appropriate for the measurements that are available in a given application.

In this work, the objective was to reduce the joint angle tracking error. In many applications, it may be useful to control other variables such as contact force, center-of-pressure on the foot, progression of the center-of-mass, and end-point

position. Also, in this implementation the tracking error was weighted equally throughout the movement cycle. In some applications, it may be useful to weight certain phases of the movement cycle more heavily than others.

Summary

A neural network control system has been evaluated with regards to its potential for use in FNS system. The PG/PS control system (described in Chapter 3) was evaluated in a series of studies on computer simulated musculoskeletal models. These studies demonstrated that the PG/PS control system is capable of automatically customizing its properties to control a given musculoskeletal system. In this regard, it has been shown to successfully address the issues of variability across subjects, measurement noise, mechanical disturbances, modulation of movement frequency, system stability, inter-segmental dynamic coupling, and the use of biarticular muscles. The time-averaged learning algorithm used by the PG/PS control system was shown to result in rapid customization times. In addition, the PG/PS control system was demonstrated to provide the capabilities of adapting to respond to on-line changes in musculoskeletal system properties and resisting mechanical disturbances. The success of the PG/PS control system in this evaluation indicates that it may provide significant improvements to existing FNS control system technology and suggests that the technique should be investigated further.

Tables

$$\tau_{m_k}(t) = A_k(t) * A_{TA_k}(t) * A_{TV_k}(t) \quad (1)$$

$$A_k(t) = a_{1_k} * A_k(t-SP) + a_{2_k} * A_k(t-2*SP) + b_{0_k} * r_k(t-SP) \quad (2)$$

$$A_{TA_k}(t) = 1 - (\theta_k(t) - \theta_{o_k})^2 / \theta_{w_k}^2 \quad (3)$$

$$A_{TV_k}(t) = (k_{\dot{\theta}_k} * (\dot{\theta}_{\max_k} - \dot{\theta}_k(t))) / (k_{\dot{\theta}_k} * (\dot{\theta}_{\max_k} + \dot{\theta}_k(t))) \quad (4)$$

$$r_k(t) = \gamma_{0_k} + \gamma_{1_k} * (PW_k(t) - D_k) + \gamma_{2_k} * (PW_k(t) - D_k)^2 + \gamma_{3_k} * (PW_k(t) - D_k)^3 \quad (5)$$

$$PW_k(t) = PW_{MAX_k} * z_k(t) \quad (6)$$

Table 1. Muscle model equations.

τ_m	= muscle torque	θ_w	= torque-angle width
A	= activation factor	$k_{\dot{\theta}}$	= torque-vel. slope
A_{TA}	= torque-angle factor	$\theta_{\max}$	= max. shortening vel.
A_{TV}	= torque-vel factor	$\gamma_0, \gamma_1, \gamma_2, \gamma_3$	= rec. curve coefficients
a_1, a_2, b_0	= linear dynamics param.	PW	= stimulus pulse width
r	= recruitment	$PW_{\max}$	= maximum pulse width
SP	= stimulus period	D	= recruitment deadband
$\theta, \dot{\theta}$	= joint angle, deriv.	z_k	= PS outputs
θ_o	= reference angle		

$$A_{TAa_k}(t) = 1 - ((\theta_{a_k}(t) - \theta_{ao_k}) - (\theta_{b_k}(t) - \theta_{bo_k}))^2 / \theta_{aw_k}^2 \quad (1)$$

$$A_{TAb_k}(t) = 1 - ((\theta_{b_k}(t) - \theta_{bo_k}) - (\theta_{a_k}(t) - \theta_{ao_k}))^2 / \theta_{bw_k}^2 \quad (2)$$

$$A_{TV_k}(t) = (k_{\dot{\theta}_k} * (\dot{\theta}_{\max_k} - (\dot{\theta}_{ak}(t) + \dot{\theta}_{bk}(t)))) / (k_{\dot{\theta}_k} * (\dot{\theta}_{\max_k} + (\dot{\theta}_{ak}(t) + \dot{\theta}_{bk}(t)))) \quad (3)$$

Table 2. Biarticular muscle model equations. The equations for the biarticular muscle are those listed in Table 1, with the exception of the torque-angle and torque-velocity terms, which are described above.

