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Knee Joint Movement Control Using Hybrid Neuro-prosthesis Based on Persistent D-well Time Allocation Strategy and Overcoming Muscle Fatigue: Simulation Approach

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Original Article

Abstract

Introduction: Hybrid neuroprostheses are used in the rehabilitation of individuals with spinal cord injuries. These hybrid neuroprostheses consist of a robot that moves the knee joint mechanically and a functional electrical stimulation (FES) part that moves the knee joint through electric current stimulation. The main challenge in the use of hybrid neuroprostheses is muscle fatigue due to electrical stimulation. This study endeavored to reduce muscle fatigue through timing between robot and FES using Persistent D-well Time.

Materials and Methods: A mathematical equation was used to model the knee movement in a hybrid neuroprosthesis. A differential equation was used to describe muscle fatigue. The simulation time was determined to be 100 seconds and the goal of simulation was considered to be the regulation of the knee joint at a 60 degrees angle. Simulation time was divided into stages and a time interval was set for each stage. At each stage, FES was active for a certain amount of time. After this duration until the end of the time frame of the stage, switch occurred between the FES and the robot based on the muscle fatigue value.

Results: At the end of the simulation, the knee was regulated with a root mean square error of 0.79 degrees at the reference angle. Using robots in the timing method reduced muscle fatigue and the muscle fatigue value was limited in a bounded range between 0.94 and 0.97.

Conclusion: The timing method simulated in this study can be effective for knee movement control. Based on the results, it is expected that this method be used in the controlling of hybrid neuroprosthesis in practice, during which the exercises prescribed by the therapist are rehearsed and muscle fatigue increment needs to be avoided in the client simultaneously.

Keywords: Hybrid neuroprosthesis, Functional electrical stimulation, Muscle fatigue

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Introduction

Hybrid neuroprostheses are tools used in the rehabilitation of individuals with nervous system damage. Hybrid neuroprostheses consist of a robot that has the task of mechanically moving the joints of the injured person and an electrical stimulation that makes them work by sending electric current to the muscles (1). Electrical stimulation plays an important role in rehabilitation with hybrid neuroprosthesis. However, despite its significant effect on the rehabilitation of the patient, sending an electric current to the muscles causes muscle fatigue which can disrupt the rehabilitation process (2).

In the 1970s, the idea of hybrid neuroprosthesis was first proposed as a tool in the movement recovery of individuals with nervous system damage (3). In the last decade, the use of functional hybrid neuroprostheses has been expanding (1), and since

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2011, a commercial sample of these prostheses that provides the possibility of movement for the legs of individuals with spinal cord injury has been offered (4). These prostheses provide the possibility of movements for the rehabilitation of the injured individual that are not possible with customary rehabilitation tools, such as wheelchairs or orthoses (5). Hybrid neuroprostheses provide the possibility of rehabilitation of injured individuals outside the clinical setting (5).

Typically, the presence of more than 1 therapist is required for the rehabilitation of an individual with nervous system injury; moreover, it is difficult to coordinate between therapists during rehabilitation, and their fatigue is also considered a challenge in the rehabilitation of the injured individual. One of the significant advantages of using hybrid neuroprostheses is that it eliminates the need for the performance of rehabilitation movements by the therapist (5). Presently, expanding and improving the use of hybrid neuroprostheses and their control, in various fields such as torque control or prosthetic control with brain interface circuits of the injured individual, is one of the novel topics of interest in rehabilitation research centers (4).

Hybrid neuroprostheses have various types, such as wearable prostheses for walking, combined prostheses with a treadmill, and knee hybrid neuroprosthesis (6). In knee hybrid neuroprosthesis, the goal is to move the knee in a desired path or regulate it at a desired angle (Figure 1) (7).

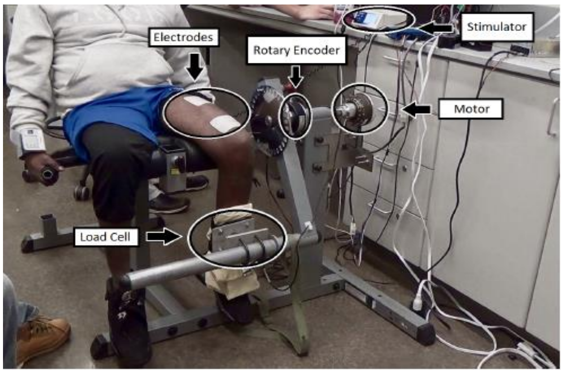

Figure 1. Hybrid neuroprosthetic device and its components

The movement of the knee joint is performed by the hybrid neuroprosthesis using the torque produced by the robot or the torque obtained from the current obtained through functional electrical stimulation (FES). To determine the amount of torque of the robot or the amount of torque of electrical stimulation, controllers for the robot and electrical stimulation are needed (8 and 9). Due to the importance of muscle fatigue, it seems important to determine a method for the selection of the robot controller or electrical stimulation controller, and activation of one of them to prevent an increase in muscle fatigue (10).

