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# Closed-Loop Robust Controllers with Fuzzy Gain Scheduling for FNS Assisted Walking of Paraplegics

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**Abstract**

The FNS closed-loop control for assisted walking of paraplegics is studied on the five-link biped model. The design objectives is that the tracking errors of the joint angles reference trajectories must be reasonably bounded. The disturbances affecting the musculoskeletal model come mainly from the uncertain nonlinear dynamics of the muscle actuator. Two robust control schemes are proposed: the Sliding Mode control and the LQR control with fuzzy gain scheduling. The fuzzy scheduler output provides the relative degree (weights) of the system uncertainty according to the joint angles tracking error. These fuzzy weights schedules the appropriate gain from the control gain vs. tracking error interpolated function. It turns out that the additional tuning of the control moments by the muscle inverse dynamics Neural Network is essential for the successful tracking. The extensive simulations show that the performance of the Neural Network static learning depends on the initial position of the musculoskeletal system, and the Neural Network weights initialization. The simulation results demonstrate that the desired uncertainty attenuation properties of the proposed control algorithms have been achieved. These control schemes can be used as a prototype of the real FNS control schemes.

## 1 Introduction

Functional Neuromuscular Stimulation (FNS) is the application of controlled electrical currents to the neuromuscular system with the aim of restoring control over abnormal or absent skeletal movement. FNS has been developed as a rehabilitative technology for people with spinal cord injuries. In this case the muscles and nerves above and below the spinal cord injury may still be functional, while the communication pathway from the motor control centers in the brain and musculature system has been served. FNS offers a method of potentially controlling the portion of the body that lost communication with the brain, providing a suitable electric signal (pulse) via electrodes to the paralyzed muscles.

Control of the motor response in FNS is generally achieved by varying the current-pulse duration or amplitude and thus the number of motor units. This technique is termed recruitment modulation of muscle force. The term temporal summation refers to the gradation of force by varying the rate of excitation of motor units and, as result, the force produced by each motor unit. Thus it may be seen that although the fundamental contractile element of muscle is the muscle fiber, the fundamental element of muscle control is the motor unit.

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Most of the present successful FNS control schemes are open-loop approaches. Frequently their prespecified stimulation parameters are determined by trial-and-error. For instance, during crutch and walker-supported ambulation, the control signals are adjusted in the laboratory until the desired lower extremity movements are produced (Kralj and Bajd, 1989). These systems show the following main problems (Allin and Inbar, 1986; Abbas and Chizeck, 1995) which must be addressed before FNS systems can be used on a clinical basis:

1. Each patient is different. The musculoskeletal properties vary from person to person and the stimulation parameters must be customized for each individual in order to generate a proper control signal and, as result, a proper movement.

2. Musculoskeletal system properties may change while the system is functioning. For example, system properties change due to muscle fatigue.

3. Mechanical disturbances to the musculoskeletal system are always present.

Feedback control is an obvious choice to improve open-loop control performances. Nevertheless its performance have been limited by absence of the accurate system model, inaccurate output measurements, effects of the muscle fatigue, and the difficulty of controlling muscle contractions to the degree necessary for well-coordinated motions. These difficulties are strongly coupled together. The lack of knowledge about musculoskeletal biomechanics and the dynamics of the human body, that made it very difficult to implement closed-loop control schemes for anything beyond the simplest of motor tasks ( Yamaguchi, 1989). To overcome these limitations a modern control designs use such hybrid control schemes as neural network based adaptive feedforward control and feedback control (Abbas and Chizeck, 1995), or mixed fuzzy logic and adaptive control (Vukobratovic and Timcenko , 1996).
In our research we are dealing with the design of a closed-loop robust controller for FNS assisted walking (i.e. standing and ambulation with crutches (Kralj and Bajd, 1989)). In practice a four channel stimulator with surface electrodes is used for this clinical application of FNS, since the simplified description of the desired movement can lead to a significant reduction in the number of muscles needed to be stimulated. It is apparent that the major motions during locomotion take place in the sagittal plane and involve extension/flexion at the hip and knee and dorsiflexion/plantarflexion at the ankle.
The main extensor muscles of the knee are grouped together under the name quadriceps group. It is responsible for advancing the swinging leg during walking. All four muscles in the quadriceps group are innervated by the femoral nerve. The harmstring group of muscles extend the hip and/or flex the knee. In walking, as the foot leaves the ground to take a step forwards, the harmstrings contract momentarily, in order to reduce the load on the partially flexed leg. As hip flexion begins and the leg starts to move forward, the harmstrings immediately relax thus allowing knee extension in the swinging leg to occur. The harmstrings are supplied by branches of the sciatic nerve. The most important dorsiflexor of the ankle is the tibialis interior. It is used in walking to bend the foot up and so prevent stubbing of the toes as the swinging leg advances. This muscle is innervated by a branch of the peroneal nerve. The two large and powerful muscles responsible for plantarflexion of the ankle are the gastrocnemius and the soleus. Both muscles are active during the toe-off phase of the walking cycle.
The described processes can be modeled on a simplified skeletal models that are known as the biped. The biped is a class of legged system that attempt to imitate the human-type locomotion. During preliminary analysis and computer simulation the 5-link humanwise biped robotic model is used. This model is sufficiently complicated and nonlinear to make a control law design to be very difficult. It has attracted throughout the years the attention of researches, and for today,

nearly all known control algorithms have been used to control the biped locomotion. Meanwhile, in these algorithms the actuator dynamics have not been taken into account at all or have been defined as an ideal DC motor dynamics.

In the case of FNS we have a muscle as a highly nonlinear saturated actuator. Muscle dynamics include nonlinear time-varying and stimulation history dependent activation dynamics, contraction dynamics, force-length dependence, and force-velocity dependence. The uncertainty about these dynamics behaviour can seriously degrade the controller performance. The specific to FNS closed-loop control problem is the low limit of 20 Hz of the harmstrings and quadriceps stimulation frequency. There is no any insurance that control robustness would be preserved by the such low frequency control signal. The above-listed constraints on the control of the nonlinear coupled biped locomotion dynamic combined with uncertain saturated muscle dynamic make Functional Neuromuscular Stimulation a very challenging control problem.

Today a lot of FNS control schemes are based on the Neural Network algorithms which strive to find a proper weights of the heuristic open-loop control net. In our research we try to explore this approach further combining the Neural Network schemes with a robust control algorithms. This is apparent since by definition a robust controller is insensitive to parametric and model uncertainties. The recent investigation (Tzafestas *et al.* , 1996) examine the effectiveness of robust Sliding Mode control applied to human-sized biped robots but not to the physiological model. The Sliding Mode control is based on Lyapunov stability theory, and has a good reputation in controlling the nonlinear uncertain systems, s.a. the robotic systems. The classical LQR control is an example of the optimal (robust) control. It is known for optimal disturbance attenuation for the model reference control of the linear system. But even in the case of the LQR control the system can lose stability as result of the high frequency update of the optimal control gain (Shimkin and Feuer, 1988). In order to avoid this the fuzzy gain scheduling algorithm is proposed (Passino and Yurkovich, 1998). It takes as inputs the joint angles tracking errors and provides as outputs the values of the control gains according to the specifically derived fuzzy rules.

It must be stressed again that in the FNS problem, the robust performances of the LQR and the Sliding Mode controllers may not be preserved by the low frequency stimulation and highly nonlinear actuator behaviour. In these conditions, the controller's efficiency can be increased by the coupling of robust control algorithms with Neural Networks that account for muscle dynamics and predict the muscle dynamics parameters variations. Such hybrid system can help to solve a highly complicated control problem of the nonlinear musculoskeletal system that contains model and parametric uncertainties, and inviolated physiological constraints on control signals.

This work presents the design of a neurofuzzy enhanced closed-loop robust controller for FNS assisted walking. The proposed control scheme consists of the Neural Network tuned robust Sliding Mode and LQR controllers with fuzzy gain scheduling.

