A Computer Simulation Study on Closed-Loop Functional Electrical Stimulation Controller Based on Model Predictive Control with Simplified Parameter Estimation

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論文題目　A Computer Simulation Study on Closed-Loop Functional Electrical Stimulation Controller Based on Model Predictive Control with Simplified Parameter Estimation

（簡易的パラメータ推定を用いたモデル予測制御に基づく閉ループ型機能的電気刺激制御器の計算機シミュレーション研究）

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Doctoral Thesis

Thesis Title

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英文 Abstract

Title : A Computer Simulation Study on Closed-Loop Functional Electrical Stimulation Controller Based on Model Predictive Control with Simplified Parameter Estimation

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A functional electrical stimulation (FES) is an effective method to restore or assist the paralyzed limbs of stroke survivors or spinal cord injury patients that can improve their activities of daily living. However, the FES-based movement control system needs a proper controller to achieve desired functional movement. The purpose of this study was to develop a capable FES controller using a combination of a linear model predictive control (MPC) and a nonlinear transformation. Considering practical application, the use of an average model for the MPC was examined and a simple parameter estimation method was developed to determine the value of the controller parameter. The control performance of the proposed MPC-FES controller along with the parameter estimation method was examined in controlling the 1-DOF wrist joint movement through computer simulation using 15 healthy and 1 paralyzed subject models. The proposed controller was also compared with a fuzzy FES controller. The proposed MPC-FES controller with estimated parameter value worked properly and was superior to the fuzzy controller in tracking capability, compensating muscle fatigue, and rejecting external disturbance. The proposed controller along with the parameter estimation method was suggested to be useful and effective for the FES-based movement control system and expected to be tested in a real environment as the next step.

和文アブストラクト

論文題目 : 簡易的パラメータ推定を用いたモデル予測制御に基づく閉ループ型機能的電気刺激制御器の計算機シミュレーション研究

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機能的電気刺激（FES）は，脳卒中患者や脊髄損傷患者の麻痺した手足を回復または補助し，日常生活動作を改善するための有効な方法である。しかし，FES を用いた動作制御システムは，所望の機能的動作を実現するために適切な制御器が必要である。本研究の目的は，線形モデル予測制御（MPC）と非線形変換を組み合わせて，高機能な FES 制御器を開発することである。実用性を考慮して，MPC に平均的モデルを使用することを検討し，制御器パラメータの値を決定するための簡単なパラメータ推定法を開発した。提案した MPC-FES 制御器とパラメータ推定法の制御性能について，15 名の健常者と 1 名の麻痺者を表現したモデルを用いた計算機シミュレーションにより，手関節 1 自由度運動制御において検討した。また，提案した制御器とファジーFES 制御器の比較も行った。提案した MPC-FES 制御器は，パラメータ推定値を用いて適切に動作し，追従性，筋疲労の補償，外乱の除去においてファジー制御器より優れていることが確認された。提案した制御器とパラメータ推定法は，FES を用いた動作制御システムに有効であることが示唆され，次の段階として実環境でのテストが期待される。

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Chapter 1

General Introduction

1.1 Background

Humans perform various activities in their daily lives such as grasping, reaching, writing, standing, walking, and so on by using their movement system. Human movement occurs due to coordination between the central nervous system (CNS), spinal cord and muscles where the CNS sends command signals (electrical signals) to the muscles through the spinal cord and these electrical signals cause contractions in the muscles to generate forces that move the limbs. This kind of movement is called voluntary movement. When voluntary movement is unable to be generated, this condition is referred to as paralysis. Damage to any of the three components above (CNS, spinal cord and muscle) results in paralysis in humans, causing loss of ability to perform functional movements in daily life. Paralysis can be categorized based on the affected area such as paralysis on both sides of the same body part (Diplegia) such as both arms or both legs, paralysis on one side of the body part (Hemiplegia) such as arm and leg on the same side, paralysis on one limb (Monoplegia) such as arm or leg, paralysis on lower limbs (Paraplegia) such as both legs and torso, and paralysis on all limbs (Quadriplegia/Tetraplegia).

Stroke is one of the cerebrovascular diseases that is currently the most important health problem that causes many sufferers to experience death and paralysis worldwide [1], [2]. In 2016, nearly 14 million people suffered from stroke and of these, nearly 8.5 million stroke survivors experienced paralysis due to this disease [2]. Most of the paralysis that occurs is the loss of functional movement in both upper and lower limbs due to loss of motor control coordination. In addition to stroke, spinal cord injury (SCI) is one of the main causes of partial or complete loss of functional movement in the patient's limbs [3].

The loss of basic functional movements in daily life such as grasping, reaching, writing, standing, walking, and so on in stroke and SCI patients causes a decrease in their quality of life (QoL) and increases dependence on the help of others around them. Identification of the level of stiffness in the joints of the paralyzed limbs in a patient after stroke through mechanical measurements and EMG showed a greater level of stiffness compared to normal people [4]. If the paralyzed motor function is not treated immediately, it will lead to muscle atrophy and disuse syndrome that cause the functional movement ability to decrease significantly and even more severely with time [5]. Therefore, rehabilitation training for stroke and SCI patients to restore lost functional movement of paralyzed limbs is very important to maintain and regain the motor functions ability thus increasing their independence in daily life and improving their QoL.

Functional Electrical Stimulation (FES) is one of the methods for assisting or restoring paralyzed limbs of stroke and SCI patients, which can be used for activities of daily living and in rehabilitation training. For over two decades, many research groups have reported that paralyzed motor function caused by stroke and SCI can be restored using FES, which is performed by applying electrical stimulation to intact peripheral nerves and muscles in order to elicit muscle contraction [6]-[10]. Some studies have shown that functional movement restoration using FES provides promising outcomes in increasing the muscle strength and the range of motion (ROM) of the paralyzed limbs [11]-[15], and promoting the neural system remodeling to have new motor abilities [12]. In addition, rehabilitation training of paralyzed limbs using FES has better outcomes compared with conventional training [11], [15] and robotics-based training [13].

In general, rehabilitation training using FES on the upper paralyzed limbs (e.g. tetraplegia patients) is performed first rather than the lower paralyzed limbs. The

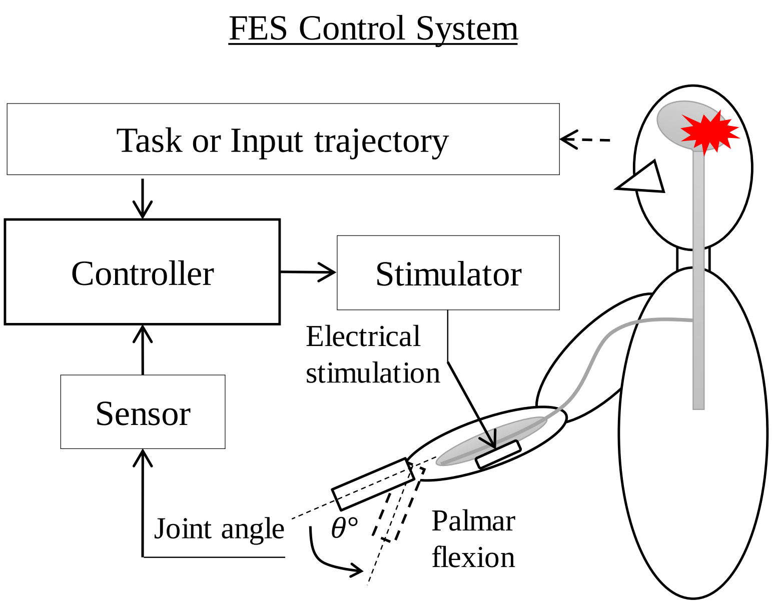


Figure 1.1: Illustration of the application of FES control system for limb joint movement restoration.

reason is that basic functional movements in daily life activities mostly involve the upper limbs. In addition, the role of the lower paralyzed limbs can be replaced by the recovered upper limbs, for example, moving using a wheelchair. Therefore, rehabilitation of the paralyzed upper limbs is very important to do first, especially in tetraplegia patients. On the other hand, most applications of FES systems are intended as neuroprosthesis for upper paralyzed limbs that can be used in daily life activities by assisting paralyzed users to perform basic tasks such as reaching and grasping a spoon to eat, reaching and grasping a glass of water to drink, and so on. The application of FES as a neuroprosthesis to assist paralyzed users to perform basic functional movements such as reaching movements requires a controller that has high accuracy tracking control performance [16]. However, designing a FES controller for such applications is not easy, because the response characteristics of the stimulated patient's muscle have strong nonlinearity, large latency, and time-varying [17]. The most widely applied controller in clinical practice is the open-loop controller which is chosen because of its ease of design and use. However, the drawback of the open-loop controller is that its performance depends on the stimulation profile set at the beginning of training which requires a lot of effort from the medical staff to customize the stimulation profile for each patient. In addition, open-loop control systems are unable to compensate for muscle fatigue and eliminate the effects of external disturbances. Therefore, researchers have developed more closed-loop control systems to overcome the shortcomings of open-loop control and it is still an open problem in FES research. An illustration of the application of a closed-loop FES control system for upper limb joint movement restoration is shown in Fig. 1.1.

In our FES research group, FES controllers realized with conventional PID [16], [18], fuzzy controllers [19], [20], and learning type controllers [21]-[23] have been developed and tested for both upper and lower limbs restoration. PID controllers have been tested to control wrist joint movement in healthy subjects [16] and in a hemiplegic patient [18]. Based on the evaluation results, the PID controller was only able to provide good control results for targets with slow movements whether tested with normal subjects or a hemiplegic patient. When tested for targets with fast movement, the PID controller is difficult to achieve the desired target angle where the time delay in the control result of the PID controller was too long. This shows that the PID controller is difficult to overcome the large latency in stimulated muscle response. Therefore, fuzzy controller [20] and learning type controller [21] were developed to overcome the problem. The fuzzy controller showed better tracking control performance compared to the PID controller when tested to control the extension movement in the knee joint of normal subjects [20]. The learning type controller [21] was realized by using a combination of feedforward controller (ANN) and feedback controller (PID), and when tested to control the wrist joint movement of the normal subjects with fast movement, the tracking control performance was better than using only PID controller. The advantage of a feedback controller is the ability to compensate for characteristic changes and disturbances in a controlled system. On the other hand, if the feedforward controller is realized with the inverse model of the dynamic system, the advantage of the feedforward controller is that has the ability to predict the appropriate electrical stimulation intensity. However, although the learning type controller has high tracking control accuracy and could decrease the time lag error significantly, it requires a learning process with large iterations.

In another FES research group, FES controllers were realized using model predictive control (MPC) which also had good tracking control performance with high accuracy [24]-[26]. MPC is an optimal control technique that has been widely used in industry. MPC consists of feedforward prediction and feedback correction in its structure to produce optimal control output. MPC uses a model of the controlled system explicitly to predict the behavior of the system over a prediction horizon. In addition, constraints on the inputs and outputs of the controlled system such as the range of control signals and output responses can be imposed in its formulation, so that the control system can operate according to the desired performance [27], [28]. Therefore, with its advantages, MPC is considered to be useful for neural control applications and can be a candidate for realizing a capable closed-loop FES controller. In [24], an FES controller was realized using nonlinear MPC to control the extension of the knee joint. However, nonlinear MPC requires an accurate nonlinear model of the system to obtain good tracking control performance and to identify an accurate model in practical applications is a difficult task. In addition, another issue to be solved is that the heavy computational load of nonlinear MPC when performing the optimization process is not suitable especially for the application of FES as a neuroprosthesis because it requires super-fast and expensive computing devices. To reduce the computational burden of nonlinear MPC, other researchers realized an FES controller using a combination of a linear MPC and input-output feedback linearization [25], [26], which provides quite good control tracking results although not as good as nonlinear MPC. Although the FES controller based on the combination of a linear MPC and input-output feedback linearization in previous studies showed promising tracking control performance without the need for a learning process, it has the disadvantage that the initial parameter adjustments for both the prediction model used in MPC and input-output feedback linearization must be identified in advance for each patient in each control experiment. Such a process of model parameter identification is time-consuming and tends to be a burden for patients and medical staff in rehabilitation training, and does not seem to be suitable for FES control as a neuroprosthesis. Therefore, in order to solve the problem described above, this thesis aimed to develop a capable FES controller that can be used to restore or assist paralyzed limbs of stroke or SCI patients. Research objectives are described in detail in the following section.

1.2 Research objectives

The objectives of this research are divided into general objectives and specific objectives, which are explained as the following.

1.2.1 General objectives

- To develop a FES controller which is capable to provide a high tracking accuracy in controlling the upper limb joint movement of paralyzed patients,
- To realize the FES controller based on a combination of linear MPC and a simple nonlinear transformation,
- To develop a simplified parameter estimation method for the proposed FES controller.

1.2.2 Specific objectives

- Design the linear MPC with no active constraints and a simple average prediction model in order to obtain a simple formulation and fast computation,
- Utilize a nonlinear transformation realized by using a simple nonlinear function to transform the linear solution of the output of MPC to a nonlinear solution,
- Test the feasibility of the proposed controller in controlling the 1-DOF of wrist joint movement with repetitive movements through a computer simulation study,
- Evaluate the effectiveness of the average model used in the linear MPC

combined with the nonlinear transformation in dealing with individual differences and nonlinear characteristics during the 1-DOF of wrist joint movement control process through computer simulation study,

- Propose a simple estimation formula to determine the initial value of the proposed controller and evaluate the effectiveness of the proposed parameter estimation method,

- Compare the control capability of the proposed controller with a fuzzy-FES controller in tracking control, muscle fatigue compensation, and disturbance rejection.

1.3 Outline

This thesis is divided into five chapters and described as follows.

Chapter 1: General Introduction

This chapter consists of a brief explanation of the background of this study, followed by research objectives and an outline of this thesis. The subsequent chapters can be summarized as follows.

Chapter 2: Design of FES Controller Using a Combination of Linear MPC and Nonlinear Transformation

This chapter describes the design flow of the proposed FES controller based on cascading linear MPC with nonlinear transformation by utilizing the averaging model and simple nonlinear functions to realize the proposed FES controller. The development of the upper limb musculoskeletal model for FES control applications as well as model validation for the purpose of FES control studies through computer simulation are also described in this chapter.

Chapter 3: Preliminary Test of MPC-FES Controller in Wrist Joint Control

The computer simulation test to evaluate the capability of the proposed FES controller in controlling the 1-DOF wrist joint movement for repetitive movement with different range of motion is described in this chapter. The effectiveness of the average model used in MPC and the nonlinear function in realizing the nonlinear transformation are also examined and discussed in this chapter.

Chapter 4: Simplified Parameter Estimation Design for MPC-FES Controller

This chapter describes the development of the parameter estimation method to determine the initial value of the parameter of the proposed FES controller. The computer simulation test of the MPC-based FES controller along with its parameter estimation tested in controlling 1-DOF wrist joint movement is described in this chapter. The comparison of tracking control performance of the proposed controller using different methods in determining the controller parameter value is also presented in this chapter.

Chapter 5: Comparison of Tracking Control Performance Between MPC-FES Controller and Fuzzy-FES Controller

In order to show that the proposed FES controller and the parameter estimation method work effectively and have practical utility in FES movement control, the comparison of the control capability of the proposed method and a fuzzy-FES controller in tracking control, muscle fatigue compensation, and disturbance rejection is presented in this chapter.

Chapter 6: Concluding Remarks

This chapter summarizes the overall presented study and explain the future work as extension of this study.

Chapter 2

Design of FES Controller Using a Combination of Linear MPC and Nonlinear Transformation

2.1 Introduction

This chapter describes the design flow of the proposed FES controller based on cascading a linear MPC with a nonlinear transformation to control the 1-DOF of wrist joint movement. The block diagram of the FES controller used in this study is shown in Fig. 2.1. The proposed FES controller consists of a linear MPC, a nonlinear transformation, and a limiter. The MPC-FES controller aims to regulate the electrical stimulation intensity (u_t) at time instant k fed to the musculoskeletal system to produce controlled movement (θ) so as to follow the desired trajectory movement (θ_d). Since the MPC used in this study is a linear type, in order to control a nonlinear system such as the wrist joint movement induced by FES, the nonlinear transformation is cascaded with linear MPC to obtain a nonlinear solution. Nonlinear transformations have been widely used in combination with linear controllers such as PI controller [29] and PID controller [30]. This approach was also used by nonlinear MPC to solve nonlinear control problems [27]. Another method used two linear MPCs in series configuration to solve nonlinear problems [31]. Nonlinear MPC is more difficult to realize because it requires a very accurate model of the controlled system. In addition, nonlinear MPC requires a long computational time to obtain the optimum solution. Therefore, linear MPC is chosen over nonlinear MPC in this study because the speed of computation time of linear MPC is faster than nonlinear MPC making it more suitable for FES control which requires fast execution time in practical applications.

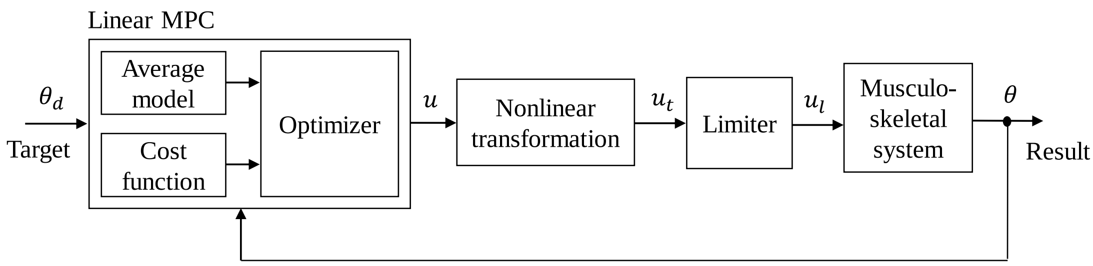


Figure 2.1: Block diagram of the FES controller based on the cascade of linear MPC and nonlinear transformation.

Most of the research on FES controller development is conducted through computer simulation before being implemented in real environments or clinical practice to validate the feasibility of the developed controllers and their parameter adjustment methods [21]-[23], [26]. The process of controller design and testing in computer simulation is easier and faster than in a real environment. Moreover, the effectiveness, robustness, and stability of the developed controller can be ensured before being applied to real subject tests. However, a musculoskeletal model for FES control applications must be prepared in advance. Musculoskeletal models can be used to predict the behavior of the system being controlled. There are two types of stimulated skeletal muscle models most commonly used for FES control applications, namely Hammerstein and Hill muscle models [17]. Both muscle models are empirical models where parameter values can be determined based on the response characteristics of the stimulated musculoskeletal system of a real subject [23], [32].

In this study, the MPC-FES controller would be tested to control the 1-DOF wrist joint movement through computer simulation. Therefore, the development of the musculoskeletal model of human arm for FES control along with the method of measuring the static and dynamic responses of the stimulated muscles of healthy subjects are described first in this chapter. Then, to confirm that the human arm musculoskeletal model is feasible to be used for computer simulation studies, a validation test was conducted by applying the FES controller that has been developed

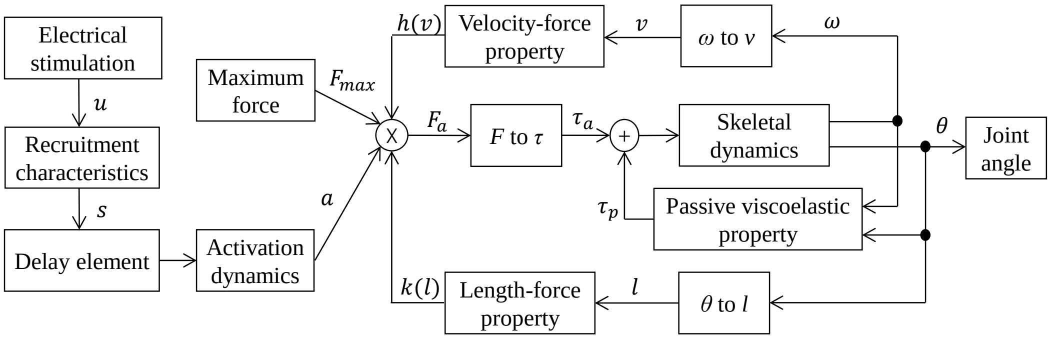


Figure 2.2: Block diagram of the musculoskeletal model for FES.

in previous studies where the FES controller was realized using a PID controller and has been tested to control the wrist joint movement of healthy subjects [16] and hemiplegic patients [18]. In the next section, the design flow of the proposed controller is presented.

2.2 Musculoskeletal model for FES control

2.2.1 Musculoskeletal model of human arm

The musculoskeletal model of the human arm for FES control used in this computer simulation study was adopted from Watanabe et al. [23], which was used to predict the joint movements developed by the electrical stimulation. The controller would be tested to control the palmar flexion movement of the wrist joint stimulating the flexor carpi radialis (FCR) muscle which was described by the Hill-type muscle model. The block diagram of the musculoskeletal model for FES control application is shown in Fig. 2.2. The electrical stimulation u delivered to the muscle limb will elicit muscle contraction (active force F_a) to generate active torque τ_a. The resultant of active torque τ_a and passive torque τ_p on limb joint then produce a limb movement θ. The active force F_a is determined by multiplication of muscle activation a, maximum force

F_{max}, length-force relationship $k(l)$, and velocity-force relationship $h(v)$ as described as follows,

$$F_a = aF_{max}k(l)h(v) \tag{2.1}$$

$$F_{max} = 2.2 \text{ PCSA} \tag{2.2}$$

where v and l are muscle contraction velocity and length, respectively. The maximum muscle force produced F_{max} was determined by PCSA (physiological cross sectional area) adopted from [33]. Stimulation intensity u delivered to the muscle was set 1.0 in normalized scale. Recruitment characteristic represents the relationship between recruited muscle fibers s and the stimulation intensity u was adopted from [34] as described as follows,

$$s(u) = u_c \tanh\big(u_h(u - x_c)\big) + y_c \tag{2.3}$$

where u_c, u_h, x_c, and y_c are constants. The first order differential equation was used to express the muscle activation dynamics a that represents the normalized active state of the muscle [35] which is described as follows,

$$\frac{da}{dt} = \frac{1}{t_r}(s(t-L) - a)(s(t-L) + \frac{1}{t_f}(s(t-L) - a) \tag{2.4}$$

where t_r and t_f are time constants and were set to 20 ms and 200 ms, respectively [23]. The delay element L represent the delay time in response to electrical stimulation and the range values are 10-50 ms [17]. In this study, the delay L value for all subject models were set to 50 ms in order to approximate the latency and time constants of step response in healthy subject which were about 100 ms and 300 ms, respectively [23]. The activation dynamics equation then was integrated to determine the active state of the muscle.

The force-length property represents the relationship between the maximum force production through the range of lengthening and shortening of the muscle fiber. The force-velocity property represents the relationship between the maximum muscle force production and muscle contraction velocities during shortening and lengthening. The length-force relationship $k(l)$ and velocity-force relationship $h(v)$ were adopted from [36], [37] as described as follows,

$$k(l) = 1 - \left(\frac{l - l_o}{0.5l}\right)^2 \tag{2.5}$$

$$h(v) = \frac{v_{max} - v}{v_{max} + 2.5v} \qquad (v \leq 0 : \text{shorthening}), \tag{2.6}$$

$$h(v) = 1.3 - 0.3\,\frac{v_{max} + 2.5v}{v_{max} - 2.5^2 v} \qquad (v > 0 : \text{lengthening}) \tag{2.7}$$

where l_o is the optimum muscle length and the value was determined from [33]. v is the contraction velocity and v_{max} is the maximum contraction velocity whose value was determined from [38].

Active torque τ_a was obtained by multiplying the active force F_a and the moment arm $r_f(\theta)$ as follows,

$$\tau_a = F_a r_f(\theta) \tag{2.8}$$

where $r_f(\theta)$ was modeled by a polynomial equation as a function of joint angle θ for each movement developed by each muscle [33]. Passive torque τ_p is produced by the passive element around the limb joint. The passive torque for the joint movement was modeled as a damper and nonlinear spring adopted from [39] as described as follows,

$$\tau_p = k_0\theta + c_0\dot{\theta} + k_1(\exp(k_2\theta) - 1) \tag{2.9}$$

where θ and $\dot{\theta}$ were joint angle and angular velocity, respectively. Constants k_0, c_0, k_1, and k_2 were determined for each joint movement with some adjustments to generate the acceptable range of motion [23]. Each joint movement was considered a pendulum movement and the Lagrange method was used to derive the motion equation of skeletal dynamics. The parameter values of the skeletal model such as the length of the body segment, the mass of the body segment, and the moment of inertia of the body segment were taken from [23].