$A_{TAa,b}$	= biarticular torque-angle factor for joint angles a, b
θ_a, θ_b	= joint angles for two joints spanned by the muscle
θ_{ao}, θ_{bo}	= reference angle at each joint spanned by the muscle
θ_{aw}, θ_{bw}	= torque angle width at each joint spanned by the muscle

One-segment skeletal model equations:

$$\sum_k \tau_{m_k}(t) + \tau_n(t) = \left(\frac{1}{8} * m * l^2 + \frac{1}{2} * I \right) * \ddot{\theta}(t) + \frac{1}{2} * m * g * l * \sin\theta(t) - K_S * (\theta(t) - \theta_o) - K_B * \dot{\theta}(t) \quad (1)$$

FB controller equations:

$$\begin{aligned} z_{PD_k}(t) &= K_P * (\theta_{d_k}(t) - \theta_{m_k}(t)) + K_D * (\dot{\theta}_{d_k}(t) - \dot{\theta}_{m_k}(t)) \\ \theta_{m_k} &= \theta_k + \theta_{n_k} \\ \dot{\theta}_{m_k} &= \dot{\theta}_k + \dot{\theta}_{n_k} \end{aligned} \quad (2)$$

Table 3. One-segment skeletal model and feedback controller equations.

τ_m	=	<i>muscle torque</i>
τ_n	=	<i>disturbance torque</i>
m	=	<i>mass</i>
l	=	<i>length</i>
I	=	<i>moment of inertia</i>
g	=	<i>gravitational constant</i>
K_S	=	<i>joint stiffness constant</i>
K_B	=	<i>joint damping constant</i>
z_{FB}	=	<i>controller output</i>
K_P, K_D	=	<i>proportional and derivative controller parameters</i>
$\theta, \dot{\theta}$	=	<i>joint angle and its derivative</i>
θ_o	=	<i>joint stiffness reference angle</i>
$\theta_m, \dot{\theta}_m$	=	<i>measured angle and its derivative</i>
$\theta_n, \dot{\theta}_n$	=	<i>measurement noise and its derivative</i>

Two-segment skeletal model equations:

$$\begin{bmatrix} \sum \tau_{m_1} + \tau_{c_1} \\ \sum \tau_{m_2} + \tau_{c_2} \end{bmatrix} = \begin{bmatrix} H_{11} & H_{12} \\ H_{21} & H_{22} \end{bmatrix} \begin{bmatrix} \ddot{\theta}_1 \\ \ddot{\theta}_2 \end{bmatrix} + \begin{bmatrix} -2h\dot{\theta}_2 & -h\dot{\theta}_2 \\ h\dot{\theta}_1 & 0 \end{bmatrix} \begin{bmatrix} \dot{\theta}_1 \\ \dot{\theta}_2 \end{bmatrix} + \begin{bmatrix} G_1 \\ G_2 \end{bmatrix}$$

where:

$$H_{11} = (\frac{1}{4}m_1 + m_2)l_1^2 + I_1 + \frac{1}{4}m_2l_2^2 + I_2 + m_2l_1l_2\cos\theta_2$$

$$H_{12} = H_{21} = \frac{1}{4}m_2l_2^2 + I_2 + \frac{1}{2}m_2l_1l_2\cos\theta_2$$

$$H_{22} = \frac{1}{4}m_2l_2^2 + I_2$$

$$h = \frac{1}{2}m_2l_1l_2\sin\theta_2$$

$$G_1 = (\frac{1}{2}m_1 + m_2)gl_1\sin\theta_1 + \frac{1}{2}m_2gl_2\sin(\theta_1 + \theta_2)$$

$$G_2 = \frac{1}{2}m_2gl_2\sin(\theta_1 + \theta_2)$$

$$\tau_c = k_{\min} e^{m_{\min}(-\theta + \theta_{\min})} - k_{\max} e^{m_{\max}(\theta - \theta_{\max})} + K_s(\theta - \theta_0) + K_B\dot{\theta}$$

Table 4. Two-segment skeletal model equations. The variables τ_m , m , l , I , g , K_s , K_B , θ , $\dot{\theta}$ are as defined in Table 3, with the subscripts 1,2 referring to joints 1 and 2 respectively.

