Optimized Fuzzy Control For Natural Trajectory Based Fes-Swinging Motion

B.S.K.K Ibrahim[1], M.O. Tokhi[2], M.S.Huq[2] and S.C. Gharooni[2]

[1]Department of Mechatronic and Robotic, Faculty of Electrical & Electronic Engineering
University Tun Hussein Onn Malaysia, Batu Pahat, Johor, MALAYSIA.

[2,3,4]Department of Automatic Control and System Engineering, Faculty of Engineering
The University of Sheffield, Sheffied, UNITED KINGDOM.

Abstract: The use of electrical signals to restore the function of paralyzed muscles is called functional electrical stimulation (FES). FES is a promising method to restore mobility to individuals paralyzed due to spinal cord injury (SCI). A crucial issue of FES is the control of motor function by the artificial activation of paralyzed muscles due to the various characteristics of the underlying physiological/biomechanical system. Muscle response characteristics are nonlinear and time-varying. After developing a nonlinear model describing the dynamic behavior of the knee joint and muscles, a closed-loop approach of control strategy to track the reference trajectory is assessed in computer simulations. Then, the controller was validated through experimental work. In this approach only the quadriceps muscle is stimulated to perform the swinging motion by controlling the amount of stimulation pulsewidth. An approach of fuzzy trajectory tracking control of swinging motion optimized with genetic algorithm is presented. The results show the effectiveness of the approach in controlling FES-induced swinging motion in the simulation as well as in the practical environment.

Keywords: Functional electrical stimulation, fuzzy logic, genetic algorithm, paraplegic

1. Introduction

FES induced movement control is a significantly challenging area for researchers. The challenge mainly arises due to many obstacles in stimulating the paralyzed neuromuscular system, such as fatigue, time-varying properties and nonlinearity of paralyzed muscles [1]. The design of control strategies can greatly benefit from a model-based approach; in principle, better muscle models mean better control. Many researchers have developed electrically stimulated muscle control ranging in levels of sophistication from simple to complex. Primarily due to the complexity of the system (nonlinearities, time-variation) practical FES systems are predominantly open-loop where the controller receives no information about the actual state of the system [2]. In its basic form, these systems require continuous user input. Practical success of this open-loop control strategy is still, however, seriously limited due to the fixed nature of the associated parameters. Accurate control of FES-induced movement can be ensured with a suitable closed-loop adaptive control mechanism. Such approach has several advantages over open-loop schemes, including better tracking performance and smaller sensitivity to modeling errors, parameter variations, and external disturbances [3].

Many control strategies have been developed to provide enhanced reproducibility of muscle responses, including fixed-parameter feedback control [4-5], model reference adaptive control [6-7], and sliding mode control

[8]. Fixed parameter feedback control involves the construction of a precise mathematical model that describes the dynamic behaviour of the controlled musculoskeletal system. As musculoskeletal is very complex, fixed-parameter feedback control techniques realised only with limited success [9]. Model-reference adaptive control does not need a precise model of the musculoskeletal system, but the control performance is satisfactory only when the closed-loop bandwidth is restricted by appropriate choice of reference model parameters [10]. Moreover, its major drawback is its complex algorithm and the problem of convergence of the parameters to be estimated. Sliding mode FES control was used to regulate knee joint angle and was tested on six neurologically intact subjects and two untrained paraplegic subjects [8]. Good tracking of a desired knee joint trajectory was achieved, but this could only be applied to mathematical model based plant. In fact, the overall model of the plant being considered is a multi-input-multi-output (MIMO) nonlinear model consisting of nonlinear lumped parameters comprising passive joint viscoelasticity and active muscle properties and segmental dynamics [11].

On the other hand, fuzzy logic control (FLC) has long been known for its ability to handle a complex nonlinear system without developing a mathematical model of the system. It is being used successfully in an increasing number of application areas in the control community. FLCs are rule-based systems that use fuzzy

*Corresponding author: babul@uthm.edu.my

linguistic variables to model human rule-of-thumb approaches to problem solving, and thus overcoming the limitations that classical expert systems may face because of their inflexible representation of human decision making. The control signal is computed by rule evaluation called fuzzy inference instead of by mathematical equations. Thus FLC is the preferred option to control this nonlinear MIMO musculoskeletal knee joint model.

This paper presents the development of strategies for swinging motion control by controlling the amount of stimulation pulsewidth to the quadriceps muscle of the knee joints. The quadriceps muscle plays a fundamental role in the main motor activities (i.e., standing up, sitting down, walking, standing posture, and climbing stairs). First, capability of the controller to control knee joint movements is assessed in computer simulations using a musculoskeletal knee joint model. The knee joint model developed in Matlab/Simulink, as described in [11] is used to develop the FLC based on reference trajectory derived from passive oscillation to control the knee joint movement. The FLC output is the controlled FES stimulation pulsewidth signal which stimulates the knee extensors providing torque to the knee joint. The swinging movement is performed by only controlling stimulation pulsewidth to the knee extensors to extent the knee and then the knee is left freely to flex in the flexion period. A FLC controller fuzzy logic controller has been developed by optimizing with GA is investigated. Finally the controllers are assessed in computer simulations as well as in validation tests through experimental work on a paraplegic in terms of tracking performance.