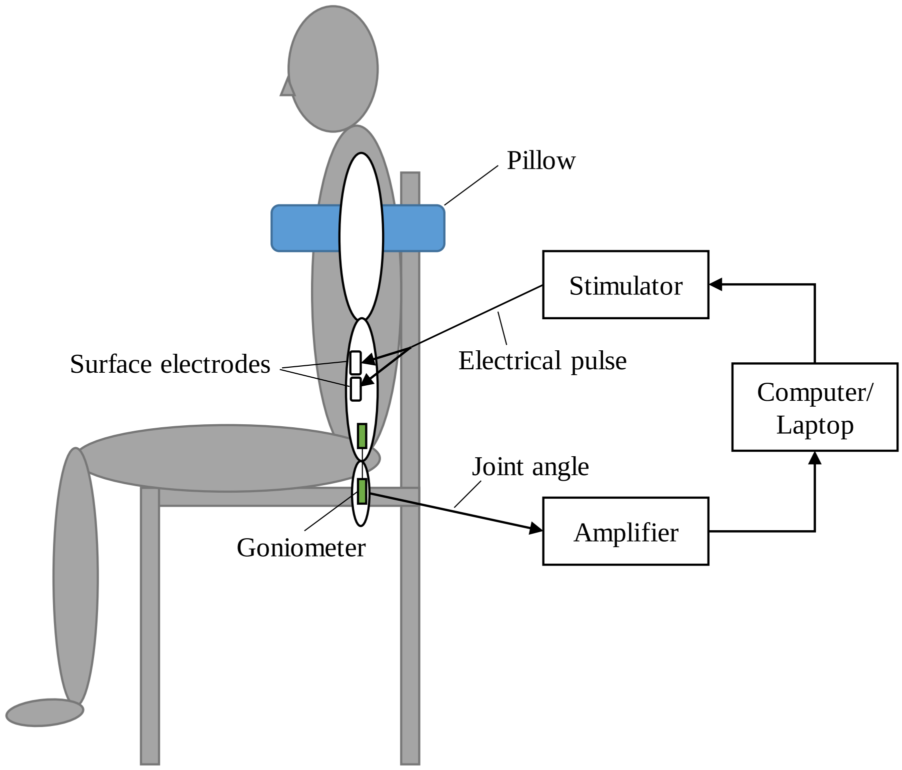


Figure 2.3: Experimental setup for measuring the static and dynamic responses of the stimulated musculoskeletal system of ten healthy subjects.

2.2.2 Development and validation of subject models

The capability of the proposed controller would be examined to control the palmar flexion movement of the wrist joint of sixteen subject models which were developed using the musculoskeletal model described in the previous section. Those subject models were divided into 10 reference subjects, 5 additional test subjects, and a paralyzed subject. Reference subject models were considered as references to create an average prediction model used in the MPC structure and a parameter estimation method for determining the value of the controller parameters. In order to obtain the reference subject models that have characteristics approximate to the real subjects, we measured the static and dynamic responses of the stimulated musculoskeletal system of ten healthy subjects and used the response characteristics to identify the values of model parameters of the reference subject models by using the same identification protocol as the previous study [23]. The experimental setup for measuring the static and dynamic responses of the stimulated musculoskeletal system of ten healthy subjects is shown in Fig. 2.3 where the subject was asked to sit on a chair and relaxed his left arm during measurement. The pillow was used in armpit as a support the left arm of the subject so that the wrist joint can move freely without making contact with the body of the subject. The measurement of the palmar flexion movement of the wrist joint was performed with the neutral position of the forearm and the initial position of the hand was in the direction of gravity as shown in Fig. 2.3. The stimulated muscle was the flexor carpi radialis (FCR). The purpose and procedure of the experiment were explained in advance to each subject and the subject's consent was obtained. This experiment was carried out based on the code of ethics for human experiments issued by the ethics committee of the Graduate School of Engineering, Tohoku University.

The measurement system consisted of a computer, a stimulator device, and an amplifier device. The output of the stimulator device is an electrical stimulation pulse train with the specification of a pulse frequency of 20 Hz, and a pulse width of 0.2 ms and the amplitude of electrical stimulation was adjusted by the computer. The electrical stimulation was applied to the FCR muscle of each subject through Ag/AgCl surface electrodes. The joint angle of the wrist joint was measured with a two-axis electric goniometer where the output was amplified using the amplifier device. In order to measure the static and dynamic responses of the stimulated muscle of each healthy subject, the first step was to determine the minimum and maximum intensity of the electrical stimulation allowed for each subject. The minimum stimulus intensity is defined as the minimum value that causes a movement above 1 deg and the maximum stimulus intensity is defined as the maximum value that causes maximum deviation of wrist joint angle without any pain felt by the subject as an impact of the electrical stimulation. The second step was measuring the static response of the stimulated muscle by applying a ramp stimulation pattern where the electrical stimulation intensity was increased gradually from the minimum intensity with an increment each second of 0.05% of the maximum intensity of each subject with a stimulation time of 20 s. The static response of the stimulated muscle was considered as an input-output relationship of the stimulated muscle of each subject. An example of the static response

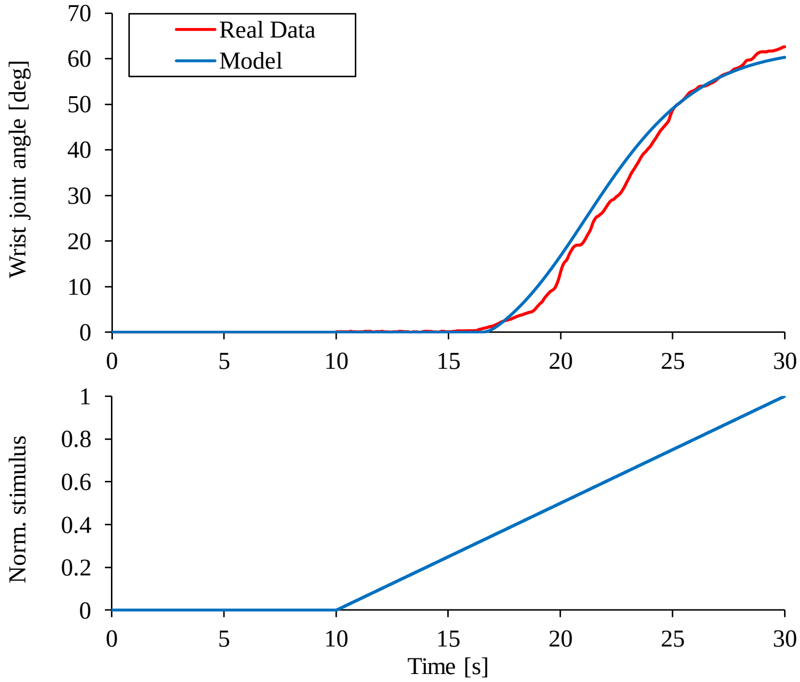


Figure 2.4: An example of the static response of stimulated muscle of healthy subject S6 (red line) and its result of the fitting process to develop subject model S6 (blue line).

of the stimulated muscle and the fitting process to develop the subject model S6 is shown in Fig. 2.4. The red line of the wrist joint angle curve is the static response of the stimulated musculoskeletal system measured from the healthy subject S6. The blue line of the wrist joint angle curve is the static response of the stimulated musculoskeletal system that showed the subject model of S6 as a result of the fitting process. The input-output relationship of reference subject models developed from 10 healthy subjects showed strong nonlinear responses with differences in slopes, range of stimulation intensities, and range of motions as shown in Fig. 2.5.

Six test subject models were considered for evaluating the effectiveness of the proposed controller where these subject models were not included in making the average prediction model used in the MPC scheme and the parameter estimation method. The test subject models were developed by changing the values of the recruitment property of the electrically stimulated muscle of the reference subject S4 in order to obtain different characteristics from reference subjects. The input-output

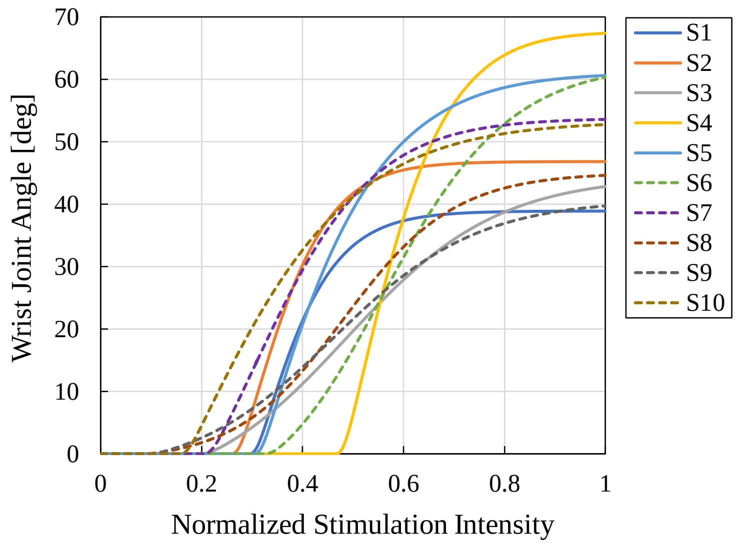


Figure 2.5: Input-output characteristics of stimulated musculoskeletal system of reference subjects.

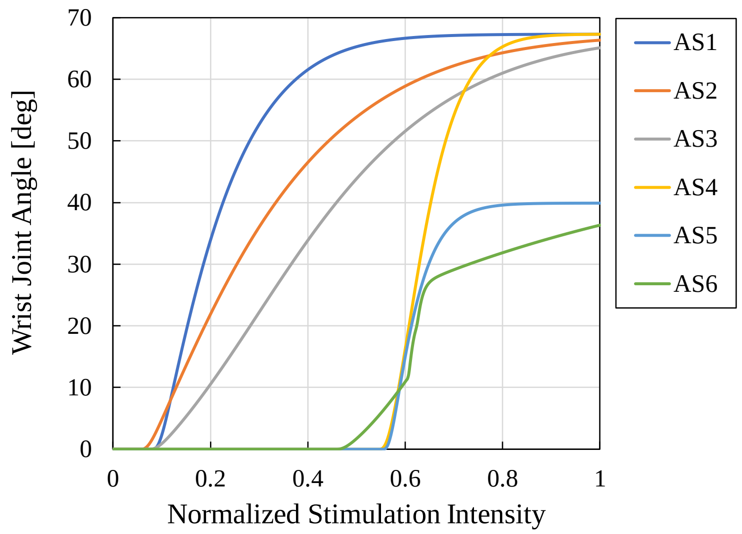


Figure 2.6: Input-output characteristics of stimulated musculoskeletal system of additional test subjects.

characteristics of stimulated musculoskeletal system of additional test subjects are shown in Fig. 2.6. The static characteristic response of the paralyzed subject model is shown by AS6, which was developed to mimic the characteristic response of the

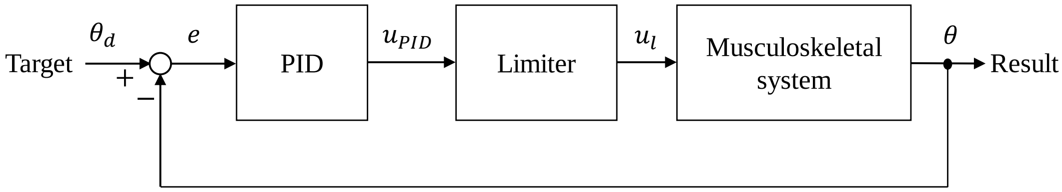


Figure 2.7: Block diagram of the PID controller used for the validation test of the developed subject models.

hemiplegic patient in the previous study [18]. The stimulated paralyzed muscle shows steep response in the input-output characteristic and has a small range of motion that causes it very difficult to be controlled using FES. The sampling frequency used to simulate the musculoskeletal model was 1 kHz. The stimulation frequency was 20 Hz which was chosen with reference to actual conditions in practical FES applications [16], [18].

The validation test was performed by testing the PID controller used in previous studies [16], [18], [21] in controlling the wrist joint movement of the developed subject models described in the previous section. The block diagram of the PID controller used for the validation test is shown in Fig. 2.7. The limiter was included to prevent the musculoskeletal system from overstimulation. The algorithm of the PID controller and its parameter determination method are described as follows,

$$u_{PID}(n) = K_P e(n) + K_I \sum_{i=0}^{n} e_i + K_D(e(n) - e(n-1)) \tag{2.10}$$

where u_{PID} is the electrical stimulation intensity as the output of the PID controller at time n, and e is error between the target trajectory movement (θ_d) and the controlled movement (θ). K_P, K_I, and K_D are the PID controller parameters that were determined using the CHR method [18] as follows,

$$K_P = \frac{0.6T}{KL}, \quad K_I = \frac{0.6\Delta t}{KL}, \quad K_D = \frac{0.3T}{K\Delta t} \tag{2.11}$$

where K is the steady-state gain of the controlled object that was determined based on

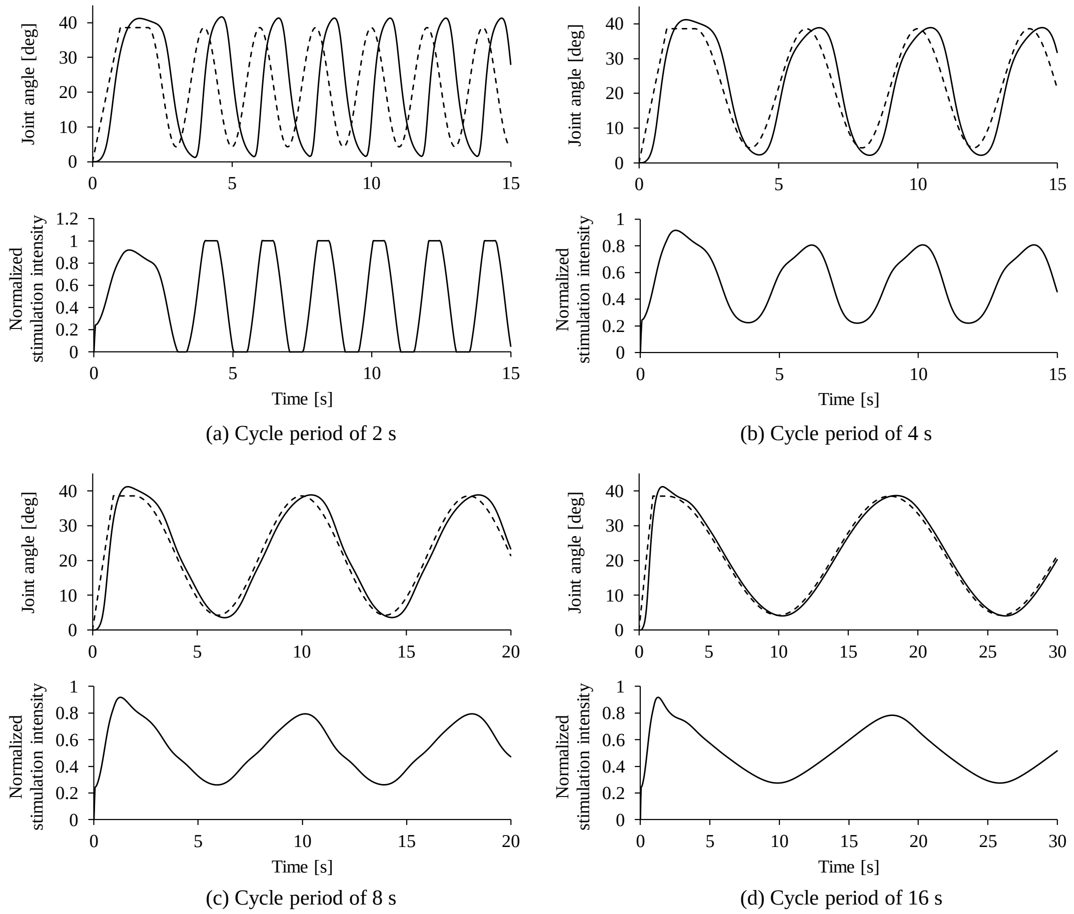


Figure 2.8: An example of control result of the PID controller in controlling the wrist joint movement of subject model S3 with different speed of movement which were 2 s, 4 s, 8 s and 16 s.

the input-output relationship of the stimulated musculoskeletal system. Δt is the sampling interval for the PID controller that was 50 ms. L and T are the latency and the time constants calculated from the step (dynamic) response of each subject model.

An example of a control result is shown in Fig. 2.8 where the PID controller was used to control the wrist joint movement of subject model S3 with different speeds of movement which were 2 s, 4 s, 8 s, and 16 s. It was confirmed that the control response for different speeds of movement had a similar result to the experimental tests in previous studies [16], [21]. The PID controller only worked well in controlling the wrist joint movement of S3 with very slow movement (cycle period of 16 s) as shown

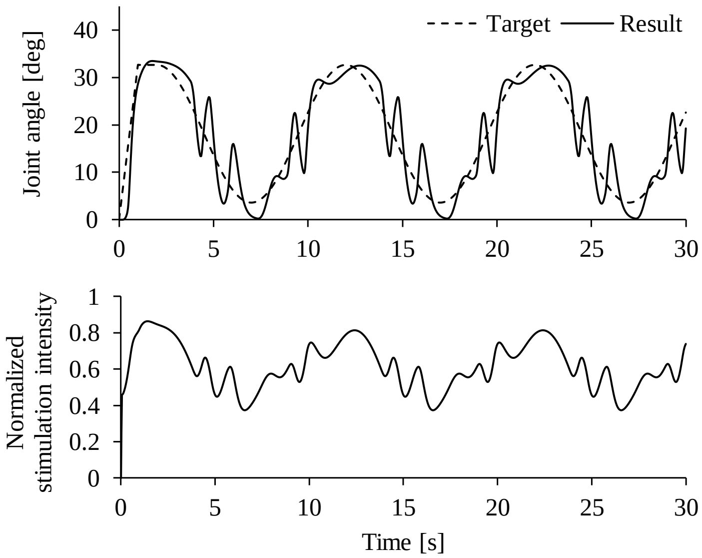


Figure 2.9: An example of control result of the PID controller in controlling the wrist joint movement of paralyzed subject model AS6 for slow movement with a cycle period of 10 s as used in the previous study [18].

in Fig. 2.8(d). When the PID controller was tested for controlling the faster movement, the delay time in the control response was getting larger. The control result became worst when it was applied to control fast movement as shown in Fig. 2.8(a) which indicated the PID controller could not solve the delay problem of stimulated muscle by FES [16].

An example of the control result of the PID controller in controlling the wrist joint movement of the paralyzed subject model AS6 with slow movement (cycle period of 10 s was used as in the previous study [18]) is shown in Fig. 2.9. The control response of the PID controller in controlling the wrist joint movement of the paralyzed subject model showed the oscillating response which had a similar response to the experimental test in the previous study [18]. The oscillating response occurred because the paralyzed subject model had a steep response of stimulated muscle and a small range of motion made the PID controller was difficult to produce the proper stimulation intensity. The controls result in the previous study [18] had a smoother response than in this study since they used 4 stimulated muscles to control the 2-DoF of the wrist joint movement of a hemiplegic patient. This result strengthens the validation test that the subject models developed in this study could approximate the response characteristic of the stimulated muscle of real subjects. Based on the result of validation tests, we considered and suggested that the subject models could be used to design and test the FES controller through a computer simulation. Therefore, the sixteen subject models would be used to test the FES controller proposed in this study.

2.3 Model predictive control

Model Predictive Control (MPC) is an optimal control technique that has been successfully used in industrial over two decades [39]. The reason for this success is the capability of MPC to produce high performance control systems capable of operating for long periods of time. However, there are some challenges in developing the robust MPC for many control applications including how to model process of system and how to design the linear MPC to solve the nonlinear system [40]-[42]. Some studies have utilized the MPC for the FES control applications [24]-[26], [43]-[62]. As mention in previous chapter, although some MPC-FES controllers developed in previous studies have a promising result, they were not implemented in clinical sites because of some issues regarding how to design the accurate model of system and how to decrease the computational load of optimization process of MPC. Therefore, in order to address above problems, the FES controller in this study was developed using a combination of linear MPC and nonlinear transformation.

In the linear MPC scheme as shown in Fig. 2.1, the output was the electrical stimulation intensity u as the result of the optimization process computed at time instance k by minimizing a cost function subject to a prediction model of the musculoskeletal system. In order to obtain a simple formulation with an analytic solution, the linear MPC with no active constraints imposed on the structure [27], [28]. The first step in designing the linear MPC is to define the cost function in order to solve the control problem. In this study, the quadratic cost function J was used as expressed as follows,

$$J = \sum_{j=1}^{N_p} (\theta_d(k+j) - \theta(k+j|k))^2 + \sum_{j=1}^{N_c} \lambda\big(\Delta u(k+j-1)\big)^2 \tag{2.12}$$

and in the vectors forms,

$$\mathbf{J} = (\boldsymbol{\theta}_\mathbf{d} - \boldsymbol{\theta})^T (\boldsymbol{\theta}_\mathbf{d} - \boldsymbol{\theta}) + \boldsymbol{\Delta}\mathbf{U}^T \lambda \boldsymbol{\Delta}\mathbf{U} \tag{2.13}$$

where $\boldsymbol{\theta}_\mathbf{d}$ is a vector of the target trajectory movements $\theta_d\ (k)$ that has the same dimension as the predicted output variable $\boldsymbol{\theta}$. N_P and N_C are the prediction horizon and the control horizon, respectively. Δu is the change of control action in form of the change of electrical stimulation intensity used to calculate the electrical stimulation intensity u that will be fed to the nonlinear transformation. An incremental method of the electrical stimulation intensity ($u(k) = u(k\text{-}1) + \Delta u(k)$) was applied to obtain a zero offset of steady-state error [28]. λ is a tuning parameter to obtain the optimized control action and desired tracking control performance of MPC and its value must be set greater than zero to acquire the stability of closed-loop performance [27], [28]. In cost function, not only the current values but also the predicted values of the controlled system are required to be minimized in order to acquire the optimized control action. Therefore, the model of the system is required to calculate the predicted values.

The second step in designing the linear MPC is to develop the prediction model to represent the dynamic behavior of the system, that is the stimulated musculoskeletal system. In this study, the prediction model was realized by an average model created using the average value of step responses of ten reference subjects' models as mentioned in the previous section. The purpose of using the average model instead of the nominal model was to eliminate the modeling and its parameter identification process for a new subject in practical application thus decreasing time-consuming at the beginning of the experimental setup. The design flow of the average model is shown in Fig. 2.10. In order to obtain the dynamic behavior of the stimulated muscle, the step input of stimulation intensity was applied to the FCR muscle of each reference subject model was set to 50% of maximum stimulation intensity and its step response model was measured. Then, by averaging those step responses, the average step response that will be used to make the average prediction model was obtained as shown in Fig. 2.11.

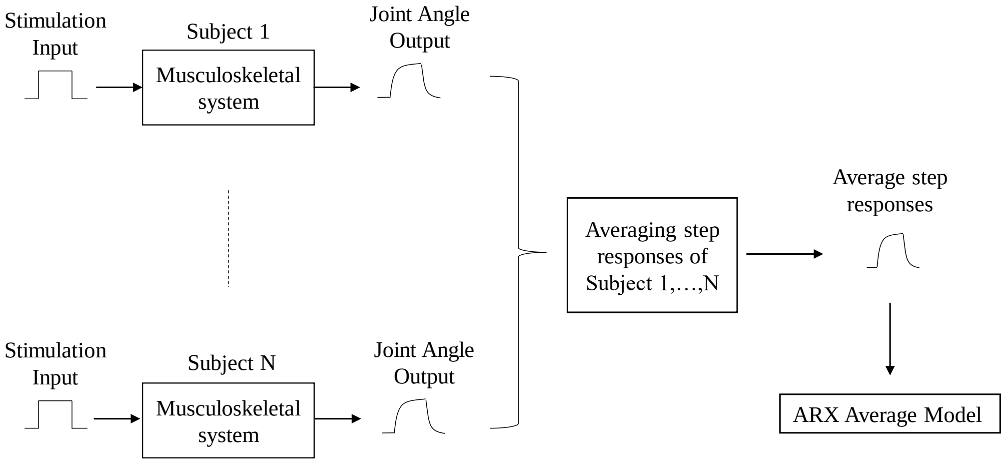


Figure 2.10: Design flow of the average model.

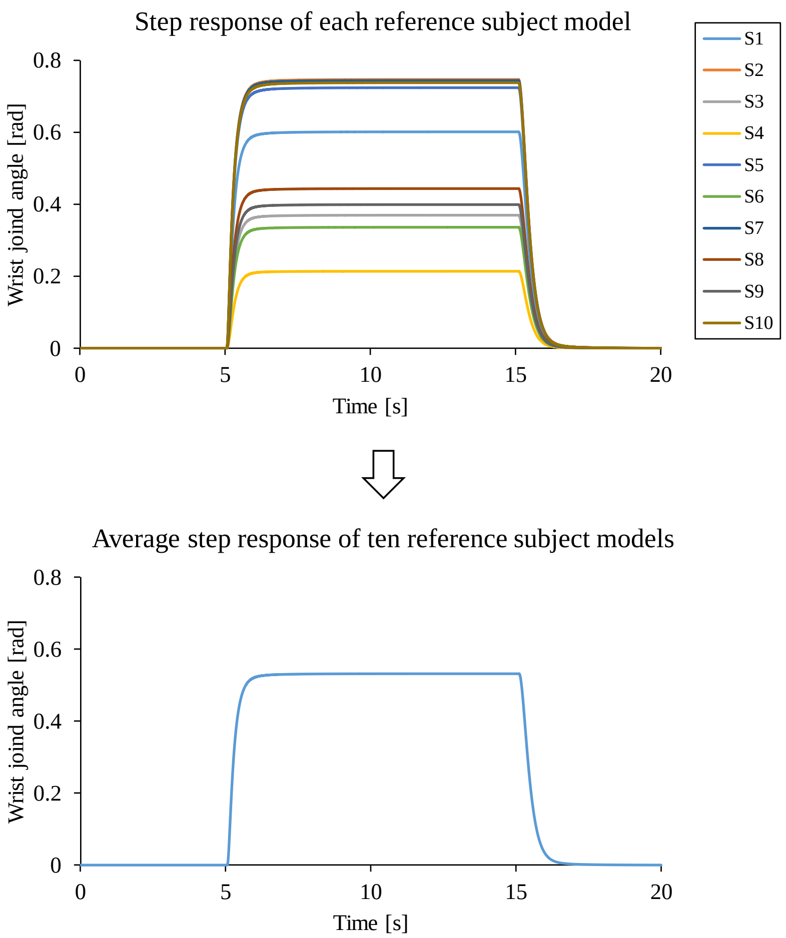


Figure 2.11: Average step response for creating the average prediction model.