τ_c	=	passive joint constraint torque
$k_{\min}, k_{\max}$	=	nonlinear constraint scaling factor
$m_{\min}, m_{\max}$	=	nonlinear constraint slope factor
$\theta_{\min}, \theta_{\max}$	=	nonlinear constraint min, max angles

Muscle Model Parameters

PW_{max}	100 μsec
D	3.501 μsec
γ_0	0
γ_1	0.0190900
γ_2	-.0001152
γ_3	0.00000026
SP	0.05 sec
a_1	0.667900
a_2	-0.100100
b_0	20.0 (-20.0)
k_θ	0.20
θ_{max}	600.0 $^\circ/sec$
θ_o	-20.0 $^\circ$ (20.0 $^\circ$)
θ_w	100.0 $^\circ$

Skeletal Model Parameters

m	10	kg
I	0.1	kg $\cdot m^2$
l	0.4	m
K_s	20	Nm/ $^\circ$
K_D	1.0	Nm/ $^\circ/sec$

Table 5. Musculoskeletal model parameters for one-segment system. This table lists one set of parameters used for the one-segment musculoskeletal model. All parameters of the two muscles were the same with the exception of the muscle input gain (b_0) and the joint angle at optimal muscle length (θ_o), which have two values listed in the table.

Muscle Model Parameters

	b_o	θ_o	θ_w
<i>vasti</i>	-54.0	50°	60°
<i>biceps</i>	6.5	0°	60°
<i>iliopsoas</i>	13.0	90°	120°
<i>gluteus</i>	-21.6	0°	80°
<i>hamstrings</i>	-32.4	50° (40°)	60° (70°)
<i>rectus</i>	8.6	60° (40°)	40° (50°)

Skeletal Model Parameters

	thigh	shank
m	7.58 kg	3.75 kg
I	0.126 kg · m ²	0.065 kg · m ²
l	0.41 m	0.435 m
K_s	20 Nm/°	5 Nm/°
K_D	1.0 Nm/°/sec	3.17 Nm/°/sec
k_{REF}	2.6	10.5
k_{MAX}	8.7	3.1
m_{REF}	5.8	11.8
m_{MAX}	1.3	5.9
θ_{REF}	-30°	-6°
θ_{MAX}	110°	110°

Table 6. Musculoskeletal model parameters for two-segment system. This table lists the set of parameters used for the two-segment musculoskeletal model. All parameters of the muscles were the those listed in Table 4, with the exception of the muscle input gain (b_o), reference angle (θ_o), and the width of the torque angle curve (θ_w), which are listed above. The two-segment skeletal model utilized both linear and nonlinear joint angle constraints.

Figures

Figure 1. Neural network control system block diagram. This figure shows the various components of the neural network control system and of the musculoskeletal system to be controlled. The musculoskeletal system consists of two muscles (a flexor and an extensor) and a single skeletal segment. The Pattern Generator, PG, consists a set of coupled unit pattern generators, uPG, and produces a set of oscillatory signals, x_k . The Pattern Shaper, PS, consists of a set unit Pattern Shapers, uPS. Each uPS filters signals from the PG to provide an activation signal, z_k , to the muscle. The feedback controller can be used provide a trigger input to PG and servo-control input to the PS. The adaptation can be used to adjust the parameters of both the PS and the PG. The joint angle output, θ , is compared to the desired angle, θ_{des} , to generate an error signal which drives the feedback controller and the adaptation. The box labelled DT generates the desired trajectory signal and is triggered by input from the PG.

Figure 2. Muscle model block diagram. This diagram shows the various components of the musculoskeletal model. The model consists of four components: the recruitment curve, the linear dynamics, the torque-angle multiplicative factor, and the torque-velocity multiplicative factor. The equations describing this muscle model are given in Table 1.