This work is organized as follows. Section 2 contains general block-scheme chart of the control problem. In Section 3 we described a 5-link biped locomotion model and a musculoskeletal model. Section 4 contains the derivation of the continuous-time LQR controller with fuzzy gain scheduling and Sliding Mode controllers. Section 5 describes the Neural Network based stimulator block. Section 6 presents the simulation results, and
section 7 presents the conclusions and our future research plans.

## 2 General Structure of the Control Problem

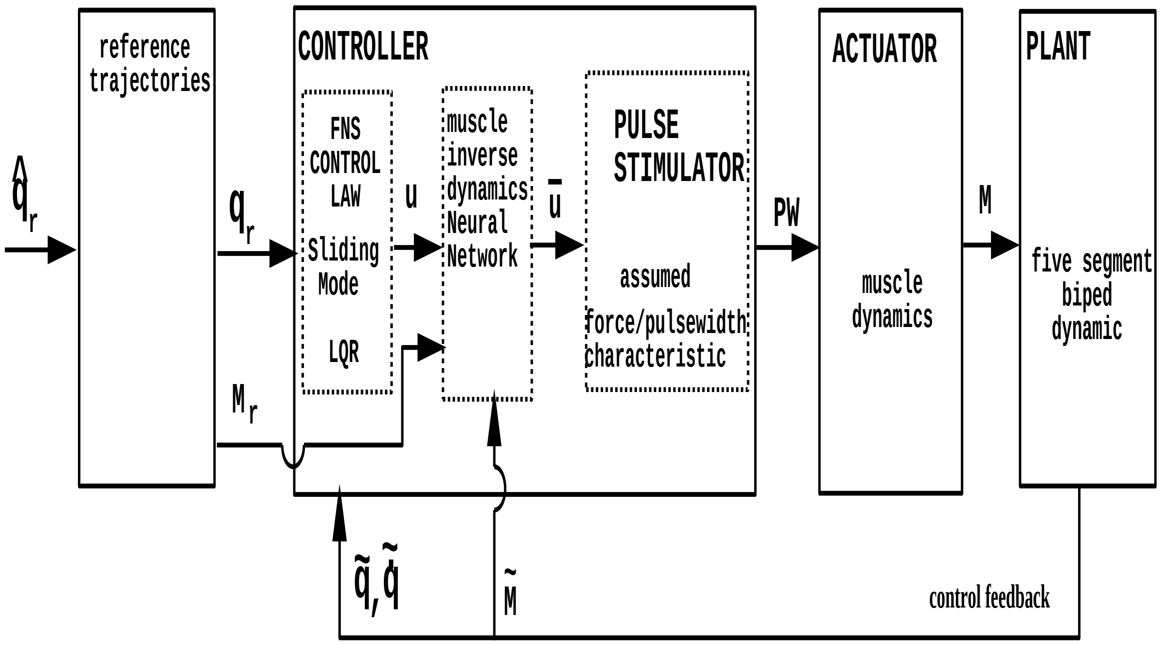



Figure 1: Block-scheme of the control problem.

The FNS control problem (Fig.1) is formulated as a tracking of the joint reference trajectories (angles) with the prescribed performance.
Reference trajectories that reference joint angles $q_r$, velocities $\dot{q}_r$ and accelerations $\ddot{q}_r$ are calculated before every walking step from the ouput angles measurements and healthy subject gait data (Oderkerk and Inbar, 1991). It is a difficult task to track a healthy subject gait since paraplegic subject cannot repeat fully the movements of the healthy body. The reference angle trajectories $q_r$ of a subject with the spinal cord injuries are obtained by minimizing the applied moments at the cost of the stimulation time. These trajectories are founded to be in some vicinity of the healthy subject reference trajectories $\hat{q}_r$.
The plant under consideration are the 5-link biped locomotion dynamics (section 3). These dynamics are driven by the joint moments $M$ from the musculotendon actuator. The employed original descriptive model of the FNS stimulated muscle allows to simulate the variation in recruitment of the muscle fiber motor units, the muscle fatigue and muscle spasticity effects (section 3).
The stimulated muscles are driven by the FNS controller output signal $PW$ that is a pulse with proper pulsewidth. The controller block consists in the controller, muscle inverse dynamics Neural Network, and the pulse stimulator. In our research we use alternatively Sliding Mode and LQR controllers (section 4). Controller calculates the control joint torques $u$ using the fuzzy gain scheduling. These control torques are tuned by the Neural Network approximation of the muscle dynamics inverse model (section 5). The pulse stimulator block transforms the resulted torques $\bar{u}$ to the muscle stimulation pulse with a proper pulsewidth $PW$. This transformation is carried out by some reasonable force/pulsewidth approximation ( Dorgan and O'Malley, 1997), that will be described later (section 5).

# 3 Five-Link Biped Musculoskeletal Model

## 3.1 General assumptions

A five segment footless biped model (Fig.2) was chosen to simulate the human body. Five segments are usually considered to be the minimum number needed to preserve important characteristics of gait, such as the roles of the knee joints and upper body.
The following assumptions were made in the application of the model and stimulation scenario

- Only saggital plane motion was included.
- Only a single-leg-support phase was considered.
- Ground reaction forces were not taken into account.
- Walking is considered to occur only upon smooth level surface and to be completely undisturbed by external forces.
- It is assumed that paraplegics with good upper body strength and control will be able to prevent falls and restore balance using crutches.
- The selectivity of the stimulation (of individual muscles) is assumed to be perfect.

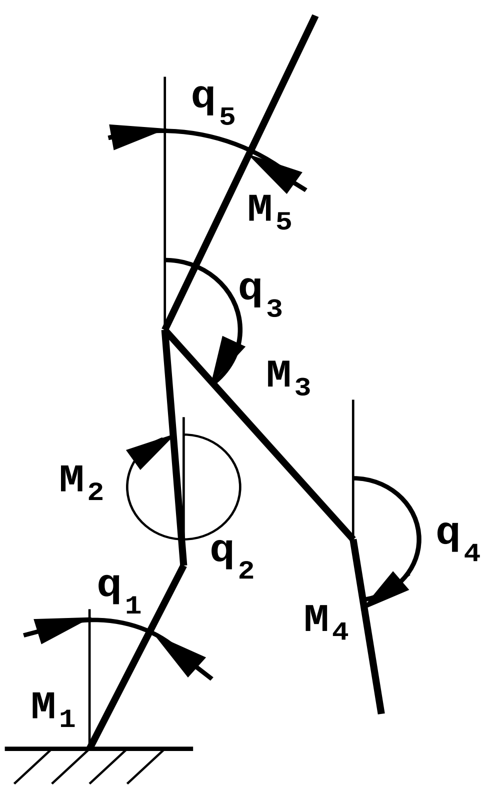



Figure 2: Five segment biped model.

### 3.2 Dynamic equations of motion

The five segment biped is shown in Fig.2. It consists of the trunk segment and two legs, each containing a shank and thigh segment. These links are connected via rotating joints. The rotation sectors are limited by the physiological constraints. The matrix equation of its motion is (Tzafestas *et al.* , 1996)

$$H(q)\ddot{q} + C(q,\dot{q})\dot{q} + G(q) = M \tag{1}$$

where
$H(q)$ is a $5 \times 5$ moment of inertia matrix,
$C(q,\dot{q})$ is a $5 \times 5$ matrix specifying centrifugal and Coriolis effects,
$G(q)$ is a $5 \times 1$ gravity terms matrix ,
$M$ is a $5 \times 1$ vector of applied joint torques (moments),
$q$, $\dot{q}$, $\ddot{q}$ are $5 \times 1$ vectors of joint angles, velocities, and accelerations.
The inertia matrix $H(q)$ is symmetric positive definite. It depends on the joint position $q$. The centripetal torques vary with the square of individual joints velocities, while the Coriolis torques vary with the products of velocities at different joints. The Eq.(1) is defined in detail in Appendix.

