Introduction

Exercises for rehabilitation of spinal cord injury patients include standing, walking and cycling induced by electrical stimulation. In this study, we focus on FES cycling which is safer and easier than the others and shows improvement in the cardiovascular function and muscle forces.

As far as the control scheme is concerned, most clinically-used FES systems adopt a simple on/off scheme or a feedforward scheme based on the predetermined stimulation pattern. The stimulation pattern method is advantageous over the on/off control method in terms of fine control. In the stimulation pattern method, “the standard stimulation pattern” is generated based on the EMG of normal subjects and then tuned to each patient through burdensome trial-and-error modifications. Therefore, the EMG of many normal subjects in each motion should be measured and analyzed. The stimulation pattern should be tuned according to any change in the physical condition of the patient such as the maximum muscle force.

Though some simulation studies have reportedly obtained the optimal stimulation pattern [Yamaguchi and Zajac, 1990], they usually used experimental data of normal subjects, such as the reference joint torque or the joint angle trajectories, to calculate the performance index. It follows that these methods cannot provide an optimal stimulation pattern for a specific patient because “the optimal joint torque or the optimal joint angle trajectories for patients with different physical conditions” cannot be obtained from experiments. It has been claimed as a validation of their methods that the stimulation pattern is similar to the EMG of normal subjects. However, these methods are even less practical if the patient’s body condition is significantly different from that of a normal subject. One good example is the limitation in muscles available for stimulation. Moreover, they require tuning of the stimulation pattern.

As a first step to avoid the above drawbacks, we proposed a simple proportional-and-derivative (PD) control scheme based on a mathematical model for the neuromuscular system and the body-segmental system. The real-time feedback control was possible with our scheme, and the results from the scheme could be utilized for a feedforward control, e.g. the stimulation trajectory obtained during the steady-state cycling could replace “the nominal stimulation pattern”. Employing the proposed scheme, we could eliminate the restrictions described above, and quantitatively analyze the internal body variables, such as the joint reaction force and the muscle force, during each movement. A similar approach was done for the biomechanical analysis of rowing by our colleagues [Hase and Yamazaki, 2002].

We focused on the lower extremities that play an important role in cycling. The human body was represented by a 7-rigid-link system where each joint angle was controlled by one neural pair. The cycling motion was optimized by applying the genetic algorithm to find the parameters which minimize the performance index.
Method

1. Simulation Model

Fig. 1 shows the entire model structure for the real-time FES control used in this study. The higher neuronal system generates a first-order delayed output from the feedback signal. The output corresponds to the motion plan in the dimension of the joint torque and is thus termed as the quasi-joint torque. The lower neuronal system converts the quasi-joint torques to electrical stimulation intensities. The musculoskeletal system generates a body motion by numerical integration of the equation of motion with the electrical stimulation as input. The information about the body motion, e.g. joint angles and ground reaction forces, are fed to the higher neuronal system through a feedback loop such as the somatic sensory system.

Fig. 1 schematics of FES control based on a neuronal model with a feedback system

a. Higher neuronal system

The higher neuronal system consists of six neuron pairs (three for each side). The dynamics of the neuron pair is shown in equation (1-1) through equation (1-3) which is a modified form of the neural oscillator [Williamson 1998]. It has the sensory feedback term $feed_i$ as input so that it acts as a first-order delay system against the $feed_i$ signal. The two neurons mutually inhibit each other because the weighting coefficient of interconnection $\delta$ is negative (fixed to -2) and only the positive internal states of the other neuron, i.e. max($u_{i1},0$) and max($u_{i2},0$), are used in (eq. 1-2) and (eq.1-3).

$$\tilde{n}_i = \max(u_{i1},0) - \max(u_{i2},0) \quad (1-1)$$
$$\tau u_{i1} = -u_{i1} + \delta \max(u_{i2},0) + feed_i \quad (1-2)$$
$$\tau u_{i2} = -u_{i2} + \delta \max(u_{i1},0) - feed_i \quad (1-3)$$