Figure 3. Biarticular muscle model. This diagram shows the various components of the biarticular muscle model. The model consists of the four basic components of the uniarticular model: the recruitment curve (**REC**), the linear dynamics (**DYN**), the torque-angle multiplicative factor (A_{TA}), and the torque-velocity multiplicative factor (A_{TV}). The muscle generates torque at two joints, τ_a and τ_b . θ_a , θ_b , and $\dot{\theta}_a$, $\dot{\theta}_b$ indicate the two joint angles and their derivatives. A separate torque-angle relationship is used at each joint, but each uses both joint angles as inputs. Both joints use the same torque-velocity relationship which takes both joint velocities as inputs. The equations describing this muscle model are given in Table 2.

Figure 4. Skeletal models. This diagram shows the three different skeletal models used in the evaluation of the control system: the one-segment model in the swinging pendulum configuration, the one-segment model in the inverted pendulum configuration, and the two-segment model. θ indicates the joint angles, l indicates the length of the segment, and the subscripts h and k indicate the hip and knee angles, respectively.

Figure 5. Control system configurations. These four block diagrams illustrate the four different control system configurations used in the simulation studies described in the text. *FF* indicates the feedforward control system which was used during the evaluation studies described in the text; *FF/FB* indicates the combined feedforward and feedback control system; *FF/AD* indicates the adaptive feedforward controller; and *FF/AD/FB* indicates the adaptive feedforward control system with feedback which was used during the training sessions described in the text.

Figure 6. Swinging pendulum: training the control system. These data were generated in the training phase of the automated customization procedure on the one-segment musculoskeletal system in the swinging pendulum configuration with parameters listed in Table 5. The bottom plot shows the outputs of the Pattern Generator, $x(t)$; the next plot shows the output of the Pattern Shaper, $z(t)$, which is the activation signal provided to the muscle; the third plot shows the applied muscle torque τ ; and the top plot shows the joint angle trajectory, θ , and the desired joint angle trajectory, θ_{des} . The PG output is cyclic and does not change as the training session progresses. The operation of the learning algorithm adapts the filtering properties of the PS, resulting in improved tracking.

Figure 7. Swinging pendulum: feedforward control. These data were generated in the evaluation phase of the automated customization procedure on the one-segment musculoskeletal system in the swinging pendulum configuration with parameters listed in Table 5. The bottom plot shows the outputs of the Pattern Generator, $x(t)$; the next plot shows the output of the Pattern Shaper, $z(t)$, which is the activation signal provided to the muscle; the third plot shows the applied muscle torque τ ; and the top plot shows the joint angle trajectory, θ , and the desired joint angle trajectory, θ_{des} . In this trial the feedback controller and the adaptation were disabled, thus only the feedforward controller was active. The actual and desired trajectories are virtually superimposed, indicating the automated customization procedure effectively customized the feedforward control system.

Figure 8. Evaluating the automated customization procedure. This plot shows the composite results of the control system customization and evaluation performed on 71 different musculoskeletal systems, as described in the text. The horizontal axis indicates the percent by which a given parameter was varied; the vertical axis indicates the rms error of the customized feedforward controller tracking, as determined in the evaluation procedure described in the text. Seven different system parameters were varied: muscle input gain (b_0), muscle torque-angle curve width (θ_w), muscle torque-velocity slope parameter (k_θ), muscle maximum shortening velocity (θ_{max}), segment mass (m), joint stiffness (K_s), and joint damping (K_B). Note that for a wide range of musculoskeletal system parameter variation, the automated customization procedure successfully customized the parameters of the feedforward control system.

Figure 9. Effect of disturbances on customization. This plot shows the effects of additive, mechanical disturbances on the adaptation procedure. The horizontal axis indicates the range of the zero-mean uniformly distributed disturbances and the vertical axis indicates the rms error of the tracking error during the evaluation phase of the run. The feedforward control system was trained while the disturbances were being applied and the feedback controller was active. It was evaluated in a disturbance-free environment when only the feedforward controller was active. Note that the disturbances degrade the quality of the customized control system, but even at very high disturbance levels the rms error is less than 5° .

Figure 10. Effect of measurement noise on customization. This plot shows the effects of additive measurement noise on the adaptation procedure. The horizontal axis indicates the range of the zero-mean uniformly distributed measurement noise and the vertical axis indicates the rms error of the tracking error during the evaluation phase of the run. The feedforward control system was trained while the measurement noise was being added and the feedback controller was active. It was evaluated in a noise-free environment when only the feedforward controller was active. Note that even at high levels of measurement noise the rms error of the feedforward control system is less than 2° .