### 3.3 FNS stimulated muscle model

Muscle is a neural controlled mechanical impedance, meaning that the neural input determines the relation between the numbers of recruited motor units and output active force. For our research the comprehensive muscle model ( Dorgan and O'Malley, 1997) was specially adapted for simulation of the main physiological processes in electrically stimulated muscles. The processes in the system are modeled at 100 $Hz$ frequency sampling, and the stimulation frequency is 20 $Hz$. Recruitment level $z(k)$ and resulted muscle forces $f(k)$ are calculated at the start of each stimulation period $50\,ms$ and are held constant through it (same as in (Abbas and Chizeck, 1995)).
The muscle model is described by the mutually coupled second order dynamics of the active $n(k)$ and postactive $r(k)$ motor units (MU) of the stimulated muscle fibers:

$$\begin{array}{l}
z(k+1) = \left\{ \begin{array}{ll} sat[0.5\arctan(10PW(k+1)-4)+0.2146], & \text{if } k+1 \bmod 5 = 0 \\ z(k), & \text{otherwise} \end{array} \right. \\
n(k+1) = sat[0.8n(k) + (1-r(k)-n(k))z(k+1)] \\
r(k+1) = sat[0.4r(k) + 0.05n(k)sign[n(k)-0.45]\sum_{j=k-10}^{k-1} n(j)] \\
f(k+1) = \left\{ \begin{array}{ll} sat[0.3f(k) + 0.21\sum_{j=k-4}^{k} n(j)], & \text{if } k+1 \bmod 5 = 0, \\ f(k), & \text{otherwise} \end{array} \right.
\end{array} \tag{2}$$

where whole number of the muscle fiber MU is normalized to one. The model constants and coefficients are fitted according to examples in ( Dorgan and O'Malley, 1997). The models for agonists and antagonists muscles differ only in sign of parameters. The agonists muscle has the positive recruitment and force, and the antagonists muscle has the negative ones.
The presented model Eqs.(2) reflects the physiological processes in muscle fibers during the muscle excitation by the electric pulse from the stimulator. The active MU $n(k+1)$ are recruited from the pull of the available for activation purpose motor units $[1 - r(k) - n(k)]$. Only these MU contribute to the overall force $f(k+1)$ generated by the muscle. After the stimulation the previously active MU will become inactive, or postactive motor units $r(k+1)$. The postactive MU don't generate the muscle force, and their dynamics depend on stimulation history of the previous 10 samplings. It is assumed that the postactive MU are released to the available for

activation purpose MU for the aim of re-recruitment with a smaller rate than the available MU are activated with. This assumption makes possible to model the significant nonlinearities associated with muscle contraction, such as the muscle fatigue. This effect is caused by the increasing in the stimulation intensity ( Gait *et al.*, 1996), and is modeled as a large number of the stored (unreleased) postactive MU

$$sign[n(k) - 0.45] \sum_{j=k-10}^{k-1} n(j)$$

in the $r(k+1)$ postactive motor units equation.
The main assumption on the application of this model is that the nonlinear behaviour of this simulation model degrades the close-loop control performance in the same way as the muscle dynamics in the real FNS applications ( Dorgan and O'Malley, 1997).

# 4 Proposed Robust Control Laws.

Consider the locomotion dynamics model Eq.(1). As it was shown above, the disturbances and uncertainties in this system are inevitable. Hence the parameter matrices can be divided into a nominal and perturbed parts

$$H(q) := H_0(q) + \Delta H(q)$$
$$C(q, \dot{q}) := C_0(q, \dot{q}) + \Delta C(q, \dot{q})$$
$$G(q) := G_0(q) + \Delta G(q)$$

The important reason to parameter perturbation are the state tracking errors

$$e(t) := q - q_r \tag{3}$$

which appears in the system matrices as the trigonometric functions arguments (Appendix).
The muscle actuator is an another source of uncertain bounded disturbances which are caused by nonlinear dynamics of muscle Eq.(2). It should be pointed out that the part of the muscle dynamic uncertainty is canceled by Neural Network inverse model. This allows to limit the robust control gains to the physiologically reasonable values.
Hence we can rewrite the system model Eq.(1) as

$$(H_0(q) + \Delta H(q))\ddot{q} + (C_0(q, \dot{q}) + \Delta C(q, \dot{q}))\dot{q} + (G_0(q) + \Delta G(q)) = M + d \tag{4}$$

where $d$ is a $5 \times 1$ vector of actuator dynamic uncertainties, or

$$H(q)\ddot{q} + C(q, \dot{q})\dot{q} + G = M + \mu \tag{5}$$

where $\mu$ is the combined uncertainty.
These different forms of the plant equation will be used for the control laws derivation.

## 4.1 LQR control law with fuzzy gain scheduling

Consider the locomotion dynamics equation Eq.(4). It can be rewritten as

$$\ddot{q} = (H_0(q) + \Delta H(q))^{-1}[-(C_0(q, \dot{q}) + \Delta C(q, \dot{q}))\dot{q} - G + M + d] \tag{6}$$

and with the Eq.(3) we obtain

$$\ddot{e} = (H_0(q) + \Delta H(q))^{-1}(C_0(q,\dot{q}) + \Delta C(q,\dot{q}))\dot{e} + \tau + H^{-1}(q)d \tag{7}$$

where

$$\tau = H^{-1}(q)[-\ddot{q}_r - C(q,\dot{q})\dot{q}_r - G + M] \tag{8}$$

is the input signals vector.
The classical LQR control has a well known general form for $\tau \rightarrow u$

$$u = -R^{-1}B^T Pe \tag{9}$$

where $P$ is the numerical solution of the nonlinear Ricatti equation

$$\dot{P} + PA + A^T P - PBR^{-1}B^T P + Q = 0 \tag{10}$$

and the system matrices $A$ and $B$ are formed from the Eq.(7) matrices $H_0, \Delta H, C_0, \Delta C, G$.
It is not recommended to calculate the control Eq.(9) on every simulation step, since the persistent update of the control gain can cause the lost of the system stability (Shimkin and Feuer, 1988). Hence, some preliminary set of control gains is calculated off-line for the system Eq.(9). During stimulation these gains are scheduled by the Fuzzy Gain Scheduling algorithm (Passino and Yurkovich, 1998).
As it was already mentioned, the system matrices perturbations are caused by the tracking errors of the joint angles, which entries the $H$ and $C$ matrices as the arguments of the trigonometric functions (Appendix).
Define

$$\begin{array}{ll} e_c = cos(e) & \text{for } H(q) \text{ matrix} \\ e_s = sin(e) & \text{for } C(q,\dot{q}) \text{ matrix} \end{array}$$

and recall that the musculoskeletal system dynamics have the physiological constraints on the joint angles, and consequently on the joint angles tracking error, to be in one $\pi$ period, as opposed to the case of the biped robot with rotational joints. For extreme perturbations cases ($cos(e_{ij}) = 1 => sin(e_{ij}) = 0$) the tracking errors don't have simultaneously the same impact on the both system matrices. Hence, for these and the nominal cases (zero errors), the control gains can be calculated off-line and then interpolated some control gain vs. relative tracking error function. The relative tracking error for every joint is considered as

$$\delta e_i = e_{ci} - e_{si} \tag{11}$$

These errors are the input for the fuzzy logic membership functions (Fig.3) for every joint. The membership functions (*'neglarge'*- negative large, *'poslarge'*- positive large, *'posnegsmall'*- positive or negative small), - indicate the degree to which the linguistic value appropriately describes the $\delta e_i$ certain value. The number of the membership functions is not limited to three. It can be increased, or they can be smoothed to the gaussian form. The fuzzy output provides the relative degree (weights) of the system uncertainty according to the relative tracking error. These fuzzy weights schedules the appropriate gain from the control gain vs. relative tracking error interpolated function.