In effect, the hybrid neuroprosthesis is the combination of an electrical stimulator and a robot controlled by a computer. All that is discussed in this study about the system model and its control is related to the prosthesis. The robot consists of a motor and a controller. The motor, which is connected to the computer, moves the knee automatically and mechanically based on the value of the knee joint displacement error (error in following the reference path). The intensity of the electric stimulation current is determined by the controller based on the tracking error of the reference path, and the electric current is applied to the quadriceps muscles through the electrodes. The angle of the knee joint is measured by a rotary encoder and sent to the controlling computer in the form of an electrical signal. What is needed from the robot in controlling the hybrid neuroprosthesis system is to determine its torque for the movement of the knee joint, which in this study is calculated by the computer controlling the robot. The amount of torque produced by the knee in the physical environment is measured by the load cell and sent to the computer as an electrical signal.

In the research by Bao et al. (11), a feedback linearized nonlinear model predictive controller was used to control the electric stimulation and the robot to control the movement of the knee joint, but the muscle fatigue values were not reported. In the study by Sae et al. (12), a controller based on iteration was designed for electrical stimulation, but the robot and its effect in reducing fatigue were not considered. In another study (13), a nonlinear predictive model controller was used to control FES in knee hybrid neuroprosthesis. Bao et al. (14) used a tube-based model predictive controller with the aim of robustifying the knee hybrid neuroprosthesis.

In an approach with control allocation, after determining the control signal value of the model predictive controller, this control signal was distributed between the robot controller and the electrical stimulation controller by solving the optimization problem (15). In some previous studies, although muscle fatigue values were reported, a method to reduce muscle fatigue was not proposed (13, 15).

The major innovation in the reviewed studies was related to controller design; however, high complexity of the controller design in the simulation phase will challenge the implementation of the controller in practical testing. Furthermore, the limitations of movement for the therapist, as well as the limitations of robot actuators and electrical stimulation, make the practical implementation of some controllers difficult or impossible. To date, no method has been presented to prevent and overcome the increase in muscle fatigue by timing the application of robot and FES. Therefore, the present study was conducted with the aim to provide a method to prevent the increase of muscle fatigue in the knee hybrid neuroprosthesis by determining the timing for the use of the robot and FES with the persistent D-well time switching method.

Materials and Methods

This study investigated the determination of a schedule for the use of robots and electrical stimulation so that the knee is set at a certain angle and muscle fatigue does not increase.

A- The Muscle-joint Model

To simulate the function of the knee hybrid neuroprosthesis, a mathematical model of knee movement dynamics is needed to simulate the function of this prosthesis by numerically valuing the terms and parameters of this model. Models describing robotic systems are used to describe the dynamic model of the prosthesis (4). One of the common equations for modeling the dynamics of hybrid neuroprosthesis is the Euler-Lagrange equation (16, 4). This equation provides a torque-based model of the hybrid neuroprosthesis system, according to which the torque values are the driving force for joint movement. In other words, the Euler-Lagrange model provides the possibility to calculate the values of the angle, angular velocity, and angular acceleration based on the torque values of the system. The efficiency of a model is determined based on the efficiency of the application of that model, and different models of the same system can have advantages over each other in different applications. The Euler-Lagrange model has a non-linear description of the system, so it does not have linear approximation errors. The parameters used in this model are suitable for adjusting the model and do not include unnecessary parameters. Moreover, the relationships of the control signal and the torques are not complex relationships (19).

The Euler-Lagrange dynamic equation for the knee hybrid neuroprosthesis that has 1 degree of freedom is expressed as equation (1) (17). In figure 2, a schematic view is presented to determine the torques and angles in equation (1).

Equation (1): Euler-Lagrange dynamic equation

$$J\ddot{\theta} + G - \tau_p = \tau_{ke} + \tau_m$$

In this figure, θ is the angular position of the knee joint, ϕ is the anatomical angle of the knee joint, *m(t)* τ is the torque of the robot, and *i(t)* is the intensity of the electric current, which was used for electrical stimulation.

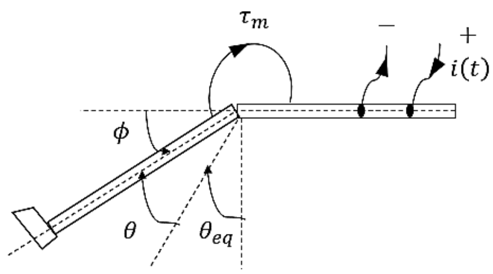

Figure 2. Schematic view of the dynamic model of hybrid neuroprosthesis

The expressions $\theta,\ \dot{\theta},\ and\ \ddot{\theta} \in R$, respectively, specify the angular position, angular velocity, and angular acceleration for the leg to the sole of the foot. The moment of inertia is described by $J \in R$. Gravitational torque was determined by the expression $G(\theta)$, which is equal to $mgl_c \sin(\theta + \theta_{eq})$. In the expression $G(\theta)$, the values of $m\,, g, and\ l_c \in R^+$ indicate mass, gravitational acceleration, the distance between the knee joint, and the center of mass of the shank, respectively. The angular position of the knee joint is the angle that this joint makes with the angle θ_{eq} during displacement. θ_{eq} is the equilibrium point of the lower part of the leg relative to the vertical axis (6). As is shown in figure 1, the equilibrium point is the position where the result of the forces on the lower part of the foot is zero. The torque obtained from the robot was expressed as τ_m. The term τ_p describes the passive torque, which was the torque caused by passive dynamics such as tendons and ligaments. The torque of the knee joint, which is the result of FES, was described by the term τ_{ke}. The expression of passive torque, τ_p, can be expressed using equation (2) (18).