The average step response was modeled based on the autoregressive with exogenous input (ARX) structure model and its model parameters were identified using the system identification toolbox 9.13, MATLAB ver. R2020b. The transfer function model that represents the average ARX model is expressed as follows,

$$\frac{\theta(z)}{U(z)} = \frac{-4.6711e{-}05\ z^{-1} + 4.8991{-}05\ z^{-2}}{1 - 2.2171\ z^{-1} + 0.7145\ z^{-2} + 1.2229\ z^{-3} - 0.7204\ z^{-4}} \tag{2.14}$$

where θ is the wrist joint output of the average model in radian and u is the input electrical stimulation in normalized scale. In this study, the transfer function model then was converted to the state-space model in order to make it easier in calculating the predicted output values and the state-space representation is a better choice if the linear MPC would be developed to deal with the MIMO system. The state-space representation of the average ARX model is expressed as follows,

$$x_p(k+1) = \mathbf{A_p} x_p(k) + \mathbf{B_p} u(k) \tag{2.15}$$

$$\theta(k) = \mathbf{C_p} x_p(k) \tag{2.16}$$

$$\mathbf{A_p} = \begin{bmatrix} 2.2171 & -0.7145 & -1.2229 & 0.7204 \\ 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}, \qquad \mathbf{B_p} = \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \end{bmatrix},$$

$$\mathbf{C_p} = [0 \quad 0 \quad -4.6714e-05 \quad 4.8991e-05]$$

Here, x_p is a state variable. $\mathbf{A_p}$, $\mathbf{B_p}$, and $\mathbf{C_p}$ are the matrices of the average ARX model. The state-space representation of the average ARX model expressed by Eq. (2.15)-(2.16) could not be used directly in MPC structure since the incremental method of the electrical stimulation intensity was used. Therefore, the state-space representation of the average ARX model needs to be expanded to the augmented state-space model [27] in advance before imposed on the MPC structure. The augmented state-space model is express as follows,

$$\mathbf{x}(k+1) = \mathbf{A}\mathbf{x}(k) + \mathbf{B}\Delta u(k) \tag{2.17}$$

$$\theta(k) = \mathbf{C}\mathbf{x}(k) \tag{2.18}$$

$$\mathbf{A} = \begin{bmatrix} 2.2171 & -0.7145 & -1.2229 & 0.7204 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & -4.6714e-05 & 4.8993e-05 & 0 & 1 \end{bmatrix}, \quad \mathbf{B} = \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix},$$

$$\mathbf{C} = \begin{bmatrix} 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

Here, $\mathbf{x}$ is the state variable vector, θ is the output variable at time instance k. and $\mathbf{A}$, $\mathbf{B}$, $\mathbf{C}$ are matrices of the augmented state-space model. The predicted output variables $\boldsymbol{\theta}$ and the future control movement $\boldsymbol{\Delta}\mathbf{U}$ vectors are described as follows:

$$\boldsymbol{\theta} = [\theta(k+1\,|\,k)\ \ \theta(k+2\,|\,k)\ \cdots \theta(k+N_p\,|\,k)]^T \tag{2.19}$$

$$\boldsymbol{\Delta}\mathbf{U} = [\Delta u(k)\ \ \Delta u(k+1) \cdots \Delta u(k+N_C-1)]^T \tag{2.20}$$

where N_P and N_C are the prediction horizon and the control horizon, respectively.

The control sequence $\boldsymbol{\Delta}\mathbf{U}$ was calculated by minimizing the cost function $\mathbf{J}$ in Eq. 2.13 as follows,

$$\boldsymbol{\Delta}\mathbf{U} = (\boldsymbol{\Phi}^T\boldsymbol{\Phi} + \lambda\mathbf{I})^{-1}\boldsymbol{\Phi}^T(\boldsymbol{\theta}_\mathbf{d} - \mathbf{F}\mathbf{x}(k)) \tag{2.21}$$

where $\mathbf{F}$ and $\boldsymbol{\Phi}$ are matrices of the predicted state variables $\mathbf{x}$ and the future of control movements $\boldsymbol{\Delta}\mathbf{U}$, respectively. Based on a receding horizon strategy [28], the output of MPC is only the first element $\Delta u(k)$ of the control sequence $\boldsymbol{\Delta}\mathbf{U}$ used for calculating the control action $u(k)$ which is then fed to the nonlinear transformation.

2.4 Nonlinear transformation

In cascaded with linear MPC, a nonlinear transformation was used to map the output of linear MPC as a linear solution to obtain a nonlinear solution. This approach was inspired by the perceptron in dealing with nonlinear problems where the nonlinearity of the data can be modeled with a linear combiner and the output of the perceptron is determined by taking the value of the nonlinear transformation. In this study, 4 types of nonlinear functions were tested in order to explore the possibility of using a different nonlinear function in cascading with the linear MPC to deal with a nonlinear system. Those nonlinear functions were the parametric rectified linear unit (PReLU) function, the hyperbolic tangent (Tanh) function, the binary sigmoid (BS) function, and the polynomial function (Poly). The PReLU function was considered to realize the nonlinear transformation because the input-output characteristics of the musculoskeletal system show a logistic curve with a wide range of linear regions that determines the slope of the curve. The Tanh and BS functions were considered because the logistic curve can be generated with these functions. The Poly function was considered in order to utilize the curve of input-output characteristic of the musculoskeletal system of each subject explicitly as the nonlinear transformation. The wrist joint angle was normalized by its maximum value before being modeled by using the polynomial function.

The mathematical expressions of the PReLU, Tanh, BS, and Poly functions are shown as follows,

$$u_t = f_1(u) = \begin{cases} \alpha_1(u-u_{\min}) & \text{for} \quad u-u_{\min} \geq 0 \\ 0 & \text{otherwise} \end{cases} \tag{2.18}$$

$$u_t = f_2(u) = \begin{cases} \tanh(\alpha_2(u-u_{\min})) & \text{for} \quad u-u_{\min} \geq 0 \\ 0 & \text{otherwise} \end{cases} \tag{2.19}$$

$$u_t = f_3(u) = \begin{cases} \dfrac{1}{1+e^{-\alpha_3(u-u_{\min})}} & \text{for} \quad u-u_{\min} \geq 0 \\ 0 & \text{otherwise} \end{cases} \tag{2.20}$$

$$u_t = f_4(u) = \begin{cases} \sum_{i=0}^{6} b_i(\alpha_4(u-u_{\min}))^i & \text{for} \quad u-u_{\min} \geq 0 \\ 0 & \text{otherwise} \end{cases} \tag{2.21}$$

Here, u and u_t are the input and output of the nonlinear transformation, respectively. $\alpha_1 \sim \alpha_4$ are the slope parameters of each nonlinear function. u_{min} is the minimum electrical stimulation intensity that is required to produce the wrist joint movement.

The minimum stimulation intensity was imposed on the nonlinear function to reduce the delay error in the control responses. $b_0 \sim b_6$ are the polynomial coefficients that have different values for each subject model. The output of the nonlinear transformation was set equal to zero when the difference value of input u and the minimum stimulation u_{min} was smaller than zero because only the positive value of the stimulation intensity is effective for practical FES application [16], [21].

The output of linear MPC tends to have a larger value than the maximum stimulation intensity when it was used to control a wide range of motion because there was no active constraint imposed on the MPC. In addition, only the Tanh and BS functions were capable to avoid overstimulation since both functions are bounded functions. Therefore, the limiter was used in cascading with the musculoskeletal system to prevent the overstimulation during the controlling process of a limb joint movement when the PReLU or Poly function was applied to realize the nonlinear transformation. The upper and lower bounds of the stimulation intensity of the limiter were determined based on the range of stimulation intensity allowed for each subject.

2.5 Chapter summary

The model of the electrically stimulated musculoskeletal system is an essential element for the computer simulation study of FES controller development. The musculoskeletal model of the wrist joint for FES control application was designed and presented in this chapter. Ten subject models were developed based on the static and dynamic response of the stimulated musculoskeletal system of healthy subjects. These subject models were considered reference subjects for making the average model used in the MPC structure and for developing the estimation formula to determine the controller parameter. Five additional test subject models and a paralyzed subject model were also prepared for testing purposes. In addition, the validation tests of developed subject models were conducted, and the same characteristics as those observed in the PID control tests in the previous studies were confirmed by computer simulations. This is a useful result that demonstrates the validity of the computer simulation tests used in this thesis.

The FES controller for tracking control application was designed based on cascading the linear MPC and the nonlinear transformation. The linear MPC with no active constraints and the average model was considered to realize the FES controller in order to obtain a simple design and a few parameter adjustments. The developed controller was expected to solve the nonlinear systems such as wrist joint movement controlled by FES.

Chapter 3

Preliminary Test of MPC-FES Controller in Wrist Joint Control

3.1 Introduction

This chapter describes the evaluation method of the proposed FES controller based on cascading of the linear MPC with the nonlinear transformation. First, the proposed controller was tested to control the 1-DOF wrist joint movement with a small range of motion in order to explore the control capabilities of the designed controllers clearly. The purpose of the first test is to explore the effect of the use of the average prediction model used in the MPC scheme without the nonlinear transformation. In this test, we compare the tracking control performance of linear MPC when the prediction model was realized using the nominal model and average model. The second test was performed to compare the effect of the use of nonlinear transformation. In this case, the nonlinear transformation was realized using the PReLU function.

The next step was testing the tracking control capabilities of the proposed controller with 4 different types of nonlinear function to deal with different range of motions of wrist joint movements in order to explore the possibility using different nonlinear function to realize the nonlinear transformation. Control performance of the proposed controller was evaluated and discussed at the end of this chapter. The parameter values of the linear MPC and the nonlinear transformation were determined using manual adjustment. In this chapter, the proposed controller was evaluated in controlling wrist joint of healthy subject models only while evaluating for paralyzed subject model is presented in chapter 5.

3.2 Computer simulation test to evaluate the effectiveness of the average model used in linear MPC

3.2.1 Evaluation methods

The proposed FES controller was tested in controlling the 1-DOF wrist joint movement (palmar flexion) by stimulating the flexor carpi radialis (FCR) muscle for repetitive movement with a small range of motion. For the first test, in order to compare the tracking control performance of linear MPC when the prediction model was realized using the nominal model and average model, the MPC was expected able to follow the target movement trajectory which was a sinusoidal pattern with a cycle period was 4 s and the desired range of motion was from 0 deg to a maximum deviation of 30 deg. The limiter to prevent overstimulation was not also applied in order to get knowledge of the range of stimulation intensity as the output of the linear MPC. Therefore, the control action in the form of the regulated stimulation intensity could be larger than the maximum stimulation allowed for each subject model. For simulation purposes, five subject models (S1-S5) with different input-output characteristics of stimulated musculoskeletal system developed in chapter 1 were used in this test. The nominal model of each subject which used by linear MPC was obtained from the step response of its musculoskeletal system. From the step responses of five subject models then were averaged to obtained the average step response which would be used to develop the average model.

The tracking control performance was evaluated by calculating the mean absolute error (MAE) as expressed as follows,

$$MAE = \frac{1}{K}\sum_{K}\left|\theta_d(k) - \theta(k)\right| \quad \text{[deg]} \tag{3.1}$$

Here, K, θ_d, and θ represent the number of sampled data, target trajectory movement, and controlled movement, respectively. The linear MPC has 3 tuning parameters: N_P, N_C, and λ since the nonlinear transformation was not used in this test. The response of the musculoskeletal system was influenced by time delay (latency) and sampling time

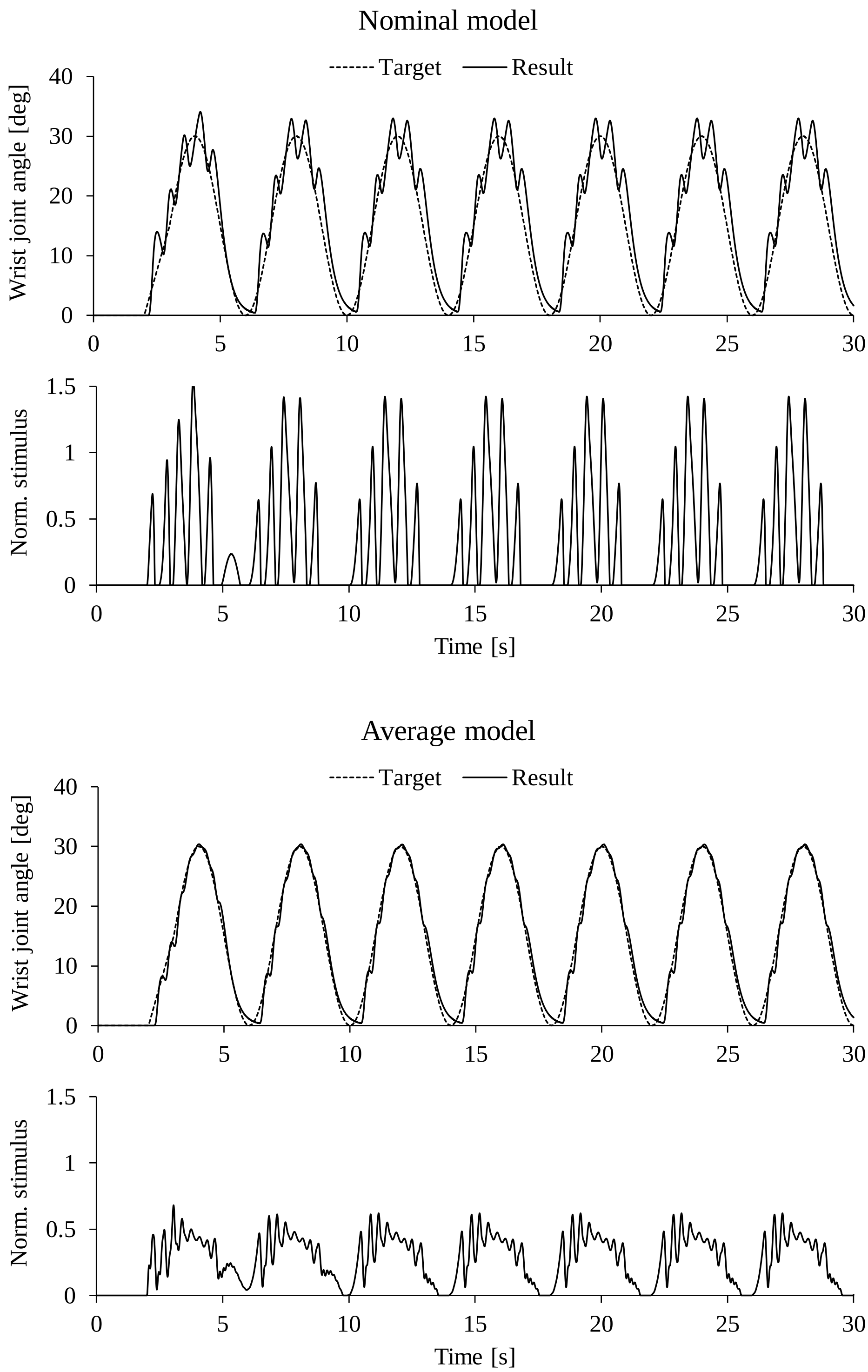


Figure 3.1: An example of the control results of the linear MPC with the nominal model (top) and the average model (bottom) applied in controlling the wrist joint angle in subject S1.

thus the parameters N_P and N_C was determined based on the ratio of time delay and sampling time. The value of λ was selected not too small since it used to suppress the aggressivity of control action. The value of N_P, N_C, and λ are 100, 1, and 1, respectively. The parameter's value of MPC was fixed for all trials.

3.2.2 Results and discussions

Figure 3.1 shows an example of the comparison of tracking control performance of linear MPC with the prediction model realized using the nominal and the average models applied in controlling wrist joint movement of subject S1. From the control result, the linear MPC could track the input trajectory for both models with small errors. However, the control response of the linear MPC with the average model had a better response than using the nominal model in subject S1. When the nominal model was used, the control result had a large oscillating response in the stimulation intensity and it tends to be larger than its maximum values when the target movement reached above 20 deg. The oscillating might be caused by the constraint was not considered to be imposed to the MPC structure [64].

The comparison of MPC performance for five subject models by using the evaluation index of MAE is shown in Fig. 3.2. The linear MPC with the average model had smaller values of MAE than by using the nominal model for subjects S1, S2, and S3 and had larger values of MAE than by using the nominal model for subjects S4 and S5. However, the different values of MAE for subjects S4 and S5 between the average model and the nominal model were not significant. The linear MPC was still able to track the given input trajectory with a small tracking error although not using a very accurate model. This result indicated that the average model could be used in the linear MPC structure and is still feasible to be considered for the realization of the MPC-FES controller [64], [65]. We also evaluated the effect of different values of N_P which were 51, 100, 200, and 300 where the other parameter values were the same. The comparison of the linear MPC performance for different values of prediction horizon, N_P where the MAE values were calculated for five subject models is shown in Fig. 3.3. Based on the result, it seems that the linear MPC performance depends on the values

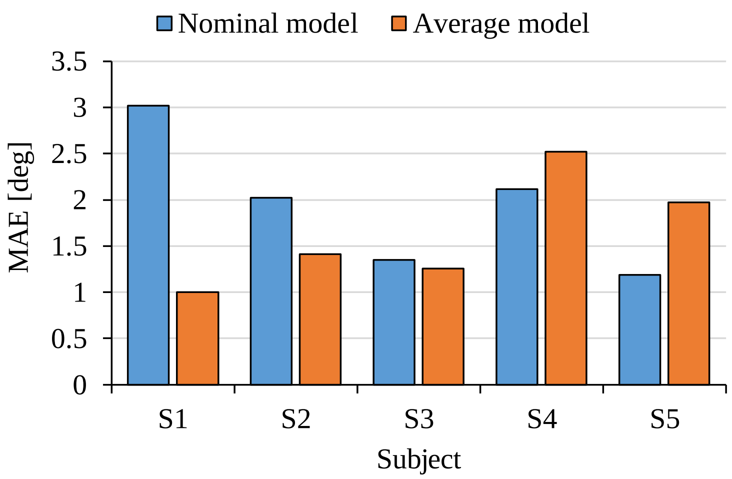


Figure 3.2: Comparison of the linear MPC performance with the nominal model and the average model for five subject models by using the evaluation index of MAE.

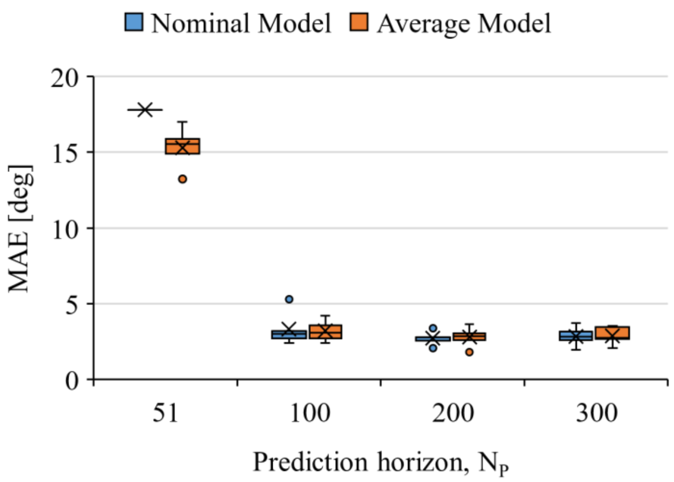


Figure 3.3: Comparison of the linear MPC performance for different values of prediction horizon, N_P. The MAE values were calculated for five subject models.

of N_P. When we set the N_P with a large value of about 200-300 then the tracking performance was improved, however, the time lag of output response increased as N_P increased. When the value of N_P with a small value of about 51 then the tracking performance was very poor which shows the linear MPC could not follow the input trajectory. However, this result also shows that the average model still worked properly

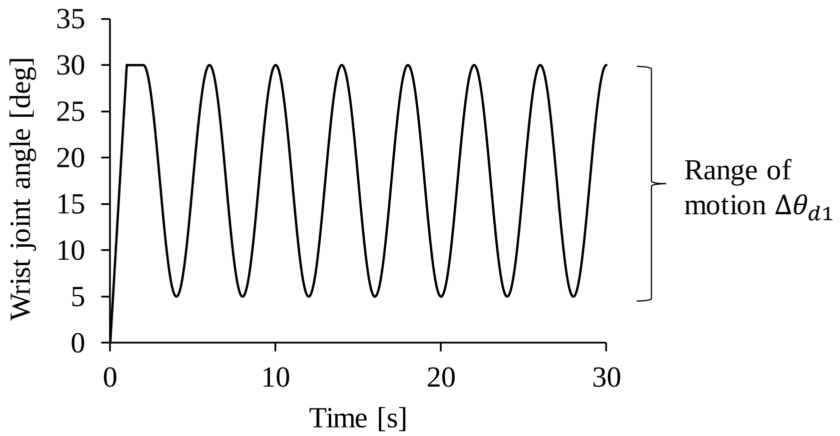


Figure 3.4: Definition of target movement trajectory for small ranges of motion of target movement trajectory.

although the parameter values of the linear MPC were changed [64]. The average prediction model used in the linear MPC was considered to be useful for eliminating the identification process of a new user and may possibly reduce the time-consuming at the initial setup of the rehabilitation process using FES. Indeed, to strengthen the conclusion, we need to develop and test the average model with more subjects as will be presented in the next section.

3.3 Computer simulation test with small range of motion

3.3.1 Evaluation methods

In this section, the proposed FES controller would be tested in controlling the 1-DOF wrist joint movement by stimulating the FCR muscle for repetitive movement with small range of motion (target θ_{d1}) where the range of motion was set from 5 deg to 30 deg. The minimum target angle was changed because in the previous simulation test, the linear MPC was difficult to track the small target angle below 5 deg since we only used a single stimulated muscle to generate the wrist joint movement. The sinusoidal pattern with a cycle period of 4 s shown in Fig. 3.4 was considered as the target movement trajectory. At the beginning of the movement trajectory, a

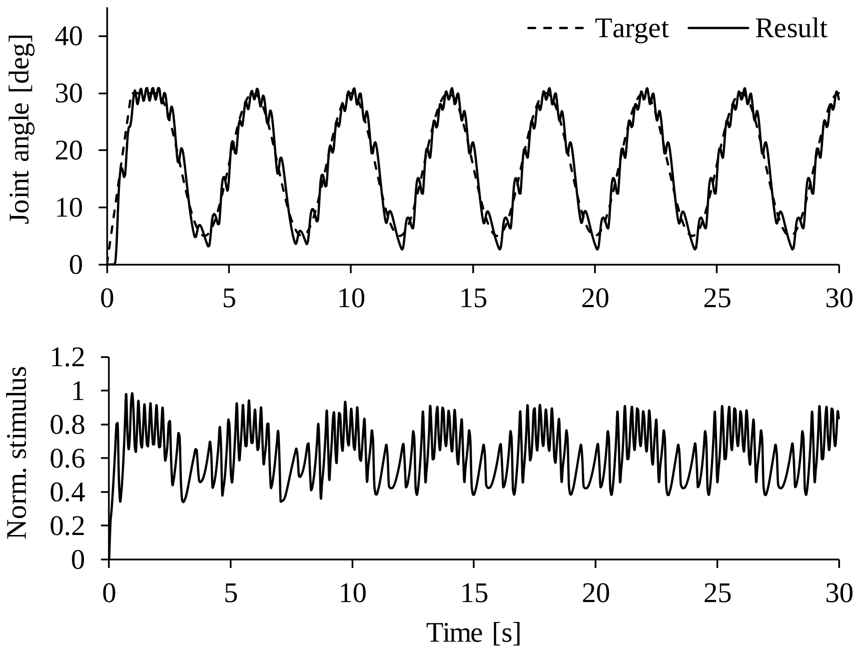
Table 3.1: Optimum values of α of PReLU function and minimum stimulation u_{min} of each subject model.