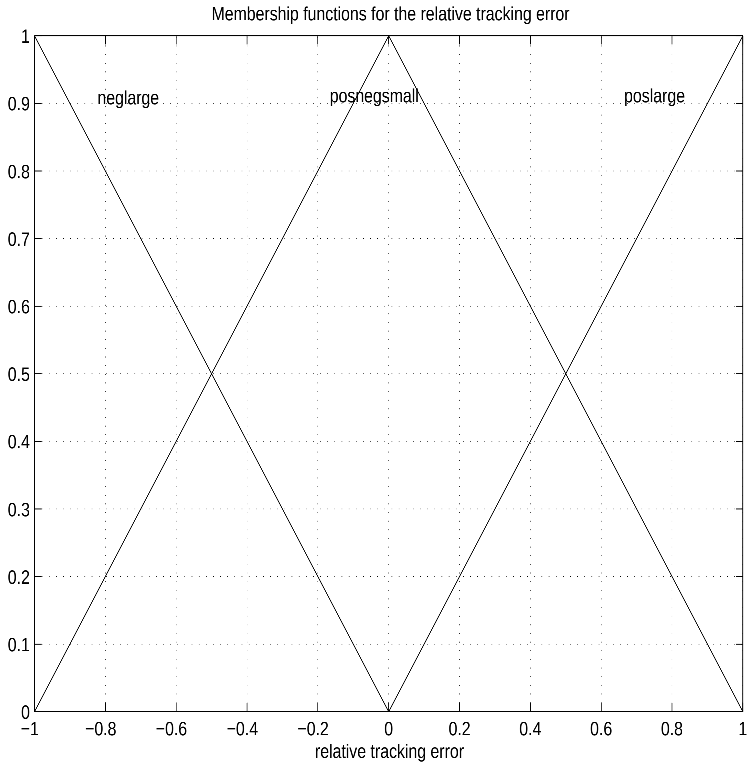



Figure 3: Fuzzy gain scheduler: the membership functions for the relative tracking error (*'neglarge'*- negative large, *'poslarge'* - positive large, *'posnegsmall'* - positive or negative small).

## 4.2 Proposed Sliding Mode control law

Let rewrite the Eq.(5) of the dynamics of 5-joint biped rigid musculoskeletal system

$$H(q)\ddot{q} + C(q,\dot{q})\dot{q} + G = M + H(q)\mu \tag{12}$$

The next properties of Eq.(12) can be exploited:
(P1) $H(q)$ is symmetric positive definite matrix for all $q \in \Re^5$
(P2) the terms in Eq.(5) are uniformly bounded.
Let $q_r$ the desired trajectory to be tracked and define the following vector signal

$$s(t) = \dot{e} + \Lambda e \tag{13}$$

where $\Lambda \in \Re^{5\times 5}$ is an arbitrary, constant, symmetric positive-definite matrix.
Then

$$\dot{e} = -\Lambda e + s \tag{14}$$

Note that as $e \to 0, s = \dot{q} - \dot{q}_r$ and Eq.(5) is rewritten

$$H\dot{s} + H\ddot{q}_r + C(s + \dot{q}_r) + G = M + H\mu \tag{15}$$

Consider a Lyapunov function

$$V = \frac{1}{2}s^T s > 0 \tag{16}$$

Differentiating Eq.(16)

$$\dot{V} = s^T H^{-1}[M - H\ddot{q}_r - C(s + \dot{q}_r) - G + H\mu] \tag{17}$$

The problem is to find control $u$ s.t.,

$$\dot{V} < 0 \tag{18}$$

Consider

$$u = H(\ddot{q}_r - s) + C(s + \dot{q}_r) + G - \gamma H sign(s) \tag{19}$$

where $\gamma > \mu$.
Hence with $M \to u$

$$\dot{V} = -s^T s - s^T \gamma sign(s) + s^T \mu < 0 \tag{20}$$

Therefore the tracking error $e$ converges to zero asymptotically and the control Eq.(19) the one we should employ.
Finally, a continious sliding entry of controller Eq.(19) is used to avoid chattering

$$u_s = -\gamma H \frac{s}{||s|| + \delta} \tag{21}$$

Control Eq.(21) implementation depends from more detailed knowledge about bounds on the uncertainty $\mu(t)$, that can be estimated, for example, by some special fuzzy logic algorithm.

# 5 Muscle Inverse Dynamics Neural Network and Pulse Stimulator Block

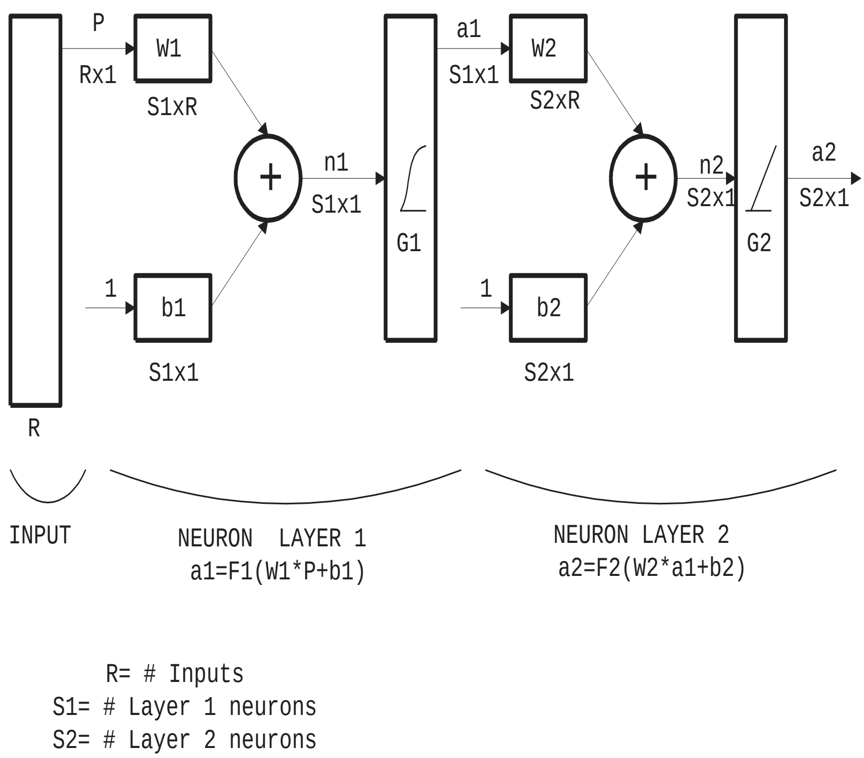



Figure 4: The muscle inverse dynamics Neural Network architecture.

The proposed robust controllers are insensitive to the model uncertainties due to their flexibility in control gains. Meanwhile, in the case of the large perturbation, the high control gains are unfeasible because of the physiological constraints on the joint torques. One of the ways to reduce the system uncertainty is to cancel the actuator (muscle) unknown nonlinear dynamics. To do this the muscle inverse dynamics Neural Network makes the approximate cancellation

of the FNS muscle dynamics. The exact cancellation seems to be impossible and unnecessary, since the applied robust controllers can deal with the reasonably bounded uncertainties.
The applied Neural Network (Fig. 4) is implemented in the backpropagation algorithm. Its input signals are the estimation of the applied moments $\tilde{M}(k-1)$, control moment $u(k)$, and the next sample reference moments $M_r(k+1)$. The output signals are the tuned joint control moments $\bar{u}$.
In order to decouple the musculoskeletal dynamics the joint moments $M_i$ are transformed to the joint muscle forces $F_i$. The details on the linear connection of the joint moments to the joint muscle forces can be found in Appendix. The musculoskeletal dynamics decoupling allows to design the separate muscle inverse dynamics Neural Network ($NN_i$) for every joint. According to the legend of the Fig.5 the input vector is

$$P_i = [\tilde{F}_i(k-1)\ u_i\ F_{ri}(k+1)]$$

and $R = 3$, $S_1 = 1$, $S_2 = 1$. The input layer transfer function is $G_1 = logsig$ nonlinear function, and the hidden layer transfer function $G_2 = purelin$ linear function. In all, the Neural Network function for every muscle has the following form