Equation (2): Calculation of passive torque

$$\tau_p = d_1(\phi - \phi_0) + d_2\phi + d_3 e^{d_4\phi} - d_5 e^{d_6\phi}$$

The expression $\phi \in R$ is the anatomical angle of the knee joint and was obtained from the expression

$\phi = {}^{\pi}/_{2} - \theta - \theta_{eq}$. The values of the parameters $d_i \in R \forall i \in \{1,2,\ldots,6\}$, ϕ_0, and θ_{eq} were determined based on the characteristics of the individual being treated with a hybrid neuroprosthesis. Knee extension torque (τ_{ke}), which is caused by electrical stimulation, was described by equation (3) (13).

Equation (3): Calculation of knee tension moment

$$\tau_{ke} = (c_2\phi^2 + c_1\phi + c_0)(1 + c_3\dot{\phi})\alpha_{ke}\mu$$

In equation (3), the parameters $c_j \in R\forall j \in \{0,\ldots,3\}$ are coefficients that are valued according to the individual under treatment, and the expression α_{ke} determined the amount of muscle activation and μ determined the amount of muscle fatigue.

The amount of electric current used for electric stimulation $[i(t)]$ was calculated using equation (4) (19). In this regard, the term u_{ke}, which is the electric stimulation control signal, was mapped to the intensity of the electric stimulation current. I_t is the minimum value of current intensity that causes movement in the knee joint and I_s is the minimum value of current intensity that causes maximum muscle contraction.

Equation (4): electric current intensity for electric stimulation

$$i(t) = I_t + u_{ke}(I_s - I_t)$$

Muscle fatigue ($\mu \in [\mu_{min}, 1]$), which is caused by the implementation of electric current by the electrical stimulation of the neuroprosthesis, can be modeled using the dynamics presented in the study by Riener et al. (20). For fatigue, a value between zero and 1 is considered, which is numerically soft and has no unit. If the muscle is not tired, the value will be equal to 1, and if the muscle is completely tired, that is, the muscle does not have enough force to move the joint, the value will be equal to zero (17). As, in the knee neuroprosthesis, electrical stimulation current is applied to the quadriceps muscles, in the present study, muscle fatigue was defined as fatigue in the quadriceps muscles. The expression related to muscle fatigue dynamics is given in equation (5). In this study, the model described in equation (5) was used to determine the amount of muscle fatigue.

Equation (5): Dynamics of muscle fatigue

$$\dot{\mu} = \frac{(\mu_{min} - \mu)\alpha_{ke}}{T_f} + \frac{(1-\mu)(1-\alpha_{ke})}{T_r}$$

$\mu_{min} \in (0,1)$ expresses the minimum possible amount of muscle fatigue. T_f is the time constant of muscle fatigue and T_r is the time constant of muscle recovery. Muscle activation was modeled with the differential equation of equation (6) (21). In this regard, $T_a \in R^+$ was the time constant of muscle activity.

Equation 6: Muscle activity

$$T_a\dot{\alpha}_{ke} = -\alpha_{ke} + u_{ke}$$

To use controller design methods, it seems necessary to convert the differential equation of system dynamics into the state space equation. The equation of the state space of the hybrid neuroprosthesis system can be represented by equation (7). The dynamic differential equation of the hybrid neuroprosthesis was transformed into the state space model. In the presented model for the state space of hybrid neuroprosthesis, the state space variables were:

$x = [x_1\ x_2\ x_3]^T = [\theta\ \dot{\theta}\ \alpha_{ke}]^T$, and the system inputs were $u = [u_1\ u_2]^T = [\tau_m\ u_{ke}]^T$, which are the system control signals.

Equation (7): State space of the hybrid neuroprosthesis system

$$\dot{x} = f(x,u) = \begin{bmatrix} x_2 \\ \frac{1}{J}(u_1 + \tau_{ke} - \tau_p - G) \\ \frac{u_2 - x_3}{T_a} \end{bmatrix}$$

B. The Proposed Control Strategy

1) The Control System: Robot torque and electrical excitation torque due to simulation are calculated using robot control signal and FES control signal, and these signals are produced by a robot controller and FES controller. In this study, 2 proportional integral derivative (PID) controllers were optimally used for robot control and electric stimulation control (22). The use of a PI controller prevents excessive and unnecessary computational complexity in the design of controllers for robots and electrical stimulation. Due to the use of switching, the coefficient gains of the robot controller and the coefficient gains of the electric stimulation controller were calculated independently without considering the other controller.

In hybrid neuroprosthetics, the control signals are calculated using a computer and based on the knee joint tracking error signal, then, the robot control signal is applied to a mechanical axis and the knee joint is moved by this axis. After being mapped to the electric current, the value of the electric stimulation control signal is applied to the quadriceps muscles through the electrodes, and by stimulating them, it causes the knee joint to move. Therefore, the switch determines which of the controllers is used to move the knee at any given moment. The control signal for the robot was determined in the interval [0, t] seconds using equation (8). k_{PR}, k_{IR}, and k_{DR} coefficients are proportional, integral, and derivative coefficients of the controller (23).

