Chapter 10

Artificial Motor Control

INTRODUCTION

If the physiological motor control system is impaired we can try to support its function artificially. Such support may involve the mechanical function, actuation, sensing or the motor control itself. In the previous chapters, artificial support of mechanics, actuation and sensing have been discussed (chapters 7-9). This chapter will discuss artificial motor control (figure 10-1).

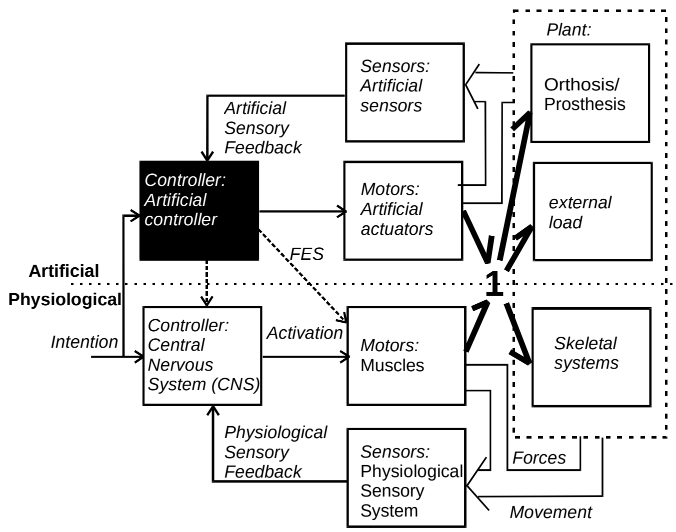


Figure 10-1 Schematic block diagram of an assistive system that supports the impaired neuromuscular system. Subject of this chapter is artificial motor control

OBJECTIVES

This chapter will:

- show that artificial motor control systems act in parallel to the affected physiological control system, with the task to support this system effectively
- show that the artificial motor control system can have several objectives:
  - to contribute in real time contol of a motor function
  - to train the CNS by externally applied stimuli with the objective to assist in relearning the physiological motor control by the CNS
  - to influence the operation and tuning of the physiological motor system by applying constant stimuli (neuromodulation)

CONTENT

10.1 Introduction

When assisting the impaired motor control system artificially, three systems can be conceived to act in parallel:

- the *physiological feedforward control system*. Under voluntary control detailed motor tasks can be controlled or learned motor programs can be initiated.
- the *physiological feedback system (reflex system)*, adapting the control actions to improve the interaction with the environment.
- the *artificial control system*, generating additional control actions to support the impaired physiological control system.

The artificial system has to support the execution of motor tasks intended by the user. This requires that the artificial system is under control of the user. *SECTION 10.2* will present approaches for this user control.

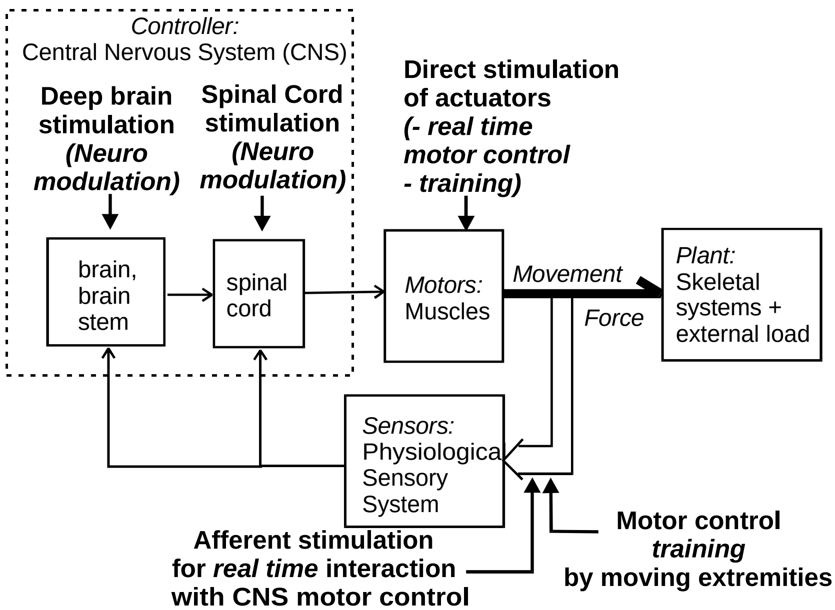


Figure 10-2. Interactions with the CNS for artificial motor control

The current chapter is focussing on the design of the artificial control system. This system may have several *types of interaction* with the physiological control system (figure 10-2):

1. *Real time control of motor function (SECTION 10.3):* In stead of applying a constant modulating stimulus to improve the setting of CNS control system, artificial supplementary motor control can also be applied to take over or influence a motor function in a real time manner. Also in this case, it is important to consider that the artificial control is supplementary to the affected physiological control, such that the combination of both systems has an improved functionality. In the case of real time functional motor control, the interaction with the physiological control system may be at several hierarchical levels. The CNS may be stimulated to activate motor patterns (*SECTION 10.3.1*), afferent signals may

be supplied to modulate the CNS motor control (*SECTION 10.3.2*) or physiological or artificial actuators may be directly controlled (*SECTION 10.3.3*). Artificial human motor control systems do not only interact with the physiological system at several levels, but are, like the physiological system, often designed in a *hierarchical* manner (Andrews et al. 1989; Veltink et al. 1996a). The hierarchical organization of artificial control of human motor function will be discussed in *SECTION 10.3.4*.

2. *Training of the CNS by externally applied stimuli:* The CNS can learn by training. This phenomenon is mostly called 'plasticity' (*SECTION 10.4*). The application of artificial motor control results in patterned afferent stimuli to the CNS. This excitation may help the CNS to relearn functional patterns.
3. *Neuromodulation:* The central Nervous System is a complex hierarchical control system in which each control level receives control signals from higher levels. If the the control systems at certain levels do not receive adequate modulating signals from higher levels, they become incorrectly tuned. Therefore, these control systems will not perform adequately. In the case of neuromodulation (*SECTION 10.5*), a constant modulating stimulus is applied to the CNS in order to improve the tuning of these control systems (Holsheimer 1998).

10.2 The human controller

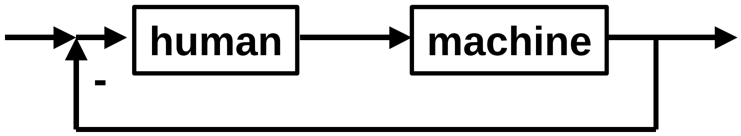
10.2.1 INTRODUCTION

In the application of rehabilitation devices, the patient is more than just a passive mass-spring-damper system of which the properties must be improved. The human is a very versatile controller of his/her own body, in combination with the environmental constraints imposed, such as a rehabilitation device. For an optimal design, the combined system of human and device should be optimized, taking advantage of the potential of both. Especially, the potential of the human controller to continuously and rapidly adapt to the environment is a property which is not easily incorporated in a technical device.
For the motivation and well-being of the patient it is also better to enable him/her to control the environment, and to provide sufficient information such that the patient will feel secure and stable.

