THE ROYAL SOCIETY

Model-based development of neuroprostheses for paraplegic patients

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In paraplegic patients with upper motor neuron lesions the signal path from the central nervous system to the muscles is interrupted. Functional electrical stimulation applied to the lower motor neurons can replace the lacking signals. A so-called neuroprosthesis may be used to restore motor function in paraplegic patients on the basis of functional electrical stimulation. However, the control of multiple joints is difficult due to the complexity, nonlinearity, and time-variance of the system involved. Furthermore, effects such as muscle fatigue, spasticity, and limited force in the stimulated muscle further complicate the control task. Mathematical models of the human musculoskeletal system can support the development of neuroprostheses. In this article a detailed overview of the existing work in the literature is given and two examples developed by the author are presented that give an insight into model-based development of neuroprostheses for paraplegic patients. It is shown that modelling the musculoskeletal system can provide better understanding of muscular force production and movement coordination principles. Models can also be used to design and test stimulation patterns and feedback control strategies. Additionally, model components can be implemented in a controller to improve control performance. Eventually, the use of musculoskeletal models for neuroprosthesis design may help to avoid internal disturbances such as fatigue and optimize muscular force output. Furthermore, better controller quality can be obtained than in previous empirical approaches. In addition, the number of experimental tests to be performed with human subjects can be reduced. It is concluded that mathematical models play an increasing role in the development of reliable closed-loop controlled, lower extremity neuroprostheses.

Keywords: model; simulation; functional electrical stimulation; neuroprosthesis; motion control; paraplegic patient

1. INTRODUCTION

Neuroprostheses on the basis of functional electrical stimulation (FES) may be used to restore motor function in patients with upper motor neuron lesions. The underlying neurophysiological principle is the generation of action potentials in the uninjured lower motor neurons by external electrical stimulation (for review, see Quintern 1998).

The possibility of evoking involuntary contractions of paralysed muscles by externally applied electricity was already known in the 18th century (Franklin 1757). However, after these initial feasibility demonstrations more than 200 years were to pass until functionally useful movements of paralysed muscles could be evoked by electrical stimulation. In the 20th century, the development of FES for skeletal muscle was inspired by the development of the artificial cardiac pacemaker (Hyman 1930; Furman & Schwedel 1959). The first demonstration of standing by FES without additional mechanical bracing in a spinal cord injured patient was reported by Kantrowitz (1960). He applied electrical stimulation to the quadriceps and glutei muscles via surface electrodes. The first portable neuroprosthesis for the lower extremities in patients with upper motor neuron lesions was developed by Liberson *et al.* (1961). They stimulated the peroneal nerve with surface electrodes in hemiplegic patients to prevent foot drop during the swing phase of gait. One decade later, several implantable FES systems for lower extremity applications in hemiplegic patients (Waters *et al.* 1975) and paraplegic patients (Cooper *et al.* 1973; Brindley *et al.* 1978) were developed and tested. The functional gain provided by these early systems was limited by the simple on–off stimulation protocols and the low number of stimulated muscle groups. Subsequently, several groups developed multichannel neuroprostheses with more sophisticated stimulation sequences and stimulation via surface electrodes (Kralj *et al.* 1983; Malezic *et al.* 1984) or percutaneous wire electrodes (Marsolais & Kobetic 1987). In the last 15 years the rapid progress in microprocessor technology has provided the means for computer-controlled FES systems (Petrofsky & Phillips 1983; Thrope *et al.* 1985; Keller *et al.* 1996), which enable flexible programming of stimulation sequences or even the realization of complex feedback (closed-loop) control strategies.

However, current commercially available neuroprostheses for the lower extremities still work in the same fashion as the first peroneal nerve stimulator (Liberson *et al.* 1961) or the early multichannel systems, which were developed in Ljubljana, now in Slovenia (Kralj *et al.*

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1980). Whereas other neuroprosthetic devices, e.g. the cochlea implant, the phrenic pacemaker, and the sacral anterior root stimulator for bladder control, have grown into reliable, functionally useful, commercially available neuroprostheses (Peckham *et al.* 1996), lower extremity applications are far away from this stage of development.

There are several reasons for this backlog in the development of lower extremity neuroprostheses. The human body is a multiple-link, unstable inverted pendulum. The neurophysiological and biomechanical processes underlying the generation of FES-induced movements are highly nonlinear with respect to both space and time. Therefore, it is difficult to determine the appropriate stimulation pattern that is required to obtain the desired limb motion. Complex multijoint movements, for instance ascending and descending stairs, are very difficult to control with open-loop systems. Effects such as muscle fatigue, spasticity, and limited force in the stimulated muscle as well as the influence of voluntary upper-body efforts further complicate the control task.

The use of mathematical models can improve and accelerate the development of lower extremity neuroprostheses significantly. A model that describes the relevant properties of the subject whose movement is to be controlled can enhance the design and test of control strategies applied to FES. Mathematical models have been developed, for instance, to predict the feasibility of specific FES-induced movements (e.g. Khang & Zajac 1989), to derive and optimize open-loop and closed-loop controllers (e.g. Riener & Fuhr 1998), or to be incorporated in a controller to determine better the required stimulation patterns (e.g. Veltink *et al.* 1992*a*). Furthermore, models that describe the neurophysiological and biomechanical processes underlying the generation of FES-induced movements can also provide significant insight into the internal muscle dynamics (e.g. Dorgan & O'Malley 1998). They may help to optimize force production and movement generation in FES applications.

The purpose of this article is to show how mathematical modelling and simulation can support the development of neuroprostheses. After presenting a short overview of neuroprostheses and modelling, four different model applications are discussed: the use of models may support (i) neurophysiological investigation of FES-activated muscles, (ii) biomechanical motion analysis, (iii) model-based design and test of control strategies, and (iv) movement control during the use of a neuroprosthesis. Two examples are presented that show how models support neuroprosthesis design. It is concluded that a model-based approach appears to be a potential means for developing a reliable, functionally useful neuroprosthesis also for lower extremity applications.

2. NEUROPROSTHESES: PRINCIPLES AND PROBLEMS

(a) *Release of nerve action potentials by means of FES*

In this and the following subsections a short overview of neuroprosthesis function and the problems related to artificial muscle activation is presented (for details, see Quintern 1998). Although FES is often referred to as 'muscle stimulation', mainly nerve fibres innervating a muscle are stimulated, irrespective of the type and localization of the electrodes. This, of course, requires that the respective lower motor neurons are preserved. Electrical stimulation activates the motor neurons and not the muscle fibres, because the threshold for electrical stimulation of the motor axons is far below the threshold of the muscle fibres (Mortimer 1981).

In neuroprostheses, pulsed currents are applied, each pulse releasing a separate action potential in neurons which are depolarized above threshold. Not only the current amplitude of the externally applied stimulation pulse, but also the duration of the pulse, its pulse width, determines if a specific neuron is recruited. The threshold value above which a neuron is recruited depends on its size, the electrical properties of the neuron and electrodes, the position of the electrodes relative to the neuron, and the type of electrodes. When electrical pulses of low intensity (low charge per pulse) are applied, only large low-threshold neurons which are close to the electrodes are recruited. With increasing intensity of the pulses, also small neurons with higher thresholds and neurons which are located further away from the electrodes are recruited (Gorman & Mortimer 1983).

When FES is applied to the neuromuscular system, muscle force increases with the number of recruited motor units (spatial summation), and therefore modulation of pulse width or pulse amplitude can be used to control muscle force (Crago *et al.* 1980*b*; Gorman & Mortimer 1983; Durfee & MacLean 1989; Popovic *et al.* 1991). Another possible method of controlling muscle force in FES applications is modulation of the stimulation frequency (temporal summation). However, the frequency range is limited, as low-stimulation frequencies produce unfused single twitches rather than a smooth muscular contraction or tetanus. On the other hand, muscle force saturates when stimulating with frequencies above 30 Hz. With increasing frequencies, the muscle is also subjected earlier to fatigue (Brindley *et al.* 1978).

Stimulation systems and electrodes can be grouped into external, percutaneous and implanted systems. In external systems the control unit and stimulator are outside the body. Surface electrodes are used that are attached to the skin above the muscle or peripheral nerve, whereas in percutaneous systems wire electrodes pierce the skin near the motor point of the muscle. In implanted systems both stimulator and electrodes are inside the body. Different kinds of implanted electrodes are used. They can be inserted into muscle (e.g. on muscle surface: epimysial electrodes), nerve (epineural electrodes), or fascicle (intrafascicular electrodes), or surround the nerve (nerve cuff electrodes).

(b) *Natural versus artificial muscle activation*

An action potential evoked by FES and propagating to the muscle is indistinguishable from a physiologically triggered action potential. However, there are fundamental differences between FES and the natural physiology of nerve activation. Compared with the physiological recruitment order, recruitment with FES is inverted (Gorman & Mortimer 1983). When low muscle forces are desired, and thus low-intensity electrical stimulation pulses are applied, mainly rapidly fatiguing large motor units are activated. With the same electrode position and constant stimulation intensity, the same motor units remain activated, which defeats the goal of spatial summation. In addition to these recruitment problems most current neuroprostheses trigger the action potentials in the recruited motor neurons of the respective nerve simultaneously. This is different from the central nervous system (CNS), which triggers action potentials asynchronously. Therefore, in artificial activation the stimulation frequency must be above the range of 12–16 Hz to achieve a relatively smooth tetanus (Jaeger *et al.* 1989). All these differences compared with the natural way of nerve activation cause early fatigue of the muscles, a main problem of neuroprostheses. Additional factors which decrease the fatigue resistance of paralysed muscles are atrophy and changes in fibre type composition (Grimby *et al.* 1976).