Equation (8): Robot control signal in the time interval [0,t]

$$\tau_m = k_{PR}e + k_{DR}\dot{e} + k_{IR}\int_0^t e\,d\tau$$

The optimal control method was used to determine the controller coefficient gains ($\bar{k}_R = [k_{PR}\ k_{DR}\ k_{IR}]^T$) (24). These coefficient gains are determined in such a way that according to equation (9), they minimize the cost function [J(e(t))] in the time interval [0,t] seconds

Equation (9): Cost function

$$\bar{k}_R = [k_{PR}\ k_{DR}\ k_{IR}]^T = \underset{k_{PR},k_{DR},k_{IR}}{\arg\min} \int_0^t e^2 d\tau$$

The electrical excitation controller was illustrated by equation (10). The coefficients of the electric stimulation controller ($\bar{k}_F = [k_{PF}\ k_{DF}\ k_{IF}]^T$) are also calculated in the [0, t] second interval using the optimization method and according to equation (11).

Equation (10): Electrical stimulation controller

$$u_{ke} = k_{PF}e + k_{DF}\dot{e} + k_{IF}\int_0^t e d\tau$$

Equation (11): The controller gains of FES

$$\bar{k}_F = [k_{PF}\ k_{DF}\ k_{IF}]^T = \underset{k_{PF},k_{DF},k_{IF}}{\arg\min} \int_0^t e^2 d\tau$$

2) Time Allocation Strategy: In this study, the switching method was used to determine the timing of the use of the robot and electrical stimulation. A switching system is a system that consists of a set of controllers and systems that are controlled in such a way that this set has a common output or outputs. Each of the systems that make up the switching system is called a subsystem. In switching systems, the switching method determines which of the subsystems the output or outputs of the system will be obtained at any instant. Figure 3 shows the block diagram of the switching system for the knee neuroprosthesis.

Switching has various methods; the method that was used in this study was the Persistent D-well Time (PDT) switching method. The main advantage of timing the use of the robot and the electrical stimulation with PDT switching method is that there is no need to remove the electrical stimulation to overcome muscle fatigue. Rather, the robot is used when fatigue is increasing, the muscle is recovered, and after recovery, electrical stimulation can be used again. This switching method consists of a set of steps, each step is characterized by the expression P+i for i with values between 0 and n. Each stage P+i consists of two durations τ and T. The duration τ defines the proper persistence time, during which only 1 subsystem can be active for τ seconds. In the time period T, which is called the period of persistent time, each of the subsystems can be active for a certain time depending on the switching conditions, provided that the total time of activation of the subsystems does not exceed T seconds.

In this study, only electrical stimulation was active during the time τ. During time T, muscle fatigue was checked. If the amount of muscle fatigue was greater than a certain value, which is called the threshold value, the electrical stimulation was disabled and the robot was activated; otherwise, the electrical stimulation remained active. Figure 4 shows a diagram of the PDT switching method for the knee hybrid neuroprosthesis.

To simulate knee rehabilitation, the angle of the knee joint in the hybrid neuroprosthesis model must be equal to a certain value during the simulation time; this certain value is called the reference signal. The angle of the knee joint varies physically between 0° and 90°; thus, according to previous studies (11, 13, 14, 17, 25-27), an angle between these values should be considered in the simulation. In this study, similar to the study by Nunes et al. (26), a reference signal that had a constant value of 60 degrees for 95 seconds was considered.

In the therapeutic applications of hybrid neuroprostheses, it is important to avoid applying sudden movements to the patient's body in the treatment process, in order to maintain health and prevent injury. For this reason and in order to avoid sudden movement of the knee joint, the reference signal was gradually increased from 0 degree to reach the desired level of 60 degrees in the period of 0 to 5 seconds. In effect, any sudden change in the displacement of the knee was prevented in the practical use of hybrid neuroprostheses in the simulation by gradually changing the value of the reference signal to reach a constant value.

