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.

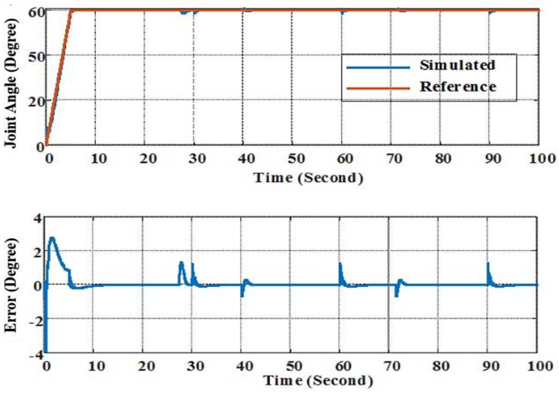

Figure 5. Knee angle and reference signal (top diagram) and error signal (bottom diagram)

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.

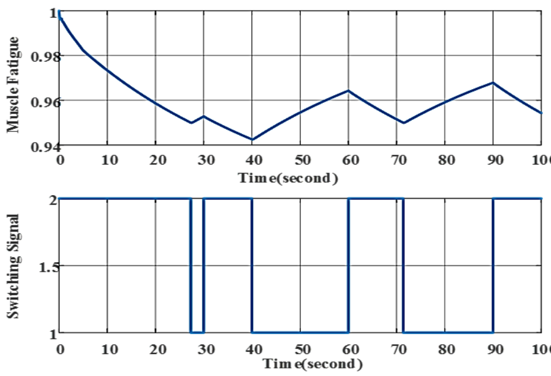

Figure 6. Amount of muscle fatigue (top diagram) and switch signal (bottom diagram)

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.

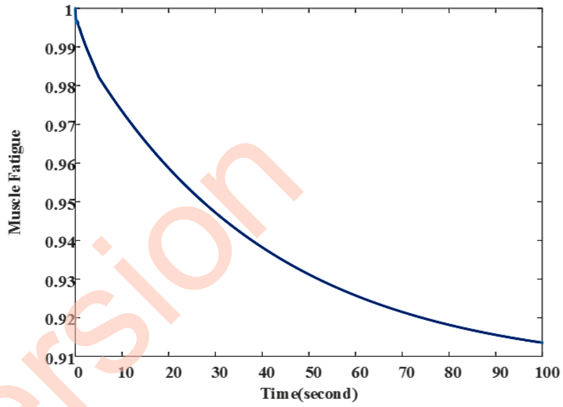

Figure 7. Amount of muscle fatigue resulting from FES

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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Authors' Contribution

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Data collection: Shazan Ghajari
Analysis and interpretation of the results: Shazan Ghajari
Manuscript preparation: Shazan Ghajari, Reyhaneh Kardehi Moghaddam, Hamid Reza Kobravi, and Naser Pariz
Specialized scientific evaluation of the manuscript: Shazan Ghajari, Reyhaneh Kardehi Moghaddam, Hamid Reza Kobravi, and Naser Pariz
Confirmation of the final manuscript to be submitted to the journal website: Shazan Ghajari, Reyhaneh Kardehi Moghaddam, Hamid Reza Kobravi, and Naser Pariz
Maintaining the integrity of the study process from beginning to publication, and responding to the referees' comments: Shazan Ghajari, Reyhaneh Kardehi Moghaddam, Hamid Reza Kobravi, and Naser Pariz

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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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