Subject	Optimum value of α of PReLU function	Minimum Stimulation
S1	0.55	0.31
S2	0.45	0.27
S3	1.35	0.24
S4	0.30	0.48
S5	0.45	0.32
S6	0.75	0.35
S7	0.65	0.22
S8	1.10	0.17
S9	1.60	0.15
S10	0.70	0.18
AS1	0.30	0.09
AS2	0.65	0.08
AS3	0.90	0.10
AS4	0.20	0.56
AS5	0.30	0.57

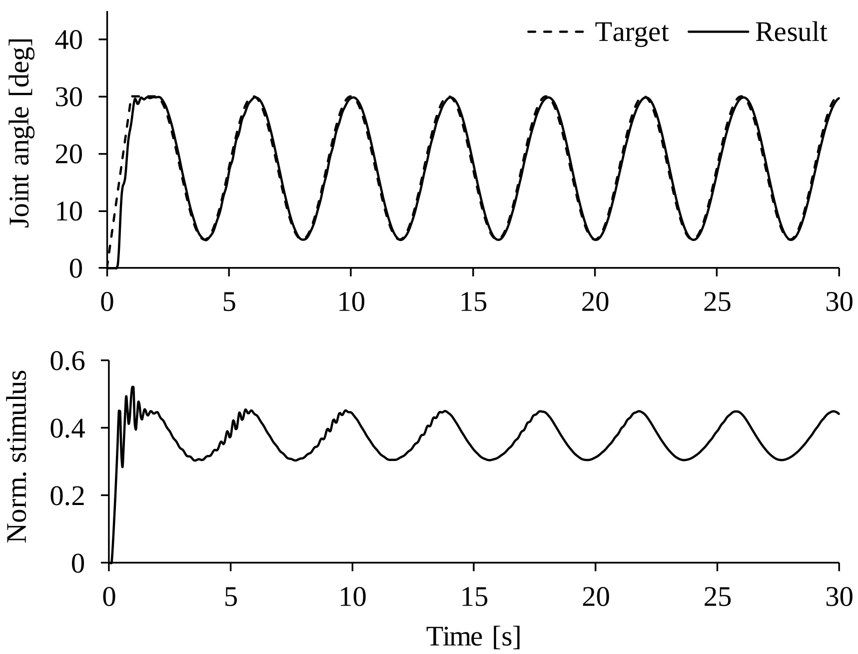
combination of a ramp pattern 1 s and a constant value of 1 s was used in order to make it easy in changing the range of motion and frequency of the sinusoidal pattern. The evaluation method of this test was almost similar with the previous section but the FES controller was realized using a combination of the linear MPC with the PReLU function and we increased the number of reference subject models and additional tested models. The ten reference and five additional test subject models as presented in previous chapter were used to test the control capability of the proposed controller. The tracking control performance was evaluated by calculating the mean absolute error (MAE) for time intervals 2-30 s as expressed by Eq (3.1). The MPC-FES controller has four tuning parameters: N_P, N_C, λ, and α. Parameter values of the MPC-FES controller were determined using the same method as in the previous section. The value of N_P, N_C, and λ was set to 80, 5, and 0.01, respectively. The value of N_P was set with a smaller value to make the optimization process faster. In this test, the parameter values of MPC were fixed for all control trials. The slope parameter value of α of PReLU function for each subject model was adjusted manually to acquire the appropriate value which shown by the smallest value of MAE. The optimum values of α of PReLU function and minimum stimulation u_{min} of each subject model are summarized in Table 3.1.

3.3.2 Results and discussions

Figure 3.5 shows an example of the comparison of tracking control ability between linear MPC without and with nonlinear transformation in regulating the wrist joint movement of subject S1 to follow the given target movement trajectory. In the example, the nonlinear transformation was realized using the PReLU function. Both combinations were able to follow the trajectory of the target movement. However, the linear MPC without nonlinear transformation had poor tracking performance which was indicated by large oscillation in the control response. The regulation of appropriate electrical stimulation intensity for the desired movement could not be acquired by only using the linear MPC and seems to be difficult in dealing with the musculoskeletal system in subjects with strong nonlinear responses and large latency such as subject S1. In addition, the utilization of the average model used in the linear MPC could not be used to obtain the predicted output that represents the expected behavior of the system being controlled because the average model is an inaccurate model [65]. This may one of the reasons why the linear MPC without nonlinear transformation had a poor tracking performance. Moreover, the value of N_P was set to 80 in this test smaller than used in the previous section which may cause a larger oscillation in the control response. However, this result strengthens the previous result that the average model could work whether developed using five or ten reference subject models. Therefore, we suggested the average model should be developed by using a large number of reference subject models that have different response characteristics of stimulated muscle to ensure that it could deal with the subject variation.



(a) Linear MPC without nonlinear transformation



(b) Linear MPC with nonlinear transformation

Figure 3.5: An example of control result by the linear MPC controller (a) without and (b) with nonlinear transformation of subject S1, respectively. The PReLU function was used to realize the nonlinear transformation.

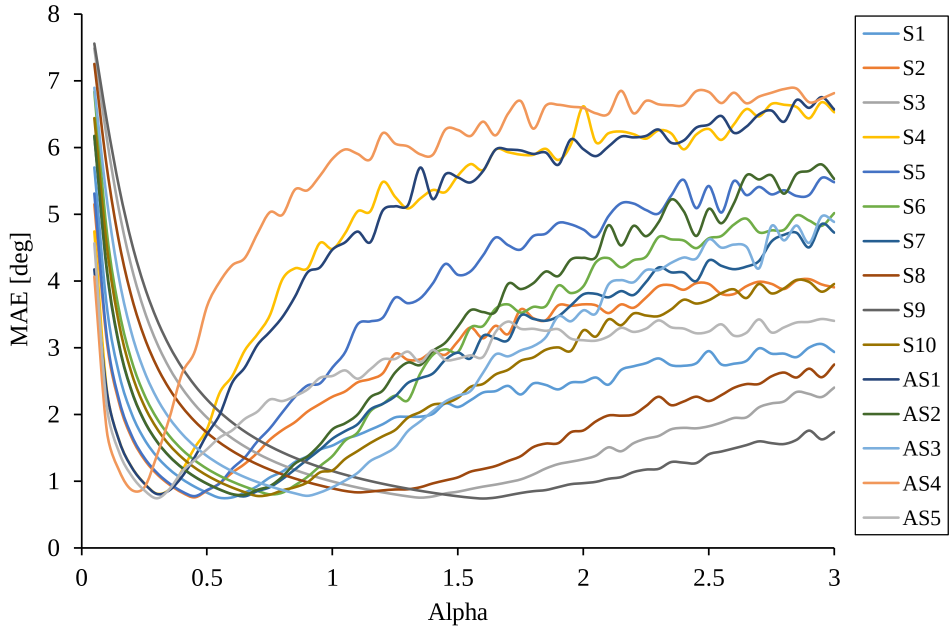


Figure 3.6: An example of the manual adjustment process to determine the appropriate value of α of PReLU function of each subject model. The MAE was calculated with the range of α from 0.05 to 3 with increment of 0.05.

The control result of the linear MPC with nonlinear transformation had promising tracking performance compared to using only the linear MPC where significant improvement could be obtained. This result indicates that the nonlinear transformation with an appropriate value of α could produce an appropriate electrical stimulation intensity for desired target movement. The nonlinear transformation could be considered as an important element of the proposed FES controller. The nonlinear transformation also could be considered a nonlinear gain for the output of linear MPC which amplified the control signal with the proper gain and this gain depends on the value of α. The optimum values shown in Table 3.1 were determined by evaluating the tracking control performance of the MPC-FES controller by changing the value of α for each control trial until the smallest value of MAE was achieved. Figure 3.6 shows the relationship between MAE and the value of α of the PReLU function. From this relationship, we could see that the slope parameter of nonlinear transformation has an optimum (unique) value of α for each subject model to achieve a good tracking control performance.

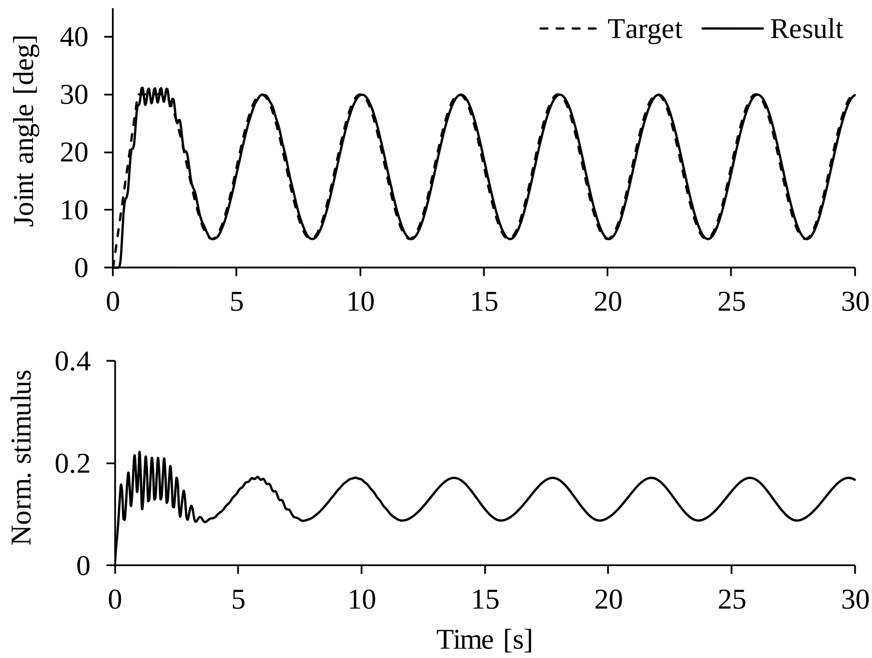


Figure 3.7: An example of control result by the MPC-FES controller tested in subject AS1. The PReLU function was used to realize the nonlinear transformation.

The tracking control performance of the proposed MPC-FES controller in additional test subject model AS1 is shown in Fig. 3.7. The MPC-FES controller also worked well in controlling the wrist joint movement of subject model AS1 although its step response was not included in creating the average model used in MPC structure. Based on the result, we suggested that the average model can be applied although the step responses of new subjects were excluded in the average model development. The proposed MPC-FES controller was still able to regulate an appropriate electrical stimulation for desired target movement although the average model imposed in the MPC was an inaccurate model. We considered that the utilization of the average model has the advantage to eliminate the modeling and its model parameter identification process of a new subject. Therefore, the time-consuming of the initial setup for practical FES application could be reduced significantly by using this method.

Figure 3.8 shows the comparison of the tracking control performance of the linear MPC without and with the nonlinear transformation for all subject models is shown in

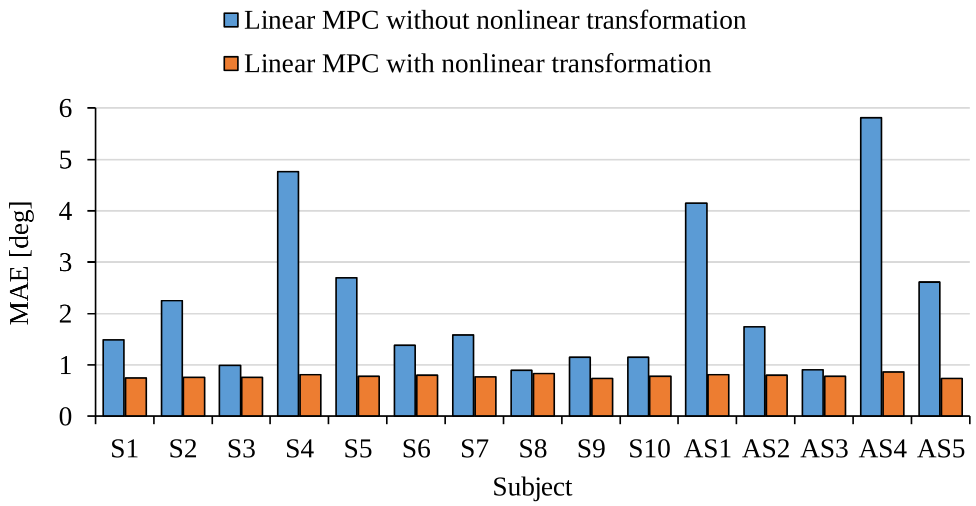


Figure 3.8: Comparison of tracking control performance of the linear MPC without and with nonlinear transformation for all subject models by using the evaluation index of MAE. The PReLU function was used to realize the nonlinear transformation.

Fig. 3.8. The linear MPC without nonlinear transformation shows large values of MAE larger than 4 deg for subjects with a highly nonlinear response characteristic with large slopes such as subjects S4, AS1, and AS4, which indicated the controller could not work well. It might be caused the range of stimulation intensity in those subjects was too narrow, thus the controller was difficult to regulate the appropriate value. On the other hand, for subjects with a low nonlinear response characteristic with small slopes such as subjects S3, S8, S9, and AS3, the MPC-FES controller had good tracking control performance with small values of MAE below 1.5 deg. Based on this result, the linear MPC without nonlinear transformation could only be used to deal with a linear system or a system with low nonlinear response characteristics. It also could be said that if the slope of input-output of static characteristic is large (e.g. subject S4) then the linear MPC without nonlinear transformation could not adjust the proper gain in consequence large oscillating response occurred. And if the slope of input-output of static characteristic is small (e.g. subject S3) then the linear MPC without nonlinear transformation could adjust a better controller gain that makes the occurrence of oscillating response not too large. The significant improvement in reducing the values

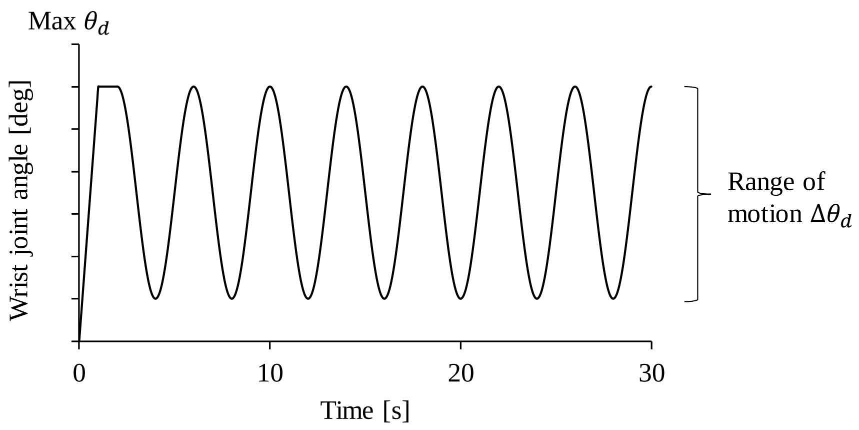


Figure 3.9: Definition of target movement trajectory for different ranges of motion (target θ_{d1}, θ_{d2}, and θ_{d3}).

of MAE below 1 deg was performed by the linear MPC with nonlinear transformation for both reference subject models and test subject models. This result strengthens our hypothesis in [65] that the FES controller can be realized using a combination of a linear MPC and a nonlinear transformation. Therefore, the proposed controller was suggested to be applicable and useful for practical movement restoration systems using FES. The proposed controller has the advantages of the simple design procedure and has a few parameters adjustment with a promising tracking control performance. Indeed, the manual adjustment was still used in this test to determine the values of controller parameters, therefore we also developed the parameter estimation method that presents in the next chapter.

3.4 Computer simulation test with different ranges of motion

3.4.1 Evaluation methods

In practical FES applications, a small range of motion such as target θ_{d1} is commonly used to avoid the occurrence of fast muscle fatigue. Since this study was

Table 3.2: Optimum values of α of each nonlinear function of each subject model.

Subject	Optimum value of α			
	PReLU	Tanh	BS	Poly
S1	0.55	0.65	2.40	0.15
S2	0.45	0.50	2.00	0.10
S3	1.35	1.80	5.80	0.90
S4	0.30	0.45	1.20	0.15
S5	0.45	0.50	2.00	0.20
S6	0.75	1.05	3.20	0.50
S7	0.65	0.70	3.00	0.25
S8	1.10	1.45	4.40	0.55
S9	1.60	2.10	6.60	1.00
S10	0.70	0.80	3.80	0.30
AS1	0.30	0.30	2.80	0.05
AS2	0.65	0.65	4.80	0.15
AS3	0.90	0.95	4.60	0.20
AS4	0.20	0.35	1.00	0.05
AS5	0.30	0.45	1.20	0.10

conducted in a computer simulation, we added targets θ_{d2}, and θ_{d3} to observe the capability of the proposed controller in dealing with medium and wide ranges of motions. The FES controller was realized using a combination of the linear MPC and 4 types of nonlinear functions (PReLU, Tanh, BS, and Poly functions). The ten reference and additional test subjects as presented in the previous chapter were used to test the control capability of the proposed controller. The sinusoidal pattern with a cycle period of 4 s shown in Fig. 3.9 was considered as the target movement trajectory. The range of motion of the target θ_{d1}, θ_{d2}, and θ_{d3} were set to 5-30 deg, 0-50% of Max θ, and 10-90% of Max θ, respectively. The Max θ was defined as the maximum deviation of the wrist joint angle of each subject model. The relative error (NMAE) calculated for time intervals 2-30 s was used to evaluate the tracking control performance of the MPC-FES controller. The relative error was defined as a ratio between the MAE to the range of motion of each target movement trajectory. The relative error is expressed as follows,

$$NMAE = \frac{MAE}{\Delta\theta_d} \times 100[\%] \tag{3.2}$$

Here, $\Delta\theta_d$ represents the range of motion of the wrist joint movement. The MAE value was calculated using Eq. 3.1. The values of α of each nonlinear function of each subject model were determined by using manual adjustment where the appropriate value was chosen when the smallest value of MAE was achieved. The optimum values of α of each nonlinear function of each subject model are summarized in Table 3.2. The linear MPC parameter values used the same values as in the previous section.

3.4.2 Results and discussions

Figure 3.10 shows the comparison of the control responses of the MPC-FES controller with different nonlinear functions tested in subject model S1 with desired target movement trajectory was target θ_{d1}. The value of slope parameter α of each nonlinear function using its optimum value is shown in Table 3.2. The optimum value of α of the PReLU, Tanh, BS, and Poly functions for subject S1 were 0.55, 0.65, 2.4, and 0.15, respectively. The control responses showed that the linear MPC in cascading with different nonlinear functions was able to track the given target movement trajectory. At the beginning of the movement trajectory, the controller could not reach the target angle quickly since the initial value of stimulation was set at zero. However, the controller with the BS function had a fast response at the beginning of stimulation as shown in Fig. 3.10(c), it was because the output of this function is non-zero in its origin although the minimum stimulation value was imposed on this function. The control response of the controller with the Poly function for subject S1 had a greater oscillating response in the stimulation intensity than the other as shown in Fig. 3.10(d), however, some subjects had the smallest oscillating response. The oscillation in control responses also appeared in some subjects for PReLU, Tanh, and BS functions. Therefore, it was difficult to consider which nonlinear function had the best tracking control performance based on the appearance of the oscillation in control responses.

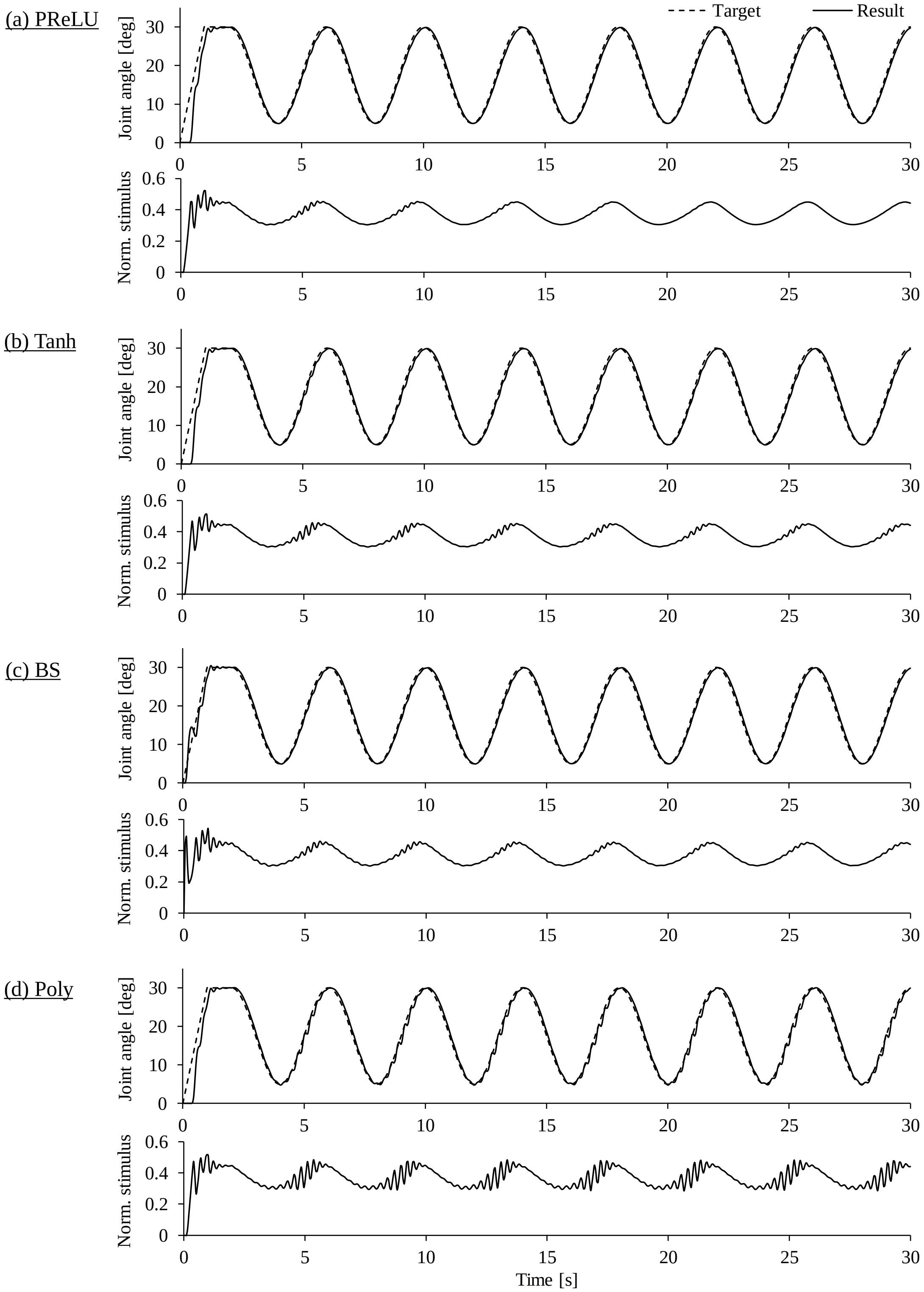


Figure 3.10: An example of control results of the linear MPC in cascading with different nonlinear functions (subject S1 with the target movement trajectory θ_{d1}). The values of α of each nonlinear function used their optimum values.

Figure 3.11 shows the NMAE values of control results for target θ_{d1}, θ_{d2}, and θ_{d3}, calculated for all reference and test subjects. The figure shows the comparison of the performance between nonlinear functions when the value of α used their optimum values. The difference in the NMAE for the different targets was not significant. Figure 3.11 also shows when using their optimum values of α, the linear MPC with the Tanh function had the smallest error for targets θ_{d1} and θ_{d2}, and the linear MPC with the BS function had the smallest error for target θ_{d3}. With the Tanh function, the controller seems more appropriate to be applied to control a small range of motion of the wrist joint movement since it has a fast response for a small target angle. However, if it is intended to control the wrist joint movement at around the maximum joint angle, the control response becomes slower that difficult to reach the target angle. On the other hand, the linear MPC with the BS function has a better performance for controlling the wrist joint movement at around the maximum joint angle since it has a faster response. However, the high amplification tends to make an overshot in the control response at the beginning of stimulation for a small target angle due to the non-zero value at its origin. The Poly function also provided a good tracking control performance with a small tracking error. However, the identification process to determine the coefficients of the polynomial function for a new subject is required. Therefore, it is not preferable for practical FES applications because it will increase the time-consuming of the initial setup. In dealing with a small and wide range of motion of target movement trajectories, the PReLU function could be very the potential to realize the nonlinear transformation which provided a better tracking control performance with the Tanh function. As seen in Fig. 3.11, the average error of the PReLU function was almost the same as the average error of the Tanh and BS functions for small target angle and wide target angle, respectively. Therefore, the PReLU function could be considered to be useful to realize the MPC-FES controller with the advantage of a light computational load than the other nonlinear functions.

The empirical parameters adjustment method of the MPC was preferred where the values were set as fixed values for all subject tests and target movement trajectories. We assumed that the changing of these values was not required for individual subject tests because the prediction model of linear MPC in our study was implemented using

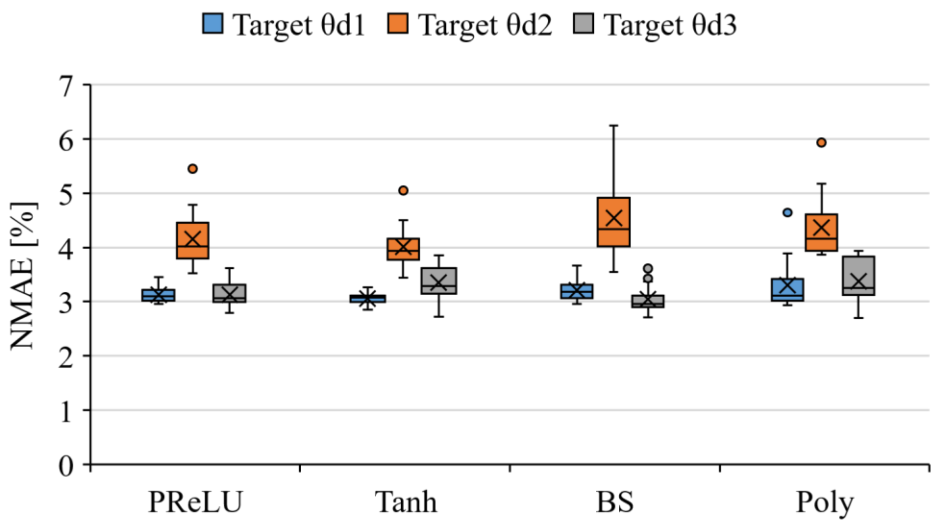


Figure 3.11: Comparison of tracking control performances of the cascade linear MPC with different nonlinear functions using their optimum values. The relative error values for target θ_{d1}, θ_{d2}, and θ_{d3} were shown. The NMAE values were calculated for all reference and test subjects.

a fixed model (the average model). In the other studies [25],[26], the fixed values of the MPC parameters were also adopted although they used the nominal model of the individual subjects in realizing the prediction model of the MPC. It may be because the MPC parameter such as a tuning parameter of λ only used to adjust the aggressivity of the control action to acquire the desired control performance [27], [28]. In addition, the purpose of our study was to design the controller with fewer parameter adjustments. Therefore, we considered only the slope parameter of the nonlinear transformation that required the initial adjustment for individual subjects.