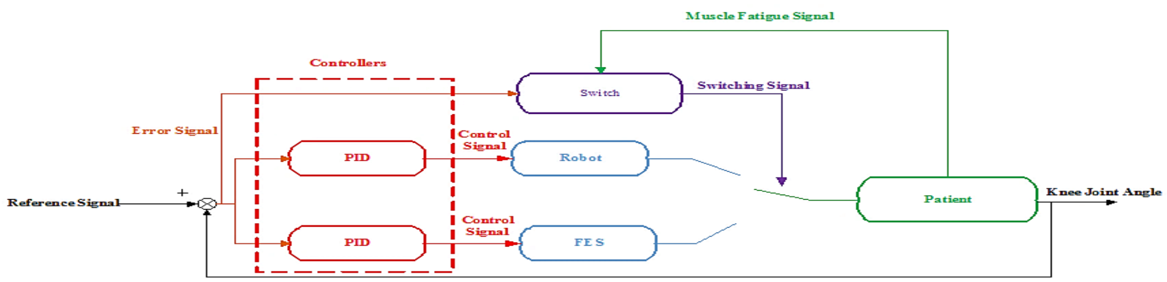

Figure 3. Block diagram of the switching system of hybrid neuroprosthesis

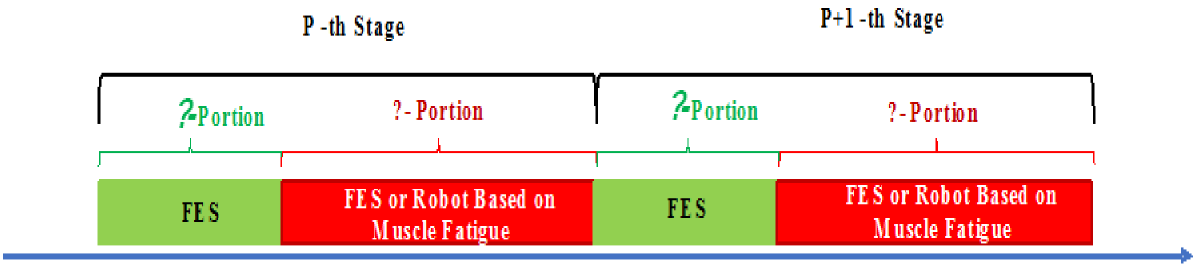

Figure 4. Schematic of PDT switching method for knee prosthesis

The switch occurs when switching conditions occur, which include when muscle fatigue occurs and when the subsystem is active. Therefore, a frequency is not defined for switching. In hybrid neuroprosthetics, switching will occur whenever the switch condition is detected by the computer, for example, in this study, it was determined for the computer that when the fatigue parameter is less than 0.95 (the muscle becomes more tired), from electrical stimulation to If the robot switches, if the fatigue becomes less than 0.95 twice in 1 second, the switch will occur with a frequency of 2 Hz, and if fatigue does not drop to less than 0.95 in 1 second, the switch will not occur.

The timing of electrical stimulation using robot and FES can be expressed by the switch signal in equation (12). The switch signal is usually a natural number that specifies the subsystem that is active (28). In effect, each number represents a subsystem. For example, if we have 4 subsystems, the switch signal with a value of 1 means that the first subsystem is active, and the switch signal with a value of 4 means the fourth subsystem is active. The determination of the subsystem equivalent to each switch signal is the responsibility of the designer. Moreover, what is important in determining the switch signal is the switching condition, which in this article included the two conditions of muscle fatigue and time. In equation (12), the term $\delta_p(t) \in N$ is the value of the switch signal at each step p and for each moment t, and the term μ_{th} is the threshold value for muscle fatigue. The value of the switch signal for electric stimulation was considered equal to 2 and its value for the robot was considered equal to 1.

Equation (12): Timing using robot and FES (switch signal)

$$\delta_p(t) = \begin{cases} 2\,, t \le \tau \\ \begin{cases} 2\,, \mu < \mu_{th} \\ 1\,, \mu \ge \mu_{th} \end{cases}, \tau < t \le T \end{cases}$$

The state space equations of the switched system can be rewritten as $\dot{x}_{\delta_p(t)}$ in equation (13). The state space equation at each moment was determined based on the value of the switch signal. When the switching signal determines the robot controller, the system dynamics is described by the state space equation $\dot{x}_1$, and when the switching signal determines the FES controller, the system equation is described by the state space equation $\dot{x}_2$.

Equation (13): State space of the switching system

$$\dot{x}_{\delta_p(t)} = \begin{cases} \dot{x}_1 = \begin{bmatrix} x_2 \\ \frac{1}{J}(u_1 + \tau_{ke} - \tau_p - G) \\ \frac{u_2 - x_3}{T_a} \end{bmatrix} ; \delta_p(t) = 1 \\ \dot{x}_2 = \begin{bmatrix} x_2 \\ \frac{1}{J}(u_1 + \tau_{ke} - \tau_p - G) \\ \frac{u_2 - x_3}{T_a} \end{bmatrix} ; \delta_p(t) = 2 \end{cases}$$

C. Simulation Studies

The importance of simulation for controllers is to avoid spending money as well as avoid possible risks and damages in case of unfavorable performance of a controller in practical testing (29). Through the use of simulation, it is possible to identify and fix possible errors in calculations and mathematical relationships of a controller.

To simulate the model, its parameters need to be estimated based on the human sample. In the present study, to simulate the proposed method with the aim of avoiding reference to the basic sources of modeling, a large part of the assumptions were based on the parameters of the study by Kirsch et al. (25). The values of the model parameters are presented in table 1.

The simulation was performed in MATLAB (version 2019). The simulation frequency was considered to be 100 Hz. This frequency corresponds to the sampling frequency of the neuroprosthesis in practical use (13 and 30), the resulting sampling of this frequency is not so slow that a significant amount of system information is lost, and it is not so fast that its laboratory implementation requires complex technology. For this reason, the simulation frequency of 100 Hz is a suitable value for sampling and simulating with the necessary precision in measuring the performance of the hybrid neuroprosthesis.

Table 1. The value of the parameters in knee hybrid neuroprosthesis model

Parameters in knee hybrid neuroprostheses model	Value	Parameters in knee hybrid neuroprostheses model	Value
Mass (kg)	69.4	Time constant of muscle fatigue (s)	29.17
Moment of inertia (kg/m)	0.19	Time constant of muscle recovery (s)	48. 09
The distance between the knee joint and the center of mass of the shank (m)	0.37	Time constant of muscle activation (s)	0.26
Minimum stimulation current (mA)	18.1	Equilibrium position of knee (rad)	1.2
Saturation stimulation current (mA)	60	Gravitational constant (m/s^2)	10
Minimum muscle fatigue	2.61×10^{-9}		

Simulation was done for a period of 100 seconds (18). In a period of 100 seconds, the transfer of the system output value from the transient response to the permanent response, and the stabilization of the system output in the permanent response could be seen. In addition, this duration of simulation was sufficient to investigate the pattern of muscle fatigue, and therefore, this duration was suitable for studying the behavior of the system in the simulation and assessing the performance of the controller. Proportional, integral, and derivative coefficients were calculated to be 1.87, 0.65, and 0.92 for the electric stimulation controller and 231.17, 454.32, and 45.39 for the robot controller, respectively.