Another problem in neuroprostheses is posed by the influence of spasticity. Spasticity is not a single symptom, but rather than a number of unrelated signs that occur, for example, in patients suffering from an upper motor neuron lesion (Young 1994). Different aspects of spasticity, for example the increased muscle tone, exaggerated stretch reflexes, and the occurrence of spasms and flexion reflexes, may change when applying artificial electrical stimulation to the paralysed muscle (Lance 1980; Walker 1982; Quintern 1998). Spasticity is a major concern when reconstructing functional movements by FES, since the movement may be disturbed by an unexpected and thus unpredictable spasm (Dietz *et al.* 1981).

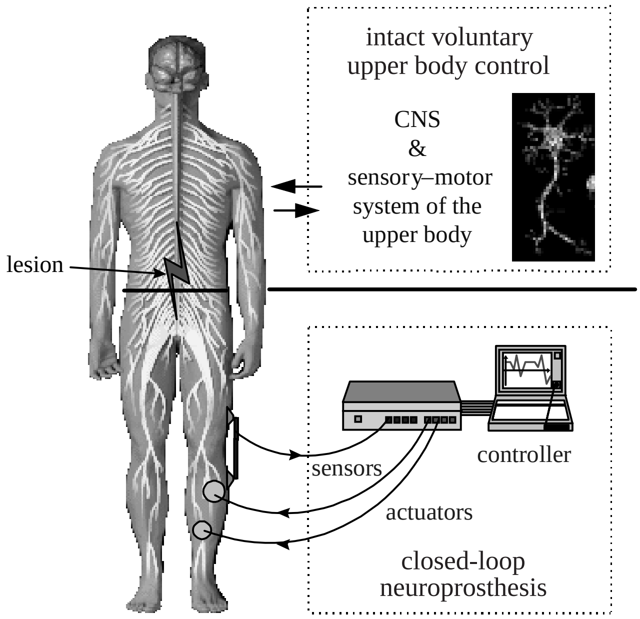


Figure 1. Scheme of a paraplegic patient equipped with a closed-loop controlled neuroprosthesis including sensors (e.g. goniometers), actuators (stimulator, electrodes, muscles), and the controller. The sensory–motor system of the upper body is still intact. Voluntary upper-body interactions may disturb the control of the lower limbs.

(c) *Open-loop versus closed-loop control*

Current neuroprostheses for the lower extremities have not found wide acceptance for clinical use. The gain of mobility in terms of walking speed and distance is limited. Complex movements with high coordination requirements, such as ascending and descending stairs, are as yet impossible. The reason for this limited function is that all commercially available systems are open-loop systems. Open-loop systems do not provide sensor feedback to determine the stimulation pattern. In contrast, a fixed empirically determined stimulation pattern is used to drive the paralysed muscles (Kralj & Bajd 1989; Kobetic & Marsolais 1994). Therefore, neither external disturbances (e.g. forces, obstacles, varying stair heights) nor internal disturbances (e.g. muscle fatigue, spasms) can be compensated.

Implementation of closed-loop (feedback) control strategies may allow also control of more complex movements (figure 1). Closed-loop control means that the actual state of the system, for example body posture and ground reaction forces, is recorded by sensors and fed back to a controller. On the basis of the measured signals, the controller then determines the stimulation pattern that is required to fulfil a specific movement task. Disturbances, such as external forces, muscle fatigue and spasticity can be recognized and the stimulation pattern readjusted, hence resulting in a smooth and successful movement. Most closed-loop systems were developed for control of force and angle at single joints only (Crago *et al.* 1980*a*; Bernotas *et al.* 1987; Hatwell *et al.* 1991; Veltink *et al.* 1992*a*; Yoshida & Horch 1996; Quintern *et al.* 1997). Only little work has been done in the field of closed-loop control of multijoint movements such as standing (Jaeger 1986), standing up and sitting down (Mulder *et al.* 1992), and walking (Durfee 1993; Franken *et al.* 1994).

Existing lower extremity neuroprostheses require paraplegic patients to use their arms during the movement, both to compensate for limited leg-joint moments and to maintain balance (figure 1). Voluntary contributions of the trunk and arms are difficult to predict, and thus to incorporate in a control strategy. However, if the FES controller does not account for voluntary contributions, artificial and natural control could adversely interfere, resulting in undesired or even dangerous motion and increased upper-body effort. To coordinate artificial and voluntary control in a neuroprosthesis, one possible approach is to adjust the stimulation to the estimated voluntary contribution of the patient, e.g. by recording the hand reaction forces (Donaldson & Yu 1996). Also other so-called 'patient-driven' strategies have been presented in the literature, where the influence of voluntary upper-body interactions is incorporated in the neuroprosthesis controller (Davoodi & Andrew 1996; Riener & Fuhr 1998; Matjacic & Bajd 1998). Experimental validation is currently being carried out.

The performance of closed-loop approaches is still not satisfying in terms of disturbance compensation, upper-body incorporation, variable step adjustment, or movement smoothness. This is one of the main reasons why current systems are not so far applied clinically. The use of models can significantly enhance the design and test of closed-loop control strategies applied to FES. Time-consuming and perhaps troublesome trial and error experimentation can be avoided, or at least shortened, and the number of experiments with humans can be reduced, both of which will accelerate the development of neuroprostheses. Furthermore, physiologically based mathematical models can provide significant insight into relevant activation and contraction processes. This insight may help us to understand better and eventually avoid the disadvantageous effects occurring during FES, such as increased muscular fatigue. Eventually, muscle force production and the resulting movement may be optimized to obtain better functionality.

3. MODELLING OVERVIEW

(a) *What are the purposes of modelling?*

The two most important purposes of a model are that it can promote an understanding of its object and that it can predict the behaviour of that object (Zahalak 1992). An 'understanding' can be provided by describing a complicated phenomenon in terms of a limited number of simpler concepts. This can be achieved by dividing the system into single components and modelling each component separately ('reductionist approach'). In this way, a good model allows an insight into the relevant processes of the object. A good model will also enable one to assess how a system will behave in situations that cannot be experimentally validated.

These two functions of comprehension and prediction (Zahalak 1992) are not necessarily linked. A model that describes its relevant properties by elementary concepts usually enables the prediction of these properties. On the other hand, there are quite formal predictive models, so-called 'black box models' that are derived from simple statistical or measured input–output data sets. These modelling approaches contribute little or nothing to an understanding of the system whose behaviour they predict.

(b) *Model types*

Depending on the direction in which the neurophysiological and biomechanical processes are represented in the model, one can distinguish 'direct' and 'inverse dynamic models'. Direct dynamic models (also called forward dynamic models) are used to calculate the internal processes in the same order in which they occur in the real system. The input in such a model are various stimulation parameters or complex stimulation patterns, the output are usually joint torques or limb movements. Contrary to the direct dynamic model, an inverse dynamic model describes the processes underlying FES-induced movements in the opposite direction: the input to the model is a measured or desired movement trajectory, the model then predicts the stimulation pattern, or any other internal quantity, which is necessary to achieve the predefined movement (Wells 1967; Chao & Rim 1973). In the control of FES-induced single-joint movements, the use of an inverse dynamic model has been shown to be a promising strategy to control joint angle (Hatwell *et al.* 1991; Hausdorff & Durfee 1991; Veltink *et al.* 1992*a*; Quintern *et al.* 1996, 1997). A similar approach is well-known in robotics as computed torque control (Craig 1986). Inverse dynamic models are also being used in biomechanical motion analysis to compute joint moments and other internal quantities (Bajd & Bowman 1982; Munih & Kralj 1997). However, when a redundant system with more muscles than degrees of freedom is considered, a unique solution is no longer possible and additional optimization procedures have to be applied.

A rather common modelling approach in neuroprosthetics is the consideration of the three different model compartments: muscle activation, muscle contraction, and body-segmental dynamics (Khang & Zajac 1989; Veltink *et al.* 1992*b*; Tashman & Zajac 1992; Schutte *et al.* 1993; Riener *et al.* 1996*b*). Activation dynamics describes the effect of temporal and spatial summation of muscle force and, therefore, may comprise the excitation and conduction of action potentials, the neuromuscular transmission, and the electrochemical–mechanical activation process within the muscle fibres, especially the calcium dynamics. The contraction dynamics describes the mechanical contraction and relaxation of muscle and tendon including their length and velocity-dependent properties. The body-segmental dynamics usually incorporates the joint kinematics, angle-dependent muscle moment arms, and limb anthropometry (geometry, mass, moment of inertia). Equations of motion are applied to compute joint movements from joint moments taking into account gravitational, inertial and Coriolis effects.