OBJECTIVES
This section will show:
- Dynamic properties of the human controller
- Limitations and adaptation
- What systems can be controlled?
- The human as supervisor of the rehabilitation device

10.2.2 THE DYNAMICS OF A FEEDBACK CONTROL LOOP WITH A HUMAN CONTROLLER

In Figure 10-3 a feedback control loop is shown in which the human is the controller. This situation can be found in many daily life situations, e.g. in driving a car, flying an airplane, steering a ship, driving an electric wheelchair, etc. It is essential to notice that the human is a part of the closed-loop structure, and that the properties of the human as a controller in combination with the dynamics of the system to be controlled determines the behavior of the feedback system. The system in figure 10-3 is more elaborated in figure 10-4, in which the interfaces between the human and the system are also incorporated. The human must have some sort of display in which the behavior



of the system is shown (e.g. the control panel of a ship). In many direct control situation the

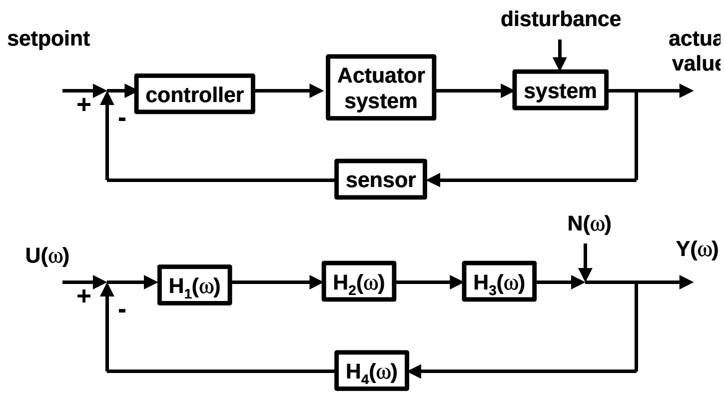


Figure 10-3 A feedback control loop with a human controlling a machine. for an optimal control the machine properties should be designed such that the system can be controlled by the human Block scheme of the system with the human controller. There are two inputs to the system, setpoint U(ω) and disturbance N(ω)

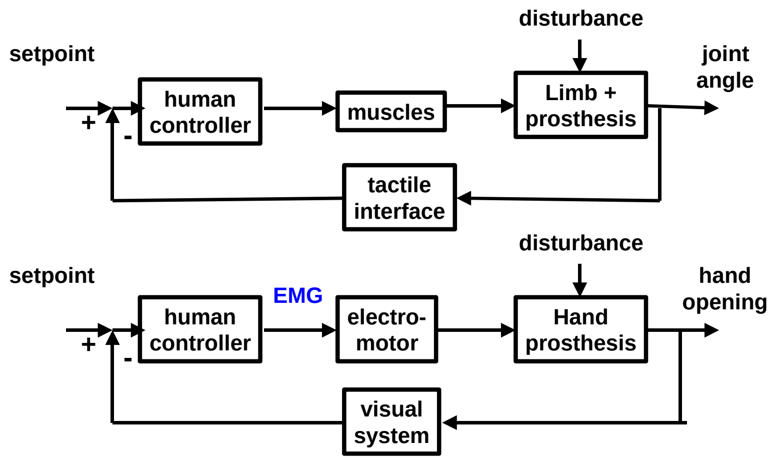
Figure 10-4 Block scheme of the system with the human controller. There are two inputs to the system, setpoint U(ω) and disturbance N(ω)

human is aware of the behavior by direct sight, and by the information received from the vestibulary system, tactile organs and proprioceptive sensors in the muscles.
Two types of behavior are important. The control behavior describes to what extent a desired setpoint or trajectory can be followed. An example of control behavior is following the curves in the road while driving a car. The disturbance behavior describes to what extent disturbances entering the system can be rejected such that they do not have an effect on the desired course. An example is the steering corrections to heavy wind blows. From the block scheme in figure 10-4 it can be seen that the resulting position Y(ω) of the system is a function of two inputs, the setpoint (trajectory) U(ω) and the disturbances N(ω):

$$Y(\omega)=\frac{H1(\omega)H2(\omega)H3(\omega)}{1+H1(\omega)H2(\omega)H3(\omega)H4(\omega)}U(\omega)+\frac{1}{1+H1(\omega)H2(\omega)H3(\omega)H4}N(\omega)$$

In a control loop the effect of an input to the system on the output is the forward path divided by one plus the open loop. The same system could be written in the time domain, but then the multiplication of transfer funtions should be replaced by convolution integrals. For an optimal performance the transfer function from U(ω) to Y(ω) should approach one. This is achieved when H1(ω)*H2(ω)*H3(ω) >> 1 and H4(ω) = 1. In addition, for an optimal disturbance rejection the transfer function from N(ω) to Y(ω) should be zero. This is achieved when H1(ω)*H2(ω)*H3(ω)*H4(ω) → ∞.

In figure 10.5 two examples are shown of this control loop in a biomechatronics context, one in which the joint angle of an above-knee prosthesis is fed back by a



tactile interface, and one in which the hand opening of a hand prosthesis is fed back by the visual system. Clearly, the dynamics of the sensory systems play an important role in the dynamic behavior of the whole system. Especially the time-delays in the feedback systems have an important impact on the performance. The theoretical optimal behavior of the system can not be achieved, since the dynamics of the system components limit the optimal control gains.

Figure 10.5 Examples of closed-loop control of biomechatronic devices

As for any closed-loop control system the control settings should be adjusted such that stability of the system is maintained while optimal performance is achieved. For analysis of the stability of the closed loop system, the open loop system should be taken into account. For simplicity reasons (but not loosing any generality!) this system is reduced to the human control system H_m (ω) and the system to be controlled H_s(ω), see figure 10-6. The open loop transfer function becomes H_m(ω)*H_s(ω). From this open-loop transfer function the phase margin and/or the amplitude margin should be analysed in order to determine if the system is stable. A system is unstable if for a certain frequency the phase lag is –π (rad) or more while the gain is one or higher. It is sometimes difficult to imagine what the result is of an unstable system, since almost all systems in daily life are stable. Especially the human is a excellent controller, which only function with stable systems. Unstable systems start oscillating until they reach one of their physical limits. The result is then trivial, e.g. a stick on the ground is the result of the failure to balance it in the upright position. Stability margins are calculated as the phase margin (-π - phase lag) at the frequency where the gain is one, or the amplitude margin which is one minus the gain at the frequency where the phase lag is -π.

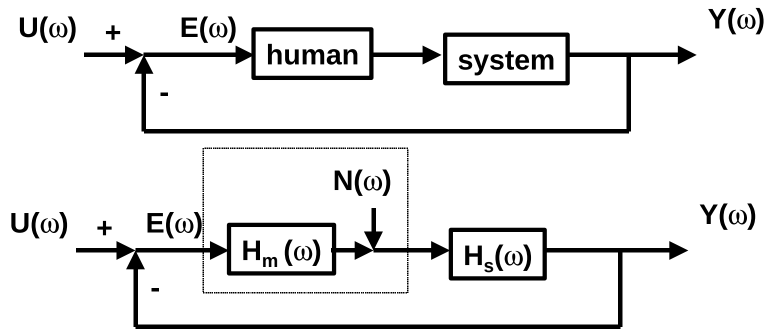


Figure 10.6 Simplified system with the human as controller. McRuer & Jenkins (1967) predicted that the humans would strive for the optimal control behaviour by adapting there dynamic behavior such that an optimal servo-system remains, by
$H_m(\omega)*H_s(\omega) = 1/j\omega$

In the past many experiments have been done with the human as controller. The control behavior was adapted from experiment to experiment, but it was not well understood why the humans were adapting their behavior. A major breakthrough in the theory of manual control was due to the work of McRuer & Jenkins (1967), who stated that the humans were always striving to optimal servo-behavior of the combined system of human and plant. The optimal servo-behavior would be obtained when $H_m(\omega)*H_s(\omega) = 1/j\omega$, i.e. the human being adapts its behavior such that the combined system behaves as an integrator. In a bode –plot an integrator has a slope of –1 in the amplitude plot, and a constant phase lag of $-\pi/2$. If the open-loop transfer function becomes an integrator, the input-output behavior becomes

$$H_{uy}(\omega) = \frac{Y(\omega)}{U(\omega)} = \frac{\frac{1}{j\omega}}{1+\frac{1}{j\omega}} = \frac{1}{j\omega + 1}$$