The threshold value for muscle fatigue was determined to be 0.95. The closer the amount of muscle fatigue is to 1, the less fatigue is experienced by the individual. By choosing the value of the muscle fatigue threshold close to 1, it is possible to measure the conditions in which the PDT switching method has the best and even the most ideal performance. A switching threshold of higher than 0.9 has also been reported in previous studies (16).

According to the study by Wang et al. (31), the values of the persistent D-well time and the period of persistence are determined by observing two conditions:

1. The persistent D-well time (τ) must be less than the active duration of each subsystem to which the switch is made.
2. The period of persistence (T) must be greater than the total active time of all the switched subsystems in the period of time T.

By complying with these two conditions, it is possible to determine the values of persistent D-well time and the period persistence manually and without restrictions. In the present study, each stage of 30 seconds was considered to include a proper persistence time (τ) equal to 10 seconds, and duration of the period of persistence (T) equal to 20 seconds. The ratio of 2 to 1 and the value of 30 seconds were chosen to make it possible to check and diagnose the simulation results more accurately and clearly. To check the simulation results, the amount of knee joint angle error in following the reference angle and a small amount of muscle fatigue were measured.

Results

During first 5 seconds that the reference signal had a transient value, the tracking error value of the reference signal changed from -0.4 degrees to 1.5 degrees. The highest amount of error occurred at 0.9 seconds. After 0.9 seconds, the tracking error of the transient part of the reference signal decreased and reached about 0.5 degrees in the fifth second of the simulation. From the fifth second to the hundredth second, the reference signal had a constant value. From the fifth to the eighth second, the angle of the knee joint gradually increased from the reference signal, and at about the eighth second, it reached its maximum value. During this period, the error value increased from -0.2 degrees to 0.5 degrees. From the eighth to the tenth second of the simulation, the error value decreased and reached zero.

At the moments of the switch from electric stimulation to the robot (i.e., 27.33, 29.73, 59.97, and 89.99 seconds), the error value increased to 1 degree, and then after 1 second, this value dropped to -0.08. Finally, it reached zero within 6 seconds. During the switch from FES to the robot, the error increased slightly. For example, at 60 seconds, when the switch occurred, the error increased by 1.2 degrees, but after 1 second, it decreased to -0.07 degrees, and after 4 seconds, it reached zero.

In 39.72 and 71.37 seconds, fluctuating behavior occurred with a maximum error of -0.5 degrees in a period of 2 seconds, and after 2 seconds, the error was equal to zero. These times were equivalent to the moments when the switch from the robot to FES occurred. The sum of square error (root mean square: RMS) at the time of simulation was equal to 0.79 degrees. Figure 5 shows the angle diagram of the knee joint along with the reference signal and the error diagram.

The graph of muscle fatigue (μ) is shown in Figure 6. Muscle fatigue decreased from 1 to 0.95 in the period of 0 to 28 seconds.

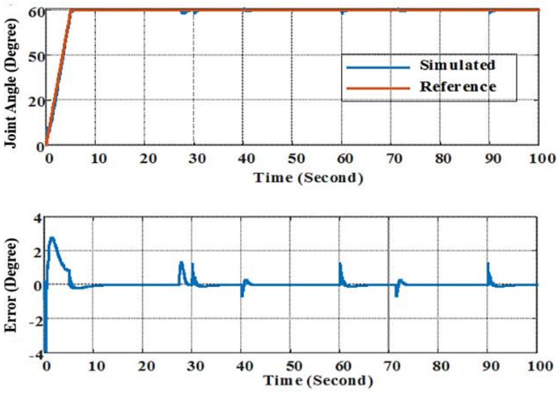

Figure 5. Knee angle and reference signal (top diagram) and error signal (bottom diagram)

With the switching from FES to the robot in the 28th second, the speed of muscle fatigue and the value of μ decreased in the period of 28-30 seconds. In the 30th second, the switch from the robot to the FES occurred, and until the 41st second, the μ value decreased to 0.94. In the 40th second, the switch from FES to the robot occurred, and the rate of increase in muscle fatigue decreased. By the 60th second, the μ value reached about 0.96. In the 60th and 90th seconds, there was a switch from the robot to FES, and the amount of muscle fatigue decreased to 0.95 until the 71st and 100th seconds, respectively, but did not decrease to lower than this value. Furthermore, at about the 70th second of the simulation, the switch from FES to the robot occurred, and from this time to the 90th second, the value of μ increased to 0.97 as the speed of muscle fatigue decreased. The switch signal diagram is shown in figure 6.