There exists a great variety of different muscle activation and muscle contraction dynamics models, which differ in complexity according to the task which has to be solved by the model. Zahalak (1992) divides muscle models into microscopic and macroscopic model classes. Microscopic models describe the detailed processes occurring within the muscle fibres on a cross-bridge level (Huxley 1957; Hatze 1977; Riener & Quintern 1997; Dorgan & O'Malley 1998). Conversely, in macroscopic models the muscle is represented as one single component with viscoelastic properties (Hill 1938; Zajac 1989) or as a black box comprising a linear or nonlinear higher-order transfer function (Crochetiere *et al.* 1967; Hannaford 1990; Bobet *et al.* 1993; Donaldson *et al.* 1995; Gollee 1998; Bobet & Stein 1998). A common macroscopic approach to model nonlinear biological systems is to block partition the system into a 'Hammerstein' structure, where a static nonlinearity is followed by a dynamic linear subsystem (Hammerstein 1930; Hunter & Korenberg 1986). A simple activation dynamics model can be derived, where the static nonlinearity represents the isometric recruitment curve and all of the muscle dynamics are assumed to be linear (Bernotas *et al.* 1986; Durfee & MacLean 1989; Hausdorff & Durfee 1991; Chia *et al.* 1991; Durfee 1992; Tashman & Zajac 1992). Such models ignore nonlinear muscle dynamics (Bobet & Stein 1998), time-delays due to finite conduction velocities in the membrane system (dead times), and time-varying properties such as muscle fatigue and potentiation. Hunt *et al.* (1998) have shown that, despite the widespread use of the Hammerstein model, it is not an accurate representation of isometric muscle. Nevertheless, its simplicity dedicates its choice in many neuroprosthesis applications. With regard to the two main purposes of a muscle model, comprehension and prediction, the microscopic models provide a deeper understanding of the function of individual muscles than the macroscopic models. Both types of models predict some, but not all, experimentally observed muscle phenomena.

Body-segmental dynamics models can also differ in complexity. In sophisticated models, joint moment arms are generally computed on the basis of musculotendon paths expressed by muscle origins, insertions, and, if necessary, intermediate muscle path points (Delp *et al.* 1990). In simplified models these moment arms can be represented as algebraic functions of joint angles that have been fitted to measured moment arm curves from the literature (Riener & Fuhr 1998). Another simplification is to separate passive viscoelastic muscle properties from the active muscle properties, and to assign the viscoelastic properties to the joints in order to keep the number of muscle parameters low (Riener & Fuhr 1998). Passive elastic properties can be modelled by double exponential equations (Mansour & Audu 1986), which can also account for the influence of the adjacent joint angles (Riener & Edrich 1999). Passive viscous joint moments are often, if not neglected, modelled by simple linear damping functions (Riener & Fuhr 1998).

When designing a model for neuroprosthesis development, the model approach to be chosen and the level of simplification depend on the exact research question being asked and the motor tasks being assessed (Winters 1995*a*). There is not a single model that can be applied to all tasks to be solved. If only the inputs and outputs of the system are of concern, then the black box approach is probably the most logical. On the other hand, if there is a desire to understand certain internal components or to associate properties of the whole system with one of the internal components, then the more complex, physiologically based reductionist approach has an obvious advantage. There is, however, a cost associated with the choice of model. A more sophisticated model may be better in replicating the system's behaviour over a wide range of operation, but can suffer from higher computational costs, challenges in model parameter identification and validation, and difficulties in interpreting or even obtaining results (Winters 1995*a*).

(c) *Parameter identification*

Before a muscle model or a more general musculoskeletal lower limb model can be used for neuroprosthesis development, model parameters must be identified. These can be derived through scaling values found in the literature or through direct experimental measures (Durfee 1992). An example of the former can be found in the work of Hatze (1977), who created a rather comprehensive muscle model based on sliding-filament mechanics, and used it to predict the behaviour of human motion (Hatze 1981). Because the model is based on the experimental evidence derived from frog and cat muscle, one is forced into numerous assumptions and extrapolations to assign values to the many constants contained in the model. Contrary, direct measurements minimize the number of assumptions required to parameterize the model.

Parameter identification through direct measurements can be performed in two different ways. First, by feeding a forward dynamic model and the real system with an identical input signal (e.g. stimulation pattern) and comparing model output with the measured output (e.g. joint angle). Second, if an inverse dynamic model can be derived from the direct dynamic model, the model output is compared with the input to the real system after feeding the model with the measured output signal. In both algorithms the parameters are obtained by solving an optimization problem, where the error between the compared signals is minimized. Several parameter-identification procedures were developed to adjust muscle models to specific individuals (Durfee & MacLean 1989; Chia *et al.* 1991; Van Zandwijk *et al.* 1996; Riener & Quintern 1997). Further approaches exist to identify also lower-limb models (Franken *et al.* 1993; Riener *et al.* 1996*b*; Kearney *et al.* 1997; Zatsiorsky & Seluyanov 1983).

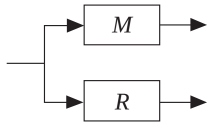
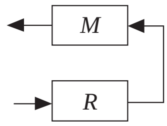
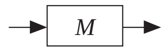
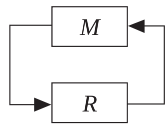
For larger-scale musculoskeletal models, only a subset of the model parameters are typically of significance for a given movement task (Winters 1995*a*). The use of sensitivity analyses (Lehman & Stark 1982) can help in understanding better model causality and how certain model parameters influence certain model behaviours. On the basis of a sensitivity analysis, insensitive parameters can be determined, and the model can be simplified for the class of tasks under investigation. Additionally, from an understanding of how parameter changes influence model outputs, parameter-identification procedures can be developed.

4. MODELLING IN NEUROPROSTHESIS DEVELOPMENT

With regard to the main purposes of muscle models, comprehension and prediction, two main areas can be distinguished, where the use of mathematical models can improve the development of lower-extremity neuroprostheses. First, models can offer much insight into the nature of FES-induced muscle activation and movement generation, and second, they can be used to predict the behaviour of the real system, i.e. the paraplegic patient, when stimulating the paralysed muscles. In this paper, the following four model applications will be discussed in more detail.

(i) Neurophysiological investigations: a mathematical model that describes the underlying biophysical processes and is able to capture relevant muscle properties can provide significant insight into internal dynamics. A better understanding of how artificially activated muscle works can help to optimize muscle force output.
(ii) Biomechanical motion analysis: calculating biomechanical quantities by inverse dynamic models is a convenient, non-invasive method, to gain insight into muscle coordination principles and muscle behaviour.
(iii) Design of control strategies: a computer simulation based on an accurate model of the musculoskeletal system can be used to design and test open-loop or closed-loop FES controllers. A neuroprosthesis can be optimized with regard to functional performance (e.g. tracking error), muscle fatigue, joint loading, upper-body effort, number of sensors and electrodes, etc.
(iv) On-line model application: model components can be implemented in the controller, for example, as an observer or as a predictor to better determine the required stimulation patterns. This can significantly improve controller performance during FES.

How the model is connected via its inputs and outputs to the real system depends on its application, and is

application	input, output	flow chart
(*a*) neurophysiological investigations	$IN_M = IN_R$; comparison of OUT_M and OUT_R	
(*b*) biomechanical motion analysis	$IN_M = OUT_R$; assessment of OUT_M	
(*c*) design of e.g. closed-loop control strategies	no real components	
(*d*) on-line model application	$IN_M = OUT_R$; $IN_R = OUT_M$;	

description: $IN_M \rightarrow$ $\boxed{M = \text{model}}$ $\rightarrow OUT_M$ $IN_R \rightarrow$ $\boxed{R = \text{reality}}$ $\rightarrow OUT_R$

Figure 2. Configuration of model and real components for different model applications. Note that in applications (*b*) and (*d*) the model block M contains inverse dynamic model parts. In applications (*c*) and (*d*) the model also comprises a model of the technical components including the controller.

depicted in figure 2. Components of the real system include control unit, stimulator, electrodes, stimulated human subject, sensors, amplifier, etc. The model block contains a mathematical description of the real system and it can include a forward or inverse dynamic model of the patient, the technical components (e.g. sensors) as well as the controller.

(a) *Neurophysiological investigations*

For neurophysiological investigations the model must be able to describe the phenomenon to be studied. It is important that the model is composed of a limited number of simpler concepts represented by physiologically based submodels. All the submodels must be identified, i.e. their parameters should be derived through scaling values found in the literature or through direct experimental measures (see § 3c). Then the entire model can be verified by comparing model output with the measured output (e.g. muscle force or joint angle) after feeding the model and the real system with an identical input signal (e.g. stimulation pattern) (see figure 2). If simulated and measured output agree within a certain range, one can assume that the model retains the essential global characteristics of the real system.

Further simulation runs can then provide significant insight into the internal processes. The subdivided model structure allows an investigation of how the global characteristics depend on certain submodels. For example, by varying certain model parameters or removing and adding submodels, one can study how each submodel influences the global model output. Since each submodel represents some physiological part of the real system, one can assign the observations to the underlying physiology.

Models that describe the neurophysiological processes underlying the generation of FES-induced movements have been developed to provide insight into the effects of fibre excitation (McNeal 1976; Rattay 1988), muscle fatigue (Giat *et al.* 1993), nonlinear summation of muscle force (Riener *et al.* 1996*a*; Dorgan & O'Malley 1998), and spasticity (Bajd & Bowman 1982; Vodovnik *et al.* 1984; He 1998). A better understanding of such effects can help to optimize force production in FES applications. To improve the design and increase the effectiveness of electrical stimulation-induced leg cycle ergometry, Schutte *et al.* (1993) presented a model that provides a better understanding of the factors that influence the force production capabilities of the stimulated muscles, the ability of the muscles to produce the desired movement, and the metabolic demands of the contractions. Similarly, Riener *et al.* (1996*b*) presented a model of the knee that allows a determination of the optimum set of muscles that should be stimulated in order to obtain minimum ab-/adduction and rotational joint load for a given motion task. Other musculoskeletal models were developed to study multijoint coordination in larger-scale systems and the contribution of muscle reflexes (Winters 1995*a*,*b*). The knowledge of muscle reflex behaviour is of great interest not only during natural movements, but also for neuroprostheses. Models that describe the flexion reflex may enhance the understanding of the underlying spinal mechanisms. Similarly, a better insight was gained in simulation studies of the central pattern generator in the lamprey (McClellan & Jang 1993). The flexion reflex can be activated, for example, when stimulating the peroneal nerve with surface electrodes. It provides a compound flexion synergy at the hip, knee and ankle joints. Thus, it can be used to initiate the swing phase in walking.