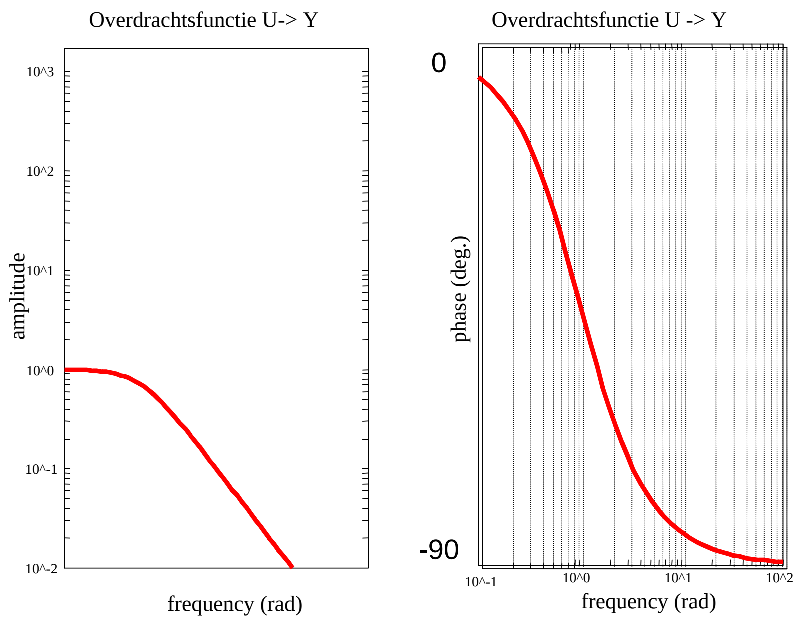
This system is a first-order system (low-pass filter) in which the lower frequencies can be tracked quite good, but the higher frequencies can not be tracked. A bode-plot of the system is shown in figure 10-7.

If the open-loop system would be an integrator, the system would be stable since no phase lag of $-\pi$ is achieved. However, the human being has also some limitations. McRuer & Jenkins (1967) developed the following model of the control behavior of the human being:

$$Hm(\omega) = Km\frac{1+j\omega\tau 1}{1+j\omega\tau 2}.\frac{1}{1+j\omega\tau 3}.e^{-j\omega\tau_v}$$

In which K_m, τ_1 and τ_2 are adjustable parameters to adapt to the plant, the low-pass filter with τ_3 are the limitations and inertia due to the neuromusculoskeletal system, and τ_v are the pure time-delays resulting from the transport and processing in the nervous system.

From the last two terms, the time-delay τ_v dominates the behavior for relevant frequencies $\omega < 3$ rad/s, and often the transfer function is written with an equivalent time-delay τ_e in which also the limitations of the neuromusculoskeletal model are incorporated:



$$Hm(\omega) = Km\frac{1 + j\omega\tau 1}{1 + j\omega\tau 2}.e^{-j\omega\tau_e}$$

Figure 10-7 A bode-plot of an optimal servo-system.

10.2.3 HUMAN CONTROL OF RELATIVELY FAST MOTOR TASKS WHICH CANNOT BE CONTROLLED IN A CONTINUOUS MANNER

In many cases, especially related to mobility, the human operator is not able to continuously control the body movements because they are too fast. In the case of walking, for example, muscles are thought to be controlled by a pattern generator in the central nervous system (Duysens et al. 1998), acting mainly open loop, and, additionally, via reflexes. This process is controlled consciously at a higher level in a supervisory manner.

If affected mobility functions are to be supported by biomechatronic systems, their control can be linked to the physiological pattern generator by tracking the state of the system from signals which can be measured from the body. These can be signals from the central nervous system, muscle activation signals, forces and body movements. Such control is often implemented in finite state control schemes (Andrews et al. 1989).

Also at the conscious level of mobility control, the motor control activities can often be described in terms of finite states: walking, standing, sitting down, standing up, walking up stairs. The intention of persons to perform these task can also be detected by measuring signals from the human body (intention detection) (Andrews et al. 1989; Veltink et al. 1995).

It should be noted that upper extremity tasks can often not be described in such finite state schemes and require the continuous human controller concepts described in the previous section.

10.2.3.1 Hierarchical control

Artificial motor control is often hierarchically organized, like the physiological control system (chapter 5: figure 10-8) (Chizeck et al. 1988; Andrews et al. 1989; Veltink et al. 1996a). The high level control detects the intention of the user (what task is to be performed and in what manner) and gives sensory feedback to the user. The intermediate level control coordinates the control of several muscles and joints to implement certain movement tasks. The low lever control controls the actual actuation system, which may be stimulated muscles or artificial actuators.
Each of these control levels may interact with the user, exchanging information or via mechanical interaction (especially at the low level).

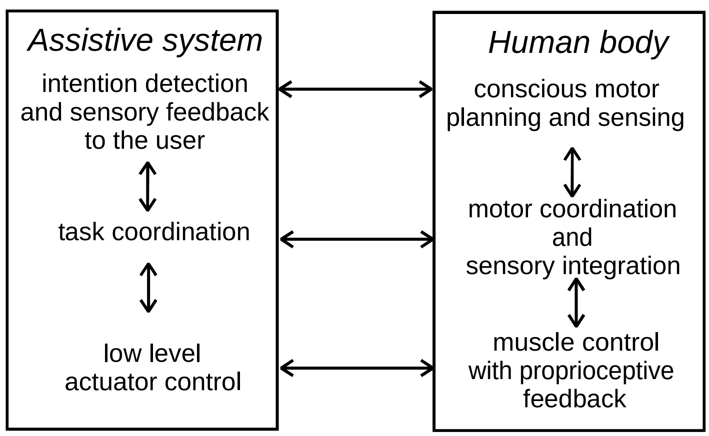


Figure 10-8 Artificial motor control systems are often hierarchically organized in accordance with the hierarchical organization of the physiological motor control system (Chizeck et al. 1988; Andrews et al. 1989; Veltink et al. 1996a)

10.2.3.2 Finite State control

High and intermediate level control is often implemented using Finite State Machine control (or Rule Based) schemes (figure 10-9,10) (Chizeck et al. 1988; Andrews et al. 1989; Willemsen et al. 1990; Veltink et al. 1996a; Sweeney et al. 2000). In these schemes, movements or processes are divided into sequential states and the change from one state to another is determined by conditional (IF.... THEN....) rules. In each state and during the transfers certain control actions can be specified or lower level control schemes applied.

The rules for transition from one state to the other (transisition rules) can be either handcrafted on the basis of an analysis of the task and experience or it can be derived automatically using machine learning techniques (Kirkwood et al. 1989), “cloning” the behavior of an example

Alternative to finite state control, neural networks and fuzzy systems are used to control motor tasks on high and intermediate (Heller et al. 1993; Kostov et al. 1995; Ng et al. 1997; Sweeney et al. 2000).

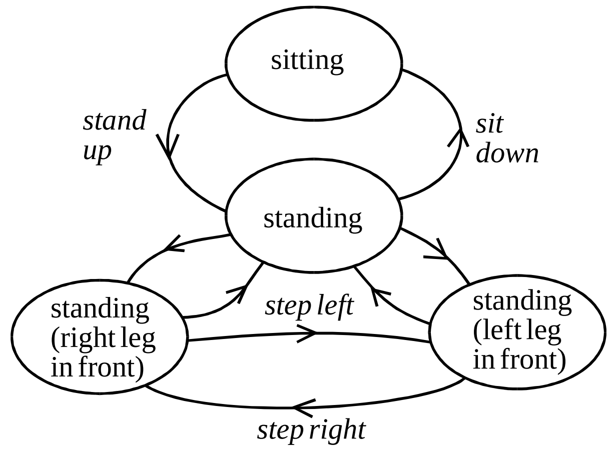


Figure 10-9 Finite state control scheme for an intention detection system for control of FES supported standing-up, standing and stepping in paraplegics (Veltink et al. 1996b). Sensory information used was inclination of legs (using accelerometers) and crutch forces. The intention detection scheme allowed support of these movement tasks without the need for explicit commands from the user.