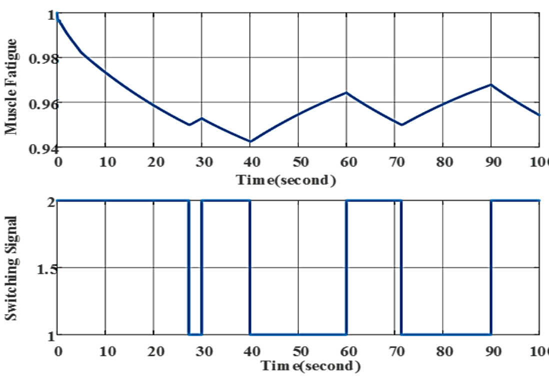

Figure 6. Amount of muscle fatigue (top diagram) and switch signal (bottom diagram)

To check the performance of the proposed method, the amount of muscle fatigue was compared with that in the method in which only FES was used. Figure 7 shows the amount of muscle fatigue for the method in which only FES was used. The amount of muscle fatigue increased continuously, and at the end of the simulation, the μ value was approximately equal to 0.92, which was, respectively, 20% and 50% higher compared to the highest and lowest amount of muscle fatigue obtained by the proposed method.

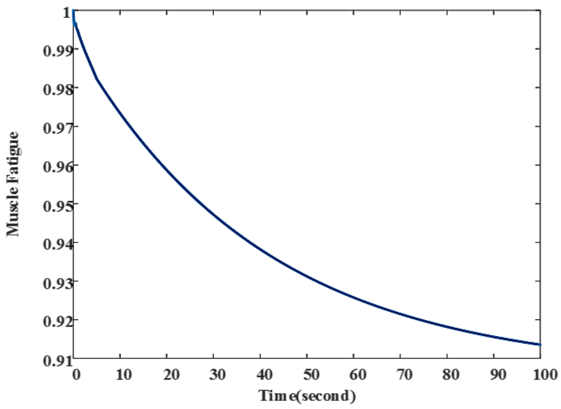

Figure 7. Amount of muscle fatigue resulting from FES

Discussion

In this study, the control of knee movement was simulated using a hybrid neuroprosthesis with the approach of overcoming muscle fatigue. For the first time, the PDT switching method was used to employ the robot and FES, and the knee joint angle was set in the reference angle. In this simulation, muscle fatigue was changed within a certain range and its continuous increase was prevented during the rehabilitation period, thus overcoming muscle fatigue.

The prominent feature of the studies that use the Euler-Lagrange model is the determination of the moments of the system. These torques (for a combined robot torque and FES torque prosthesis) are obtained using control signals that are calculated by the computer. Another important issue in these prostheses is the designing of the controller for the reduction of muscle fatigue. The innovation of this study was in the design of the controller with the switching method based on PDT switching. The purpose of designing this controller was, first, to move the knee in the path determined by the therapist or specialist, and then, to control muscle fatigue, so that it is delayed and its amount is limited.

In this simulation, the adjustment of the knee angle in the reference signal was successfully performed and the error value for the knee joint in following the reference signal was an acceptable value. The value of μ, which was determined as the muscle fatigue parameter in the simulation, did not decrease to below the threshold value that was intended for it and was within a certain limit during the simulation. According to the obtained results, it can be concluded that, by using the PDT switching method, robots and FES were used for the hybrid neuroprosthesis of the knee in such a way that the movement of the knee joint was well controlled and muscle fatigue was overcome.

The parameters used in the model used for simulation are divided into two categories. One category includes the parameters that have fixed values such as gravity or parameters that have a certain value according to the patient’s physical conditions such as the weight of the patient. The second category of parameters includes those that need to be determined according to the physical condition of the patient, such as moment constant, muscle fatigue constant, and muscle activity constant. The estimation method is used to determine these parameters. In the study by Kirsch et al. (25), the estimation of the parameters of the hybrid neuroprosthesis model was based on the numerical values obtained from the physical condition and appearance characteristics of the patient (such as weight, recovery time constant, and muscle fatigue time constant). In the present study, the same values were used in the simulation.

The difference between the method of the present study and the study by Kirsch et al. (25) was in the design of the controllers and the distribution of the control signal between the electric stimulation and the robot. Kirsch et al. (25) used the predictive model controller to calculate the control signal, and this control signal was distributed between the robot controller and the FES. However, in this study, the system state equation was rewritten in the form of a switched system, the PID controllers were designed optimally with the PDT switching method, and the value of the switch signal for the selection of the robot controller or FES at any moment was calculated according to muscle fatigue.

Tracking the reference trajectory

In contrast to the present study, where reference signal tracking was done and was successful, in the study by Kirsch et al. (13), in the proposed method for using electric stimulation and robots in controlling the knee neuroprosthesis, the knee joint failed to follow the reference signal. Moreover, in the study by Bao et al. (15), the reference signal was not followed to control the neuroprosthesis. In the simulation study by Kirsch et al. (32), which used a method based on switching for knee prosthesis, the maximum tracking error was reported to be about 40 degrees, which is a high value, while in the present study, the maximum error value was 2.5 degrees. The research by Nunes et al. (26) was a simulation study based on a fuzzy model. In their study, the knee joint failed to follow the transient value of the signal and followed the reference path with an RMS error of 3.75 degrees (26), while the RMS error value in the present study was 0.79 degrees, which is a significant improvement compared to the results reported in the study by Nunes et al.