(b) *Biomechanical motion analysis*

In biomechanical motion analysis the movement of a healthy subject or a paraplegic patient is recorded by external sensors (goniometer, gyroscope, accelerometer) or contact-free optical measurement systems (e.g. Pedotti & Ferrigno 1985). Principles of inverse dynamics have been widely used to compute internal quantities, such as joint moments, joint and bone loads, or muscle forces from the kinematic data (Winter 1990; Riener & Straube 1997) (figure 2). For some applications kinetic data are required also, as obtained from force sensors or force platforms. The intention is to gain insight into coordination principles underlying a certain class of movements, or to estimate muscle behaviour for a certain task. With respect to neuroprosthesis development, two main applications can be distinguished.

First, it is of interest to gain insight into movement coordination of healthy subjects and learn from the CNS, which stands as proof that the biomechanical system of an upright human can indeed be stabilized and controlled. Thus, the problem becomes one of emulating at least a certain subset of CNS functions (Durfee 1993). Much can be learned from the capabilities of the CNS, such as natural control of balance and gait, and particularly its ability to adapt to changing environments or to unexpected events. Of course, the details of how the controller achieves its task still remain to be discovered. The actuator channels and sensors available to a neuroprosthesis controller are of a different nature than those used by the CNS. The CNS has access to numerous motor units independently. In contrast, the neuroprosthesis, whether using surface, percutaneous, or implanted electrodes, is restricted to a gross signal interface to the muscle. Thus, it is unlikely that CNS control can be copied at any great level of detail. However, in designing a neuroprosthesis to restore balance and gait, one can get assistance by turning to the biological control system of the CNS and analysing the movement as performed by healthy subjects.

Second, biomechanical motion analysis may also be of interest to study the movement performed by a paraplegic patient equipped with a neuroprosthesis. Internal quantities such as loads in bones and joints etc. can be taken to assess the movement and, if necessary, adjust the neuroprosthesis controller. In this way the controller can be optimized in order to improve the movement and to obtain minimum load in joint, ligaments and bones for a given motion task. This can help to avoid tissue overstress or even damage.

Some, but not many, publications exist where principles of inverse dynamics have been applied to analyse certain movement tasks with respect to neuroprosthesis design. Bajd *et al.* (1982) and later Bahrami *et al.* (1997) computed joint moments and other dynamic quantities during sit-to-stand transfer of healthy and paraplegic subjects; Ferrarin (1993) studied the dynamics of paraplegic subjects who were walking with different orthosis systems; and Munih & Kralj (1997) discussed how to calculate bone loading during standing.

(c) *Design of control strategies*

Computer simulations based on mathematical models that describe the relevant properties of the subject's musculoskeletal system can enhance the design and test of control strategies applied to FES. Thus, time-consuming trial and error adjustments during experiments can be avoided, or at least shortened, and the number of experiments with human subjects reduced.

Because artificially activated muscles are nonlinear, time-varying actuators that have to balance an inverted pendulum, the control problem is difficult. In traditional approaches, the controller was usually derived by empirical methods or linear control design. Such a controller was mostly insufficient when applied to the real system. However, on the basis of a musculoskeletal model, design of better control strategies is possible. Durfee (1993) pointed out that there are two strategies that can be followed to design a controller. First, one can develop an accurate model and use it to design a high-performance controller. However, such a model may be difficult to derive and cumbersome to validate and to apply. Second, one can assume a crude model that is simpler to derive and apply, and design a low-performance controller which is capable of at least guaranteeing system stability in the presence of unmodelled muscle behaviours. Thus, the design space is one of balancing model accuracy, control methodology and controller performance.

A great variety of models with different levels of accuracy have been developed. For instance, some models exist to allow predictions about the feasibility of specific FES-induced movement tasks or about the muscles needed to accomplish a specific task (Jaeger 1986; Khang & Zajac 1989; Yamaguchi & Zajac 1990). Other models were developed to optimize open-loop stimulation patterns before applying them to patients (Bajd & Trnkoczy 1979). On the basis of rather comprehensive isometric muscle models, numerous strategies have been designed for the closed-loop control of muscle force (Wilhere *et al.* 1985; Hannaford 1990; Bobet *et al.* 1993; Donaldson *et al.* 1995; Bernotas *et al.* 1986, 1987; Gollee 1998). Many investigators have also used musculoskeletal models to derive controllers for single-joint movements (Nützel *et al.* 1990; Chizeck *et al.* 1991; Veltink 1991; Veltink *et al.* 1992*a*; Franken *et al.* 1993, 1995; Abbas & Chizeck 1995; Riener *et al.* 1996*b*). However, only little work can be found about more complex model-based control tasks such as leg swing (Veltink *et al.* 1992*b*), standing up (Mulder *et al.* 1992), and walking (Durfee 1993).

Recently, musculoskeletal models with different levels of complexity were applied to design patient-driven controllers for standing (Matjacic & Bajd 1998), standing up (Davoodi & Andrews 1996; Donaldson & Yu 1996; Riener & Fuhr 1998), and walking (Fuhr *et al.* 1998). In these approaches the influence of voluntary upper-body interactions is incorporated in the neuroprosthesis controller.

On the basis of an individually adjusted musculoskeletal model, optimal trajectories have been generated that can be used as reference input for tracking controllers

(Chou *et al.* 1995; Bahrami *et al.* 1996). Using an optimized reference input rather than a measured data set has the advantage that the desired trajectory is adapted to the individual muscle–skeletal properties of the paraplegic patient. Normally, paraplegic patients show increased muscle fatigue and changes in joint stiffness, and FES-induced joint moments are limited due to atrophy and incomplete motor unit recruitment. Therefore, the optimal movement of a paraplegic patient, for example, in terms of minimal energy consumption to avoid early fatigue, can differ from the movement performed by healthy subjects (Bahrami *et al.* 1996).

(d) *On-line model application*

To improve controller performance during the use of a neuroprosthesis, model components can be implemented in the controller. The application of linear control strategies to nonlinear systems such as physiological systems is not optimal, especially if the controller has to operate within a wide dynamic range. Nonlinear control theory provides an approach based on inverse dynamic modelling in which required input values are calculated from the desired output. The main goal of implementing an inverse model is to compensate for the nonlinearities of the musculoskeletal system. The more accurate and realistic the inverse dynamic model, the closer to reality is the feed-forward prediction of the required stimulation pattern; thus the smaller is the error to be corrected by a feedback controller. One could say that an ideal inverse dynamic model would 'cancel' the nonlinear system dynamics. Prediction of joint moments by an inverse dynamic model is also well-known in robotics (Craig 1986).

Inverse dynamic models are only satisfactory if they are well identified. In an experimental set-up this requires very careful parameter identification to adapt the inverse dynamic model to the individual subject. Moreover, not every system can be inverted, and approximations are required in these cases. Although the inverse dynamic model will never be exact, we suggest that a controller design based on approximated inverse dynamic models will still significantly improve the controller performance as compared with commonly used linear, e.g. proportional–integral–derivative (PID), controllers.

In the control of FES-induced isometric muscle force, a simple model for the recruitment characteristic and the dynamics of muscle activation was implemented in the controller to partly compensate for the system dynamics (Wilhere *et al.* 1985; Chizeck *et al.* 1988). More complex inverse dynamic approaches have shown to be a promising strategy for also controlling joint angle (Hatwell *et al.* 1991; Hausdorff & Durfee 1991; Veltink *et al.* 1992*a*; Quintern *et al.* 1996, 1997). Recently a promising approach has been presented, where the parameters of an inverse dynamic model automatically adapt to the actual situation of the stimulated muscle (Palazzo *et al.* 1998).

5. EXAMPLE 1: STAIR-CLIMBING MOTION ANALYSIS APPLIED TO NEUROPROSTHESIS DESIGN

(a) *Introduction*

Stair climbing is of particular interest in lower-limb neuroprosthesis design since stairs appear to be insurmountable obstacles for paraplegic patients usually moving in wheelchairs. Neuroprostheses have the potential of enabling the patients to ascend and descend stairs, thus enhancing the quality of their life significantly. However, FES-supported ascending and descending of stairs has not yet been solved satisfactorily. One reason for this is that going up and especially down stairs requires highly coordinative efforts of the artificial control system.

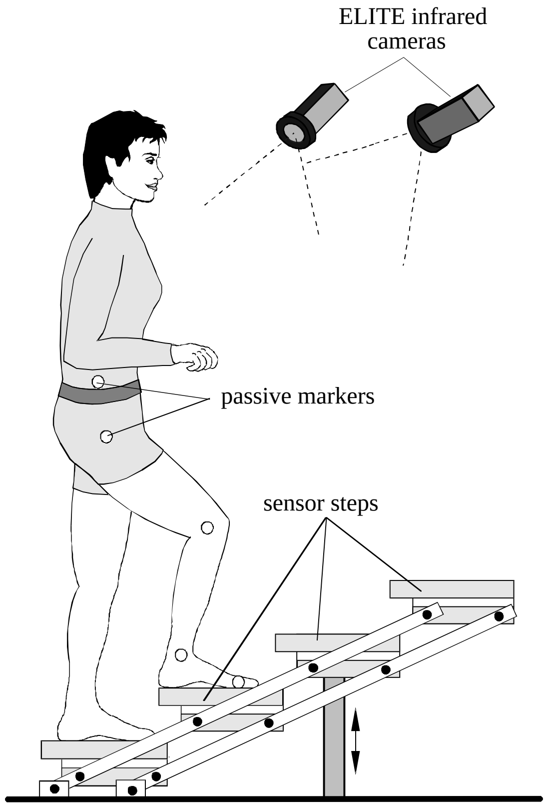


Figure 3. Experimental set-up for the measurement of movement and ground reactions during stair climbing.