$$\bar{F}_i = purelin\{W_{2i}\, logsig[W_{1i}P_i + b_{1i}] + b_{2i}\} \tag{22}$$

The network with such architecture is well known as a general function approximator. It can approximate any static function with a finite number of discontinuities, given sufficient neurons in the hidden layer (Demuth and Beale, 1996). Such static learning achieves if not perfect, but acceptable cancellation of the time dependent muscle dynamics.
The network is trained on-line by the estimated value of the joint muscle applied force $\tilde{F}_i(k)$. This estimation is separately obtained from the measured joints angles and velocities. The training vector is

$$P_i = [\tilde{F}_i(k-1)\ \tilde{F}_i(k)\ F_{ri}(k+1)]$$

It is obvious that the initial weights and biases $W_1(0), W_2(0), b_1(0), b_2(0)$ have a great impact on the successful approximation of the muscle dynamics. These weights can be determined during some preliminary stimulations that are the necessary part of any FNS procedure.
The pulse stimulator uses the Neural Network tuned control signal $\bar{F}_i$ as an argument to a pusewidth/force function approximation. This function is a second-order linear system (Lan *et al.*, 1991) with known parameters, which is driven by the the nonlinear, pulsewidth dependent input function–Muscle Recruitment Characteristic (MRC) ( Dorgan and O'Malley, 1997)

$$f(k+1) = af(k) + bf(k-1) + MRC(PW, q, t) \tag{23}$$

The Muscle Recruitment Characteristic is the relationship between the pulse width and the steady state force during stimulation. It is the static nonlinearity with time-varying parameters ( Fig.5). It can be interpretered as the fraction of muscle activated by each stimulus pulse. As the pulse width is varied, the number of fibers recruited varies, as does the amount of force generated by muscle. Although the MRC parameters vary during stimulation, its static view can be learned beforehand (Allin and Inbar, 1986). The MRC role in Eq.(23) is to aggregate all muscle dynamics uncertainties into the input signal in order to linearize the muscle dynamics. During stimulation the Neural Network learn the nonlinear muscle dynamics, and the Eq.(23) can be alternatively defined as

$$f(k+1) = a(q,t)f(k) + b(q,t)f(k-1) + MRC(PW) \tag{24}$$

The Eq.(24) makes possible to refine the static pusewidth/force function approximation, since the muscle dynamics is learned, and the pulsewidth $PW$ is known.

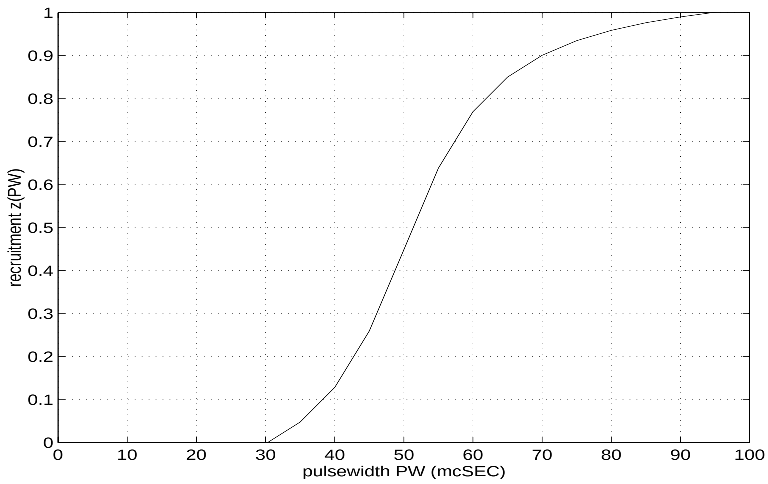



Figure 5: Muscle recruitment characteristic curve used by the stimulator block.

## 6 Simulation studies.

The simulation scenario framework of the FNS assisted walking was taken from (Oderkerk and Inbar, 1991). Physical parameters of the 5-link biped model and simulation parameters are given in Table I.

| | | | |
|---|---|---|---|
| shank's mass | $m$ | $kg$ | 4.55 |
| thigh's mass | $m$ | $kg$ | 7.63 |
| trunk's mass | $m$ | $kg$ | 49.00 |
| shank's length | $l$ | $m$ | 0.4309 |
| thigh's length | $l$ | $m$ | 0.4551 |
| trunk's length | $l$ | $m$ | 0.8270 |
| stimulation pulse frequency | | $Hz$ | 20 |
| process sampling frequency | | $Hz$ | 100 |

Table I: Physical and simulation parameters of the 5-link biped model.

The simulation results for the LQR and Sliding Mode control are presented on the Fig.(6-9). The stance and swing joints are defined according to the stick-figure initial position at the beginning of the simulation.

During simulation the so-called sliding style of walking was tested (Fig.6(a,b), Fig.8(a,b)). The advantage of this style lies in the quasilinear character of the locomotion dynamics: the stance leg would be lifted up slightly, and the swing would be transferred ahead on a nearly straight trajectory with a minimal offset distance from the ground. The sliding walking allows the application of relatively small and linear moments. The reasonable assumption was made about the perfect control on the trunk segment. Its simulation results are presented only on the stick-figure sequence (Fig.6(a), Fig.8(a)).

The simulation trials demonstrate the stable locomotion of the musculoskeletal model. The stick-figure sequences show that LQR control produce more smoothed walking then the Sliding Mode controller. This can be explained by the LQR control better adaptation to the linearized movements, possibly as a result of the fuzzy gain scheduling. It seems that LQR controlled

muscle behaviour is more efficient then in Sliding Mode control case (compare Fig.6 and Fig.8) at the cost of an increase in the joint moments values (Fig.6(c), Fig.8(c)).
The differences between the control and applied moments (Fig.6(c), Fig.8(c)) reveal that the Neural Network has difficulties to exact cancellation of muscle dynamics. It turns out that the Network weights convergence and the learning performance depends greatly on the proper network initialization. Meanwhile, numerous simulations show that without the Neural Network tuning the muscle force saturates, as a result of the high gain control values. The comparison of the first, second, and the third steps on the stick-figure sequence (Fig.6(a), Fig.8(a)) proves that the quality of the walking improves with every step. The stick-figure sequence get closer to resemble the desired sliding style of walking. Such progress is explained by the Neural Network successful learning of the muscle dynamics. Hence, the Neural Network tuning is not only necessary, but possible, for the proper tracking. The deficiency of its application is that it can operates only in some region of the musculoskeletal model initial conditions. For this purpose the center of the mass is transferred with the help of the crutches to some proper initial conditions at the end of the step. During simulation the end of the step is defined when the swinging leg is put ahead of the stance leg. This transfer is assumed leaves unchanged the muscle dynamics parameters, such as active and postactive MU number, and the force level (Fig.7, Fig.9). It is accomplished in 0.3 sec., and has been displayed on the stick-figures sequences only.
From the simulation results of the above two cases, we found that the tracking errors are reasonably bounded (Fig.6(b), Fig.8(b)). Hence the desired uncertainty attenuation properties of the proposed designs have been achieved. They can be used as a prototype of the real FNS control schemes.

# 7 Conclusions

In this paper, we have proposed the neurofuzzy enhanced robust control algorithms for FNS assisted walking of paraplegics. The LQR control with fuzzy gain scheduling and the Sliding Mode control were tested. The computer simulations demonstrate the potentials of these robust control schemes in FNS applications. It reveals also the necessity of the additional tuning of the control moments by the muscle inverse dynamics Neural Network. Considering the effect of the fuzzy gain scheduling notice that the LQR control provides more smooth locomotion than the Sliding Mode control at the cost of an increase in the joint moments values. These moments match the moments from the experimental results ( Yamaguchi, 1989; Yamaguchi and Zajac, 1991).
The decision what FNS controller is favorable can be made only during the practical verifications on paraplegic subjects. In the view of fact that it is desired to test the presented computer simulation results experimentally, we are planning in the future to advance the computer model by the muscle fatigue and spasticity effects.