The value of the error signal in following the reference path is the primary measure of the controller's performance, and based on it, the possibility of testing the controller in the physical environment can be judged. After obtaining an acceptable result in the value of the tracking error signal, other performance results of the controller can be examined. By comparing the error signal obtained from the proposed method with the reviewed studies, it can be concluded that the proposed method has an acceptable performance in tracking the reference signal and it is possible to implement it in a laboratory environment.

Muscle Fatigue Compensation

In the study by Molazadeh et al. (33), the switching method was used to control the prosthesis. Furthermore, in the study by Bao et al. (27), the switching method was applied for controllers based on artificial intelligence. However, in these two studies (27, 33) the result of the proposed switching method in terms of muscle fatigue was not investigated. In the study by Alibeji et al. (30), to reduce muscle fatigue, the switch between robot and FES was not considered, and a method based on synergy was used to reduce the effect of muscle fatigue. In this method, the control signal was also calculated using the amount of muscle fatigue. In this respect, their approach is similar to that used in the present study, which used the amount of muscle fatigue to determine the switch signal. Nevertheless, in the approach based on synergy (30), to determine the values of muscle synergy, online optimization and principle component analysis is needed. These calculations limit the implementation of this method due to their complexity and time-consuming nature.

In the study by Sheng et al. (16), a switching-based method was presented to control the hybrid prosthesis, but for the design of the controllers, defaults were considered for the attraction region of the system, which is a limitation in the system control. Despite the controlling of the amount of muscle fatigue in the simulation results of Sheng et al. (16), the limitation of the values of the controlling coefficients challenges the use of their proposed method. In one of the simulation studies of these researchers (34), a Super Twisting Sliding Mode controller was used for neuroprosthetics, and in another study (35), a robust iterative learning switching controller was used for prosthetics. In the studies by Sheng et al. (16), Molazadeh et al. (34), and Molazadeh et al. (35), like the study by Kirsch et al. (13), the fatigue threshold value for the switch was considered equal to 0.5, but in less than 10 seconds, the simulation of the muscle fatigue value reached the threshold value and an electric shock occurred to the robot. In this study with the PDT switching method, the first switch for the fatigue threshold value of 0.95 occurred after the twenty-seventh second, in other words, the occurrence of muscle fatigue was delayed.

Therefore, it seems that the PDT switching method for hybrid neuroprosthetic controllers allows switching between the robot controller and FES in such a way that muscle fatigue does not exceed a certain value during the simulation, and delays the occurrence of muscle fatigue. This process is applicable without the need for restrictive assumptions in the controller design and without computational complexity.

Limitations

Due to the existence of unmodeled dynamics and disturbance, any musculoskeletal mathematical model with any degree of accuracy, will have errors in practical implementation, which is known as model mismatch between the simulation model and laboratory results. In addition, one of the common and expected limitations in the practical implementation of simulation is a control method (36). For knee rehabilitation with neuroprosthesis in a laboratory environment, applying the numerical values of the control signals obtained in the simulation is associated with an error in knee movement control, and the supervision of an expert during the rehabilitation is necessary. In the simulation investigated in this study, muscle fatigue was modeled, but in the laboratory environment and for a human sample, several factors can affect muscle fatigue, some of which are even specific to each patient and his/her physical condition. Some factors affecting muscle fatigue, such as psychological factors, cannot be measured quantitatively. The existence of these factors also creates limitations in the practical implementation of the proposed method.

This prosthesis cannot be used while the user is walking, and in its simulation, a fixed reference signal has been used in the references. However, it is possible to use the desired time-varying signal in the simulation. For example, instead of the value of 60 degrees for the desired signal, it is enough to use a time-varying function such as the sine function or the 2t function. If in this study, from the moment of zero to the moment of 10 seconds, the reference signal is time-varying and changes with the relation $r(t) = 6t$ (in this equation, t is time).

Recommendations

For future research, it is suggested that the proposed method be implemented on the combined neural prosthesis in the laboratory environment. Moreover, in the proposed method, the effect of disturbance and unmodeled dynamics is not considered; therefore, controller design considering unmodeled disturbance and dynamics is another suggestion for future works. The use of model-free and online methods to implement the method proposed in this article is one of the areas for future studies. Due to the limitations of practical implementation, in order to implement the method presented in this study, in addition to following the treatment protocols, the supervision of an expert or therapist is necessary.

Conclusion

The PDT switching method can be considered as a solution to the challenge of using FES and robots in hybrid neuroprosthesis with the aim of preventing the increase in muscle fatigue caused by FES. This method can delay the occurrence of muscle fatigue without the need for complex control structures. The results of the simulation on the amount of knee joint displacement error and controlling the amount of muscle fatigue without the need for complex assumptions and computational limitations for the controllers indicate the effectiveness of this method in the control function and confirm the possibility of using the method proposed in the present study on a human sample.

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Conflict of Interest

The authors did not have a conflict of interest. This research was performed by Shazan Ghajari under supervision of Reihaneh Kardehi Moghaddam who is working as an associate professor at the Department of Electrical Engineering and under supervision of Hamid Reza Kobravi who is working as an associate professor at the Department of Biomedical Engineering of Islamic Azad University of Mashhad and with advice from Naser Pariz who is working as a professor at the Department of Electrical Engineering of Ferdowsi University of Mashhad. Shazan Ghajari has been studying at Islamic Azad University of Mashhad since 2016 as a PhD candidate in electrical engineering.

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