The recording and analysis of gait patterns of normal and FES-induced motions can support the development of neuroprostheses. The measured kinematics can not only serve as a reference trajectory, but also be used together with recorded ground reaction forces of the motion to compute dynamic quantities such as joint moments and powers. Joint moments and powers are of significance in assessing the gait of a healthy subject or stimulated patient.

(b) *Experiments*

One healthy subject was performing several trials of stair ascent and decent. Ground reaction forces and centre of pressure coordinates were measured by a sensor staircase construction (Riener *et al.* 1998) (figure 3). In this device a new approach to sensor arrangement permits accurate recording, especially of the centre of pressure coordinates. Data obtained were smoothed by a low-pass filter (cut-off frequency 20 Hz). The subject was ascending and descending stairs at a mean slope of 30°. This corresponds to the slope of stairs in public environments (Neufert 1984).

Spatial positions of passive reflective markers attached to the both legs at the feet (fifth metatarsal head), ankle (lateral malleolus), knee (lateral femoral condyle), hip (greater trochanter), and pelvis (upper iliac crest) were recorded by an ELITE$^{\mathrm{TM}}$ infrared-video motion analyser (BTS, Milano, Italy; see also Pedotti & Ferrigno 1985) (figure 3). A four-camera system was used to allow kinematic measurement of both legs simultaneously. Movement was recorded with a sampling frequency of 100 Hz. The ELITE$^{\mathrm{TM}}$ software computed the three-dimensional (3D) Cartesian coordinates of each marker for further analysis. Since marker positions do not exactly correlate with the required joint centres, a procedure was applied that estimates internal landmarks from the external marker positions (Frigo & Rabuffetti 1998). To reduce the influence of the measurement noise, the data were low-pass filtered by a model-based bandwidth-selection procedure (D'Amico & Ferrigno 1990). This is necessary because measurement noise strongly affects the velocity and acceleration time histories that are computed to determine joint moments.

(c) *Model*

Cartesian coordinates of joint centres recorded by the video-based motion analyser are transformed into body-related Cardan angles (Riener & Straube 1997). In a Cardan angle representation of 3D orientation (e.g. a ball-and-socket joint), three independent angles are defined, which result from an ordered sequence of rotations about the axes of a selected Cartesian coordinate system attached to one of the adjacent limbs. Angular velocities and accelerations that are required to calculate joint moments can be obtained as first and second derivatives from the joint angle data.

Equations of motion are used to describe body-segmental dynamics. For a system with n degrees of freedom and the vector of generalized coordinates $q=(q_1,q_2,\ldots,q_n)^{\mathrm{T}}$, the equations of motion can be written as follows (see also Wells 1967; Winter 1990; Riener & Straube 1997):

$$M(q)\ddot{q}+B(q,\dot{q})+T+J^{L}L=0, \tag{1}$$

where $M(q)\in R^{n\times n}$ is the inertia matrix comprising body anthropometry, $B(q,\dot{q})\in R^{n}$ specifies the Coriolis, centrifugal and gravitational moments, and $L\in R^{m}$ is the external load vector acting on the body. $T\in R^{k}$ is the generalized joint moment vector about the same axes defined for the generalized coordinates q. The joint moments control the motion of the multibody system. $J^{L}\in R^{n\times m}$ is the Jacobian matrix for external loads.

Because the motion of the mechanical system is known, whereas the applied joint moments have to be determined, the body dynamic problem is classified as an inverse dynamic problem (see § 3b). For an open-kinematic chain, the dimension of T is equal to the number of degrees of freedom ($k=n$), thus the equations of motion can be solved for the unknown control moments T. Equation (1) is algebraic in form and can be readily solved.

In the present example, equations of motion with 18 degrees of freedom representing an open-kinematic chain of the lower extremities, including feet, shanks, thighs and pelvis, are applied to compute the moments T. The inputs to the inverse dynamic problem are the kinematic data—joint angles, velocities, and accelerations—as well as the external loads that have been measured by the sensor staircase. Anthropometric parameters, such as masses, lengths, centres of gravity and moments of inertia of the subjects, were estimated by regression equations as described by Zatsiorsky & Seluyanov (1983). The system of equations (equation (1)) is solved for the unknown joint moments, providing ground reactions, angular positions, velocities, accelerations and anthropometric parameters. Once the joint moments have been computed, the mechanical power P in the sagittal plane is obtained by the product of joint moment and angular velocity.

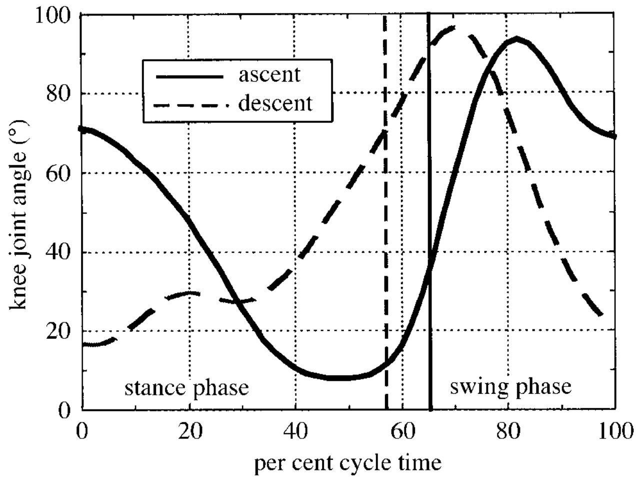


Figure 4. Knee flexion angles in ascent and descent. Full extension is at zero degrees. Foot contact occurs at $t=0$. The vertical lines indicate toe off.

(d) *Results*

Knee angles for ascending and descending stairs were compared (figure 4). The most distinct difference is that at the beginning of the gait cycle (foot contact) the knee is more flexed in ascent (71°) than in descent (17°). Furthermore, toe off and the following swing phase, where the knee becomes maximally flexed, occurs later in ascent (10% cycle) than in descent.

When comparing joint moments, there was no significant difference during swing phase (figure 5). Whereas at the beginning of the stance phase knee extension moment for descent was only half of the moment produced during ascent and the pattern was shifted with maximum knee extension moment occurring much later in stance. Joint moment patterns correspond with patterns described in the literature (Kowalk *et al.* 1996).

Most significant differences were observed in knee joint power (figure 6). For ascent, force production was high at the beginning of the stance phase. However, in descent almost no power production could be observed during the entire cycle. In contrast, there was a significant amount of power absorption (negative power) in late stance.

(e) *Discussion*

Power absorption occurs when joint motion and moment are produced in different directions. During the stance phase of descent an extension moment is produced that works against the movement to decelerate knee flexion, and thus to avoid body collapse. A similar situation occurs during sitting down, where a knee extension moment during knee flexion decelerates body movement and, finally, provides soft seat contact.

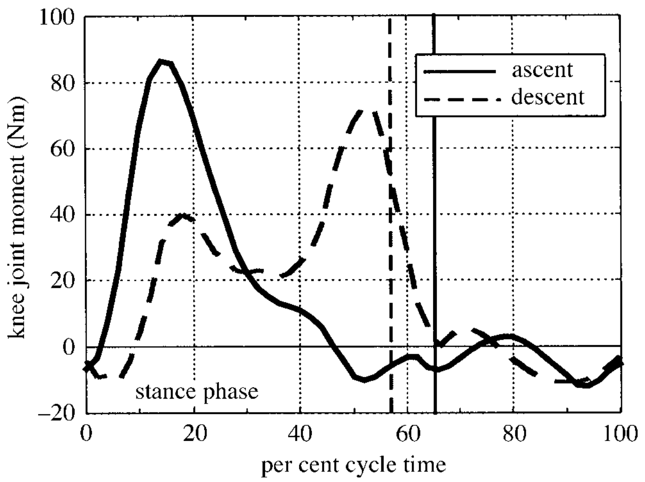


Figure 5. Knee extension moments in ascent and descent. Foot contact occurs at $t = 0$. The vertical lines indicate toe off.

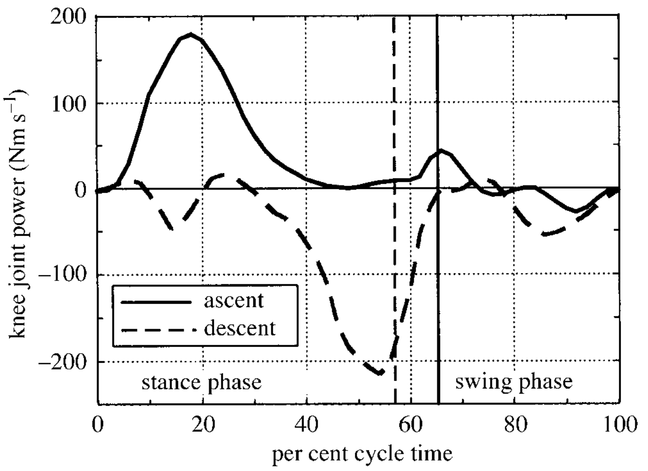


Figure 6. Knee joint powers in ascent and descent. Power production and absorption are represented by positive and negative values, respectively. Foot contact occurs at $t = 0$. The vertical lines indicate toe off.