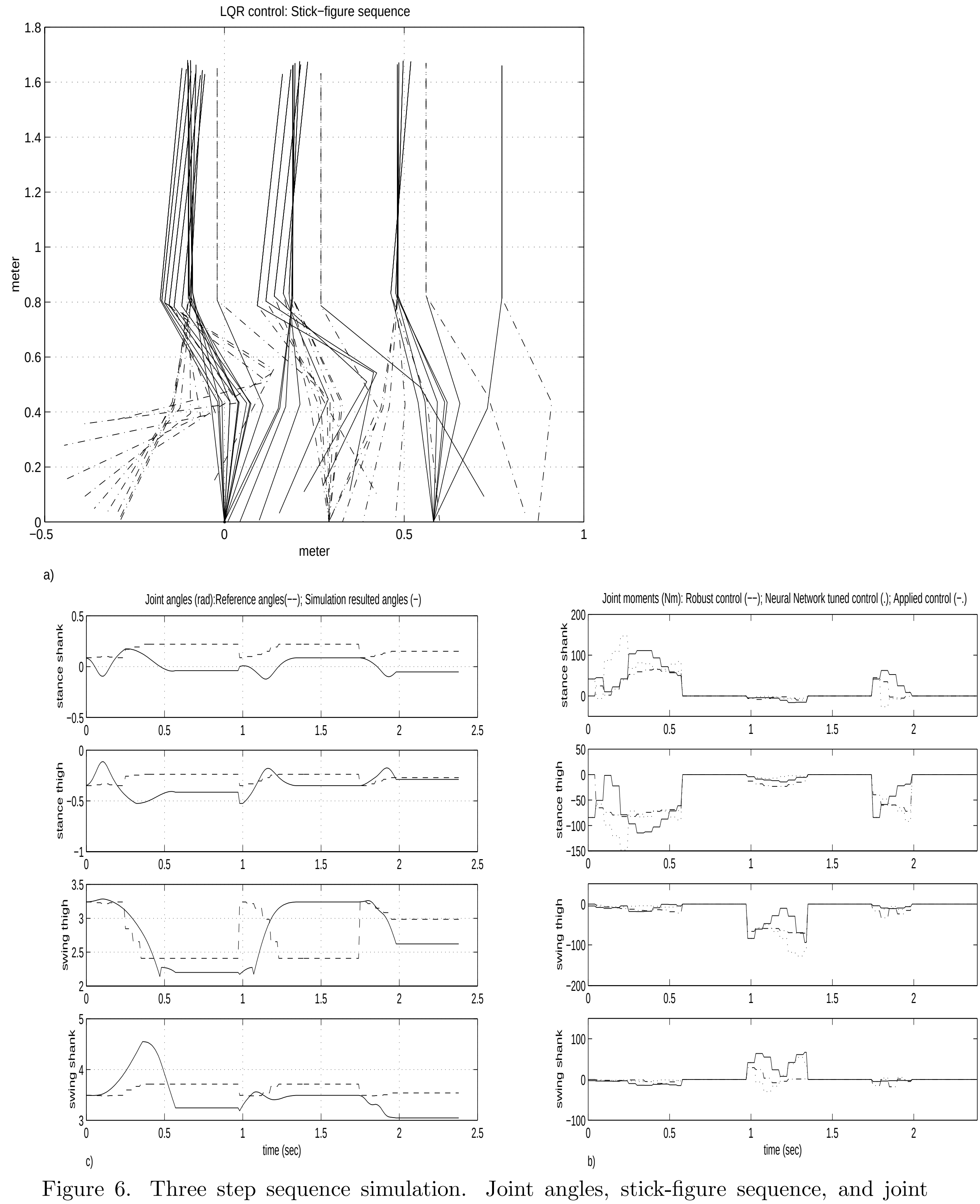



Figure 6. Three step sequence simulation. Joint angles, stick-figure sequence, and joint moments: LQR control with the fuzzy gain scheduling.

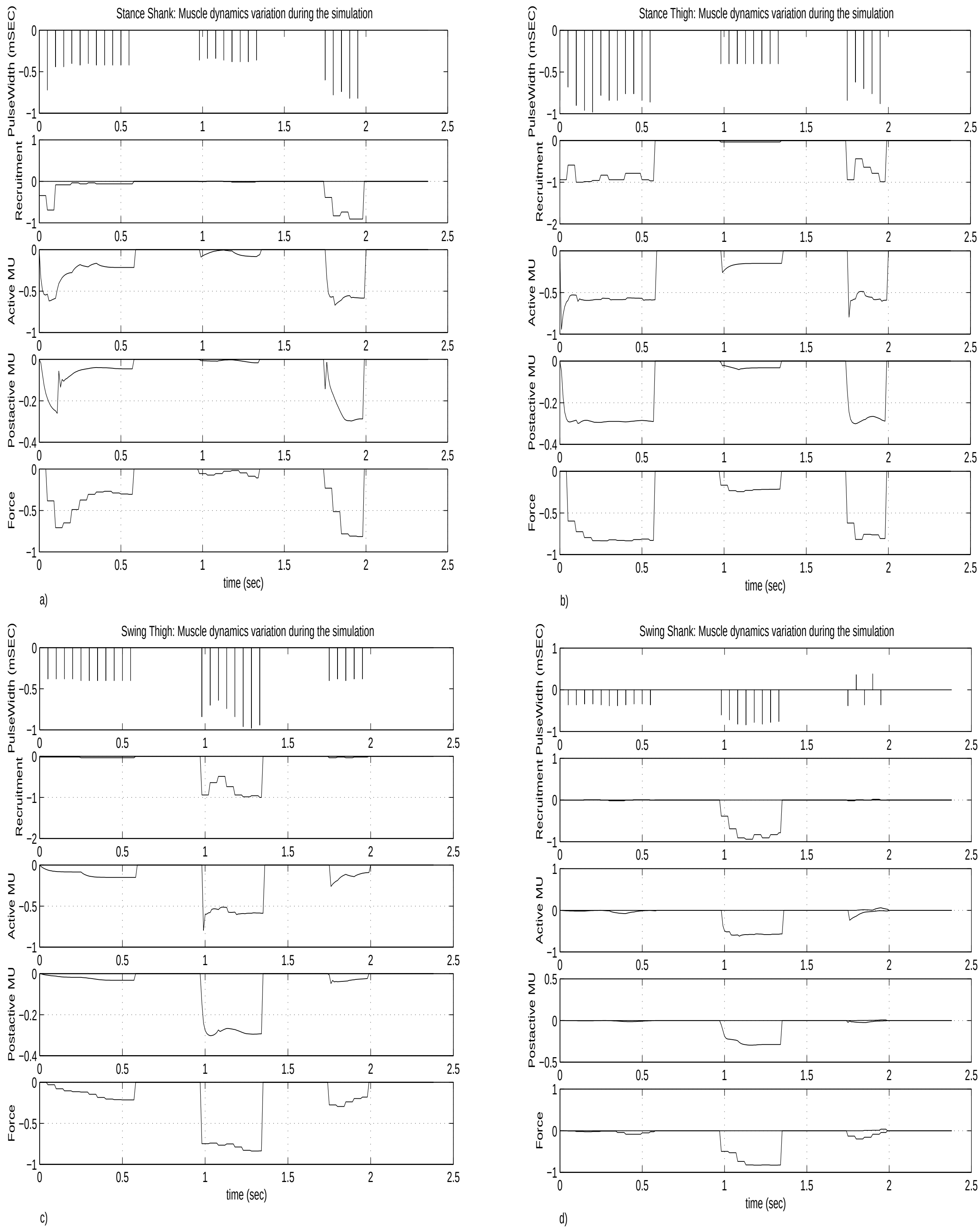
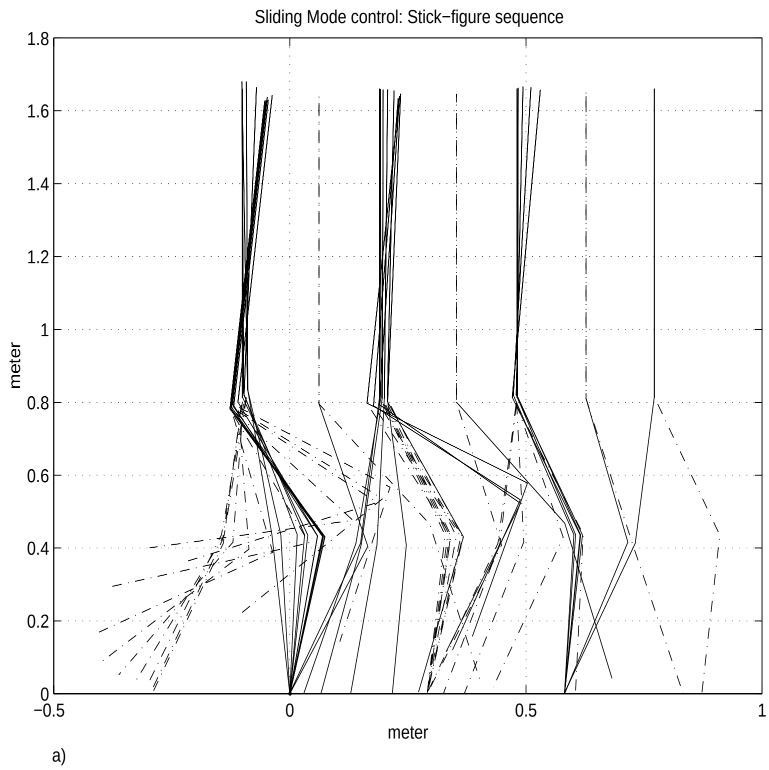
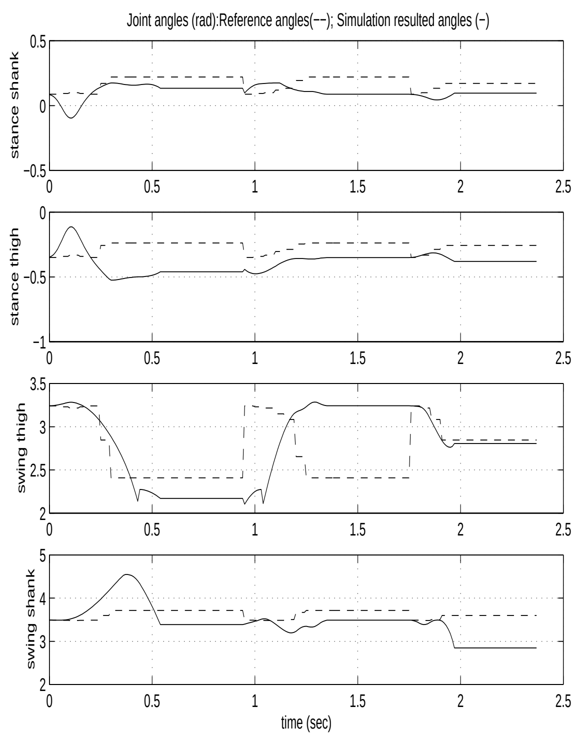