$\tilde{n}_i$: quasi-joint torque which is the output of the $i$th neuron pair
$max(u_{i1},0)$: if $u_{i1} \geq 0$ then $u_{i1}$, else 0
$u_{i1}, u_{i2}$: internal states of $i$th neuron pair controlling $i$th joint
$\tau$: time constant of internal states dynamics
$\delta$: weighting coefficient of interconnection (fixed to -2)
\( \text{feed}_i \) : feedback signal to the \( i \)th neuron pair

b. Lower neuronal system

The lower neuronal system calculates the muscle stimulation from the output of the neural oscillator, i.e. the quasi-joint torque. The relationship between the quasi-joint torque and the muscle stimulation is defined as equation (2.1). Here, the control command in the joint-torque level \( \tilde{n}_i \) is distributed to the muscle stimulation intensities \( a_m \). There are infinite combinations of muscle stimulations producing the same \( \tilde{n}_i \). Therefore, we used a static optimization method to get the optimal muscle stimulation which can minimize the muscle fatigue. Equation (2.1) was used as a constraint in the optimization. The constraint (2.2) denotes that \( a_m \) cannot be negative. It is reported that the muscle fatigue is inversely proportional to the cube of the muscle force so that the performance index \( I_{\text{static}} \) is defined as equation (2.3) which was minimized in the optimization process.

\[
\tilde{n}_i = \sum_m a_m r_{im} F_{\text{max},m} \quad (2.1)
\]

- \( a_m \): normalized stimulation
- \( r_{im} \): moment arm of the \( m \)th muscle around the \( i \)th joint
- \( F_{\text{max},m} \): maximum force of the \( m \)th muscle

\[
a_m \geq 0 \quad (2.2)
\]

\[
I_{\text{static}} = \sum_m a_m \quad (2.3)
\]

c. Musculoskeletal system

We considered the lower extremities rotating the crank, and the head, the arm, and trunk (HAT) were modeled as one segment fixed in space. The entire body was represented as a 7-rigid-link system which consists of one HAT, two thighs, two shanks, and two feet. Each joint was assumed to be a one-degree-of-freedom hinge. The pedals and the crank were modeled as one link which can rotate about the center. The feet were modeled to be connected to pedals by using linear-spring-damper elements assuming that the feet are fastened to the pedals by straps. A numerical derivation of the equation of motion based on the Newton-Euler formulation for an open-loop kinematic chain [Walker and Orin 1982] is expanded so that it can handle a multi-linkage system of the branched structure with no fixed points. Although the musculoskeletal system in this study is two-dimensional, the fundamental description of the model is based on the three-dimensional theory of the equation of motion. Therefore, it is easy to expand the model to be three-dimensional if needed.

d. Sensory feedback system

The sensory feedback system was designed as in equation (3) based on the PD control theory. The inverse dynamics was used to obtain the joint torque just to maintain the current posture so that the proportional and derivative terms can take care of the joint torque only to move the body segments away from the current posture. \( \text{feed}_i \) generates signals to get close to the target angle \( p_i \) and the target angular velocity 0. Therefore, we divided the cycling motion into four phases according to the crank angle and specified four different target angles \( p_i \) to force the crank to rotate toward the target values. Different parameters \( k_i, c_i \) were used for each phase. The best values for \( p_i, k_i, c_i \) for each phase were searched by means of the genetic algorithm (See section 2).

\[
\text{feed}_i = k_i (\theta_i - p_i) + c_i \dot{\theta}_i + \text{INV}_i(\mathbf{0}, \mathbf{0}, \mathbf{R}) \quad (3)
\]

\( \text{feed}_i \) : feedback signal to the \( i \)th neuron pair controlling the \( i \)th joint
$k, c_i$: proportional and derivative coefficients

$\theta_i, \dot{\theta}_i$: joint angle and angular velocity

$p_i$: equilibrium point (angle) of the $i$th joint

$\text{INV}(0,0,0,R)$: inverse dynamics calculating the joint torque as output with zero angular acceleration, zero angular velocity, current angle vector $\theta$, and current pedal reaction force vector $R$ as inputs.

2. Search Algorithm and Performance Index

Efficiency of the cycling motion is affected by the parameters $\tau, \delta$ in the central nervous system and $k_i, c_i, p_i$ of every four phases in the somatic sensory feedback system and also by the initial condition of the equation of motion. This is one reason why optimization of these parameters is very important. We used the genetic algorithm [Goldberg 2002], which is based on the natural selection theory, as a search method for these parameters.

First, we generate the initial population which is a group of individuals. Each individual corresponds to a chromosome which is a set of specific genes from the biological point of view. In this paper, an individual is represented by a set of the above search parameters. The cycling motion is generated for each individual in the initial population and the performance index is calculated. Then, a new population is generated through selection, multiplication, crossover and mutation processes. That is, superior individuals showing good adaptation to the environment are statistically selected and reproduced, and crossover and mutation are performed to generate the next population. From the second population, the initial conditions of the equation of motion are acquired from the data at the midpoint of the previously simulated motion.