During such movement phases, muscles perform an eccentric contraction, i.e. they generate force while they are lengthened. It is well-known that the force a muscle can produce at constant activation significantly depends on muscle velocity (Hill 1938; Zajac 1989). During eccentric contractions maximum muscle force is higher than during isometric or concentric contractions.

It can be seen that the muscle operates in different regions depending on the type of movement (stair ascent and descent) and phase of movement cycle (early or late stance phase, swing phase). This should be taken into account when developing a control strategy for a neuroprosthesis. Controller, stimulation pattern, sensor application, and the choice of muscles being activated depend on the type of movement, for example, if mainly eccentric or concentric muscle contractions occur (figure 6). Furthermore, during the movement it may be effective to switch between different control strategies. For example, during swing phase, where joint moments appear to be very small (figure 5), no stimulation or a simple on–off controller may be sufficient to gain a satisfying leg swing (Veltink *et al.* 1992*b*).

Inverse dynamic modelling was applied to compute internal quantities such as joint moments and powers. This knowledge can be used to assess the movements and support neuroprosthesis development. Additional simulation studies and experimental tests have to be performed to derive the final control strategy.

6. EXAMPLE 2: DESIGN OF A PATIENT-DRIVEN CONTROLLER FOR FES-SUPPORTED STANDING UP

(a) *Introduction*

Voluntary contributions of the trunk and arms are difficult to predict, and thus to incorporate in a control strategy. However, if the FES controller does not account for voluntary contributions, artificial and natural control could adversely interfere, resulting in undesired or even dangerous motion and increased upper-body effort. To coordinate artificial and voluntary control in a neuroprosthesis, one possible approach is to adjust the stimulation to the estimated voluntary contribution of the patient (e.g. by recording the hand reaction forces). In such a patient-driven approach the patient is able to influence or even control the stimulation of the paralysed legs. Thus, the patient's CNS is an important part of the controller, as opposed to controller-centred approaches (e.g. trajectory-tracking, path-following, phase plane control), where the patient has to submit to the controller.

Here we propose a strategy which accounts for voluntary upper-body effort in the control of FES-supported standing up. To reduce upper-body effort, we compute the stimulation pattern required to maintain the movement initiated by upper-body effort. We call this strategy 'patient-driven motion reinforcement' (PDMR). To validate the strategy it is applied to a generic two-dimensional musculoskeletal model of a subject standing up with the support of FES. The strategy is examined in the light of the following questions. Can closed-loop FES as proposed in the two strategies realize standing up and standing? Can the resulting movement be improved compared with standing up without FES support (arm support only), or open-loop FES support? Can arm forces be significantly reduced? Finally, can standing be achieved with the hip, knee and ankle joints approximately aligned?

More details about model and controller can be found elsewhere (Riener & Fuhr 1998).

(b) *Musculoskeletal model*

The model describes major properties of muscle and segmental dynamics occurring during FES. The human body is described by a three-segmental model consisting of shanks, thighs and the upper body. Feet are flat on the ground. Nine mono- and bi-articular muscle groups are modelled in the sagittal plane inducing moments about the ankle, knee and hip joints due to surface electrical stimulation (figure 7). Each group has its own activation and contraction dynamics. Input to each muscle group is the continuous time signal of the modulated pulse width and pulse frequency as provided by an electrical stimulator (figure 8*a*). Muscle activation is computed considering the effect of spatial and temporal summation by a nonlinear recruitment curve (Riener *et al.* 1996), a nonlinear activation–frequency relationship, and a linear second-order calcium dynamics (Hatze 1977) (figure 8*a*). To describe the effect of muscle fatigue and recovery a fitness function fit(t) was introduced, modified from

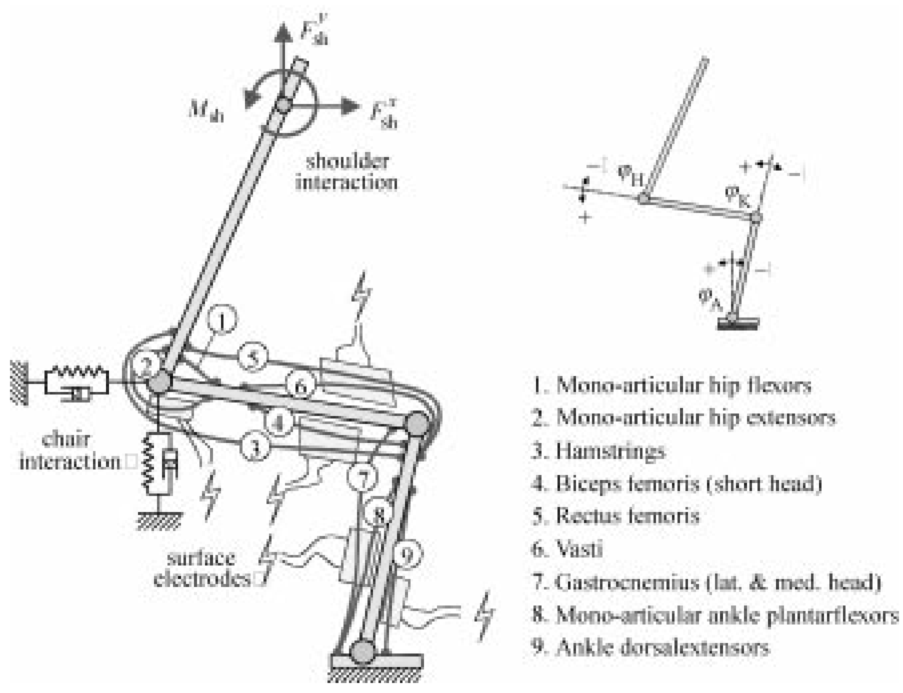


Figure 7. Three-segmental model with nine mono- and bi-articular muscle groups. All muscle groups except mono-articular hip flexors (group 1) can be activated in experiment by the electrode arrangement used in this simulation study. The figure has been adapted from Riener & Fuhr (1998).

Riener *et al.* (1996*b*), which can be expressed by the following first-order relationship:

$$\frac{\mathrm{dfit}}{\mathrm{d}t} = \frac{(\mathrm{fit}_{\min} - \mathrm{fit})a\lambda(f)}{T_{\mathrm{fat}}} + \frac{(1-\mathrm{fit})(1-a\lambda(f))}{T_{\mathrm{rec}}}, \quad (2)$$

$$\lambda(f) = 1 - \beta + \beta\left(\frac{f}{100}\right)^2 \quad \text{for } f < 100\,\mathrm{Hz}. \quad (3)$$

The variable a is the activation of non-fatiguing muscle. The minimum fitness is given by $\mathrm{fit}_{\min}$. The time constants for fatigue, T_{fat}, and recovery, T_{rec}, can be estimated from stimulation experiments (Riener *et al.* 1996*b*). The term $\lambda(f)$ is a function of stimulation frequency, while β is a shape factor. $\lambda(f)$ has been introduced to better account for the fact that muscle fatigue rate strongly depends on stimulation frequency. Finally, the activation of fatiguing muscle a_{fat} is given by

$$a_{\mathrm{fat}}(t) = a(t)\mathrm{fit}(t). \quad (4)$$

Furthermore, an additional constant time-delay (dead time) has been implemented which is responsible for finite conduction velocities in the membrane system and delays from the chemical reactions involved. The active moment developed by a single muscle group is calculated from its nonlinear moment arm and the muscle force, which is a function of maximum isometric muscle force, muscle activation, and force–length and force–velocity relationships (figure 8*b*).

In the body-segmental dynamics (figure 8*c*), total joint moment is the sum of active, passive elastic, and passive viscous joint moments. Active joint moment is the sum of the joint moments produced by each muscle group (i.e. muscle force multiplied by moment arm). Passive viscous and elastic muscle properties have been separated from the active muscle properties, and are assigned to the joints in order to keep the number of muscle parameters low. Passive viscous joint moments are modelled by linear damping functions. Passive elastic properties are modelled by double-exponential equations which account for the influence of the adjacent joint angles:

$$M(\varphi) = \exp(c_1 + c_2\varphi_{\mathrm{distal}} + c_3\varphi + c_4\varphi_{\mathrm{proximal}}) - \exp(c_5 + c_6\varphi_{\mathrm{distal}} + c_7\varphi + c_8\varphi_{\mathrm{proximal}}) + c_9, \quad (5)$$

where M is the elastic joint moment and φ the joint angle at ankle, knee, or hip; $\varphi_{\mathrm{distal}}$ and $\varphi_{\mathrm{proximal}}$ are the angles of the distal and proximal joint, respectively. The parameters c_1–c_9 have been determined by fitting the simulated joint moment curves to measured curves with a least-squares search procedure. Exact procedure and parameter values are presented elsewhere (Riener & Edrich 1999).

Equations of motion with three degrees of freedom describe the segmental dynamics of the body (see equation (1)). Interaction with the seat is derived from Pandy *et al.* (1995). A pair of nonlinear spring-dampers take into account the horizontal and vertical reaction forces (figure 7). The constraint requiring that vertical and horizontal seat reaction forces both have to be zero at seat off is satisfied by introducing the effect of sliding between upper body and chair. The model is implemented in MATLAB/SIMULINK®, and the computed motion is visualized by graphic animation. More detailed model information and model parameters are presented in Riener & Fuhr (1998).