3.5 Chapter summary

The computer simulation test showed that the proposed MPC-FES controller worked properly and was able to track the target movement trajectory with a small tracking error. The use of a simple average model can eliminate a modeling process for a new subject, thus reduce time-consuming at the initial setup for practical application. Four types of different nonlinear functions were investigated in realizing the nonlinear transformation. These functions were also able to map the output of linear MPC as a linear solution to obtain a nonlinear solution. Based on comparison of the control evaluations for all trials, the linear MPC with the PReLU function seems to be useful to realize the FES controller in dealing with different ranges of motions of joint movements. The proposed controller can be considered in practical FES applications. This work will be extended to develop the estimation method to determine the appropriate value of α to eliminate the parameter adjustment process.

Chapter 4

Simplified Parameter Estimation Design for MPC-FES Controller

4.1 Introduction

In the previous chapter, the proposed MPC-FES controller was designed to have a few parameters in order to acquire the desired tracking control performance. The linear MPC has three parameters that were the prediction horizon (N_P), the control horizon (N_C), and λ to adjust the aggressivity of control action, and the nonlinear transformation has only the slope parameter, α. The parameter values of the linear MPC were adjusted empirically by optimizing them in controlling the wrist joint movement in one subject model. Then, the optimized values were applied to other subjects or fixed for all control trials and only the slope parameter value of the nonlinear transformation for each subject was determined individually as described in the previous chapter. Based on the previous chapter, the tracking control performance of the MPC-FES controller depends on the optimum value of slope parameter α of the nonlinear transformation. However, a trial and error process method in determining the optimum value for each subject was still used which took a longer adjustment time. Therefore, in order to reduce the time-consuming determining of the initial adjustment of the slope parameter α, we developed a method to estimate the slope parameter of nonlinear transformation.

This chapter describes the design flow of the parameter estimation method of the nonlinear transformation. We hypothesize that the slope parameter of nonlinear transformation has a strong correlation with the slope (gain) of input-output of the static characteristic of the stimulated musculoskeletal system. Therefore, the parameter estimation of the nonlinear transformation was developed by utilizing the gain calculated from the input-output of the static characteristic curve of the stimulated musculoskeletal system.

4.2 Design of parameter estimation method of nonlinear transformation

4.2.1 Methods

The parameter estimation method to determine the slope parameter value of each nonlinear function was developed by utilizing the gain of the musculoskeletal systems calculated from the input-output static characteristic curve of each subject test. The slope of the curve of the nonlinear function was assumed to have a strong correlation with the slope of the input-output characteristic curve of the stimulated musculoskeletal system. In the previous study [66], this approach has been used and tested to estimate the gain of the fuzzy FES controller. The method provided a good estimated value of the fuzzy gain and was considered to be useful for practical FES application although the estimation formula was developed using a small number of reference subjects. Based on the previous results, the estimation formula to determine the slope parameter α of the nonlinear transformation was designed using the same procedure as in the previous study [66].

In order to make a clear description, as an example, we will explain the parameter estimation design of α_1 for the PReLU function and the target trajectory is target θ_{d1}. The design flow of the parameter is explained in sequence as follows:

- **Step 1**

  The first step was measuring the input-output static characteristics of ten reference subjects as shown in Fig. 2.5 (Chapter 2). From each input-output characteristic curve, the gain M_1 for each reference subject was calculated where this gain was defined as the ratio of the range of motion to the electrical

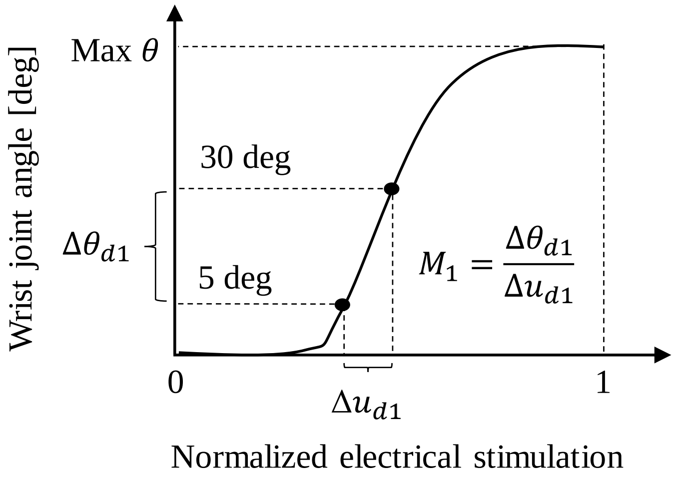


Figure 4.1: Definition of gain M_1 calculation based on the range of motion of target θ_{d1}.

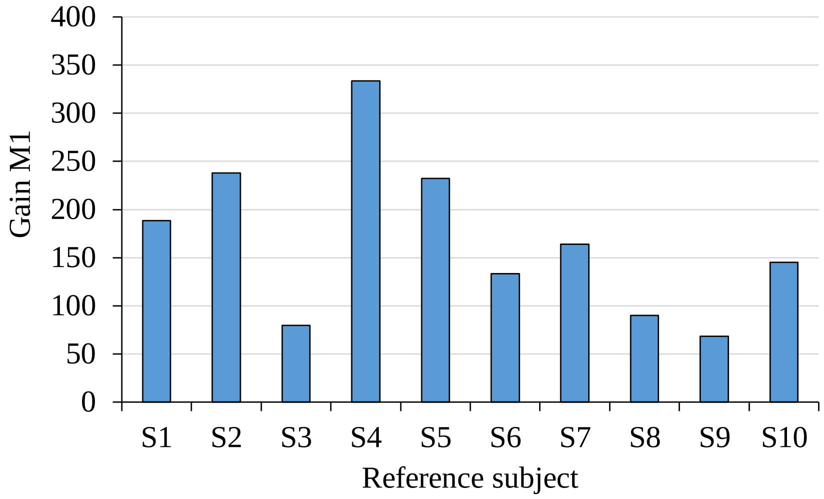


Figure 4.2: Gain M_1 values of reference subjects calculated based on the range of motion of target θ_{d1}.

stimulation intensity. The value of the range of motion was determined based on the target θ_{d1}. For instance, Figure 4.1 shows the calculation method of gain M_1 when target θ_{d1} was selected. Figure 4.2 shows the gain M_1 values of reference subjects calculated based on the range of motion of target θ_{d1}.

- **Step 2**

The second step is to perform the MPC-FES controller in controlling the wrist joint movement with target θ_{d1} as the target movement trajectory for each reference subject model in order to acquire the optimum value of α_1. For each control trial, the value of α_1 was determined manually by changing the value of α_1 for the range of α_1 from 0.05 up to 3 with increments of 0.05. We defined the optimum value of α_1 as the value that gives the best tracking control performance of the MPC-FES controller with the smallest MAE value and small oscillation in the control response.

- **Step 3**

In the last step, after we obtained the values of gain M_1 and the optimum values of α_1 for all reference subjects, then we plotted those values in order to get the relationship as shown in Fig 4.3 (a). From that, the relationship showed an exponential relationship where the large gain will give a small estimated value of the slope parameter of the nonlinear transformation. Then after we got the relationship, we performed the fitting process to create the estimation formula of α_1 as a function of gain M_1, that is $\alpha_1(M_1)$ as described in Eq. 4.1.

$$\alpha_1(M_1) = 11.68e^{(-0.04169M_1)} + 1.262e^{(-0.004351M_1)} \tag{4.1}$$

By using the design flow of the estimation formula as described above, we created the estimation formula of α for the Tanh, BS, and Poly functions with the same procedure. The estimation formula of α for the Tanh, BS, and Poly functions for target θ_{d1} were $\alpha_2(M_1)$, $\alpha_3(M_1)$, and $\alpha_4(M_1)$, respectively, as described as follows,

$$\alpha_2(M_1) = 5.925e^{(-0.01942M_1)} + 0.5388e^{(-0.0006919M_1)} \tag{4.2}$$

$$\alpha_3(M_1) = 202.64e^{(-0.06898M_1)} + 7.016e^{(-0.005299M_1)} \tag{4.3}$$

$$\alpha_4(M_1) = 3.016e^{(-0.01708M_1)} + 0.0375e^{(0.00386M_1)} \tag{4.4}$$

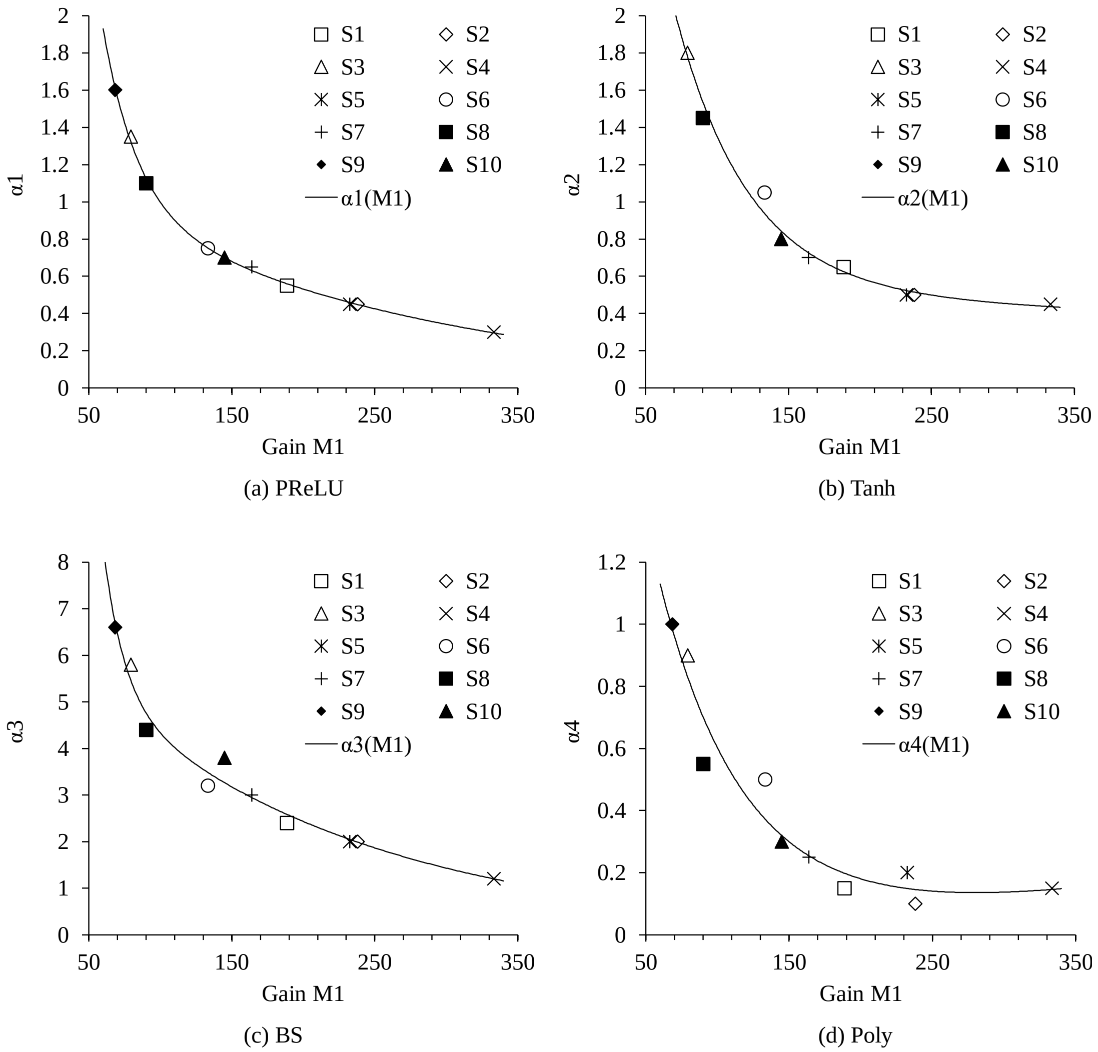


Figure 4.3: Relationship between the optimum value of α of each nonlinear function and gain M_1 of reference subjects.

The relationship between the optimum value of α of each nonlinear function and gain M_1 of reference subjects is shown in Fig. 4.3. From that, it could be seen that the relationship between the optimum value of α of each nonlinear function and the gain value M_1 have a strong exponential relationship. However, the PReLU function has the best fit than the other. Therefore, the estimation formula created from the relationship is possible to estimate the value of α for a new subject. The important thing to be noted is that by using those estimation formulas when the controller is implemented to control the wrist joint movement for a new subject, in this case, additional subjects, only the gain M calculated from the input-output static characteristic of the new subject are necessary.

For target θ_{d2}, the estimation formula of α for the PReLU, Tanh, BS, and Poly functions were $\alpha_1(M_2)$, $\alpha_2(M_2)$, $\alpha_3(M_2)$, and $\alpha_4(M_2)$, respectively and expressed as follows,

$$\alpha_1(M_2) = 1.002\text{e+}14e^{(-0.6472M_2)} + 1.702e^{(-0.00609M_2)} \tag{4.5}$$

$$\alpha_2(M_2) = 3.201e^{(-0.009588M_2)} + 0.005559e^{(0.01408M_2)} \tag{4.6}$$

$$\alpha_3(M_2) = 1.048\text{e+}14e^{(-0.6476M_2)} + 1.981e^{(-0.006336M_2)} \tag{4.7}$$

$$\alpha_4(M_2) = -7525e^{(-0.009103M_2)} + 7526e^{(-0.009103M_2)} \tag{4.8}$$

And for target θ_{d3}, the estimation formula of α for the PReLU, Tanh, BS, and Poly functions were $\alpha_1(M_3)$, $\alpha_2(M_3)$, $\alpha_3(M_3)$, and $\alpha_4(M_3)$, respectively, are expressed as follows,

$$\alpha_1(M_3) = 9.957e^{(-0.04139M_3)} + 1.747e^{(-0.006154M_3)} \tag{4.9}$$

$$\alpha_2(M_3) = 9.442e^{(-0.02139M_3)} + 0.275e^{(0.003243M_3)} \tag{4.10}$$

$$\alpha_3(M_3) = 8.474e^{(-0.03168M_3)} + 1.412e^{(-0.00475M_3)} \tag{4.11}$$

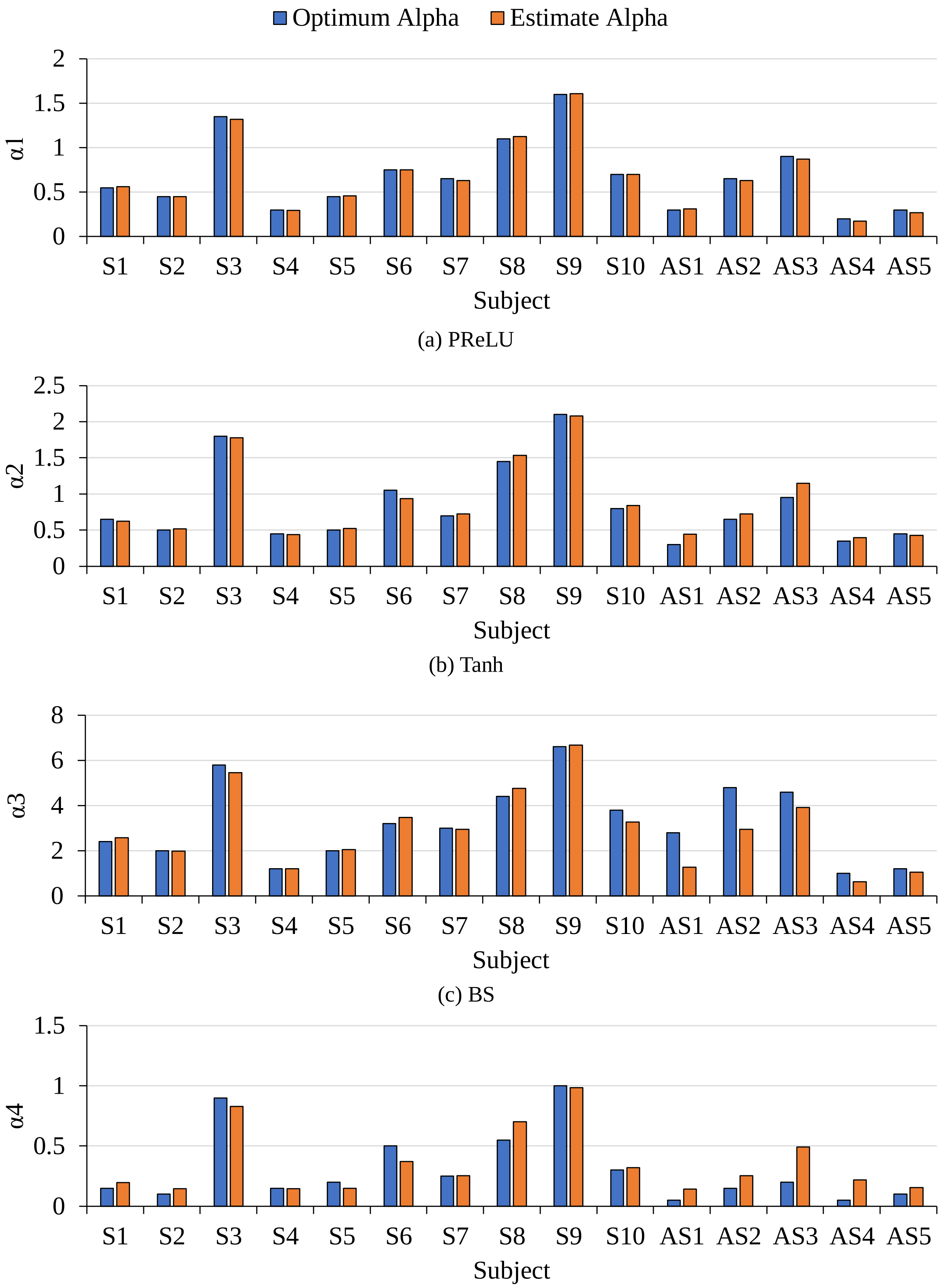
$$\alpha_4(M_3) = 4.252e^{(-0.0191M_3)} + 6.446\text{e-}16e^{(0.15M_3)} \tag{4.12}$$

Those estimation formulas of α for the PReLU, Tanh, BS, and Poly functions for target θ_{d2} and θ_{d3} were also created using the same procedure as for target θ_{d1}. The exponential function type II was used to generate the estimation formula since it has a better fit than the exponential function type I. In the previous study [66], we used the exponential function type I to develop the estimation formula for fuzzy gain because the number of reference subject models were five subject model in total.

4.2.2 Results and discussions

The evaluation methods to examine the effectiveness of the proposed method to estimate the slope parameter value of nonlinear transformation are the same as in previous chapter. First, we compared the optimum and estimated values of α. Figure 4.4 shows an example of the comparison of the optimum and estimated values of α for target θ_{d1}. The estimated values were calculated using their estimation formulas. From the comparison results, the estimation formula for the PReLU function had the best estimation values for the additional test subjects (AS1-AS5) than the other functions, it could be seen in Fig. 4.4(a). The difference between the optimum and the estimated values were not significant. The BS and Poly functions have a large difference between the optimum and estimated values for the additional test subjects (AS1-AS5). These significant differences could make the MPC-FES controller difficult to provide good tracking control performance or to follow the desired target movement because the nonlinear gain calculated by the nonlinear function becomes too large or small. Based on our investigation, this condition also occurred for target θ_{d2} and θ_{d3} where the estimation formula for the PReLU function had the best estimation values for the additional test subjects (AS1-AS5) than the other functions.

Figure 4.5 shows an example of the comparison of the tracking performance of the MPC-FES controller when using the optimum and estimated values of α of each nonlinear function for target θ_{d1}. From the results, it was clear that the parameter estimation for the PReLU function had the best performance for additional subjects, although these additional subjects were not included in making the estimation formula. The MAE values for all subjects when using the PReLU function were very small below 1 deg. The Tanh function also had a good tracking performance almost similar to the result of the PReLU function. However, the value of MAE in subject AS1 was large compared to the other subject which indicated the estimation formula for the Tanh function could not provide an estimated value as good as the estimation formula of the PReLU function.



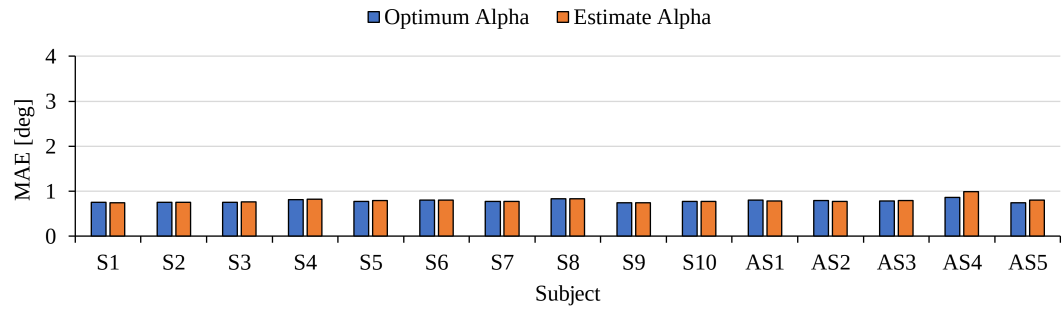
(a) PReLU

(b) Tanh

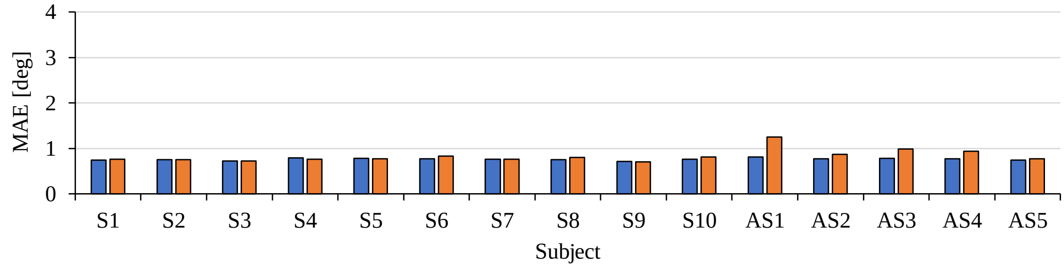
(c) BS

(d) Poly

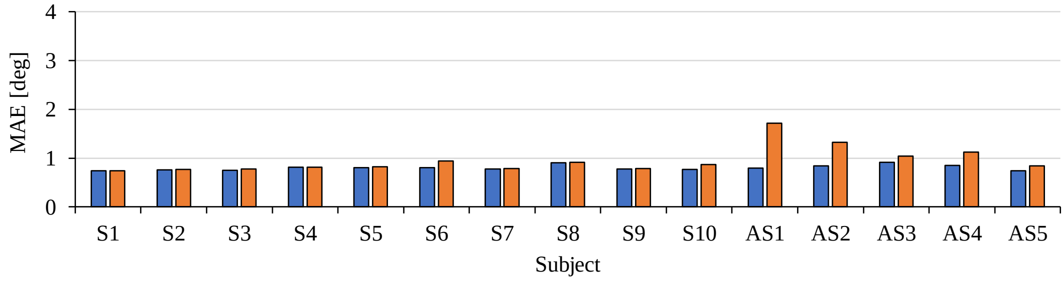
Figure 4.4: An example of the comparison of the optimum and estimated values of α of each nonlinear function for target θ_{d1}.