Figure 11. Control of movement at different frequencies. This plot shows the results of a set of simulation runs in which the customization procedure was used to train the feedforward control to generate movements at various frequencies. The horizontal axis indicates the frequency of movement, and the vertical axis indicates the rms value of the tracking error for the feedforward control system. The triangles indicate the tracking error of the feedforward controller after a training trial in which only the PS parameters were adapted. The circles indicate the tracking error of the feedforward controller after a training trial in which the parameters of both the PS and the PG were adapted.

Figure 12. Inverted pendulum: training the control system. These data were generated in the training phase of the automated customization procedure on the one-segment musculoskeletal system in the inverted pendulum configuration with parameters listed in Table 5. The bottom plot shows the outputs of the Pattern Generator, $x(t)$; the next plot shows the output of the Pattern Shaper, $z(t)$, which is the activation signal provided to the muscle; the third plot shows the applied muscle torque τ ; and the top plot shows the joint angle trajectory, θ , and the desired joint angle trajectory, θ_{des} . The PG output is cyclic and does not change as the training session progresses. The operation of the learning algorithm adapts the filtering properties of the PS, resulting in improved tracking.

Figure 13. Inverted pendulum: feedforward control. These data were generated in the evaluation phase of the automated customization procedure on the one-segment musculoskeletal system in the inverted pendulum configuration with parameters listed in Table 5. The bottom plot shows the outputs of the Pattern Generator, $x(t)$; the next plot shows the output of the Pattern Shaper, $z(t)$, which is the activation signal provided to the muscle; the third plot shows the applied muscle torque τ ; and the top plot shows the joint angle trajectory, θ , and the desired joint angle trajectory, θ_{des} . In this trial the feedback controller and the adaptation were disabled, thus only the feedforward controller was active. The actual and desired trajectories are virtually superimposed, indicating the automated customization procedure effectively customized the feedforward control system.

Figure 14. PG/PS for a two-segment system. This figure shows the PG/PS structure used in the studies on the two-segment system using uniarticular muscles. There is a pair of uPGs for each joint, and a uPS for each muscle. The four uniarticular muscles used are the three vasti of quadriceps (*vasti*), the short head of biceps femoris (*biceps*), the iliopsoas (*iliopsoas*), and gluteus maximus (*gluteus*). The learning paradigm uses the joint angle signal at each joint to update the weights of the PS units for muscles acting at that joint.

Figure 15. Effect of mechanical inter-segmental coupling. These plots show the results of an evaluation session on the two-segment musculoskeletal system. The bottom two plots show the outputs of the PS, which are the signals to the muscles acting at the knee and the hip. The top two plots show the actual and desired knee angle trajectories. The PS parameters used in this trial were obtained during training trials in which the segments were decoupled (*i.e.* the parameters were trained on one-segment systems). The poor tracking indicates that the inter-segmental coupling is significant and must be accounted for in the training of the PS parameters.

Figure 16. Controlling two-segment movements. These plots show the results of an evaluation session on the two-segment musculoskeletal system. The bottom two plots show the outputs of the PS, which are the signals to the muscles acting at the knee and the hip. The top two plots show the actual and desired knee angle trajectories. The PS parameters used in this trial were obtained during a training trial on the two-segment system. The improved tracking (as compared to Figure 15) indicates that the learning algorithm can account for the inter-segmental coupling between the two-segments.

Figure 17. PG/PS for a two-segment system with biarticular muscles. This figure shows the PG/PS structure used in the studies on the two-segment system using biarticular muscles. There is a pair of uPGs for each joint, and a uPS for each muscle. The four uniarticular muscles used are the three vasti of quadriceps (*vasti*), the short head of biceps femoris (*biceps*), the iliopsoas (*iliopsoas*), and gluteus maximus (*gluteus*). The two biarticular muscles are the hamstrings (*hams*) and rectus femoris (*rectus*). The learning paradigm uses the joint angle signal at each joint to update the weights of the PS units for muscles acting at that joint; thus, the training signal for a biarticular muscle is the sum of the error signal at the two joints.