2. System Model, Description and Control

In this study, the role of simulation based on model was, to design, test, and optimize the control strategies, thus reducing time-consuming trial and error adjustments during human experiments. We also focused on the design and evaluation of fuzzy logic control approach. Therefore, a simplified but effective fuzzy nonlinear dynamic model of the lower limb was developed.

2.1. Knee Joint Model

The shank-quadriceps dynamics are modelled as the interconnection of passive and active properties of muscle model and the segmental dynamics. The total knee-joint moment is given as [12]:

$$M_i = M_a + M_g + M_s + M_d \qquad (1)$$

where M_a refers to an active knee joint moment produced by electrical stimulation, M_s is the knee joint elastic moment and M_d is the viscous moment representing the passive behaviour of the knee joint. In this research the $M_i - M_g$ is represented by equation of motion for dynamic model of the lower limb while M_a and $M_s + M_d$ are represented by a fuzzy model as active properties of quadriceps muscle and passive

viscoelasticity respectively. A schematic representation of the knee joint model consisting of active properties, passive viscoelasticity and equations of motion of the lower limb is shown in Figure 1. The active joint moment is added with the passive joint moment as an input (torque) to the lower limb model and this will produce the knee angle as the output. The subject participating in this work was a 48 year-old T2&T3 incomplete paraplegic male with 20 years post-injury with height = 173cm and weight = 80kg. Informed consent was obtained from the subject.
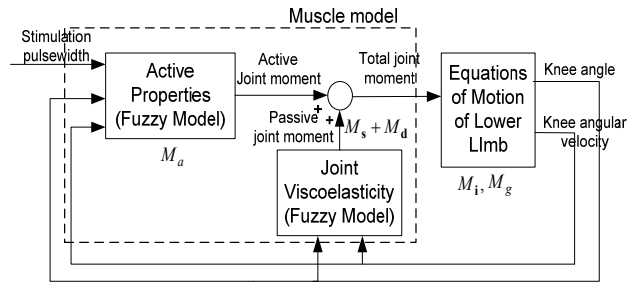

Fig. 1 Schematic representation of the knee joint model

A schematic diagram of the lower limb model is shown in Figure 2, where q_2 = shank length, r_1 = position of COM along the shank, r_2 = position of COM along the foot, θ_1 =knee angle and θ_2 =ankle angle. Hence, the dynamics of motion can be represented in the simpler form based on Kane's equations as in (Ibrahim et al., 2011). The gravitational (M_g) moment is represented by:-

$$M_g = m_1 g \cos\theta_1 r_1 + m_2 g \cos\theta_1 q_2 \qquad (2)$$

The inertial (M_i) moment of the lower limb is represented as follows:-

$$M_i = -m_2 q_2 \dot{\theta}_1^2 r_2 - I_1 \ddot{\theta}_1 - m_1 r_1^2 \ddot{\theta}_1 - m_2 q_2^2 \ddot{\theta}_1 \quad (3)$$

where, m_1 = shank mass, m_2 =foot mass, I_1 = moment of inertia about COM, $\dot{\theta}_1$ =knee angular velocity $\ddot{\theta}_1$ =knee angular acceleration g =gravity=9.81 m/s². Anthropometric measurements of length of the lower limb were made and this is shown in Table 1.
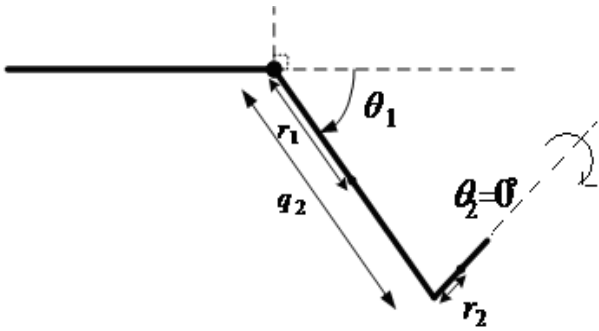
Fig.2 Lower limb model

Table 1 : Anthropometric data of subject

Segment	Length (m)
Shank length	0.426
Foot length	0.168
Approximated position of COM of shank	0.213
Approximated position of COM of soot	0.034

The knee joint model input is the stimulation pulsewidth as would be delivered in practice by an electrical stimulator. The complete model of knee joint thus developed is utilized as platform for simulation of the system and development of control approaches.