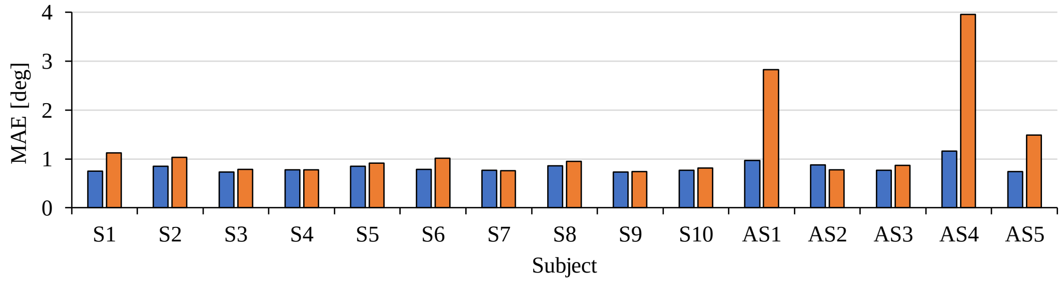
(a) PReLU



(b) Tanh

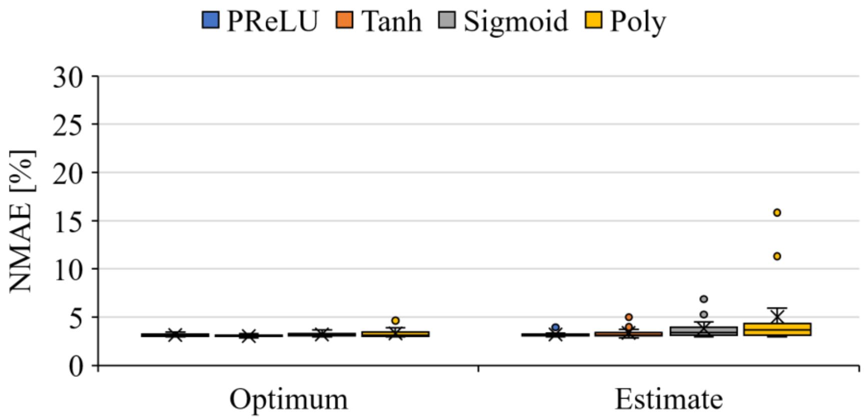


(c) BS

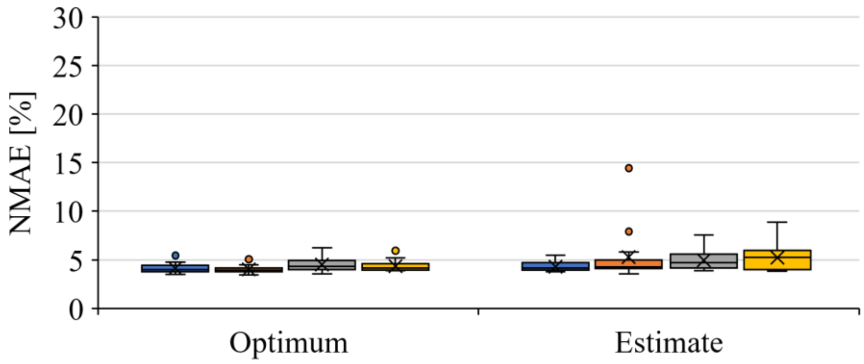


(d) Poly

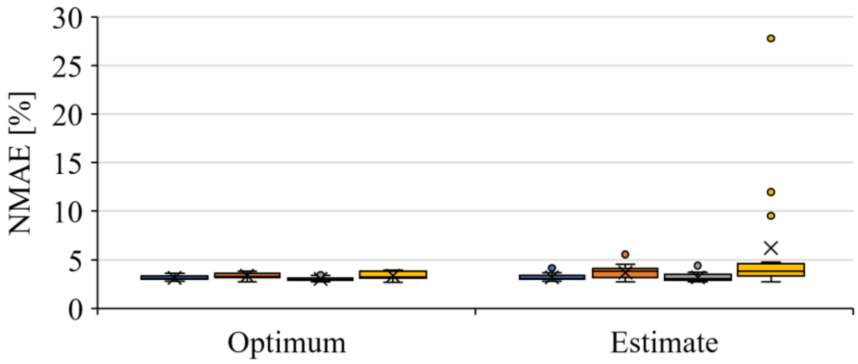
Figure 4.5: An example of the comparison of the tracking control performance of the MPC-FES controller when using the optimum and estimated values of α of each nonlinear function for target θ_{d1}.



(a)



(b)



(c)

Figure 4.6: Comparison of tracking control performances of the cascade linear MPC with different nonlinear functions using their optimum and estimated values. (a)-(c) shows the relative error values for target θ_{d1}, θ_{d2}, and θ_{d3}, respectively. The NMAE values were calculated for all reference and test subjects.

The NMAE values of the tracking control performance of the MPC-FES controller for all ranges of target motions are shown in Fig. 4.6. Each figure also shows the comparison of the performance between nonlinear functions when the value of α used their optimum and estimated values. The relative error of each nonlinear function was calculated for all reference and additional test subjects. When the optimum value of the slope parameter was used, the difference in the NMAE values for the different target movements was not significant. However, when the estimated value was applied, the PReLU function had the best performance for all target movement trajectories compared to the other function. In general, the estimation formula of the PReLU function had the best estimation in determining the slope parameter value followed by the BS and Tanh functions and the estimation formula of the Poly function had the worst estimation.

From Fig. 4.6, we could see the comparison of tracking control performance of different nonlinear functions used with the linear MPC in controlling the wrist joint movement for different ranges of target motions where this result strengthens the result of the previous chapter that the PReLU function seems to be very the potential to realize the nonlinear transformation because it can be used to deal with a small and wide range of motion of the target movement trajectories although the slope parameter was used its estimated value. The NMAE values of the PReLU function were almost the same as those of the other functions with optimum values of α, and the PReLU function had the best performance for all target movement trajectories when using the estimated values. Therefore, we considered that the linear MPC with the PReLU function and its estimation formula could be useful for practical FES applications with the advantage of a light computational load than the other nonlinear functions.

4.3 Test of PReLU function with single estimation formula for different target movement trajectories

4.3.1 Methods

The combination of the linear MPC with PReLU function and its estimation

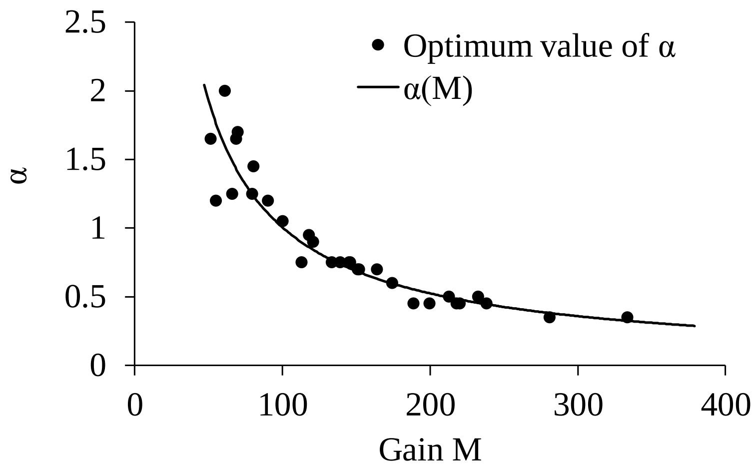


Figure 4.7: Relationship between the optimum value of α and gain M for all reference subjects and for all targets.

formula in the previous section had the best tracking control performance in controlling the wrist joint movement for different target movement trajectories. However, we need to create the estimation formula for each range of target motion. It was possible to create a single estimation formula for different target movement trajectories since we had the optimum values of α and the gain M for all reference subjects and for all targets which were 30 pair values in total. By plotting those values as shown in Fig. 4.7, then we performed the fitting process to obtain the single estimation formula as described as follows,

$$\alpha(M) = 75.886M^{(-0.939)} \tag{4.5}$$

From Fig. 4.7, it can be seen that a large variation of the slope parameter occurs when the subject has gain M smaller than 100. Therefore, the relationship between the optimum values of α and the gain M was fitted using the power function instead of the exponential function because it has a better fit result for small values of gain M.

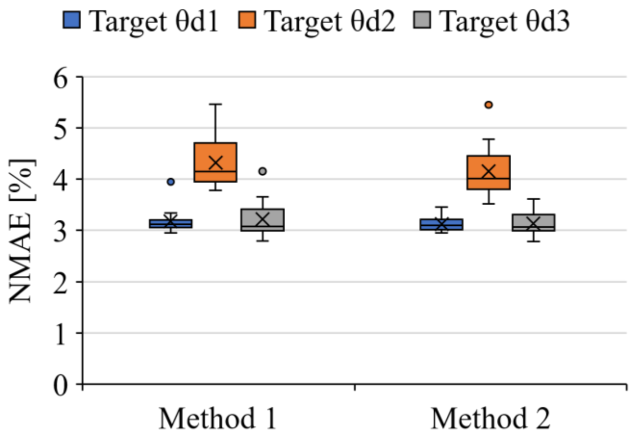


Figure 4.8: Comparison of the estimation method performance in determining the value of α of the PReLU function. The NMAE values were calculated for all reference and test subjects.

4.3.2 Results and discussions

The comparison of the parameter estimation method performance between method 1 (in the previous section) and method 2 (in this section) is shown in Fig. 4.8. From the results, method 2 had a better estimation value of α of the PReLU function showing the decrease in NMAE values for each target movement trajectory. For target θ_{d2}, the relative error was larger than targets θ_{d1} and θ_{d3}, because we included the zero angle in this target. As mentioned at the beginning of chapter 3, the MPC-FES controller was difficult to track the very small target angle because only one stimulated muscle was used in this study. In general, the estimated value of α affected the tracking control performance of the FES controller. From the results, it is considered if the estimated value of α is larger than the optimum value then the control result has an oscillating response. On the other hand, if the estimated value of α is smaller than the optimum value then the control result has a smoother response, but if the estimated value is too small then the control result has a slow response and it is difficult to achieve the target angle.

The parameter estimation method with a simple design procedure proposed in this study proved to be effective in determining the slope parameters of various nonlinear functions for a new subject. This result also strengthens our hypothesis in our previous study [66] that the gain M extracted from the input-output characteristics of the stimulated musculoskeletal system can be used to estimate the gain of the fuzzy-FES controller. Based on the control evaluation as shown in Fig. 4.6, the estimation formula for the PReLU function provides the best estimation value of the other functions because the gain M extracted from the input-output characteristic curve has a wide range of linear region where the "linear-like" slope is mostly used to distinguish between subjects [34]. Based on the comparison results between the two parameter estimation methods as shown in Fig. 4.8, it is considered that the single estimation formula (method 2) is more applicable for practical FES applications because it only uses a single estimation formula to estimate the value of the slope parameter of the PReLU function for different target movement trajectories.

4.4 Chapter summary

In this chapter, the parameter estimation method of nonlinear transformation used with the linear MPC was developed and tested in controlling a wrist joint movement. The control result showed a good tracking control performance by using the proposed method. Based on the simulation results, the estimation method was considered to be effective to determine the value of α. The linear MPC with the PReLU function along with estimated parameter value had good tracking control performance with high accuracy in controlling wrist joint movements. The gain of the musculoskeletal system has a strong exponential relationship with the value of α and can be considered as an important feature for controller development for FES applications. The simple parameter estimation method was suggested to be useful to determine the parameter value of the nonlinear transformation used with the linear MPC for practical FES applications, hence reducing the burden on patients and medical staff.

Chapter 5

Comparison of Control Performance Between MPC-FES Controller and Fuzzy-FES Controller

5.1 Introduction

This chapter described the comparison of tracking control performance between the MPC-FES controller and the fuzzy-FES controller. The fuzzy controller has been widely used for realizing the FES controller because it can be used to deal with the nonlinear system. The fuzzy controller was considered to realize the closed-loop FES controller because of its simplicity and flexibility in its design. In FES applications, fuzzy has been applied for tracking joint movement [19], [67], FES cycling [68], [69] and FES gait using cycle to cycle control [20], [70], [71]. Additionally, the fuzzy controller could be implemented easily in embedded systems for wearable FES system development [72]. Therefore, it is reasonable to choose a fuzzy FES controller in comparison with our proposed method.

In this chapter, we present the design flow and testing of the fuzzy-FES controller. The fuzzy controller was developed based on the previous study [19]. The linear MPC cascaded with the PReLU function was applied and the single estimation formula (method 2) was used to determine the value of the slope parameter of the PReLU function. Then, the control capability of the proposed method in controlling the wrist joint movement induced by FES was examined and compared with a fuzzy-FES controller. Other tests were performed to evaluate the capabilities of the proposed controller in dealing with the paralyzed subject model, compensating for muscle

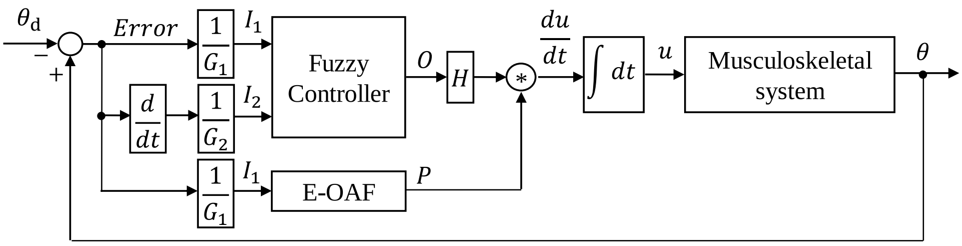


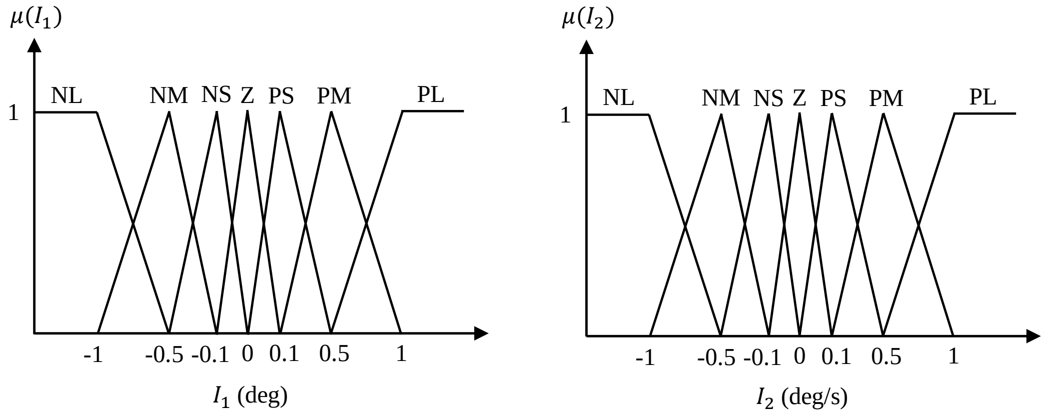
Figure 5.1: Block diagram of the modified fuzzy controller for FES.

fatigue, and rejecting external disturbance. Those problems are the common problems that must be addressed by the FES controllers in a real environment (in rehabilitation training and activities of daily living). Therefore, the proposed controller developed in a computer simulation study should be tested with the same problems in order to validate that it can be implemented in a real environment [73], [74].

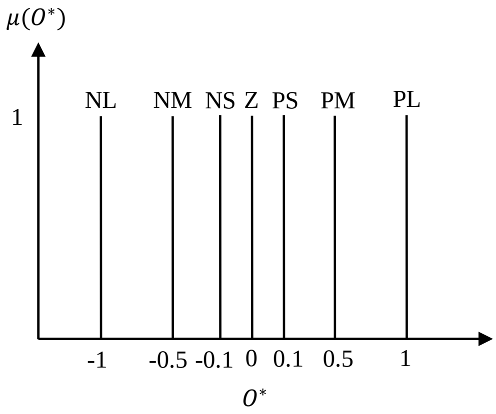
5.2 Design of fuzzy controller

The fuzzy controller from [19] was adopted in this study for comparison because it had a good performance in controlling knee extension movement compare with PID through the experimental tests. Figure 5.1 shows the block diagram of the modified fuzzy controller used in this study. Fuzzy controller has 2 inputs (input error and its derivative) and 1 output (change of stimulation intensity). Error is defined as a difference of wrist joint angle between the measured angle (θ) and the target angle (θ_d). In order to make simple adjustments to the parameters of the fuzzy controller, the input membership function (IMF) and output membership function (OMF) was modified using the normalized type. To obtain the normalized IMF, we used parameters G_1 and G_2 to scale the input error and its derivative, respectively. For the output of the fuzzy controller, the scaling factor for OMF was the parameter H which was defined as fuzzy gain.

The error-based output adjustment factor (E-OAF) was used in parallel with the fuzzy controller to reduce large errors by multiplying their output [19]. Figures 5.2 and



(a) Normalized IMFs



(a) Normalized OMF

Figure 5.2: Normalized input (I_1, I_2) and output (O) membership functions of the fuzzy controller. The fuzzy linguistic terms of the input and output variables are shown by NL (negative large), NM (negative medium), NS (negative small), Z (zero), PS (positive small), PM (positive medium) and PL (positive large).

5.3 show the IMFs and OMFs of the fuzzy controller and the E-OAF, respectively. Triangular and trapezoidal fuzzy sets were used to express the IMFs and for the OMFs, we used fuzzy singletons.

The fuzzy rules of the fuzzy controller and E-OAF are summarized in Table 5.1 and Table 5.2, respectively. The rules of the fuzzy controller were configured based on the error value of each time instant k, where if the error is negative then the output of the fuzzy controller (O) is increased and if the error is positive then the output of the

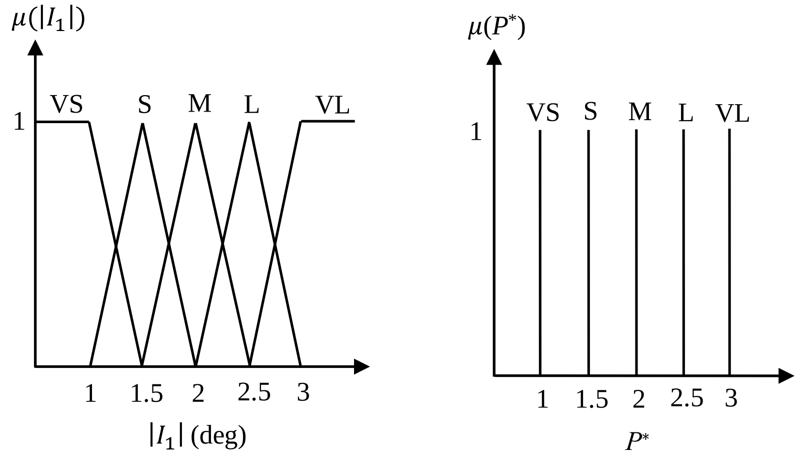


Figure 5.3: Input and output membership functions of E-OAF and the linguistic terms of the input and output variables are shown by VS (very small), S (small), M (medium), L (large) and VL (very large).

Table 5.1: Fuzzy rule sets of the modified fuzzy control for FES.

		I_1						
		NL	NM	NS	Z	PS	PM	PL
I_2	NL	PL	PL	PM	PS	Z	NS	NM
	NM	PL	PL	PM	PS	Z	NS	NL
	NS	PL	PM	PS	Z	NS	NM	NL
	Z	PL	PM	PS	Z	NS	NM	NL
	PS	PL	PM	PS	Z	NS	NM	NL
	PM	PL	PS	Z	NS	NM	NL	NL
	PL	PM	PS	Z	NS	NM	NL	NL

Table 5.2: Fuzzy rule sets of the E-OAF.

$\lvert I_1 \rvert$	VS	S	M	L	VL
P	VS	S	M	L	VL

fuzzy controller (O) is decreased. The E-OAF rules were configured based on the absolute value of the error, where if the error is large, the output of E-OAF (P) increases and if the error is small, the output of E-OAF (P) decreases. Both rules were used to drive fuzzy inference in determining the control action with the intention of electrical stimulation intensity and the rule implications in the fuzzy inference process were solved using the Mamdani method.

The defuzzification process using the center of gravity (COG) method was used to determine the crisp values of the output of fuzzy controller (*O*) and the output of E-OAF (*P*) as expressed in Eq. 5.1 and 5.2, respectively. Then, the output of fuzzy controller (*O*) with fuzzy gain H and the output of E-OAF (*P*) were multiplied to calculate the control action (Δu) as expressed in Eq. 5.3.

$$O = \frac{\Sigma\mu(O_n^*)O_n^*}{\Sigma\mu(O_n^*)} \tag{5.1}$$

$$P = \frac{\Sigma\mu\left(P_j^*\right)P_j^*}{\Sigma\mu\left(P_j^*\right)} \tag{5.2}$$

$$\Delta u = O \times H \times P \tag{5.3}$$

where $n = 1, 2, .., N$. N is the number of the linguistic term of $O*$. $\mu(O_n^*)$ is membership value of O_n^*. $j = 1, 2, .., J$. J is the number of the linguistic term of $P*$. $\mu\left(P_j^*\right)$ is membership value of P_j^*.

By using the normalized type of IMF and OMF of fuzzy controller, we only need to determine the values of G_1, G_2, and H. However, in this study, the values of G_1 and G_2 were determined as fixed values of 5 and 1, respectively where these values were optimized based on 1 reference subject and target θ_{d1}. Then the optimized values were used for all trials. The values of IMF and OMF of E-OAF were also determined by using the same way as G_1 and G_2. Therefore, only the value of fuzzy gain H that has different value for each trials.

5.3 Computer simulation tests with different speed of target movement and random movement trajectories

5.3.1 Methods

In this test, the MPC-FES controller and fuzzy-FES controller were performed to control the wrist joint movement of all subject models where the target θ_{d1} with three

Table 5.3: Estimate values of α of PReLU function and optimum values of fuzzy gain H of each subject model based on the range of motion of target θ_{d1}.

Subject	Estimate value of α of PReLU function	Optimum value of fuzzy gain H
S1	0.53	0.10
S2	0.42	0.08
S3	1.24	0.24
S4	0.27	0.06
S5	0.43	0.08
S6	0.71	0.13
S7	0.60	0.11
S8	1.06	0.20
S9	1.52	0.29
S10	0.66	0.13
AS1	0.29	0.06
AS2	0.60	0.11
AS3	0.82	0.16
AS4	0.16	0.04
AS5	0.25	0.05

different speeds of wrist joint movement was used to evaluate the controller capabilities. The speed of movement was divided into a fast (cycle period 4 s), moderate (cycle period 8 s), and slow (cycle period 16 s) movements. In addition, we also considered a random movement as a target movement to evaluate the capabilities of the MPC-FES controller and fuzzy-FES controller. The random movement trajectory with the specification of the maximum range of motion like target θ_{d1} and frequency bands of 0.25 Hz was created using a filtered random noise. Eq. 3.1 in chapter 3 was used to calculate MAE values for all reference and additional test subjects. The value of the slope parameter of the PReLU function for each subject model was estimated using the estimation formula method 2 where the value of gain M was calculated based on the range of motion of target θ_{d1}, and then the estimated value was applied for fast, moderate, slow, and random movements as shown in Table

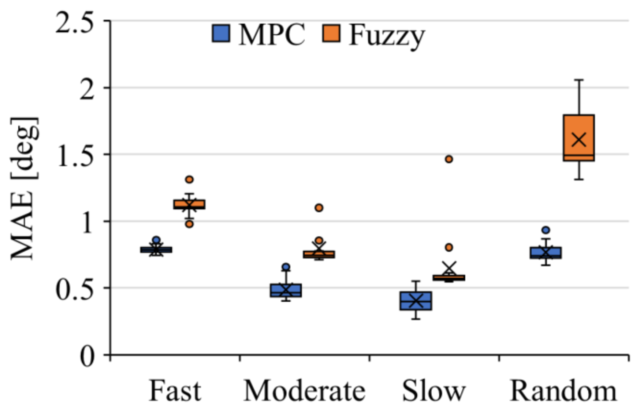


Figure 5.4: Comparison of the control results between MPC-FES controller and fuzzy-FES controller. The MAE values were calculated for all reference and test subjects.

5.3. The values of fuzzy gain H for each subject were determined using manual adjustment based on target θ_{d1} with fast movement and the other parameter values of fuzzy controller based on the previous study [19]. Then, these values of fuzzy gain H were applied for moderate, slow, and random movements. The optimum value of fuzzy gain H for each subject model is summarized in Table 5.3.