Figure 7. Three step sequence simulation. Stimulation parameters (normalized number of units): Pulsewidth, recruitment, and stimulated muscle force: LQR control with the fuzzy gain scheduling.



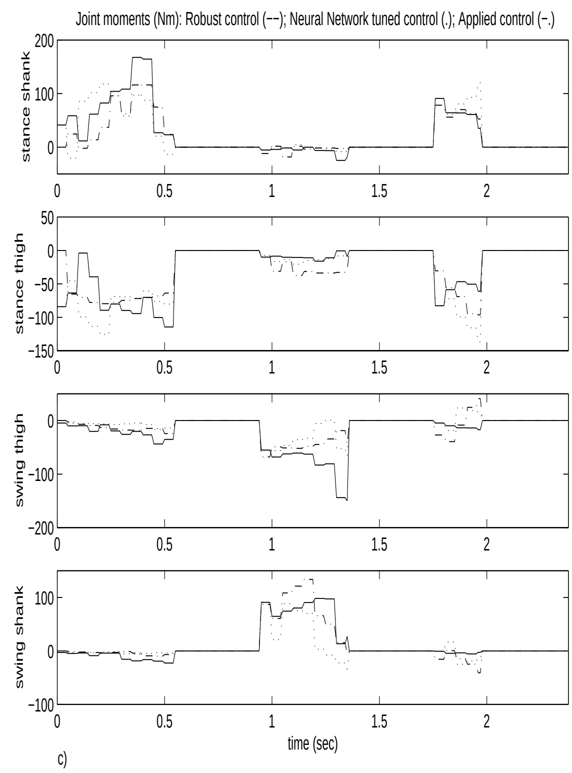




Figure 8. Three step sequence simulation. Joint angles, stick-figure sequence, and joint moments: Sliding Mode control.

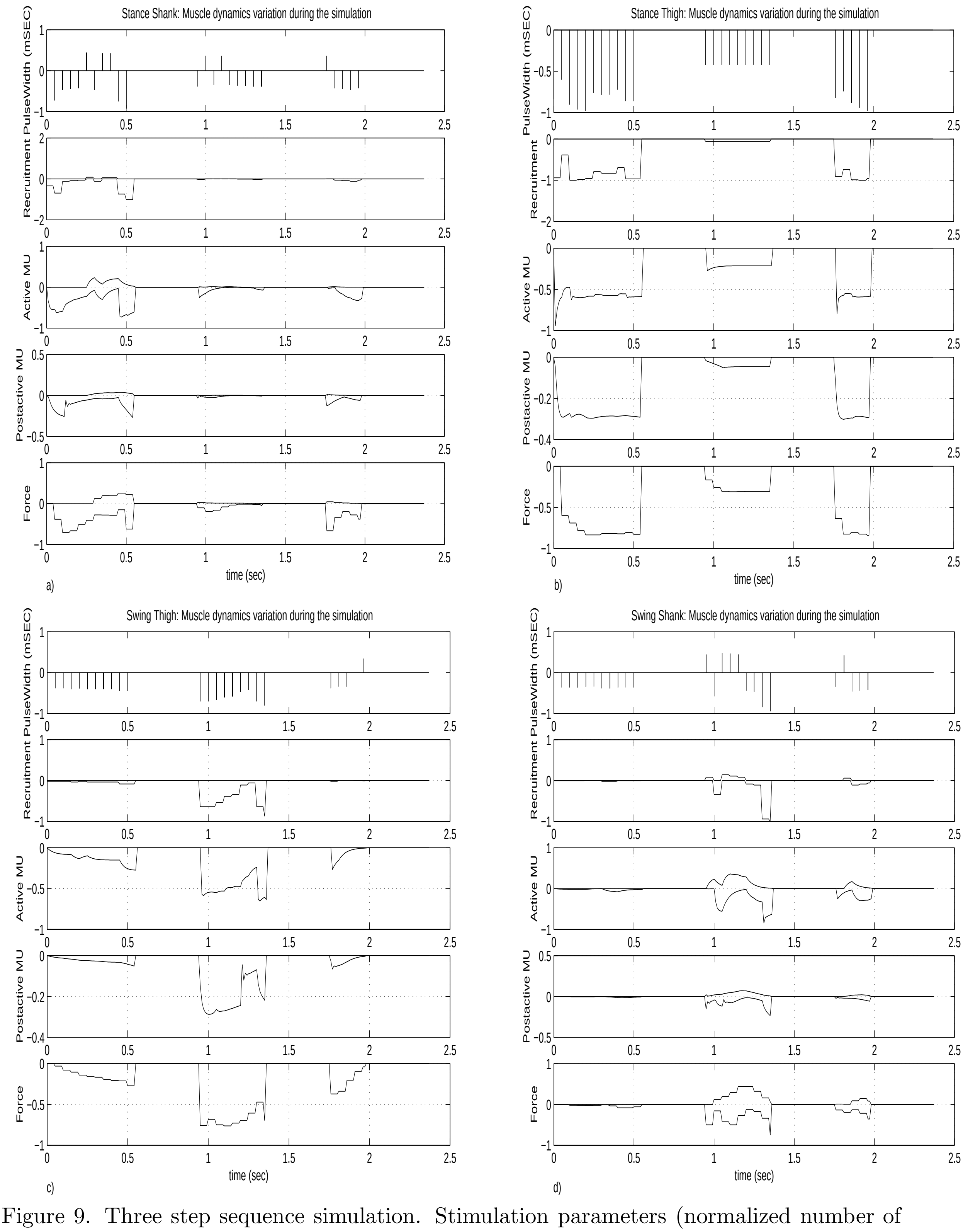



Figure 9. Three step sequence simulation. Stimulation parameters (normalized number of units): Pulsewidth, recruitment, and stimulated muscle force: Sliding Mode control.