2.2 Fuzzy Logic Control Development

2.2.1. Reference trajectory

Compromising with natural dynamics of the plant in the control of movement to produce a desired outcome is a good choice as considered in [13] and [14]. Perhaps the feature is most prominent within natural movements, performed by human or animals, as is suggested by the 'minimum torque-change' model of voluntary human arm movement [15].

This control scheme emphasises on the choice of reference trajectory with a view to overcome some drawbacks of trajectory based closed-loop FES control, viz. poor tracking and oscillating response [10]. Therefore, a reference trajectory for the knee joint is obtained from observing the subject's passive oscillation from the pendulum test. The experimental data from the first cycle of pendulum test is used as reference trajectory in order to get purely passive oscillation as shown in Figure 3. This method is different from the traditional trajectory control with some improvement; ability to swing in the subject's natural frequency.
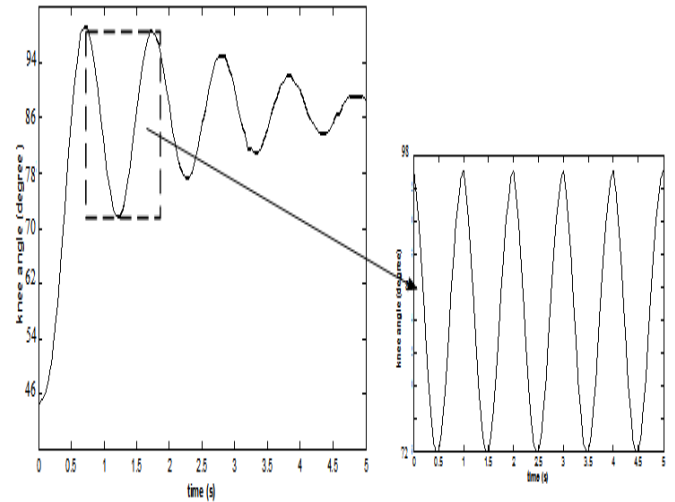

Fig.3 Reference knee joint trajectory derived from pendulum test.

2.2.2 Design of Fuzzy Control for Natural Swinging Motion

An outline of the natural swinging motion PD-type FLC (a two-input and single-output controller) is shown in Figure 4. The controller's inputs are the error and the change of error. This addition of controller input is to increase the sensitivity of the controller. Error is defined as difference between the desired trajectory and measured joint angle. The Mamdani-type fuzzy controller will regulate the stimulation pulsewidth according to the error and derivative of error. Mamdani type fuzzy inference was used due to the simplicity to formulate rules.

The control problem was to design a fuzzy controller such that the knee joint tracks the desired trajectory as closely as possible for all times in spite of the uncertainties and nonlinearities present in the system.
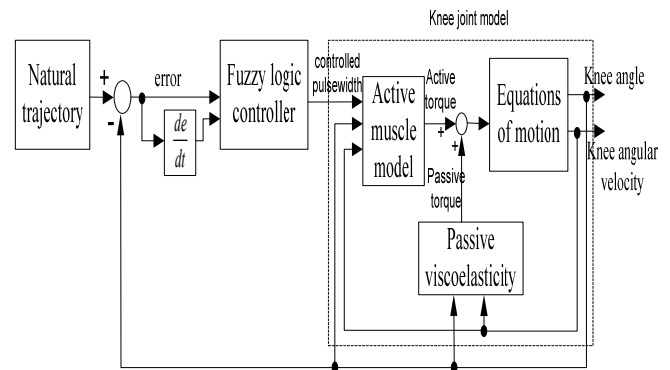

Fig.4 PD-type fuzzy control

2.2.3 Off-line tuning of Fuzzy control

Tuning a control loop refers to the adjustment of its control parameters to the optimum values for a desired control response. On the other hand, the major drawback of fuzzy control is the lack of design techniques. Most of

the fuzzy rules are human knowledge oriented and hence rules will deviate from person to person in spite of same performance of the system. The selection of suitable vector of parameters that specify the membership function (MF) involves a painstaking trial and error process.

A systematic procedure for choosing the vector of parameters that specify the MF is still not available. Consequently the tuning operations of fuzzy logic controller were suitably formulated as optimization procedures using genetic optimization techniques [16]. Triangular MFs of FLC were optimized involving 73 decision variables or parameters. Piecewise linear triangular membership functions are preferred, because of their simplicity and efficiency with respect to computability. A breakdown of optimized parameters of the fuzzy system is as follows:-

i. 3 parameters associated with the scaling factors of the three fuzzy state vectors relating them to normalized universe of discourse used by the inference method.
ii. 45 parameters relating to the triangular MFs, (3-element vector that determines the break points for each MF).
iii. 25 weighting factors to be applied to the rule between 0 and 1 for all rules.