5.3.2 Results and discussions

The comparison of the tacking control capabilities between the MPC-FES controller and fuzzy-FES controller is shown in Fig. 5.4. Based on the control performance, the MAE values for both controllers decreased as the target movement speed decreased. The MAE value of the MPC-FES controller had a smaller value than the fuzzy-FES controller for all speeds of target movement. Moreover, the average error for moderate speed of target movement using the MPC-FES controller is smaller than the average error for speed of target movement using the fuzzy-FES controller. The difference in MAE values between the MPC-FES controller and fuzzy-FES controller in controlling the wrist joint movement with random target movement was very significant. The outlier in MAE values of the fuzzy controller indicates that the

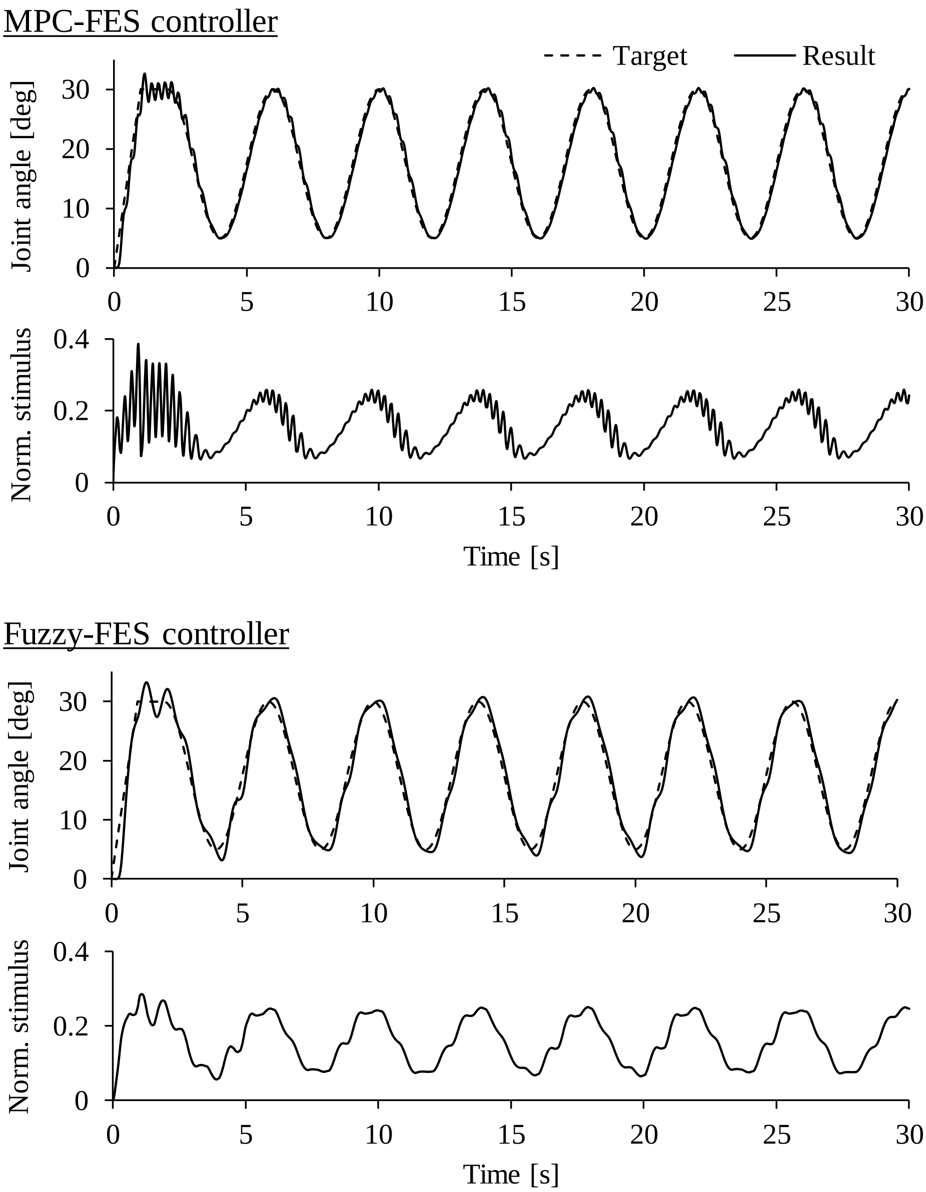


Figure 5.5: Comparison of control results of the MPC-FES controller and fuzzy-FES controller tested in test subject AS2 and target movement trajectories was target θ_{d1} with fast movement.

method of determining the parameter values of the fuzzy controller was not appropriate in some subject models. The tracking control performance of the fuzzy controller was not only dependent on fuzzy gain *H* but also on other parameters that need to be optimized individually for each trial. An example of control results of the MPC-FES

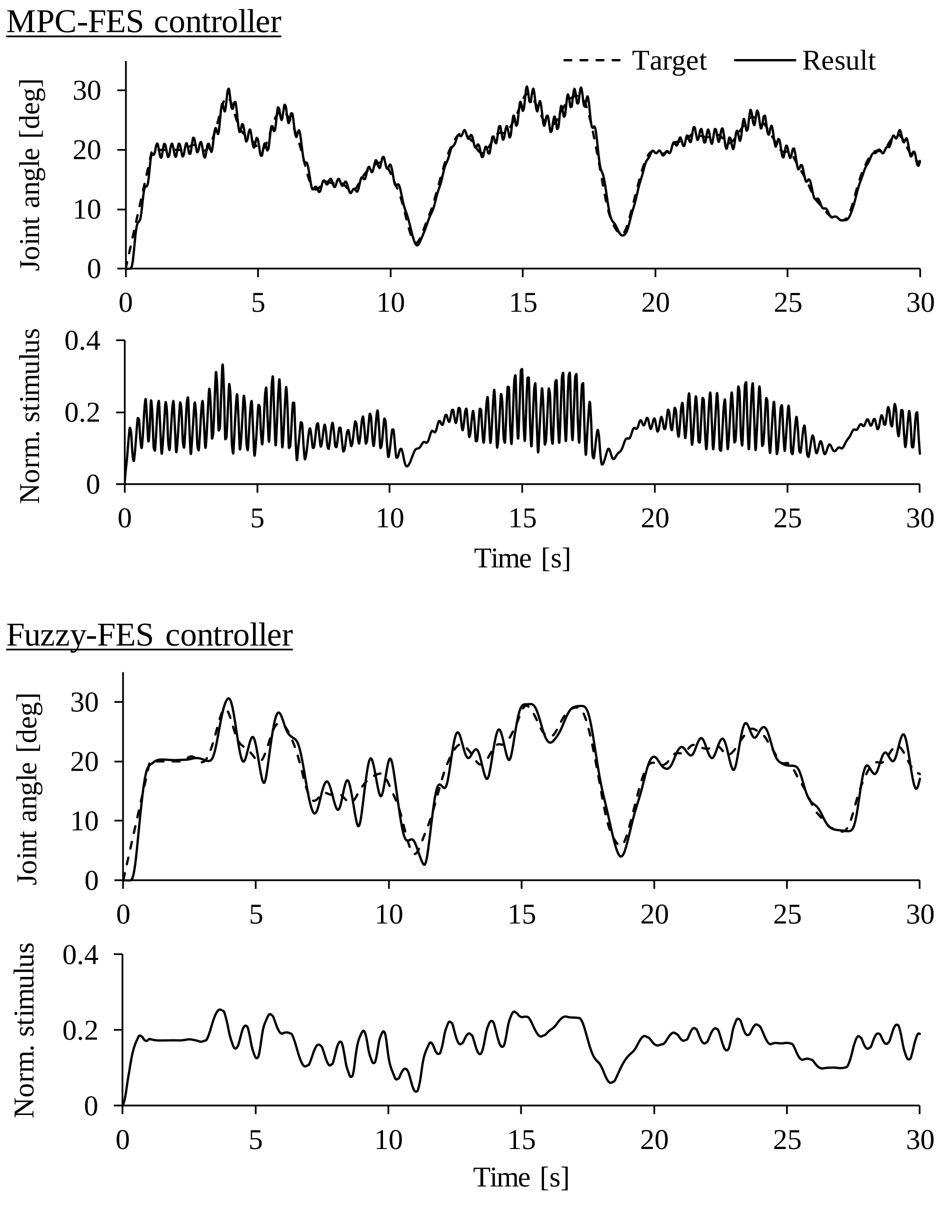


Figure 5.6: Comparison of control results of the MPC-FES controller and fuzzy-FES controller tested in test subject AS2 and target movement trajectories was target θ_{d1} with random movement.

controller and the fuzzy-FES controller tested in wrist joint control of the test subject AS2 and the target movement trajectories were target θ_{d1} with fast movement and random movement is shown in Fig. 5.5 and 5.6, respectively.

Compared to the fuzzy-FES controller as shown in Fig. 5.4, the MPC-FES controller was superior in tracking control for all different target movements, especially for fast movement control, although the slope parameter of the nonlinear transformation was determined using the single estimation formula. As shown in Fig. 5.5, the response delay in the control results of the MPC-FES controller is shorter than the fuzzy controller for each movement target trajectory. The MPC-FES controller is better at reducing the time lag error caused by muscle response delay because it has a feedforward predictor and a feedback corrector in its structure. The feedforward structure could improve the delay problem in the control response [21]. The fuzzy controller was difficult to track random movements with a frequency band of 0.25 Hz or higher as indicated by the significant difference in MAE values even though E-OAF was used in its configuration to make a fast response if a large error is detected. Although the MPC-FES controller has higher tracking control accuracy, on some reference and test subjects with random movements, oscillations appear in the control response of the MPC-FES controller when using estimated values.

Small changes in the estimated value will determine the appearance of oscillations in the control response. If the estimated value is larger than its optimum value, oscillations will appear in the control response. Conversely, if the estimated value is smaller than its optimum value, the control response is smooth. However, if the estimated value is too small, the controller will find it difficult to achieve the target angular trajectory. Based on our investigation, the difference between the optimum value and the estimated value determined by a single estimation formula is not large in most cases. Therefore, it is suggested that the estimated value can be the initial value in the parameter adjustment process if further improvement in control performance is desired.

Compared to other studies [24]-[26], the tracking control performance of the proposed MPC-FES controller is comparable to previous studies. However, the proposed controller has the advantages of an easy design procedure and only the slope parameter of the nonlinear transformation has to be adjusted at the beginning of each control experiment for a new subject test. In addition, the controller parameter values

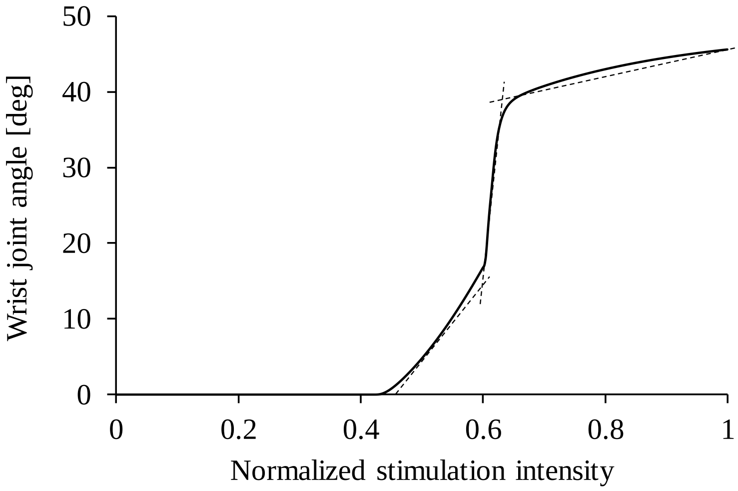


Figure 5.7: Input-output characteristic of paralyzed subject model can be divided into 3 regions with different slopes.

for individual subject tests can be adjusted easily using a simplified parameter estimation method. Since the controller design procedure along with the parameter estimation method refers to actual conditions, it is possible to apply them in practical applications. Therefore, the MPC-FES controller developed in this study could be extended to be tested in a real environment.

5.4 Computer simulation tests with paralyzed subject model

5.4.1 Methods

The input-output characteristic of paralyzed subject model has steep response for range of stimulation intensity about 0.6 - 0.65 and small range of motion. In addition, the input-output characteristic of paralyzed subject model can be divided into 3 regions with different slopes as shown in Fig. 5.7. Therefore, with such strange characteristic make determining of gain M is difficult to be calculated. In this test, the target movement trajectory was a sinusoidal pattern with a cycle period of 4 s, repetitive

Table 5.4: Optimum values of α of PReLU function and optimum values of fuzzy gain H of paralyzed subject model (AS6) based on the range of motion.

Target	Optimum value of α of PReLU function	Optimum value of fuzzy gain H
10-90%	1.00	0.10
10-75%	0.65	0.10
10-50%	0.45	0.07
10-30%	1.15	0.12
35-65%	0.20	0.04
75-90%	1.95	0.52

movement with a small and wide range of motion, (10-90%, 10-75%, 10-50%, 10-30%, 35-65%, 75-90% of maximum joint angle of paralyzed subject). These ranges were considered to explore the controller capability in dealing with different slope of input-output characteristic of stimulated paralyzed muscle.

The optimum values of the slope parameter of the PReLU function and fuzzy gain for each range of motion were determined using manual adjustment as described in chapter 3. Those values were summarized in Table 5.4. The estimated values of the slope parameter of the PReLU function were determined using the single estimation formula (method 2) as described in chapter 4. The estimated values of fuzzy gain were also determined using the single estimation formula as shown in Fig 5.8, this estimation formula was created as the same procedure as the single estimation formula of slope parameter of the PReLU function. We performed the fitting process to obtain the estimation formula for determining the fuzzy gain H as described as follows,

$$H(M) = 10.507M^{(-0.889)} \tag{5.4}$$

As shown in Fig 5.8, the relationship between fuzzy gain H and gain M shows an exponential relationship. Then, the relationship was fitted using a power function instead of an exponential function since the power function has a better fit similar case to the single estimation formula of slope parameter of the PReLU function (method 2).

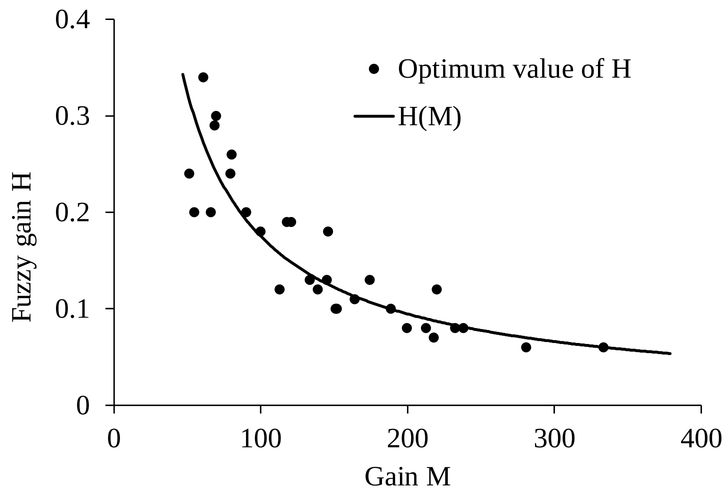


Figure 5.8: Relationship between the optimum value of fuzzy gain H and gain M for all reference subjects and for all targets.

However, the data distribution of optimum values of fuzzy gain H was not good as the optimum values of the slope parameter of the PReLU function. Therefore, the number of mismatches of fuzzy gain was larger than the slope parameter of the PReLU function which tends to cause a large error for some range of motion, especially for small gain M.

5.4.2 Results and discussions

An example of the control result of the MPC-FES controller and fuzzy-FES controller with a range of motion of 10-90% using the optimum and estimated values are shown in Fig. 5.9 and 5.10, respectively. From the results, in general, the MPC-FES controller has a better tracking control performance than the fuzzy-FES controller for the wrist joint movement of the paralyzed subject model using optimum and estimated values. Moreover, the MPC-FES controller with estimated value shows a smaller oscillating response than the fuzzy-FES controller with optimum value. The fuzzy controller seems to be difficult to track the target movement, it shows by slow control response although the optimum value of fuzzy gain was applied. We assumed

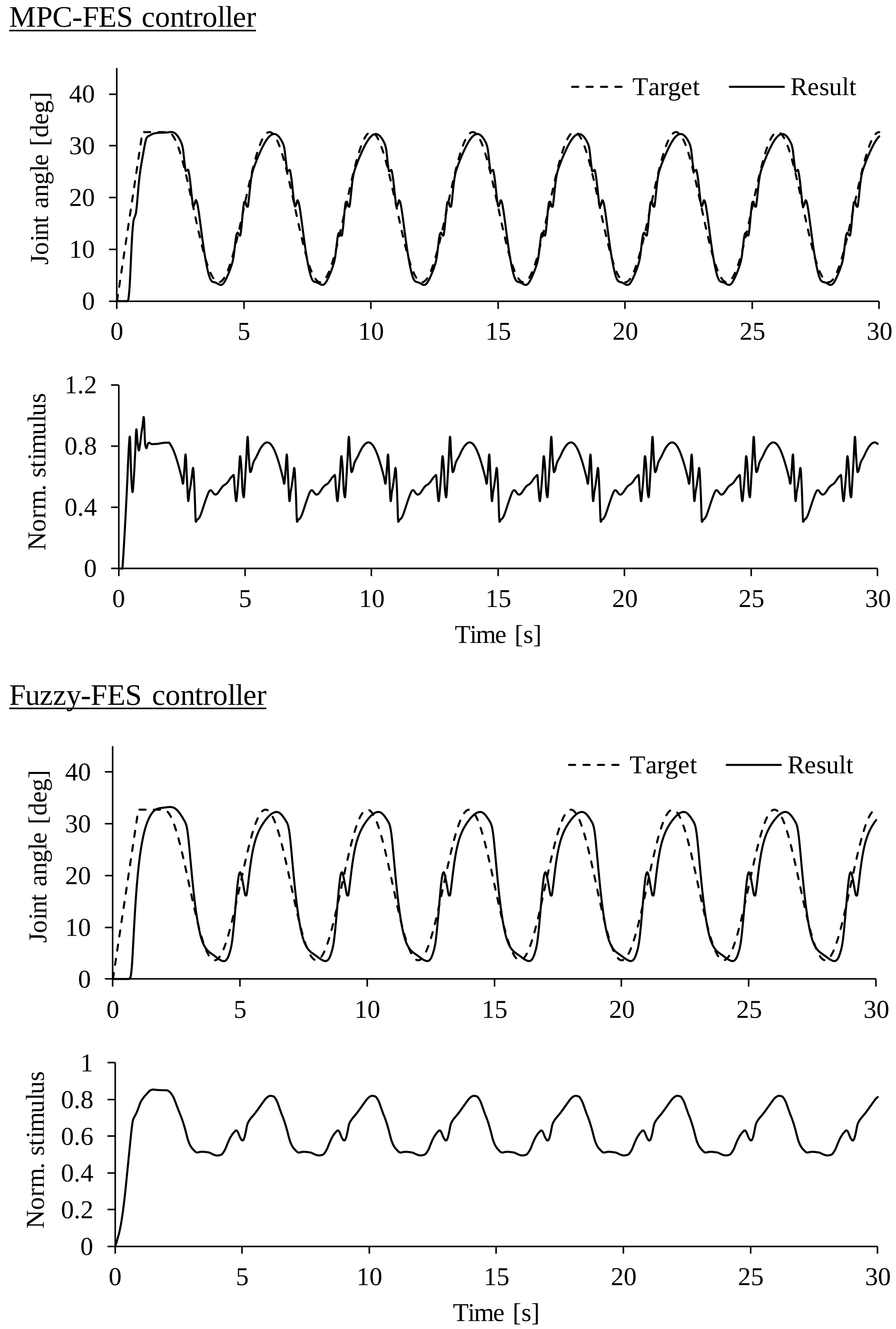
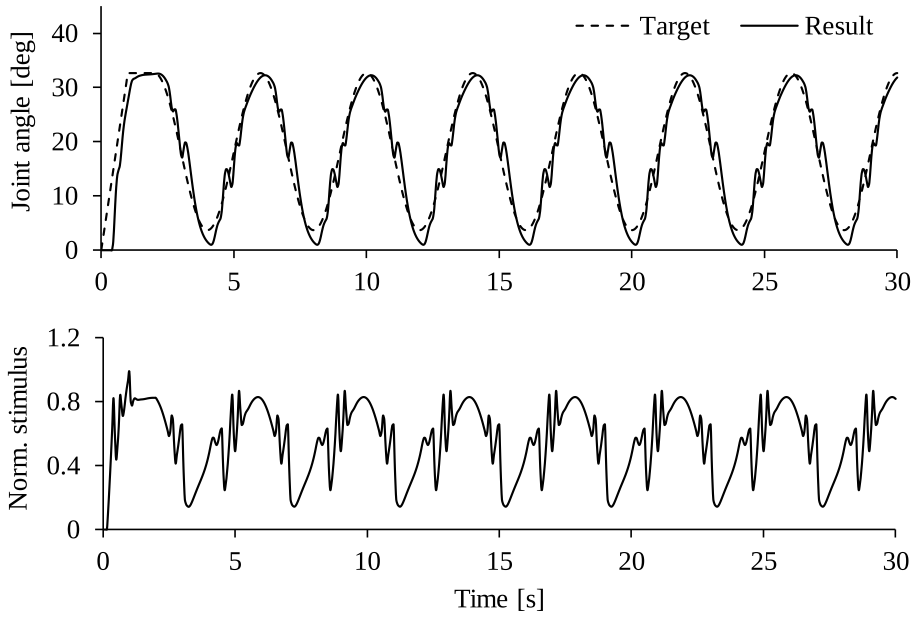


Figure 5.9: An example of control result of MPC-FES controller and fuzzy-FES controller tested in paralyzed subject model with range of target motion 10-90%. The parameter values for both controllers used the optimum values.

that the poor control response was caused by the mismatch of other parameter values of the fuzzy controller, so its tracking control performance is not only dependent on

MPC-FES controller



Fuzzy-FES controller

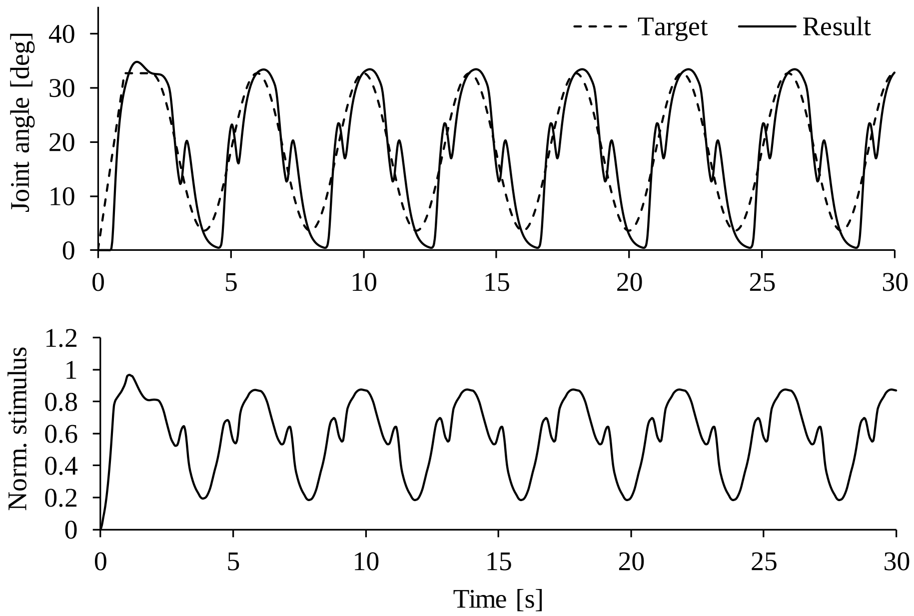


Figure 5.10: An example of control result of MPC-FES controller and fuzzy-FES controller tested in paralyzed subject model with range of target motion 10-90%. The parameter values for both controllers used the estimated values.

the fuzzy gain H. On the other hand, the MPC-FES controller has fast convergence in tracking the target movement, it was indicated by a small value of time-lag error (delay

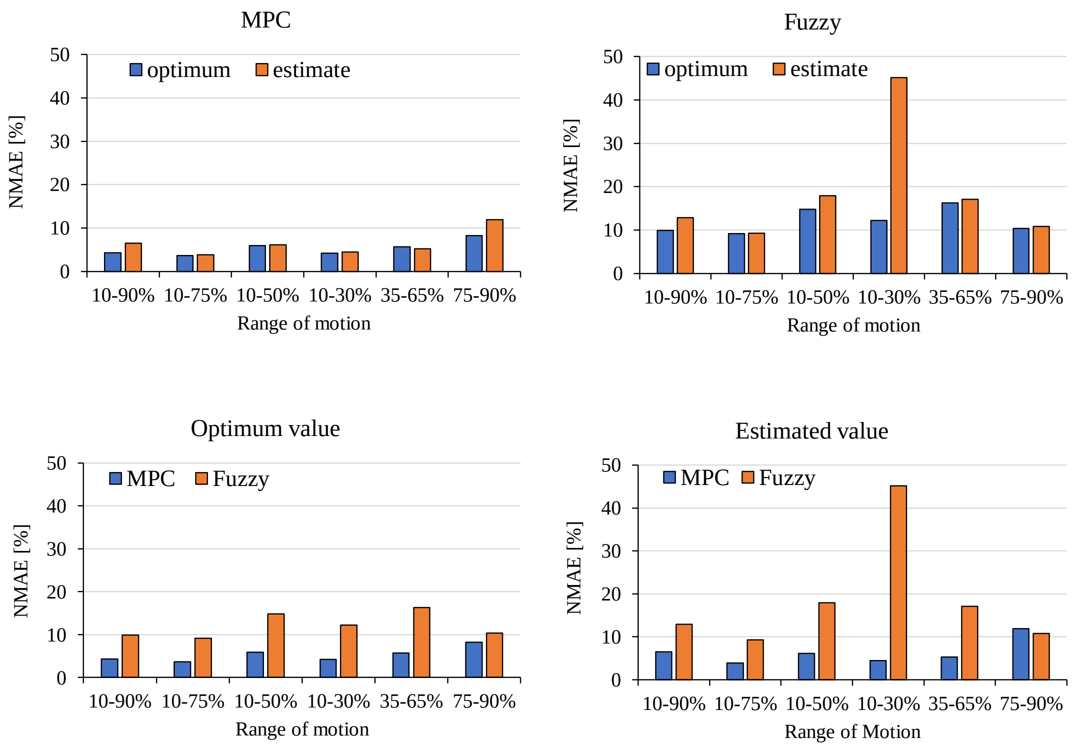


Figure 5.11: Comparison of NMAE between MPC-FES controller and fuzzy-FES controller for all target range of motion.

response). However, the oscillating response was getting larger when the target trajectory reach about 10 deg in this target movement, the slope was changed into a steep region. Therefore, the steep response of input-output characteristics and small range of motion makes the MPC-FES controller difficult to obtain satisfactory control performance. The control result of the MPC-FES controller was almost the same as the experimental result using the PID controller in the previous study [18]. However, the MPC-FES controller seems to be superior since only 1 stimulated muscle was used in this study instead of using 2 or 4 stimulated muscles.

Figure 5.11 shows the comparison of NMAE between MPC-FES controller and fuzzy-FES controller for all target range of motion. Based on the comparison result, it was clear that the MPC-FES controller had a better tracking control performance than the fuzzy-FES controller in controlling the wrist joint movement of paralyzed subject model.