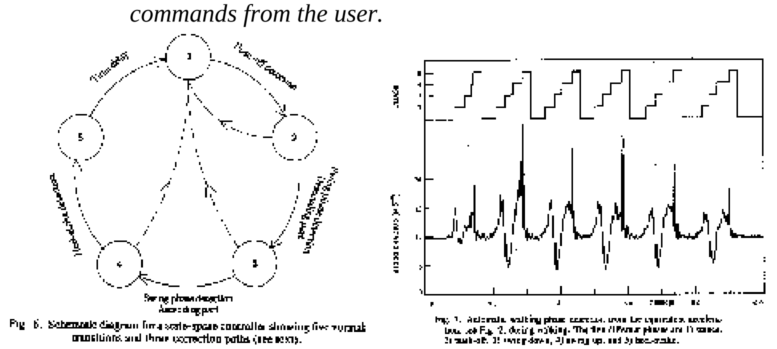


Figure 10-10 Finite state scheme for detection of swing and stance phases during walking on the basis of the signal of an accelerometer placed at the shank (Willemsen et al. 1990). On the basis of this finite state detection scheme, a drop foot stimulator was controlled.

10.3 Artificial control of motor function

The previous section discussed how a person can operate machines, which may be assistive devices. If the task to be controlled is relatively slow, like in many upper extremity tasks, the human can continuously control a limited number of physical quantities, like position (handopening) or force. If the task is relatively fast, like gait, the person can not control the movements continuously, but acts as a supervisor at a higher level, determining when to start and stop certain activities and influencing parameters like for example walking speed. In such cases the intention of the person needs to be derived via an interface and the execution of the task needs to be synchronized with the activities of the physiological control system.

This section describes approaches to actually control motor function on the basis of the command signals derived from the user. Again, we will first look at tasks which are relatively slow (*SECTION 10.3.2*), for example manual tasks, and subsequently we will discuss the control of motor tasks which are relatively fast *(SECTION 10.3.3)*.

10.3.1 CONTINUOUS MOTOR CONTROL

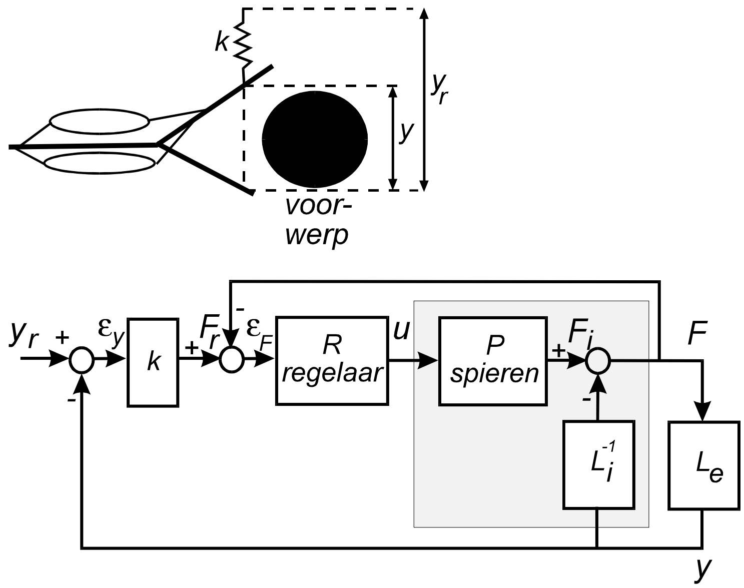
At the low and intermediate levels continuous control of certain physical quantities is required, taking account of the physical characteristics of the muscular-skeletal and assistive systems and coordination between joints. Examples are the control of hand opening or grasp force, the control of step size during gait, control of body balance, etc.

In this section we will present several examples of continuous control concerning control of hand grasp and cyclical movements / gait.

EXAMPLE 10.1 ARTIFICIAL STIFFNESS CONTROL [CRAGO, 1988 #342]
By stimulation of muscles in the lower arm basic hand grasps can be controlled. The following points need to be taken into account:

- the size and compliance of the object which is to be grasped is generally unknown (soft material / hard stone)
- if an object has been grasped, the loading of the hand changes suddenly:
  - before contact has been established, no force is exerted to the fingers (the load can be conceived as an infinitely high compliance); the muscles just have to resist the gravitational forces and the internal load of the hand (stiffness of the tissues). Under this condition, the user has to control the position (grip size y).
  - If the object has been grasped, an additional external load is imposed to the hand. Now, the user has to be able to control the grasping force F.
- it is desirable that the user can control grip size y, when there is no contact, and grip force F, when the grip has been established, by only one control signal.

Crago et al [Crago, 1988 #342] developed a control system for this purpose, of which the principle is depicted in figure 10-11. The user controls the virtual grip size y_v in series with a stiffness k by means of an input device (goniometer) which can be operated by the shoulder.



FIGUUR 10-11 *Control of hand grip by means of a simulated stiffness* k.

PROBLEM 10.1 ARTIFICIAL STIFFNESS CONTROL OF HAND GRASP: SEE END OF THIS CHAPTER

EXAMPLE 10.2 GRIP CONTROL USING SKIN SENSORY SIGNALS FOR FEEDBACK
(HAUGLAND ET AL. 1994; HAUGLAND ET AL. 1997; HAUGLAND ET AL. 1999)

When controlling grasp by FES using the scheme of example 2, the user does not sense the grasp force. It is therefore difficult for the user to control grasp force. However, it is important to minimize grasp force in order to avoid fast fatigue of the stimulated muscles.

For this reason, it is desirable to measure grasp force and control the force to a minimal level required to hold an object. Artificial force sensors on the fingers are bulky and not very user friendly in use. Haugland et al. (Haugland et al. 1994; Haugland et al. 1997; Haugland et al. 1999) therefore investigated whether it is possible to assess grip force by deriving signals from the skin sensors (see chapter 9). It appeared that these sensors, and the derived signal, are very sensitive for slip and could be very well used in the control of hand grasp force. In the control scheme used by Haugland et al., the stimulation level is continuously reduced until a beginning slip of the object is detected from the skin sensor signals. Subsequently, the stimulation is immediately increased and subsequently gradually reduced again. This scheme results in an varying activation level of stimulation just above the level required to avoid major slip.

EXAMPLE 10.3 CONTROL OF ARM MOVEMENTS USING ANTAGONISTIC VOLUNTARY CONTROL OF MUSCLES (CRAGO ET AL. 1998)

In addition to the control of hand grasp, it is valuable for part of the quadriplegic population to be able to extend the elbow by stimulation of the triceps muscle when the upper arm is in an orientation where gravity tends to flex the elbow. When the elbow is extended under these conditions, the effect of gravity is compensated and the elbow can be stretched in a larger operating range. If the user has some voluntary control of elbow flexors, he/she can change the elbow angle voluntarily by activating the elbow flexors in combination with the gravity compensating FES activated elbow extensors. In this control scheme, the orientation of the upper arm is sensed using an accelerometer.

10.3.2 CONTROL OF RELATIVELY FAST MOVEMENT TASKS WHICH CAN NOT BE CONTROLLED CONTINUOUSLY

If the task is relatively fast, like gait, the person can not control the movements continuously, but acts as a supervisor at a higher level, determining when to start and stop certain activities and influencing parameters like for example walking speed. In such cases the intention of the person needs to be derived via an interface and the execution of the task needs to be synchronized with the activities of the physiological control system (see section 10.2.3).