# References


Abbas J. J. and H. J. Chizeck H.J (1995). "Neural Network Control of Functional Neuromuscular Stimulation Systems: Computer Simulation Studies," *IEEE Transactions of Biomedical Engineering*, Vol. **42**, no. 11, p. 117–1127.

Allin J. and G. F. Inbar (1986). "FNS Parameter Selection and Upper Limb Characterization," *IEEE Transactions of Biomedical Engineering*, Vol. **33**, no. 9, pp. 809–817.

Demuth H. and M. Beale (1996). *Neural Network Toolbox*, The MathWorks Inc.

Dorgan S. J. and M. J. O'Malley (1997). "A Nonlinear Mathematical Model of Electrically Stimulated Skeletal Muscle," *IEEE Transactions of Rehabilitation Engineering*, Vol. **5**, p .179–194.

Furusho J. and M. Masubuchi (1986). "Control of a Dynamic Biped Locomotion System for Steady Walking," *ASME J.Dyn.SyS.Meas.Contr.*, Vol. **108**, p. 111–118.

Gait Y., J. Mizrahy, and M. Levi (1996). "A Model of Fatigue and Recovery in Paraplegic's Quadriceps Muscle Subjected to Intermittent FES," *ASME Transactions, J. of Biomedical Engineering*, Vol. **118**, p.357–366.

Kralj A. and T. Bajd (1989). *Functional Electrical Stimulation: Standing and Walking after Spinal Cord Injury*, Boca Raton, FL: CRC.

Lan N., P. E. Crago, and H. J. Chizeck (1991). "Feedback Control Methods for Task regulation by Electrical Stimulation of Muscle," *IEEE Transactions of Biomedical Engineering*, Vol. **38**, p. 1213–1223.

Oderkerk B. J. and G. F. Inbar (1991). "Walking Cycle Recording and Analysis for FNS-assisted Paraplegic Walking," *Medical & Biological Engineering & Computing*, p. 79–83.

Passino K. M. and S. Yurkovich (1998). *Fuzzy Control*, Addison-Wesley.

Shimkin N. and A. Feuer (1988). "On the Necessity of "Block Invariance" for the Convergence of Adaptive Pole-Placement Algorithm with Persistently Exciting Input," *IEEE Transactions of Automatic Control*, Vol. **33**, no. 8 , p. 775–780.

Tzafestas, S., M. Raibert, and C.Tzafestas (1996). "Robust Sliding-mode Control Applied to a 5-Link Biped Robot," *J. of Intel. and Robotic Systems.*, Vol. **16**, p. 167–133.

Vukobratovic M. and O. Timcenko(1996). "Experiments with Nontraditional Hybrid Control Technique of Biped Locomotion Robots," *J. of Intel. and Robotic Systems.*, Vol. **16**, p. 25–43.

Yamaguchi G. T. and F. E. Zajac (1991). "Restoring Unassisted Natural Gait to Paraplegics Via Functional Neuromuscular Stimulatiuon: A Computer Simulation Study," *IEEE Transactions of Biomedical Engineering*, Vol.**37**, p.886–902.

Yamaguchi G. T. (1989). *Feasibility and Conceptual Design of Functional Neuromuscular Stimulatiuon Systems for the Restoration of Natural Gait to Paraplegics*, Ph.D. dissertation, Stanford Univ.

# A Description of the biped locomotion dynamic equations

The dynamic equations of motion for the 5 DOF skeletal model that presented in Fig(2) are given in matrix form in Eq.(5).

$$H(q)\ddot{q} + C(q,\dot{q})\dot{q} + G(q) = M \tag{25}$$

Here we present detailed description of this equation (Furusho and Masubuchi, 1986)
Taking the leg segment first, the elements of matrices $H_1, C_1, G_1$ for $i, j = 1, .., 4$, are
for $i < j$

$$H_1(j,i) = l_i l_j cos(q_i - q_j)[-m_j p_j + \sum_{e=j}^{4} m_e] \tag{26}$$

for $i = j$

$$H_1(j,j) = l_j^2[m_j p_j (p_j - 2) \sum_{e=j}^{4} m_e] + I_j \tag{27}$$

for $i > j$

$$H_1(j,i) = H_1(i,j) \tag{28}$$

for $i < j$

$$C_1(j,i) = \dot{q}_j l_i l_j sin(q_i - q_j)[m_j p_j - \sum_{e=j}^{4} m_e] \tag{29}$$

for $i = j$

$$C_1(j,i) = 0 \tag{30}$$

for $i > j$

$$C_1(j,i) = -C_1(i,j) \tag{31}$$

and

$$G_1(j) = g l_1 sin(q_i)[m_j p_j - \sum_{e=j}^{4} m_e] \tag{32}$$

where $m_i$ is the mass of $i$th link,
$l_i$ is the length of $i$th link,
$p_i$ is the center of mass of $i$th link,
$I_i$ is the moment of inertia of $i$th link,
$g$ is the acceleration due to gravity.
Next, the equation of motion are found for the three segment chain containing the shank and thigh segments, now considered as massless, connected to the torso segment.
Hence the elements of matrices $H_2, C_2, G_2$ for $i, j = 1, .., 3$, are
for $i < j$

$$H_2(j,i) = l_i l_j cos(q_i - q_j)[-m_j p_j + \sum_{e=j}^{3} m_e] \tag{33}$$

for $i = j$

$$H_2(j,j) = l_j^2[m_j p_j (p_j - 2) \sum_{e=j}^{3} m_e] + I_j \tag{34}$$

for $i > j$

$$H_2(j,i) = H_2(i,j) \tag{35}$$

for $i < j$

$$C_2(j,i) = \dot{q}_j l_i l_j sin(q_i - q_j)[m_j p_j - \sum_{e=j}^{3} m_e] \tag{36}$$

for $i = j$

$$C_2(j,i) = 0 \tag{37}$$

for $i > j$

$$C_2(j,i) = -C_2(i,j) \tag{38}$$

and

$$G_2(j) = gl_j sin(q_i)[m_j p_j - \sum_{e=j}^{3} m_e] \tag{39}$$

These two sets of matrix equations are then combined into one five row matrix equation as follows. For $i, j = 1, 2$:

$$H(j,i) = H_1(j,i) + H_2(j,i) \tag{40}$$

$$C(j,i) = C_1(j,i) + C_2(j,i) \tag{41}$$

$$G(j,i) = G_1(j,i) + G_2(j,i) \tag{42}$$

for $i = 1, 2$

$$H(5,i) = H_2(3,i) \tag{43}$$

$$C(5,i) = C_2(3,i) \tag{44}$$

for $i, j = 3, 4$

$$H(j,i) = H_1(j,i) \tag{45}$$

$$C(j,i) = C_1(j,i) \tag{46}$$

$$G(j) = G_1(j) \tag{47}$$

and

$$H(5,5) = H_2(3,3) \tag{48}$$

$$C(5,5) = C_2(3,3) \tag{49}$$

$$G(5) = G_2(3) \tag{50}$$

The elements of the moment vector E are
for $j < 4$

$$E(j) = M_j - M_{j+1} \tag{51}$$

for $j = 4$

$$E(j) = M_4 \tag{52}$$

for $j = 5$

$$E(j) = M_5 - M_3 \tag{53}$$