All the routines are repeated for a new population and they stop when the predetermined iteration number is reached or the performance index converges. Optimization of the search parameters by applying the genetic algorithm led us to a better cycling motion in terms of the performance index. Equation (4) is used as a performance index to assess the performance of the simulated motion with the present search parameters. The suggested performance index is represented by the weighted sum of $E$, the external power applied to the ergometer, $S$, the normalized average muscle force change, and $D$, the squared deviation from the targeted cycling speed. That is, the performance index increases with a large external work, a small change in the muscle force (a smoother muscle force pattern), and a cycling speed close to the target value.

$$I_{\text{dynamic}} = E - \omega S - \zeta D$$

$$E = \min(W, W_{\text{max}})$$

$$S = \frac{1}{T} \sum_{n} \frac{1}{A_m} |\dot{F}_m| dt$$

$$D = (c - c_s)^2$$

$I_{\text{dynamic}}$: performance index in the parameter search process

$E$: index evaluating the external power

$S$: smoothness index; a small $S$ implies a smooth muscular force change with time

$D$: deviation from the desired cycling frequency

$\omega$ and $\zeta$: weighting coefficients

$W$: external power to the ergometer

$W_{\text{max}}$: predetermined maximum value of the external power

$T$: period of the simulated cycling

$A_m$: physiological cross-sectional area

$\dot{F}_m$: derivative of the muscular tensions
$c$ and $c_d$: calculated and predetermined target number of rotation per minute

$E$ is determined as the lower value of the power applied to ergometer ($W$) and the maximum power $W_{\text{max}}$ ($300\text{W}$), which is to prevent overloaded heavy pedaling that may cause harm to the patients. $S$ represents how rapidly the muscle force changes, so a small $S$ implies a smooth force pattern. $S$ is calculated according to the following procedure. The normalized muscle force change is calculated by integrating the absolute value of muscle force change rate over the simulation period and dividing the result by the physiological cross-sectional area. (If the muscle force change rate is integrated over time, we get the muscle force, not the force change.) Then, dividing the total sum of the normalized muscle force changes of all muscles by the simulation time gives us the average of the muscle force change. $D$ decreases as the cycling frequency per minute $c$ becomes close to the target value $c_d(60\text{rpm})$. The weighting coefficients, $\omega$ and $\xi$ are determined as $0$ and $0.05$ by trial and error.

Computation for one generation requires simulation of the cycling motion for all the individuals in the population and it is repeated until the performance index reaches a satisfactory value. Consequently, the computational cost of the genetic algorithm is very high, and the parallel processing should be employed. In this study, the BEOWULF system with parallel processing in the Linux environment was used for the computation.

![Fig. 2 Simulation results: joint angles and crank rotation](image)

Results and Discussion

The computer simulation result in Fig. 2 shows a periodic cycling motion with the PD control. The crank angle monotonically increased and the resulting cycling speed was $60\text{rpm}$ as was targeted in the performance index. When the crank was vertically arranged such that the pedal is on the highest position, the hip and the knee are flexed to withdraw the leg. When the pedal is on the lowest position, on the other hand, they are extended to stretch the leg. The ankle joint did not show significant rotation. The simulation results agreed with the experimental observations of normal subjects. The results suggested that the current simulation method can be
used as a real-time control method in FES cycling as well as for real-time analysis of the internal body parameters. The muscle stimulation trajectories can be used as a nominal stimulation pattern in a feedforward FES system when the feedback signals are unavailable.

Further works need to be done to confirm reliability and versatility of the current method. Firstly, the definition of optimality, i.e. how to design the performance index, should be discussed in more detail. The external work, smoothness of the muscle tension, and deviation from the targeted cycling frequency were used in the performance index in this study. A more reliable method needs to be developed to select appropriate terms and decide the weighting coefficients. Other major issues to be added and discussed include the HAT posture and the position of the patient’s hip relative to the pedal and the crank. Secondly, muscle availability must be included in the model. Although all muscles of hip, knee and ankle joints were used to generate the cycling motion in this study, available muscles are often limited due to the limited number of the stimulator channels or the patient’s physical condition. Therefore, many different questions should be answered through computer simulations. For example, what happens if only the knee extensors are available? Thirdly, availability of the feedback signals needs to be revisited. The feedback signals used in this study are not always easy to obtain. In many cases, for instance, burdensome attachment of sensors or a huge laboratory setup with expensive equipment is required to measure the joint angles and angular velocities, and the type and number of sensors determines practicality of the real-time control. Therefore, a simpler sensor setup than this study should be tested while the real-time control can be still achieved.

References