In this section we will discuss the artificial control of motor tasks which are relatively fast, in accordance with the identified user intention.

The physiological motor control can be influenced at several hierarchical levels: stimulating the CNS may trigger functional motor patterns *(SECTION 10.3.2.1)*, the CNS motor control may be modulated by applying afferent signals *(SECTION 10.3.2.2)*, or peripheral actuators may be controlled directly *(SECTION 10.3.3.3)*. Many of the artificial control systems have a hierarchical design *(SECTION 10.3.3.4)*.

10.3.2.1 Real time control of motor function by direct control of physiological or artificial actuators

In stead of having part of the CNS in the control loop, an artificial control system can be designed that controls a motor task at low or intermediate hierarchical level. The user input to this system can be given at the highest control level (intention detection). This concept has often been taken in control of mobility or hand function with FES in complete spinal cord injured persons.
The artificial control systems are often hierarchically organized, like the physiological motor control system (section 3.3.1). Finite State Control is often applied in the high and intermediate control levels (section 3.3.2). The low level actuator control often requires continuous control of certain physical quantities (section 3.3.3).

10.3.2.2 Real time control of motor function by triggering the CNS to produce functional motor patterns

The CNS has the ability to produce functional motor patterns. In cats, it has been shown that the spinal cord has the ability to produce such patterns (Prochazka 1996; Duysens et al. 1998; Van de Crommert et al. 1998). This ability has been called *the Central Pattern Generator (GPR)*. In humans, it is still a point of discussion whether the spinal cord can produce functional patterns in a self-sustained manner (i.e. without central and afferent inputs). However, the complete CNS, with afferent inputs is able to produce functional motor patterns. This capability can be used in artificial motor control systems. Kralj et al. (Kralj et al. 1983) have shown that functional stepping movements are triggered in paraplegic persons by stimulation of the *Flexion*

Withdrawal Reflex. In healthy persons, this reflex is triggered when stepping on sharp objects. The Flexion Withdrawal Reflex has been used extensively in restoring walking in complete paraplegics. The drawbacks of this application are that the response is relatively slow and variable and the reflex *habituates* (i.e. becomes less sensitive) when it is being used frequently (Granat et al. 1991). It has been shown that the sensitivity can be restored by incidental stimulation at high levels (Granat et al. 1991) (dehabituating stimulus).
Functional motor patterns can also be generated in animals by direct stimulation of the spinal cord (Barbeau et al. 1999; Grill et al. 1999). However, this has not yet been applied in humans.

EXAMPLE 10.4   STIMULATION OF THE FLEXION WITHDRAWAL REFLEX

The flexion withdrawal response can be elicited by high level stimulation of the peroneal nerve, activating afferent pain fibers. Figure 10-12 shows the hip angle response in a paraplegic subject (Granat et al. 1988). Note that the response is fairly slow, featuring a delay of approximately 0.5 s. The response after the delay is also influenced by the dynamics of the leg as a response to the activation of the hip flexors. The flexion withdrawal reflex response tends to vary in amplitude and decline in course of time (habituation). This habituation can be reduced by incidental high level stimulation (dehabituating stimulus) (Granat et al. 1991).

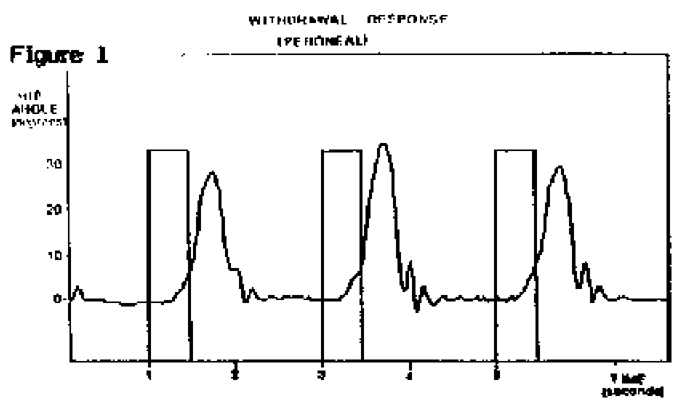


figure 10-12   Flexion withdrawal reflex response in paraplegic patients initiated by high level stimulation of the peroneal nerve (Granat et al. 1988). The figure shows the hip angle response

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10.3.2.3   Real time control of motor function by applying afferent signals to modulate the CNS motor control

In many neuromuscular diseases (stroke, spinal cord injury, etc.), the impaired neuromuscular system features increased sensitivity of reflex loops (hyperreflexia), which contributes to spastic contractions of the muscles . Several studies show that the sensitivities of these reflexes can be reduced by stimulation of afferent nerve fibers from peripheral locations (Apkarian et al. 1991; Veltink et al. 2000; Voormolen et al. 2000) (figure 10-13). Voormolen et al. (Voormolen et al. 2000) showed that the reflex sensitivity can also be reduced during the swing phase of gait.

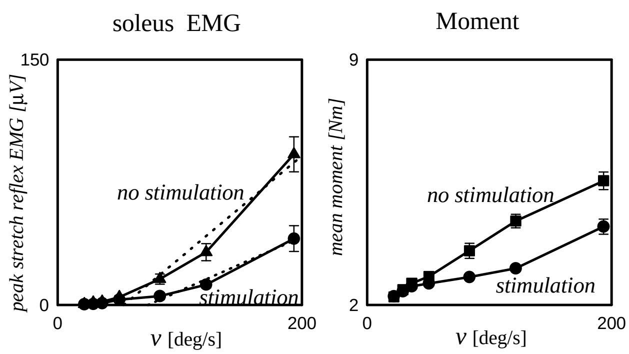


Figure 10-13 Stretch reflexes in the calf muscle are reduced by stimulation of the deep peroneal nerve. The figure shows the stretch velocity dependent reduction of the soleus reflex EMG and ankle moment. The stretch velocity is specified in deg/s of the movement imposed to the ankle joint by a servo controlled motor (Veltink et al. 2000) (also refer to figure 5-4 in Chapter 5).

EXAMPLE 10.5 CYCLE TO CYCLE CONTROL OF CYCLICAL LEG MOVEMENTS (MODEL OF GAIT) (VELTINK 1991; FRANKEN ET AL. 1995)

When Functional Electrical Stimulation (FES) is used for the generation of gait by applying a predetermined stimulation pattern, it is found that the resulting movements change when the muscles become fatigued. It has been proposed to adapt the stimulation patterns on the basis of the resulting movements of each step. If the movements change the stimulation patterns of the following steps are changed in an adaptive manner. This adaptation of stimulation patterns can be realized using a cycle-to-cycle control, specifying evaluation quantities for the gait pattern (e.g. step size, foot clearance, time of knee extension at the end of the swing phase). After each step these quantities can be evaluated and the patterns for the next step can be changed using a discrete time controller (Franken et al. 1995). The time step of this discrete time controller is taken equal to the cycle time.

The principle of this approach is described in (Veltink 1991), addressing the control of the cyclical movement of the shank by stimulation of the quadriceps (knee extensor) muscle (refer to figure 10-14 and problem 10.2 at the end of this chapter).