Figure 18. Utilizing biarticular muscles after short training trial. These plots show the results of an evaluation session on the two-segment musculoskeletal system. The bottom three plots show the outputs of the PS, which are the signals to the muscles acting at the knee and the hip. The top two plots show the actual and desired knee angle trajectories. The PS parameters used in this trial were obtained during a 20 second training trial on the two-segment system in which biarticular muscles were utilized. The tracking performance indicates that the learning algorithm can learn to utilize biarticular muscles for the control of a two-segment system.

Figure 19. Utilizing biarticular muscles after long training trial.

These plots show the results of an evaluation session on the two-segment musculoskeletal system. The bottom three plots show the outputs of the PS, which are the signals to the muscles acting at the knee and the hip. The top two plots show the actual and desired knee angle trajectories. The PS parameters used in this trial were obtained during a 200 second training trial on the two-segment system in which biarticular muscles were utilized. The improved tracking performance and the different muscle activation profiles (as compared to Figure 18) indicate that over the longer training trial the learning algorithm can fine-tune the selection of muscle activation profiles to improve tracking performance.

Figure 20. Tracking performance as muscle fatigues. These plots present the results of the experiments described in the text in which muscle input gain was varied during the course of the experiment to simulate the effects of muscle fatigue. In each plot, the horizontal axis indicates time. The bottom plot shows the time course of the changes in muscle input gain, b_0 ; the top plot shows the trajectory of the rms value of the tracking error for each of four simulation runs with the four system configurations shown in Figure 5. The rms value of the tracking error was calculated for each second as the rms value of the difference between the actual and desired trajectories over the course of the previous second. As the muscle input gain is reduced the tracking of the FF control system degrades, as does that of the FF/FB control system. The FF/AD and the FF/AD/FB control systems maintain their good tracking performance (the two traces are virtually superimposed with rms value always less than 1°) despite the changes in the muscle properties.

Figure 21. Tracking performance as muscle fatigues. These plots present the results of the experiments described in the text in which muscle recruitment offset was varied during the course of the experiment to simulate the effects of muscle fatigue. In each plot, the horizontal axis indicates time. The bottom plot shows the time course of the changes in muscle recruitment offset, g_0 ; the top plot shows the trajectory of the rms value of the tracking error for each of four simulation runs with the four system configurations shown in Figure 5. The rms value of the tracking error was calculated for each second as the rms value of the difference between the actual and desired trajectories over the course of the previous second. As the muscle recruitment offset is shifted the tracking of the FF control system degrades, as does that of the FF/FB control system. The performance in this case is worse than when the muscle input gain was shifted (Figure 20) due to the added effect of the shift in deadband of the recruitment curve. The FF/AD and the FF/AD/FB control systems maintain their good tracking performance despite the changes in the muscle properties.

Figure 22. Contribution of the servo-controller. This plot shows the contribution of the servo-control mechanism to the control system performance during trials in which additive, mechanical disturbances were applied to the musculoskeletal system. The horizontal axis indicates the range of the zero-mean uniformly distributed disturbances and the vertical axis indicates the rms error of the tracking error during the simulation trial. The solid line indicates the results from a set of trials in which only the customized feedforward control component was active. The dashed line indicates the results from a set of trials in which both the customized feedforward and the feedback control components were active. The adaptation was not active in either sets of trials. The contribution of the feedback controller is indicated by the improved tracking performance when it was active.

Figure 23. Response to pulse disturbance without phase resetting. These plots show the response of the control system to a pulse mechanical disturbance. The bottom plot shows the outputs of the Pattern Generator, $x(t)$; the next plot shows the output of the Pattern Shaper, $z(t)$, which is the activation signal provided to the muscle; the third plot shows the applied muscle torque τ ; and the top plot shows the joint angle trajectory, θ , and the desired joint angle trajectory, θ_{des} . In this trial the feedforward and servo-control components are active, but the phase resetting mechanism is not. The disturbance causes the actual trajectory to move away from the desired trajectory, but the action of the servo-controller quickly improves the tracking. In order to restore tracking performance, however, the action of the servo-controller results in large muscle torques being applied.