In the simulation runs stimulation is applied via five channels to each leg using surface electrodes. One pair of electrodes is attached to the buttocks, two pairs are attached to the thigh and another two to the shank, as shown in figure 7. Mono-articular hip flexor muscles (iliopsoas group 1) are not activated since they are difficult to reach with surface electrodes. Due to muscle atrophy in paralysed limbs and insufficient muscle recruitment during artificial activation, paraplegics generate less muscle force than healthy subjects. In this study we assume that the maximum paraplegic muscle

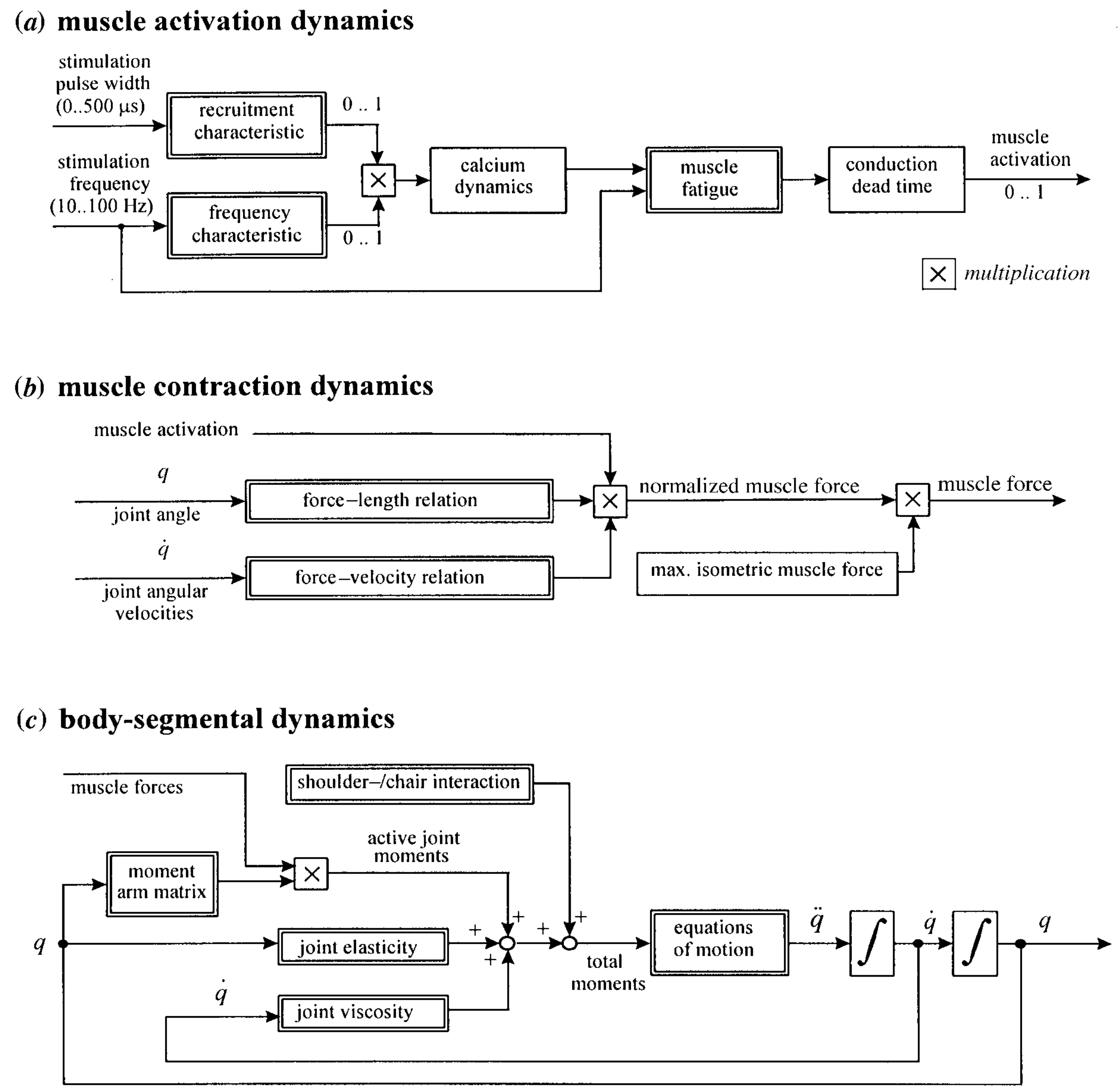


Figure 8. Flow chart of the musculoskeletal model. Each muscle comprises an activation and contraction dynamics model. The forces of the nine muscle groups are input to the body-segmental dynamics.

force available is reduced to 45% of the maximum isometric muscle force produced by healthy subjects (Delp *et al.* 1990). This amount of muscle force can be expected from a well-trained patient.

(c) *Modelling voluntary arm support*

Paraplegic patients need their arms during FES-supported movements not only to maintain balance but also to sustain the desired movement due to the available leg-joint moments being limited. Note that many patients are able to stand up even without the support of FES by arm support only using proprioceptive sensors of their upper body as well as vestibular and optical inputs to control the motion. Therefore the upper-body effort should be an integral part of any FES controller developed.

It is assumed that during open-loop and closed-loop standing up movements the patient tries to follow a trajectory he learned from past movements. For example, if the patient estimates his trunk position to be too far below its desired position at a specific instant of time, he will increase arm force to lift his body and approach the desired position. Similarly, this also holds for horizontal deviations. Assuming this behaviour, we developed a simple tracking controller to model the patient's voluntary upper-body effort. It modulates horizontal and vertical forces and a moment at the shoulder joint (figure 7) so that the shoulder follows a given reference trajectory as well as possible. Shoulder forces (F^x_{sh}, F^y_{sh}) and moments (M_{sh}) are calculated on the basis of a look-up table that was determined by using fuzzy control theory (Riener & Fuhr 1998). The resulting arm controllers yield arm support that behaves similarly to a nonlinear elastic spring that connects the desired and actual shoulder joint position: the larger the distance between the actual and the desired shoulder position, the higher the elastic forces that will be produced to reduce this distance. Comparison of simulated and measured standing up movements show satisfactory agreement (Riener & Fuhr 1998).

(d) *Control strategy*

The goal of the PDMR controller is to minimize arm forces. Compared with a similar approach suggested by

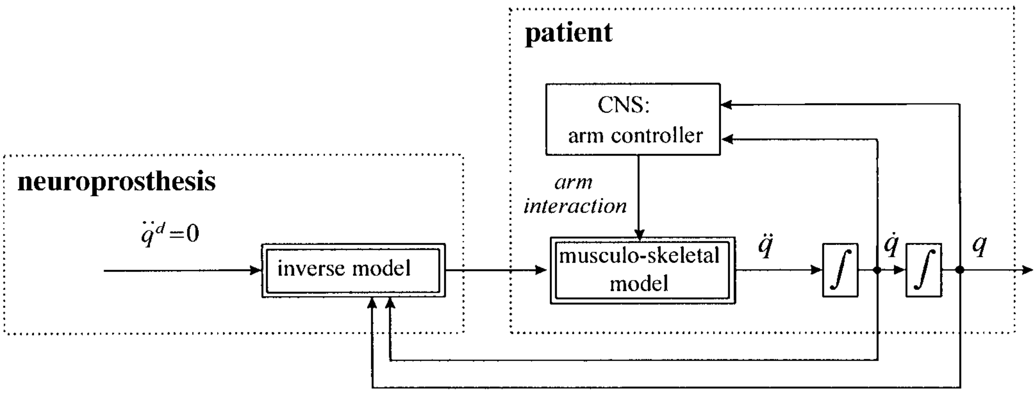


Figure 9. PDMR control strategy applied to the paraplegic patient model. Controlling and trajectory planning is performed by the patient, whereas the neuroprosthesis serves only to maintain the movement initiated by the patient.

Donaldson & Yu (1996), it does not require the recording of hand reactions. It is assumed that the patient provides sufficient arm force and is capable of controlling both the position and orientation of the trunk with his intact upper body. This allows many paraplegic patients to stand up even without the support of FES (Bahrami *et al.* 1997). In this strategy, the goal of reducing upper-body effort is approached by presenting the controller with the movement initiated by the patient's voluntary effort. Actual joint positions and velocities are fed back into an inverse dynamic model, which predicts the stimulation pulse widths required to maintain the movement (Riener & Fuhr 1998). The controller structure is shown in figure 9. The desired angular joint accelerations input $\ddot{q}^d$ to the inverse model are always set to zero, and so changes in motion are left to the patient. The FES pattern adapts to the voluntary movement the patient initiates and no reference trajectory or path is required.

The inverse dynamic model was derived from the direct dynamic model of the patient. By inverting the equations of motion of the direct dynamic body-segmental model the total joint moments required to achieve the desired motion can be easily computed from the given joint kinematics. Passive viscoelastic joint moments, muscle moment arms as well as force–length and force–velocity factors are computed as in the direct dynamic model. The redundancy of five channels stimulating eight agonistic and antagonistic muscle groups which subsequently generate moments in three joints is solved by a linear optimization algorithm. Some minor model simplifications were made. The non-observable second-order calcium dynamics was inverted and low-passed to get a smooth estimate of the required motor unit activation (input to the forward calcium dynamics). The time-delay (dead time) as well as muscle fatigue are neglected in the inverse dynamic model. To get a unique solution for the stimulation pattern we assume a constant stimulation frequency ($f=30$ Hz) while stimulation pulse width is modulated. The inverse recruitment curve is approximated by a piecewise linear function with a threshold, linear ramp, and saturation.