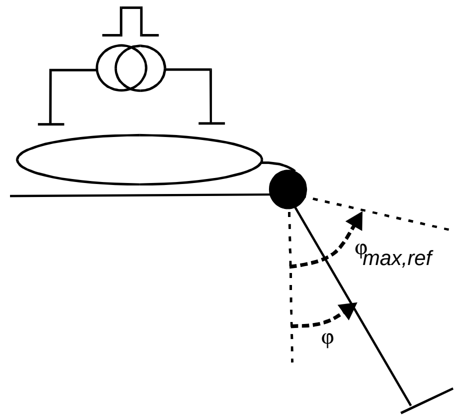


Figure 10-14 Schematic drawing of a freely swing lower leg (shank) which is moved in a cyclical fashion by electrical stimulation of the quadriceps muscles. The objective of the control of these cyclical movements was to reach the reference maximum knee angle $\varphi_{\max,ref}$ *every cycle (Veltink 1991).*

PROBLEM 10.2 CYCLE-TO-CYCLE CONTROL OF LEG MOVEMENTS: SEE END OF THIS CHAPTER

EXAMPLE 10.6 CONTROL OF BIPEDAL LOCOMOTION (GUBINA ET AL. 1974; MCGEER 1990; MCGEER 1993; VAN DER LINDE 1999A), SEE ALSO IN THE BIOMECHANICS WORKSHOP PROCEEDINGS (VAN DER LINDE 1999B)

.Several efforts have been made to realize bipedal locomotion in an artificial manner. Walking robots have been designed which implement efficient bipedal walking, implementing a stable limit cycle (McGeer 1990; McGeer 1993; Van der Linde 1999a; Van der Linde 1999b).

10.4 Training of the CNS by externally applied stimuli

The CNS is plastic, meaning that it is able to learn new behaviour on the basis of externally applied stimuli. Many of the approaches in artificial human motor control focus on the real time control of motor tasks (SECTION 3). In most cases this has appeared to be a difficult task, with limited functional results. However, it should be noted that direct motor control can also result in training of the physiological control system, resulting in improved performance without the artificial system. Ladouceur et al. (Ladouceur et al. 2000b; Ladouceur et al. 2000a) even showed that in the use of Functional Electrical Stimulation (FES) for restoration of mobility in incomplete paraplegics, the direct orthotic effect of real time stimulation of the muscles is less important than the training effect (also called carry over).

Several artificial motor control systems are specially designed to train the CNS to improve its motor control function. It is assumed that the CNS is trained by the afferent patterns that it receives from the periphery when the extremities perform functional tasks:

- In recent years, there has been a lot of effort in relearning the CNS to control walking in incomplete paraplegics and stroke persons (Dietz et al. 1998; Hesse et al. 1999). The persons are trained on a walking belt, while their weight is partly suspended by a harness and a rope. This suspension also contributes to the control of balance. During the walking training, the legs are moved by therapeuts. When the physiological motor control recovers, the support of the therapeuts can be reduced.
- Recently, the use of robotic orthoses has been proposed for this training (Hesse et al. 1999). In the upper extremities, such robotic orthoses have been developed for the training of reaching and gripping tasks (Krebs et al. 1998). These approaches often use *impedance control*. In this approach functional movements are softly imposed to a paralyzed extremity via an output impedance. In first instance, the impedance has a large stiffness (the movements are rigidly imposed). After some time, when the performance of the physiological control system has improved, the stiffness is reduced such that the physiological control system is more contributing to the resulting movements.
- Alternatively, FES systems have been specially developed to train the CNS in controlling mobility function in incomplete paraplegics and stroke patients (Bajd et al. 1989). However, it should be noted that it is not well known how this training should be optimized in order to have the maximal physiological motor control performance in minimal time.

10.5 Neuromodulation: modulating the central nervous system

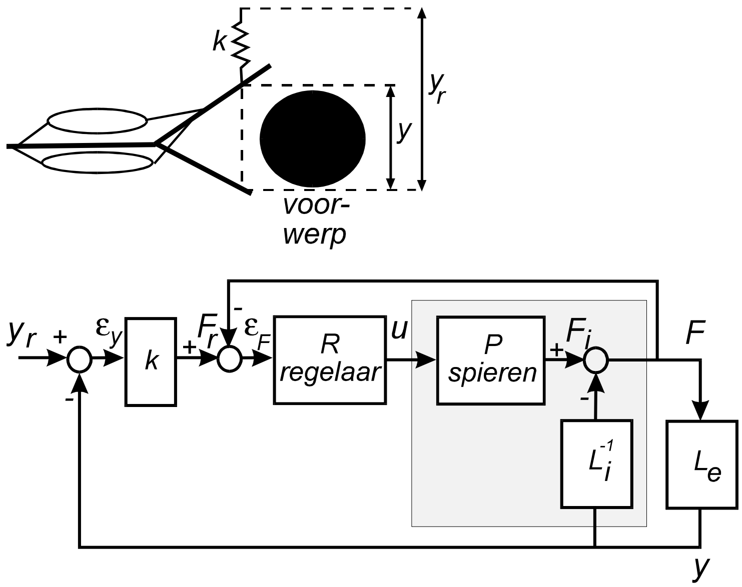
The central Nervous System is a complex hierarchical control system in which each control level receives control signals from higher levels. These signals can either constitute of reference motor patterns or can modulate the feedback control characteristics of the lower control level. These modulating signals can either enhance (excite) the feedback gain or reduce the feedback gain (inhibition) at lower control levels. In the case of disorders of the central nervous system these modulating signals may not have the right intensity. In many cases, central inhibiting inputs are absent. This may lead to non-optimal setting or even instability of spinal reflex loops, which may results in spasms or tremor. In this case, these modulating influences may be supplied by artificial stimulation of adequate parts of the CNS. The application of a constant modulating input to improves the average setting of CNS control loops is commonly called *neuromodulation*. In many cases such a treatment can be an alternative for medication, which may have comparable modulating influences. Examples of neuromodulation are deep brain stimulation for control of Parkinson (Limousin et al. 1995; Bie et al. 1999; Limousin-Dowsey et al. 1999; Marani et al. 2000) and spinal cord stimulation for the reduction of spasticity and pain (Holsheimer 1997).

EXAMPLE 7 DEEP BRAIN STIMULATION TO IMPROVE THE MOTOR PERFORMANCE IN INDIVIDUALS WITH PARKINSON

Persons with Parkinson disease suffer from a series of movement disorders (akinesia, hypokinesia, bradykinesia, tremor, rigidity, impaired postural stability: see section 6.3.2). They are normally treated with medication called *Levodopa*, which is very effective in the first years. However, after several years of treatment some persons develop motor fluctuations (variable ‘on’ and ‘off’ periods of the movement disorders) and dyskinesias, which cannot effectively be controlled any more with medication (Hilten 1993; Marani et al. 2000). In these cases, functional neuro-surgery can improve motor performance. Lesions can be made coagulation in certain centres in the brain, e.g. the pallidum (*pallidotomie*) (Bie et al. 1999). Alternatively, several brain centers can be stimulated continuously using implanted stimulators (*deep brain stimulation: DBS*) (Limousin et al. 1995; Lenders et al. 1999; Limousin-Dowsey et al. 1999). Tremor in one half of the body is greatly reduced by stimulation of the *thalamus* (the sensory integration centre of the CNS) at the contralateral side in 85% of cases (Limousin-Dowsey et al. 1999). However, thalamus stimulation does not reduce other movement disorders, like dyskinesia. Stimulation of the *sub thalamic nucleus* decreases motor disorders, allowing a reduction of Levodopa administration and, as a consequence, a reduction of dyskinesia. Stimulation of the internal pallidum decreases dyskinesias (Limousin et al. 1995; Limousin-Dowsey et al. 1999).
The exact mechanism of deep brain stimulation of the different brain centers is currently unknown. Further neurophysiological research can provide more insight, which is required for improving the design of electrodes and stimulation strategies.

PROBLEMS

PROBLEM 10.1 ARTIFICIAL STIFFNESS CONTROL OF HAND GRASP[CRAGO, 1988 #342]
(REFER TO SECTION 10.3.1, EXAMPLE 1)



FIGUUR 10-15 *Control of hand grip by means of a simulated stiffness* k.

Assume all transfer functions to be linear (including the muscles).