Figure 24. Response to pulse disturbance with phase resetting. These plots show the response of the control system to a pulse mechanical disturbance. The bottom plot shows the outputs of the Pattern Generator, $x(t)$; the next plot shows the output of the Pattern Shaper, $z(t)$, which is the activation signal provided to the muscle; the third plot shows the applied muscle torque τ ; and the top plot shows the joint angle trajectory, θ , and the desired joint angle trajectory, θ_{des} . In this trial the feedforward, servo-control components, and phase resetting mechanism are all active. The disturbance causes the actual trajectory to move away from the desired trajectory, but good tracking performance is quickly restored. Note that the large peak in muscle torque generated without phase resetting (shown in Figure 23) is not present when the phase resetting mechanism is active.

Figure 25. Percent reduction in muscle torque due to phase resetting. This plot shows the composite results of two sets of trials in which pulse disturbances were applied to the musculoskeletal system. The time of disturbance application was varied across trials. The horizontal axis indicates the time (expressed as a percent of cycle) at which the disturbance was applied; the vertical axis indicates the percent reduction in muscle torque due to the action of the phase resetting mechanism. The solid line indicates the percent reduction in rms muscle torque and the dashed line indicates the percent reduction in peak muscle torque. A reduction in muscle torque is achieved only during certain phases of the activation cycle due to the phase-dependence of the phase-resetting reflex.

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Chapter 5. Conclusions

Summary

A neural network control system (PG/PS control system) has been designed for the purpose of controlling cyclic movements in Functional Neuromuscular Stimulation (FNS) systems. The control system is implemented by a two-stage neural network that utilizes a combination of adaptive feedforward and feedback control techniques. The first stage of the neural network, the Pattern Generator, generates a cyclic pattern of activity. This stage is based upon neural models of locomotor control and displays many properties of normal locomotor control systems that are desirable in an FNS system. The signals from the Pattern Generator are adaptively filtered by the second stage of the neural network, the Pattern Shaper. This stage uses modifications to standard artificial neural network learning algorithms to adapt its filter properties.

The PG/PS control system has been evaluated in a series of studies on computer simulated musculoskeletal models. These studies demonstrate that the PG/PS control system is capable of automatically customizing its properties to control a given musculoskeletal system. In this regard, it has been shown to successfully

address the issues of variability across subjects, measurement noise, mechanical disturbances, modulation of movement frequency, system stability, inter-segmental dynamic coupling, and the use of biarticular muscles. In addition, it has been shown to provide the capability of responding to on-line changes in musculoskeletal system properties and resisting mechanical disturbances. The success of the PG/PS control system in this evaluation indicates that it may provide significant improvements to existing FNS control system technology and suggests that the technique should be investigated further.

Conclusions

Based upon the work presented in the previous chapters, the following conclusions can be drawn with regards to the design and the performance of the PG/PS control system:

- *The Pattern Generator demonstrates some of the potential advantages to be gained by incorporating the cellular and network properties of neurobiological control systems in engineering neural network control systems.* The Pattern Generator provides the control system with the many desirable features such as stable endogenous rhythm generation, frequency modulation, phase-resetting, and phase-dependent reflexes. These features of the control system

are attributable to the combination of the capacitive neuron membrane, the intrinsic pacemaker currents, and the highly structured network architecture.

- ▶ *The Pattern Shaper provides a mechanism for rapid adaptation in feedforward control of dynamic systems with input time delays.* A new learning algorithm developed in this work, *time-averaged learning*, allows the PS to account for time delays and low-pass filtering characteristics of the system to be controlled by using past neural activation in the update equation. This feature of the learning algorithm is critical to the success of this adaptive feedforward control strategy for this application. The time-averaged learning algorithm may also prove to be useful in other control system and adaptive pattern recognition applications.

- ▶ *Constrained learning can be a useful tool in neural network control system design.* This work provides several examples of how constrained learning can be used effectively in neural network control systems. The constraints on the learning paradigm can result in training times that are several orders of magnitude faster than is possible with global learning paradigms.

- ▶ *The PG/PS control system exhibits many properties of neuromotor control systems which would be desirable in an FNS control system.* The properties exhibited by the PG/PS control system include: oscillation over a range of frequencies, phase resetting, phase dependent reflexes, adaptability, feedback control, coordinated movement of multiple degree-of-freedom systems, and effective use of biarticular muscles. Many of these properties are not available using existing control strategies.