(e) *Results*

With the strategy presented here, both the hip and knee joints show fast and smooth extension movements during the early rising phase (figure 10*a*). However, as soon as the knee has reached almost full extension, it suddenly buckles by about 25°, and the ankle joint goes back into the desired dorsiflexion. After this interruption, knee and ankle extension continues and finally the body reaches an upright position. This increases the duration of the sit-to-stand transfer for more than 1 s. The buckling of the knee joint is due to insufficient lower leg muscle forces and a temporary reduction of vertical arm forces induced by the arm controller (see figures 10*a* and 11 at $t=2.2$–2.7 s). In

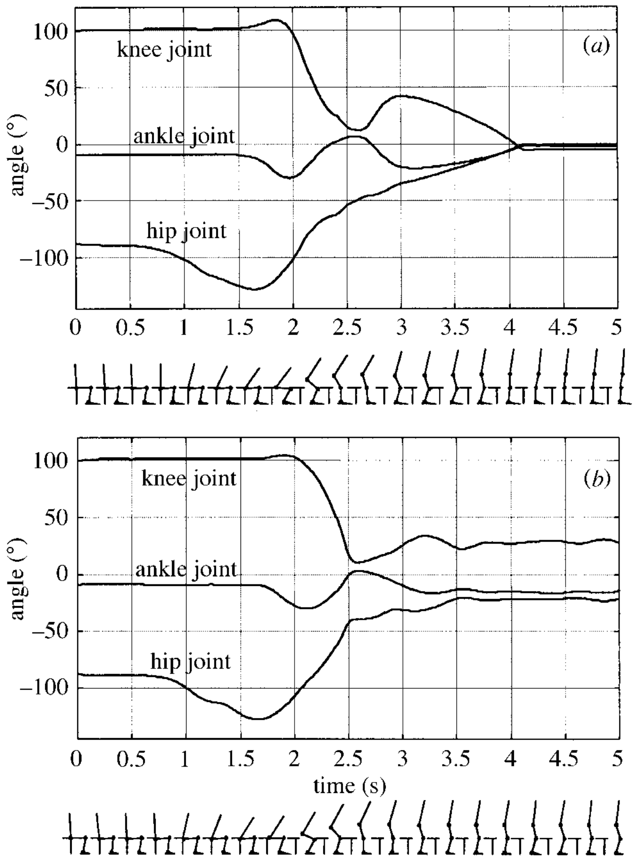


Figure 10. Simulated arm-supported movements (*a*) generated by the PDMR strategy and (*b*) without the support of FES (arm support only). Shown are ankle, knee and hip joint trajectories as well as stick figure drawings for the simulated paraplegic during the sit-to-stand transfer. Note that complete extension of the knee can only be achieved when stimulating knee extensors. Figures have been adapted from Riener & Fuhr (1998).

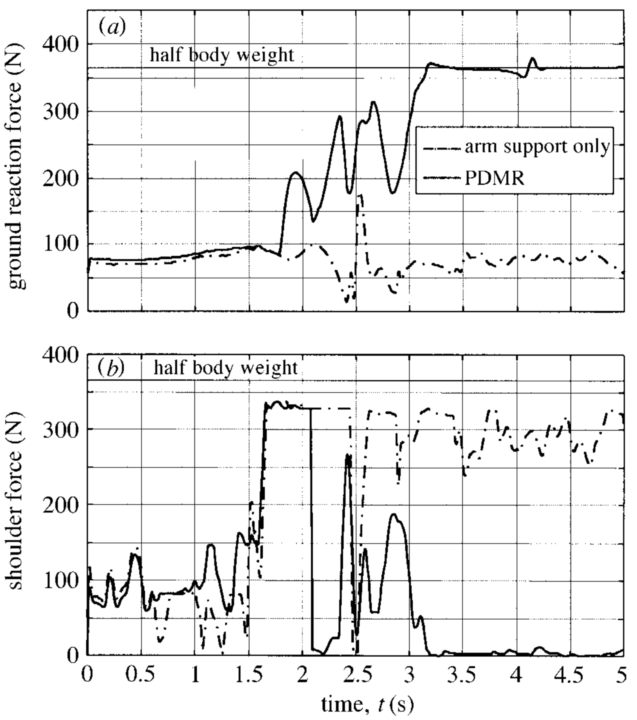


Figure 11. (*a*) Ground reaction forces and (*b*) shoulder forces for simulation results with arm support only (dash–dot line) and with PDMR (continuous line) for one-half of the body. Absolute force values result from the vector sum of horizontal and vertical ground reaction forces. Note that with arm support only (no FES), the full body weight does not have to be carried by the arms since the feet touch the ground and thus transfer part of the leg weight through the ground. Figures have been adapted from Riener & Fuhr (1998).

simulations where muscle forces of a neurologically intact subject are assumed, this effect was not observed. Although the buckling behaviour of the arm controller is not desired, it has no adverse effect on the overall movement. It rather improves posture by moving the hip position in front of the ankle joint. Standing is achieved with the hip, knee and ankle joints approximately aligned, which was impossible in simulations without FES support (figure 10*b*). Sufficient reduction of arm forces can be observed. During rising ($t = 2.2$–3.0 s) the legs carry more than 50% of the body weight (figure 11). During standing this value increases to 100%. To prevent instability, we recommend setting $\dot{q}$ equal to zero (figure 9) or switching to another control strategy during standing.

(f) *Discussion*

The generation of moments in the paralysed limbs to allow standing up is driven by the patient's voluntary upper-body effort, rather than imposing a preprogrammed reference trajectory on the patient. Furthermore, the legs carry a higher amount of the body weight so that the arm forces required were significantly lower than in movements without stimulation. Furthermore, hip, knee and ankle joints achieved improved alignment for the standing phase.

It appears that it is important to include voluntary upper-body effort in the design of closed-loop controllers for paraplegic patients. If arm support is considered as a disturbance which has to be compensated for, the controller is likely to hamper the indispensable effort of the patient. Moreover, artificial and natural control could adversely interfere, resulting in undesired or even dangerous motion and increased arm forces. With PDMR, upper-body effort can be advantageously used to allow a patient to drive the entire system dynamics. Thus, the system can benefit from the patient's ability to adapt and learn better than do technical controllers.

In the present study the inverse dynamic model is calculated from the direct dynamic model of the simulated patient. Therefore, it is capable of predicting the required stimulation pattern from the desired joint motion, while compensating partially for the nonlinearities of the system. However, prediction of the inverse model presented in this study is not exact for the following reasons: (i) the time-delay (dead time) cannot be cancelled; (ii) input constraints (e.g. force limitations of artificially activated paralysed muscle) may result in insufficient stimulator output; (iii) minor model simplifications were required to obtain an inverse dynamic model of the muscle recruitment–activation dynamics; and (iv) the kinematic input to the inverse dynamic model contains sensor noise, which complicates the prediction of the required stimulation pattern (Riener & Fuhr 1998). Thus, an ideal cancellation of the system even in the simulation is not possible, although desirable to improve the control performance. However, errors in the prediction of the required stimulation parameters will be corrected by the actions of the arms, so that the patient compensates the disadvantageous effects mentioned above and 'robustifies' the cancellation strategy.

The model presented in this section was not only used to validate the two strategies. Although not shown here, it has already contributed to the development of the PDMR strategy in a significant manner. Time-consuming and perhaps troublesome trial and error experimentation can be avoided or at least shortened, and the number of experiments with humans can be reduced, both of which will accelerate the development of neuroprostheses. In further simulation studies, the performance of the presented strategy has to be assessed with respect to internal disturbances (spasticity, muscle fatigue), different muscle properties and anthropometry, parameter errors, sensor noise, different sensor and electrode arrangements, etc. Finally, experimental studies must be performed to validate the developed strategies on several patients.

7. CONCLUSION

The functional gain of current neuroprosthesis systems for restoring posture and upright mobility in paraplegics is low and its use requires vast efforts from the patients. Despite decades of development, lower extremity neuroprostheses have not yet emerged into reliable and widespread aids for the rehabilitation of spinal-cord injured patients. The technical difficulties involved in improving simple existing neuroprosthesis systems have been underestimated. In general, attempts to improve FES by adding more stimulation channels, sensors, and other interfacing parts have resulted in more cumbersome handling and testing, and a higher failure rate of the system.

Although commercially available lower-extremity neuroprosthesis systems are still working in the same way as early prototype systems, knowledge in the field of FES-induced movements has improved considerably within the last few years. Only recently, complex mathematical models have been presented that can be used to support neuroprosthesis development.

Mathematical models have the potential to assist in many different ways. With regard to the two main purposes of muscle models, comprehension and prediction, two main model applications can be distinguished. First, models can offer much insight into the nature of FES-induced muscle activation and movement generation. A better understanding of the basic neurophysiological processes of artificially activated muscle can, for example, help to optimize force output. In addition, calculating biomechanical quantities by inverse dynamic models can provide an understanding of muscle coordination principles, and thus support the development of a control strategy for a specific movement task.

Second, models can be used to predict the behaviour of the real system, i.e. the paraplegic patient, when stimulating the paralysed muscles. Such a model enables one to infer how a system will behave in circumstances which may be far away from the necessarily limited range of experimental experience. Computer simulations based on a predictive model of the subject can be used to design and test FES control strategies, before they are applied to the patient. Model components can also be implemented in a controller to better determine the stimulation pattern required to follow a given trajectory as close as possible.

Thus, musculoskeletal models can help in the better understanding and control of the artificially activated human body, a complex nonlinear time-varying inverted pendulum. The disturbing effects of certain phenomena such as muscle fatigue and spasticity may be reduced and movement may be better controlled when using mathematical models in the design process or implementing them into a controller. This may also allow the control of complex movements with highly coordinative requirements such as stair climbing, which is of particular interest, since stairs appear to be insurmountable obstacles for paraplegic patients. The application of mathematical models in the field of FES will play an increasing role in the development of reliable, commercially available, closed-loop controlled, lower extremity neuroprostheses within the next few years.

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