QUESTIONS:

a. Determine the following transfer functions:

$$H_1(s) = \frac{F(s)}{y_r(s)} \text{ [N/m] and } H_2(s) = \frac{y(s)}{y_r(s)} \text{ [-]} \tag{10.1}$$

Assume, the muscle dynamics can be described as a critically damped second order system:

$$P(s) = \frac{F_m}{(1+s\tau_m)^2} \text{ [N]} \tag{10.2}$$

Furthermore, assume that the internal and external loads are pure compliances:

$$L_i(s) = C_i \text{ and } L_e(s) = C_e \text{ [m/N]} \tag{10.3}$$

Take a proportional (P) controller:

$$R(s) = G \text{ [N}^{-1}\text{]} \tag{10.4}$$

QUESTIONS:

b. - Under which condition are the transfer functions $H_1(s)$ and $H_2(s)$ for low frequencies ($\| j\omega \| << \frac{1}{\tau_m}$) independent of the transfer function $P(s)$ of the muscle and the internal compliance C_i?
- Determine the transfer functions $H_1(s)$ en $H_2(s)$ for low frequencies under this condition.
- Under the same condition, determine the transfer function $H_2(s)$ for low frequenies if $C_e >> \frac{1}{k}$.
- Under the same condition, determine the transfer function $H_1(s)$ for low frequencies if $C_e << \frac{1}{k}$.
- Does this transfer function imply position control before contacting an object or force control during contact with a stiff object?

Assume that the parameters of the system have the following values:

F_m = 50 N; τ_m = 20 ms; $C_i = 2 \times 10^{-2}$ m/N;

k has a values such that the change of the control signal y_r required for a change in grip size y of 10 cm if no object is touched ($C_e >> \frac{1}{k}$) is equivalent to a grip force change of 100 N if there is contact with a stiff object ($C_e << \frac{1}{k}$).

QUESTIONS:

c. - Determine the gain G at which the phase margin is at least 10 degrees and the gain margin is at least 6 dB for the extreme external loads (no contact with an object: $C_e >> \frac{1}{k}$ and contact with a stiff object: $C_e << \frac{1}{k}$). The step responses should in both cases be as fast as possible.
- If the condition of question b. satisfied (the transfer functions $H_1(s)$ and $H_2(s)$ are independent of the transfer function of the muscle $P(s)$ and of the internal compliance C_i for low frequencies ($\| j\omega \| << \frac{1}{\tau_m}$))?

d. What changes in the design of the controller R result in faster step responses for the same phase and gain margins?

PROBLEM 10.2 CYCLE TO CYCLE CONTROL OF CYCLICAL LEG MOVEMENTS (MODEL OF GAIT) (VELTINK 1991)
(REFERRING TO SECTION 10.3.2.3, EXAMPLE 10.5)

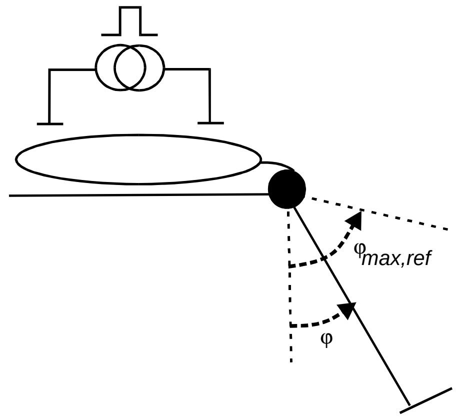


Figure 10-16 Schematic drawing of a freely swing lower leg (shank) which is moved in a cyclical fashion by electrical stimulation of the quadriceps muscles. The objective of the control of these cyclical movements was to reach the reference maximum knee angle $\varphi_{\max,ref}$ *every cycle* (Veltink 1991).

Given:
The knee extensors of the upper leg (quadriceps) of a subject are stimulated using electrodes on the skin. De person is sitting and the shank can freely move, as is schematically represented in figure 10-16 (Veltink 1991).

For this muscle-skeletal system a control strategy will be designed to control cyclical shank movements during which a reference maximal knee angle $\phi_{\max,ref}$ should be realized in every cycle. The system is excited by stimulation of the knee extensor muscle.

The following design choices have been made:

- the control is realised in discrete time. Each new cycle, the stimulation pattern is adapted on the basis of an evaluation of the maximal knee angles $\phi_{\max,n}$ in the previous cycles.
- stimulation is applied at a maximal level (maximal recruitment: the whole muscle is activated, yielding a maximal knee moment).
- each cycle, the stimulation consists of one burst of stimulation pulses. the duration $T_{on,n}$ of the burst n is varied from cycle to cycle.

In order to analyse and tune the control strategy, the muscle-skeletal system first needs to be modelled in discrete time. The time step for the discrete time analysis is the cycle time. The system is modeled on this time base, $T_{on,n}$ being the input and $\phi_{\max,n}$ the output.

The transfer function of the system is:

$$H(z) = \frac{bz}{z-a} \tag{10.5}$$

The parameters *a* en *b* of the system are determined experimentally:

1. The leg is released from a certain start angle without stimulating the muscle. The angle trajectory is measured as function of time (passive response) (figure 10-17).
2. The knee extensor muscle is stimulated each cycle in a fixed phase of the cycle using a fixed burst time $T_{on,n}$. The steady state maximal knee angle $\phi_{\max,n}$ is determined (figure 10-17)

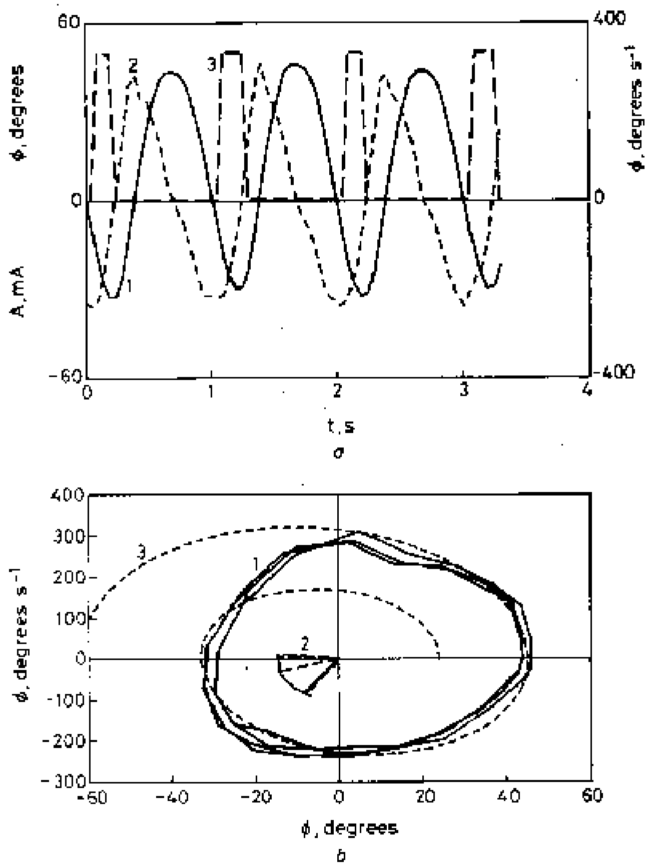


Figure 10-17 Recording of three cycles of the swinging shank muscle.
(a) as a function of time (1: knee angle, 2: knee angular velocity, 3: stimulus amplitude)
(b) in phase plane of knee angle and angular velocity (1: trajectory during stimulation, 2: cycle phase during which the quadriceps muscle is stimulated, 3: passive response of knee angle when the shank is released from a start angle) (Veltink 1991).

QUESTIONS

a. The passive response of figure 10-17 can be conceived as the impulse response of the continuous time model of the muscular-skeletal system. Draw the associated impulse response of the discrete time model which is defined above.
b. What is apparent if the order of the system in continuous and discrete time are compared? How can this be explained?

c. Determine the parameters *a* and *b* from the following measurement results:
   - The maximal knee angles in subsequent cycles of a passive response are: 60 °, 36 °, 21.6 °
   - Stimulation of the knee extensor muscle using a burst time of $T_{on} = 0.3$ s results in a steady state maximal knee angle of ϕ_{max} = 45 °.