- ▶ *The PG/PS control system design successfully addresses three of the major problems in FNS control by providing automated customization, on-line adaptation, and disturbance resistance.* By addressing each of these problems, the PG/PS control system promises to provide significant improvements to current FNS control system technology. With further development and evaluation, the PG/PS control system may eventually contribute to the successful implementation of a clinically practical lower extremity FNS system.

The work presented here is significant because it may contribute to the eventual clinical implementation of lower extremity FNS systems in the field of rehabilitation medicine. FNS systems have the potential to significantly improve the quality of life for many neuromotor impaired individuals by providing capabilities

that are not available using existing rehabilitative techniques. In order to be effectively implemented on a clinical basis, however, several components of the FNS system must be improved. The work described here addresses several of the problems faced in implementing one component of the FNS system: the FNS control system.

This work is also significant because it demonstrates some of the potential advantages to be gained by using insight obtained from the study of neurobiological systems in the design of engineering control systems. Biological systems efficiently solve many problems that are similar to those faced in many engineering applications. With an understanding of the operation of neurobiological control systems, many of their characteristic features can be reproduced. General organizational principles, cellular properties, and network architectural properties have all been used effectively in the design of this engineering control system.

Future Work

The long-term goal of this work is the development of lower extremity FNS systems which will be practical for everyday use by paraplegic individuals. To achieve this goal, improvements are required in many components of the FNS system. Such improvements might include: extended long-term reliability of the electrode system, enhanced versatility of implanted stimulator technology, and

improved functionality of the control system. The work presented in this thesis demonstrates that the PG/PS control system has the potential to provide improvements to the control component of the FNS system. Several tasks still remain in order to develop the PG/PS control system to the point where it provides an acceptable level of function to the user of the FNS system.

First, the design of the control system should be enhanced to provide the ability to generate three dimensional movements in multi-segmented, multi-limbed systems. The work presented here demonstrated the ability to generate planar movements in a computer simulated model of one- and two-segment systems. Future work could focus on enhancing the PG architecture used in this work, which was based upon the model of the Lamprey [10]. Neurophysiological data and models of other vertebrate and invertebrate systems [*e.g.* 2,7,8,13,14,15,18] could be utilized to complement the basic structure provided by the Lamprey model.

Second, the design of the PS should be modified to provide more versatility. The PS structure described above has exhibited rapid adaptation of its filtering properties which provide a mechanism for automated customization of the PG/PS control system for a wide variety of musculoskeletal systems. However, this structure is limited in its versatility for use in a variety of movements over a range of frequencies. In future work, the Pattern Shaper structure could be modified to utilize neurophysiological data and models of spinal segmental circuitry drawn from the neurophysiology literature [*e.g.* 3,4,9,12,16,19]. The cellular structure and the

network architecture could utilize models of the motoneurons, Renshaw cells, Ia-interneurons and their interactions [*e.g.* 1,5,6,11,17]. The development should focus on providing the PS network with the versatility required while maintaining the capability for rapid adaptation of its filtering properties.

Third, the PG/PS control system (in its current form and after incorporating the future developments proposed above) could be further evaluated on computer-simulated models. The models used in this study were simplified versions of the complex multi-segment, multi-limb, multi-degree-of-freedom systems that must be controlled in order to provide function to an FNS user. In future work, models of more complex musculoskeletal systems could be developed and used in the evaluation of the PG/PS control system and other control systems.

Finally, the PG/PS control system could be evaluated on human subjects. In its current form, the control system could most readily be evaluated on a seated subject for the control of a swinging leg. Protocols could be used that are similar to the ones used in the computer simulation studies presented in Chapter 4. The automated customization procedure could be evaluated using the training/evaluation phases; the on-line adaptation procedure could be evaluated using longer trials in which muscle fatigue would be significant; and the disturbance resistance could be evaluated by applying mechanical disturbances at the joint. If needed, this initial stage of the evaluation on human subjects could be followed by further development of the control system. If the initial evaluation was favorable, it could be followed by

further evaluation on human subjects in experimental situations that are more like the daily living situation of the FNS user.

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