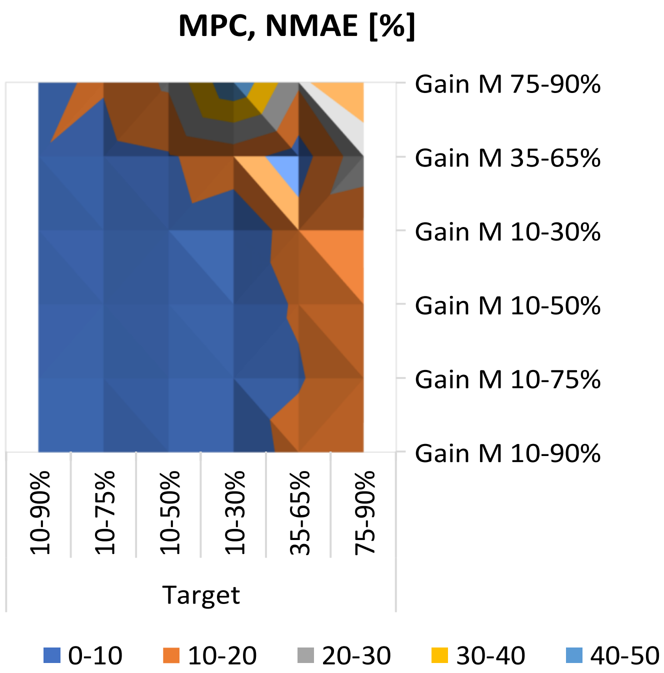


Figure 5.12: Surface plot of cross validation result in investigating the possibilities of using fix gain *M* for different range of motion in order to estimate the slope parameter of MPC-FES controller.

Table 5.5: NMAE value of cross validation result based on the range of motion.

		Range of target motion					
		10-90%	10-75%	10-50%	10-30%	35-65%	75-90%
Gain M	10-90%	6.53	4.43	7.99	4.30	13.26	10.13
	10-75%	5.31	3.84	6.25	5.85	9.18	16.92
	10-50%	4.70	3.92	6.16	5.07	10.94	15.10
	10-30%	6.14	4.42	7.45	4.45	13.78	10.32
	35-65%	9.82	6.88	9.18	14.44	5.24	26.68
	75-90%	8.79	10.80	21.71	48.73	21.69	11.92

Figure 5.12 shows surface plot of cross validation result in investigating the possibilities of using fix gain *M* for different range of motion in order to estimate the slope parameter of MPC-FES controller. The NMAE value for each trial is summarized in Table 5.5. Based on the result, when the gain *M* was determined using

related target movement, the relative error was small. It was also shown that it is possible to use gain M calculated from 10-90%, 10-75%, 10-50% range of motions since the relative error was also small for different range of motion. On the other hand, when gain M was calculated from 10-30%, 35-65%, 75-90% range of motions since the relative error was large for different range of motion. From that, it can be understood that in case of paralyzed subject model, the gain M calculated using wide range of motion will give a good estimation value of slope parameter of PReLU function. Therefore, it can be considered that if gain M calculated based on target movement could not obtain a satisfactory control performance, then gain M calculated with wide range of motion (e.g. 10-90%) can be applied.

5.5 Computer simulation tests with muscle fatigue

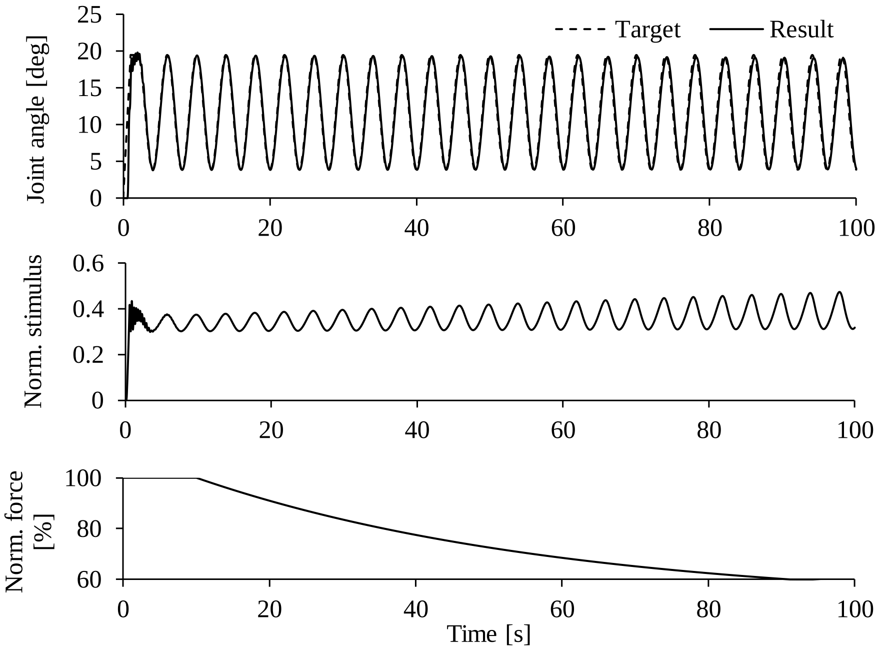
5.5.1 Methods

As mention in the beginning of this chapter that the ability of proposed controller in compensating the muscle fatigue should be validated before implemented in a real environment. Therefore, we have to create the muscle fatigue model to test the proposed controller in computer simulation study. Muscle fatigue is defined as reduction of the maximum force that a muscle can exert. The muscle fatigue of intermittent electrical stimulation was shown decreasing of the electrically elicited muscle force to 50% of maximum force [75]. In this study, muscle fatigue is modeled as an exponential decrease of maximum muscle force, $Fmax$, to 50% of its original value as a function of time with a decay constant as described in Eq. 5.5. This model was adopted from [76].

$$F_{max} = F_{max0} - \frac{F_{max0}}{2}\left(1 - e^{-\frac{t-t_f}{\beta}}\right); t > t_f \tag{5.5}$$

where F_{max0} is the original maximum muscle force, t is the stimulation time, t_f is the time when a muscle begins to fatigue, and β is a decay constant (in this study, 50 was chosen to represent the moderate fatigue). The evaluation methods used in this test was the same as computer test with paralyzed subject model in previous section.

MPC-FES controller



Fuzzy-FES controller

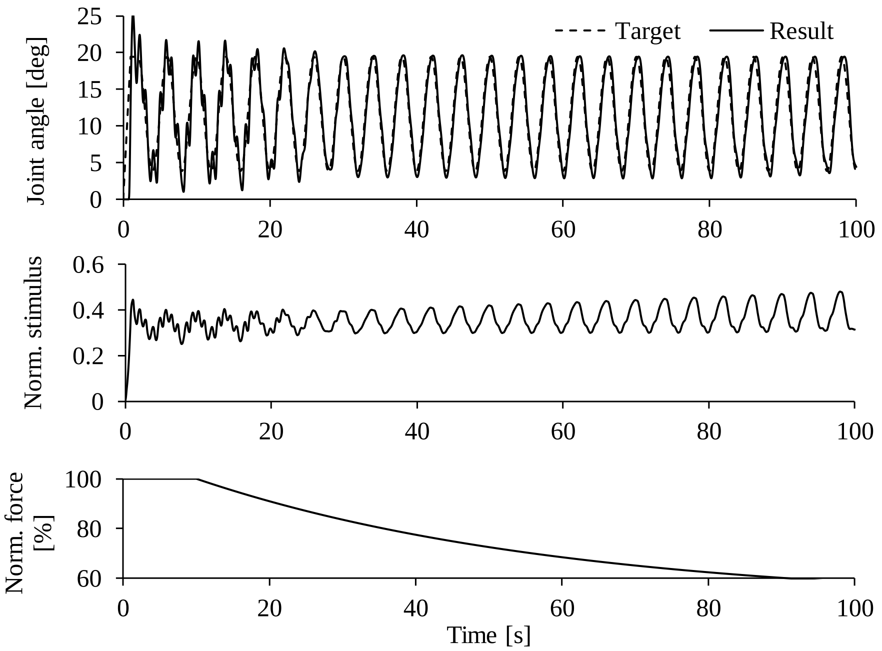


Figure 5.13: An example of control result of the MPC-FES controller and fuzzy-FES controller in controlling wrist joint movement of subject S1 under fatigue with 10-50% range of motion. The parameter values of fatigue model were t = 100 s, t_f = 10 s, β = 50, and estimated values were used for both controller parameters.

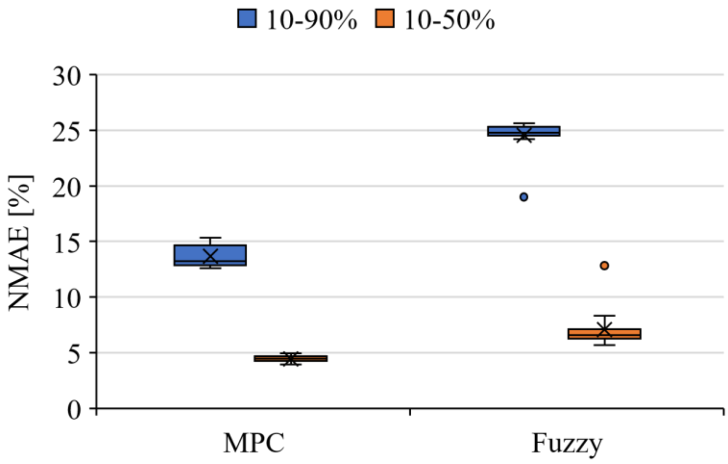


Figure 5.14: Comparison of NMAE value of control performance of the controllers for small and wide range of motion.

5.5.2 Results and discussions

Figure 5.13 shows an example of control result of the MPC-FES controller and fuzzy-FES controller in controlling wrist joint movement of subject S1 under fatigue with 10-50% range of motion. The parameter values of fatigue model were $t = 100$ s, $t_f = 10$ s, $\beta = 50$, and estimate values were used for both controller parameters. Based on the result, it shows that both controllers able to work well under muscle fatigue condition. When the fatigue begins to decrease exponentially, the controllers try to regulate or increase the stimulation intensity that indicates the controller compensate the muscle fatigue.

Figure 5.14 shows the comparison of NMAE value of control performance of the controllers for small and wide range of motion. From Fig. 5.14, it was clear that the MPC-FES controller has a better compensation of fatigue than fuzzy-FES controller. However, When the target is about max target angle, both controllers were difficult to compensate for the muscle fatigue. This result has almost the same result as in another study [73] using PID and sliding mode control, where the stimulation intensity reaches its maximum quickly.

5.6 Computer simulation tests with external disturbance

5.6.1 Methods

This test was intended to evaluate the ability of proposed controller in rejecting the external disturbance. In this computer simulation study, the external disturbance was model as a constant torque in amount 40% of maximum torque calculated from 10-90% of range of motion. Firstly, maximum torque for 10-90% of range of motion was calculated under free external disturbance, then this value was used for different range of motion tests. The disturbance was activated from 10-20 s, where this value of disturbance subtracts the torque suddenly during control process. The evaluation method to justify the ability of controllers in rejecting the external disturbance was the same as in the previous section. In addition, we calculated Ex (MAE free-disturbance for 2-30 s), E0 (MAE under-disturbance for 2-30 s), E1 (MAE under-disturbance for 2-10 s), E2 (MAE under-disturbance for 10-20 s), E3 (MAE under-disturbance for 20-30 s) to get knowledge about the effect of external disturbance.

5.6.2 Results and discussions

Figure 5.15 shows an example of control result of MPC-FES controller and fuzzy-FES controller in controlling the wrist joint movement of S1 with range of motion 10-50%. Based on the control result, MPC-FES controller could reject the external disturbance more quickly than the fuzzy-FES controller. Large oscillating response in fuzzy-FES controller caused by a mismatch in its parameter value since this test was performed using the estimated value of fuzzy gain H. The appearance of external disturbance seems to increase the joint stiffness. Figure 5.16 shows the comparison of NMAE value of the control performance between MPC-FES controller and fuzzy-FES controller under external disturbance. It seems that the MPC-FES controller was superior to fuzzy-FES controller. Fast convergence can be achieved under external disturbance using model-based controller [74]. Based on the evaluation results, the MPC-FES controller was superior compared to the fuzzy-based FES controller and is highly recommended to be tested in a real environment.

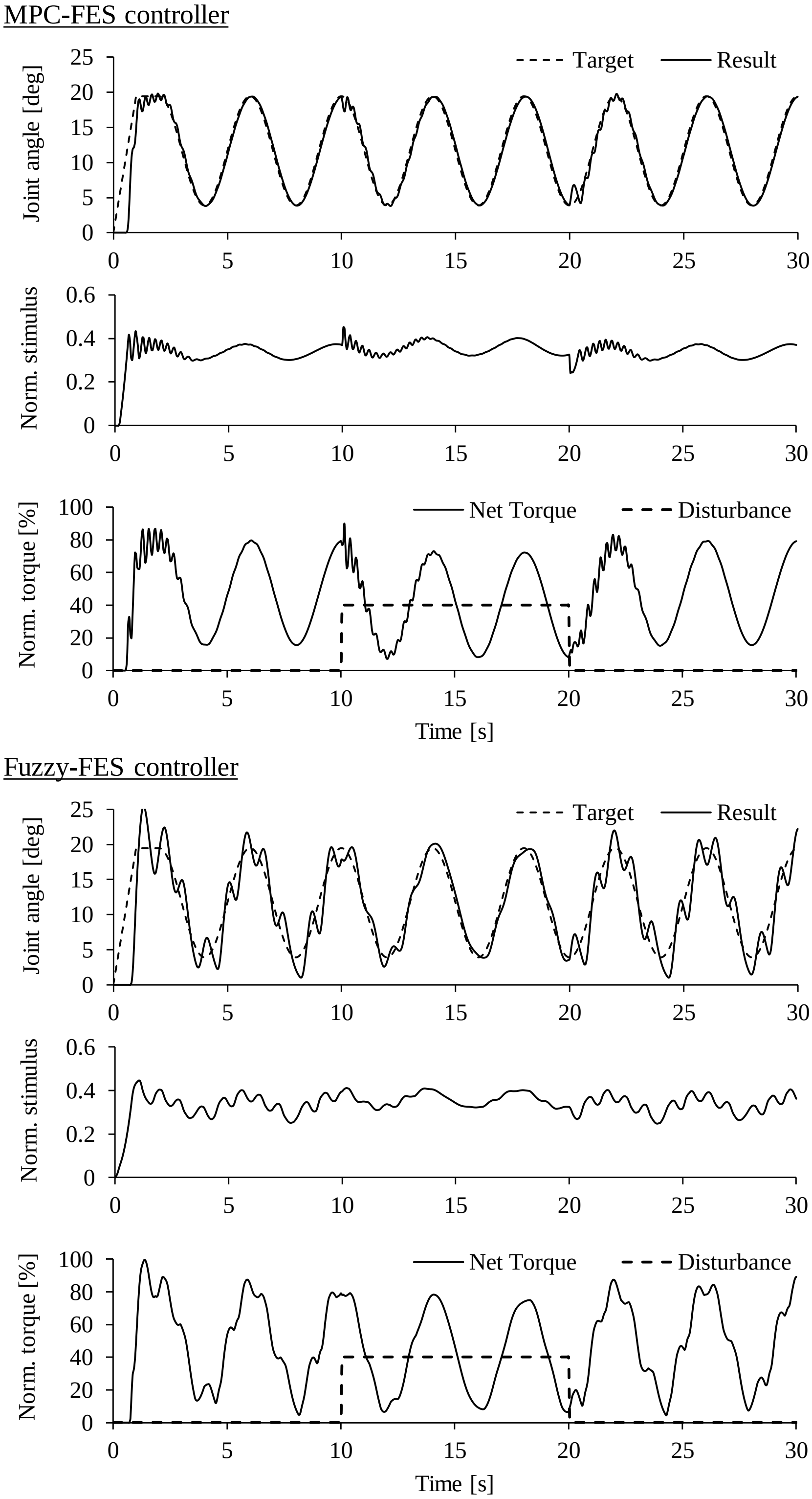


Figure 5.15: An example of control result of MPC-FES controller and fuzzy-FES controller in controlling the wrist joint movement of S1 with range of motion 10-50% under external disturbance.

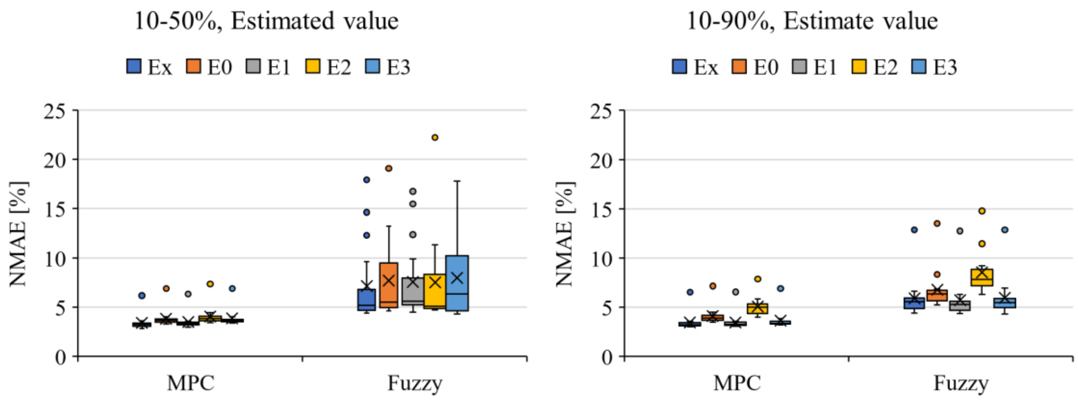


Figure 5.16: Comparison of NMAE value of control performance of the controllers for small and wide range of motion under external disturbance.

5.7 Chapter summary

In this chapter the modified fuzzy-FES controller was developed and tested in wrist joint control through computer simulation. The control results showed good tracking control performance by using the proposed method. The linear MPC with the PReLU function had good tracking control performance with high control accuracy in controlling wrist joint movements, which was superior compared to the fuzzy-based FES controller in controlling different speeds of target movement and random movement trajectories, tests with paralyzed subject model, in compensating the muscle fatigue and in rejecting the external disturbance although the value of slope parameter of PReLU function was determines using the simple estimation formula. Therefore, the MPC-FES controller along with estimation formula was considered to be applicable and useful for practical FES application (in rehabilitation training and activities of daily living) and was highly recommended to be tested in a real environment.

Chapter 6

Concluding Remarks

6.1 Summary

This thesis focused on the topic of the development of an FES controller for joint movement restoration. The motivation of this study was encouraged by the existing appropriate controller for FES application still not implemented in clinical practice although many control method has been developed in previous studies. Several findings have been obtained from this computer simulation study such as a capable FES controller that can deal with nonlinear systems and a simple parameter estimation method to determine the controller parameter.

In chapter 2, the FES controller was developed by using a combination of a linear MPC and a nonlinear transformation. The configuration was aimed to obtain a capable controller to deal with the nonlinear systems such as joint movement induced by FES. The linear MPC with no active constraints and an average prediction model was chosen to realize the FES controller. The nonlinear transformation was realized using a simple nonlinear function such as parametric rectified linear unit, hyperbolic tangent, binary sigmoid, and polynomial functions. The musculoskeletal model for FES control application was developed as requirement tool for this computer simulation study. We have developed ten subject model using the musculoskeletal model based on the static and dynamic response of stimulated musculoskeletal system of ten healthy subjects. The input-output characteristics shows strong variation among subjects that were very useful for this study. To confirm that the developed subject models could be used in the computer simulation study, we performed a validation test on the subject models using the PID controller from the previous study. Based on the validation test, the same characteristics as those observed in the PID control tests in the previous studies were confirmed. This is a useful result that demonstrates the validity of the computer simulation tests used in this thesis.

In chapter 3, we conducted the computer simulation test of the proposed FES controller that have been developed in chapter 2. The FES controller was tested in controlling the 1-DOF wrist joint movement for repetitive movement with different range of motion. Based on the evaluation results, we found that the proposed method had high tracking control accuracy. By utilizing the average model used in the linear MPC structure, the identification process to determine the model parameter values for a new subject is not necessary. Indeed, since the prediction model was not realized by an exact or nominal model, the output of the linear MPC had a poor tracking control. However, by cascading it with the nonlinear transformation, the appropriate stimulation intensity for desired target movement could be acquired. Based on the control results, it was shown that the use of nonlinear function was able to transform the output of the linear MPC assumed as a linear solution into a nonlinear. Four types of different nonlinear functions were investigated in realizing the nonlinear transformation. These functions were also able to map the output of linear MPC as a linear solution to obtain a nonlinear solution. Based on comparison of the control evaluations for all trials, the linear MPC with the PReLU function seems to be useful to realize the FES controller in dealing with different ranges of motions of joint movements.

In chapter 4, we proposed the simplified method to estimate the slope parameter value of the nonlinear transformation. Based on the simulation results, the estimation method was considered to be effective to determine the value of α. The linear MPC with the PReLU function along with estimated parameter value had good tracking control performance with high accuracy in controlling wrist joint movements. The gain of the musculoskeletal system has a strong exponential relationship with the value of α and can be considered as an important feature for controller development for FES applications. The simple parameter estimation method was suggested to be useful to determine the parameter value of the nonlinear transformation used with the linear MPC for practical FES applications, hence reducing the burden on patients and medical staff.

In chapter 5, the control capability of the MPC-FES controller was examined through computer simulation in comparison to a fuzzy-FES controller. The linear MPC with the PReLU function along with estimated parameter value had good tracking control performance with high accuracy in controlling wrist joint movements, which was superior compared to the fuzzy-based FES controller in controlling different speeds of target movement and random movement trajectories. The control capability of the MPC-FES controller was also examined in comparison to a fuzzy-FES controller to deal with a paralyzed subject model, muscle fatigue, and external disturbance. Based on the evaluation results, the MPC-FES controller was superior compared to the fuzzy-based FES controller in controlling the wrist joint movement of the paralyzed subject model and worked well in compensating the muscle fatigue and rejecting the external disturbance although the value of slope parameter of PReLU function was determined using the simple estimation formula. The MPC-FES controller along with the estimation formula was considered to be applicable and useful for practical FES application (in rehabilitation training and activities of daily living) and was highly recommended to be tested in a real environment.

6.2 Contributions

The main contributions of this thesis are the following,

- A systematic design of FES controller for joint movement restoration based on a model predictive control.
- A simple average prediction model for linear model predictive control used for FES control application.
- A simple method to transform the output of linear model predictive control by

utilizing a simple nonlinear function.

- A simple parameter estimation method for determining the initial parameter value of proposed FES controller.

6.3 Future work

Based on the evaluation results, this computer simulation study will be extended by testing the proposed method in a real environment. The design and testing procedures in a real environment can be carried out in the same way or stages as in the simulation environment, considering that this study was designed with reference to actual conditions in practical FES applications. Moreover, regarding the parameter estimation method, the design procedure and the use of the parameter estimation method can be implemented easily in a real environment since the response of the musculoskeletal system to electrical stimulation of each subject is commonly measured at beginning of rehabilitation training using FES. The measurement is performed to determine the input-output characteristic, range of motion (ROM), and range of stimulation intensity. Therefore, the gain of the musculoskeletal system can be calculated easily from the input-output characteristic and can be used to estimate the value of the shape parameter of nonlinear transformation.

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List of Publications

Journal Paper

- F. Arrofiqi, T. Watanabe and A. Arifin, "A Computer Simulation Study on Movement Control by Functional Electrical Stimulation Using Optimal Control Technique with Simplified Parameter Estimation," *IEICE Transactions on Information and Systems*, 2022. (Submitted)

International Conference Paper (Peer-reviewed)

- F. Arrofiqi, T. Watanabe and A. Arifin, "A Computer Simulation Test for Validation of Linear Model Predictive Control with Nonlinear Transformation for FES in Wrist Joint Control," *2021 6th International Conference on Intelligent Informatics and Biomedical Sciences (ICIIBMS)*, 2021, pp. 144-148, doi: 10.1109/ICIIBMS52 876.2021.9651660.

- F. Arrofiqi, T. Watanabe and A. Arifin, "Design of Parameter Estimation Method of Fuzzy FES Controller: Computer Simulation Test in Wrist Joint Control," *2022 IEEE 4th Global Conference on Life Sciences and Technologies (LifeTech)*, 2022, pp. 116-120, doi: 10.1109/LifeTech53646.2022.9754880.

- F. Arrofiqi, T. Watanabe and A. Arifin, "Development of Parameter Estimation Method for Nonlinear Transformation Used with Linear Model Predictive Control for FES: Computer Simulation Test in Wrist Joint Control, *IFMBE Proceedings, IUPESM WC2022*, 2022. (Accepted).

Domestic Conference Paper, Seminar Abstract

- F. Arrofiqi, T. Watanabe and A. Arifin, "A Basic Study on MPC with a Simple Model for FES: Computer Simulation Tests in Wrist Joint Control," *Transactions of Japanese Society for Medical and Biological Engineering*, 2021, Volume Annual59, Issue Proc, pp.793-795, 2021, https://doi.org/10.11239/ jsmbe.Annual59.793.

- F. Arrofiqi, T. Watanabe and A. Arifin, "A Validation Test of a Cascaded Linear Model Predictive Control and Nonlinear Transformation for FES by Computer Simulation in Wrist Joint Control," *Abstract: The 1st Joint Laboratory Seminar on Rehabilitation Engineering and Assistive Technology, Japan-Indonesia*, 2022.

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