A discrete-time PI controller is used for controlling the cyclical leg movement in order to realize the reference maximal knee angle. The transfer function of this controller is:

$$R(z) = \frac{G(z - z_1)}{z - 1} \tag{10.6}$$

With gain G and parameter z_1.

The controller is used as shown in figure 10-18.

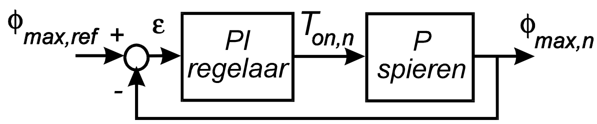


Figure 10.18 Discrete-time PI controller for the knee extensor muscle – shank system.

The poles and zeros of the total open-loop system (controller and knee extensor muscle – shank system) are represented in the z-plane in figure 10-7. The stability of the control system is analyzed using a root-locus analysis, in which the trajectory of the closed-loop poles in the z-plane for varying controller parameters are constructed in relation to the poles and zeros of the open-loop system. The closed-loop pole trajectories are indicated in figure 10-19. For a certain value of the controller gain *G*, the closed-loop poles are indicated by filled circles.

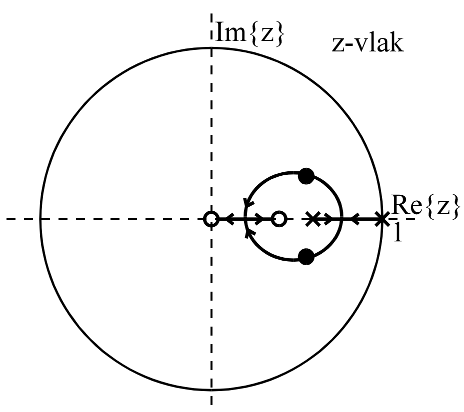


Figure 10.19 Position of poles and zeros of the closed-loop controlled knee-extensor – shank system for varying controller gain G. The poles of the closed-loop system at an intermediate gain value are indicated by the filled circles. The open-loop zeros and poles are indicated by open circles and crosses respectively.

QUESTIONS:

d. Copy figure 10-19 four times and indicate:
   I. how the poles of the closed-loop system change if the gain G of the controller is increased.
   II. how the poles of the closed-loop system change if the knee moment exerted by the stimulated quadriceps muscle decreases because of muscle fatigue.
   III. how the closed-loop pole trajectories change if z_1 is increased with 0.1.
   IV. how the closed-loop pole trajectories change if the damping of the passive system is lower.

e. Give outline of the computer algorithm which realizes the PI controller

FEEDBACK

Summary of the answers to the questions of problems 10.1 and 10.2

10.1a.
$$H_1(s) = \frac{\dfrac{P(s)R(s)kL_i(s)}{L_i(s)+L_e(s)}}{1+\dfrac{P(s)R(s)L_i(s)(L_e(s)k+1)}{L_i(s)+L_e(s)}} \ [\mathrm{N/m}] \qquad (10.7)$$

$$H_2(s) = \frac{\dfrac{P(s)R(s)kL_i(s)L_e(s)}{L_i(s)+L_e(s)}}{1+\dfrac{P(s)R(s)L_i(s)(L_e(s)k+1)}{L_i(s)+L_e(s)}} \ [-] \qquad (10.8)$$

10.1b.
- $F_m G >> \dfrac{C_i + C_e}{C_i(C_e k+1)}$ (10.9)
- $H_1 = \dfrac{k}{C_e k+1}$ [N/m] (for low frequencies: $\|j\omega\| << \frac{1}{\tau_m}$) (10.10)

  $H_2 = \dfrac{C_e k}{C_e k+1}$ [-] (for low frequencies: $\|j\omega\| << \frac{1}{\tau_m}$) (10.11)
- $H_2 = 1$ [-] (for $C_e >> \frac{1}{k}$ and $\|j\omega\| << \frac{1}{\tau_m}$) (10.12)

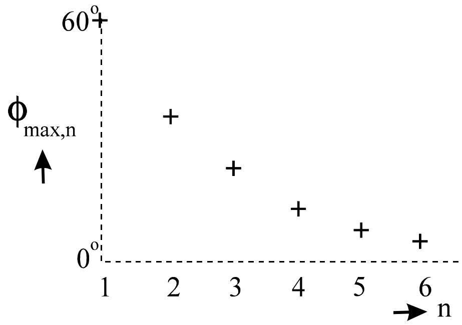
  This is position control before the object is contacted
- $H_1 = k$ [N/m] (voor $C_e << \frac{1}{k}$ en $\|j\omega\| << \frac{1}{\tau_m}$) (10.13)

  This is force control when a stiff object is contacted.

10.1c.

10.1d. PID regelaar.

10.2a.



10.2b. The continuous time response (figure 10-17) is second order sub-critically damped. This is in agreement with the dynamics of the shank conceived as a pendulum. The shank dynamics is dominant with respect to the dynamics of the muscle. The discrete time response shows a first order (exponential) behavior, because only the maximal angles of the cycles are considered.

10.2c. transfer equation (10.5) to a time domain difference equation:

$\phi_{\max,n} - a\phi_{\max,n-1} = bT_{on,n}$ (10.*)

passive response: $T_{on,n} = 0$

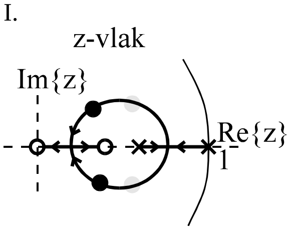
$$\Rightarrow \phi_{\max,n} = a\phi_{\max,n-1} \Rightarrow a = \frac{\phi_{\max,n}}{\phi_{\max,n-1}} = \frac{36^\circ}{60^\circ} = \frac{21.6^\circ}{36^\circ} = 0.6 \Rightarrow a = 0.6 \qquad (10.14)$$

steady state response: $\phi_{\max,n} = \phi_{\max,n-1} \Rightarrow \phi_{\max}(1-a) = bT_{on}$

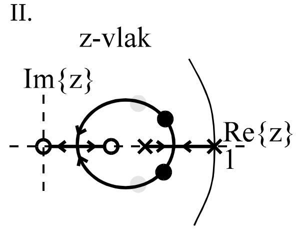
$$\Rightarrow b = \frac{(1-a)\phi_{\max}}{T_{on}} = \frac{0.4*45^\circ}{0.3s} = 60^\circ/s \qquad (10.15)$$

10.2d. See figure 10.19. The figures below show the change of the closed-loop pole trajectories (root locus analysis). The original trajectories and closed-loop pole positions are indicated in gray.

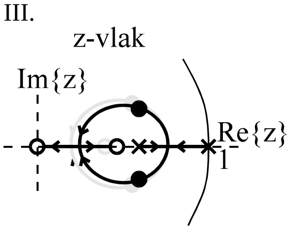
I.



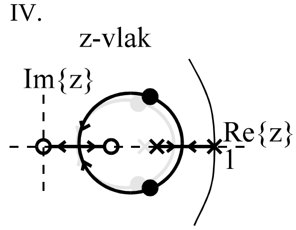
II.



III.



IV.



10.2e. Equation (10.6) yields:

$$U(z)(1-z^{-1}) = \varepsilon(z)G(1-z_1 z^{-1}) \qquad (10.16)$$

change to time domain difference equation:

$$u_n - u_{n-1} = G(\varepsilon_n - z_1\varepsilon_{n-1}) \qquad (10.17)$$

implement in PASCAL code line:

u:=u+G(epsilon-z1*epsilon_vorig);*

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