The configuration of the fuzzy expert system model is shown in Figure 5. In the fuzzification step, crisp inputs are fuzzified into linguistic values to be associated with the input linguistic variables. After fuzzification, the inference engine refers to the fuzzy rule base containing fuzzy IF-THEN rules to derive the linguistic values for the intermediate and output linguistic variables. Once the output linguistic values are available, the defuzzifier produces the final crisp values from the output linguistic values. The defuzzification method used is based on calculating the centre of gravity of the fuzzy output.

Scaling factors are applied to ensure that the domain of discourse covers the whole range [17]. Therefore, two input scaling factors are used to transform the crisp inputs into normalised inputs so as to keep their value within -1 and +1. The scaling factors are S1 for error and S2 for change of error. An output scaling factor S3 provides a transformation of the defuzzified crisp output from the normalised universe of the control output into an actual physical output (duty cycle of pulsewidth) to be fed to quadriceps muscle.
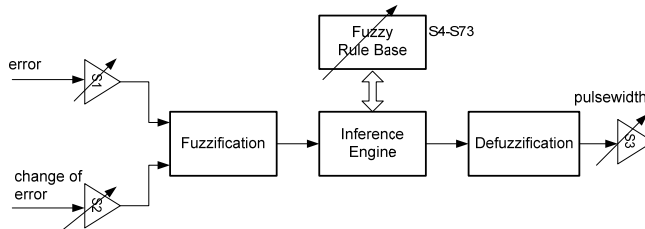

Fig. 5 A fuzzy expert system model

Evolutionary computing, GAs are globally searching techniques, which are more likely to converge to the global optimum and emulate natural genetic operators such as selection, crossover, and mutation [18]. This evolutionary algorithm in conjunction with fuzzy logic has been used successfully in biomedical engineering in various applications [19]. The GA approach is able to search many points simultaneously as well as able to avoid local optima that traditional gradient descent algorithms might get stuck in [20]. Optimization of the FL controller using GA is shown in Figure 6. The automatic optimization is implemented in MATLAB with GA Toolbox.
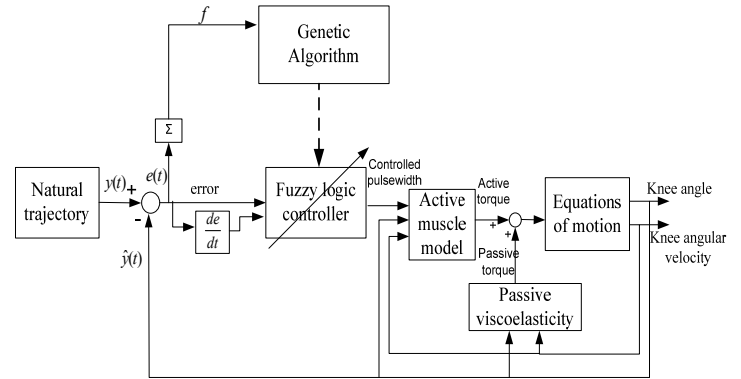

Fig. 6 GA optimization of fuzzy controller

The objective of GA optimization process is to minimize the error between the desired trajectory and actual knee angle. The error is defined as:

$$e(t) = y(t) - \hat{y}(t) \qquad (4)$$

where $y(t)$ is the desired trajectory and $\hat{y}(t)$ is the actual knee angle. The 'goodness of fit' of the identified model is determined using the objective function by minimizing the MSE:

$$f = \left\{ \frac{\sum_{i=1}^{N} (y(t) - \hat{y}(t))^2}{N} \right\} \qquad (5)$$

3. Results and Discussion
3.1. Simulation Study
3.1.1. Fuzzy Controller Optimization
A new method comprising a GA and unconstrained MF overlap to automatically design fuzzy controllers is presented. The automatic GA optimization process was set to generate up to 100 generations of solutions. Population size of GA was set to 50 and crossover and mutation probabilities were 0.8 and 0.001 respectively. The best solution was kept and the rest were discarded until there was no significant change in the mean square error (MSE) observed after the 85th generation. The

computation time taken by the GA to converge was 18 minutes and the minimum MSE achieved was 1.07°. The optimized weighting factors of all the fuzzy rules for the controller are contained in Table 2 in their corresponding cells. Figure 7 shows the optimally shaped input and output MFs of the fuzzy controller. The output has got [0,1] range of normalization as compared to [-1,1] range for inputs since the output should be always positive.

Table 2 FLC rule table with optimized weighting factors for the rules.

		Derivative of Error				
		NB	NS	ZO	PS	PB
Error	NB	ZE (0.38)	ZE (0.03)	ZE (0.49)	NS (0.05)	LO (0.59)
	NS	ZE (0.82)	ZE (0.49)	VL (0.64)	LO (0.26)	ME (0.37)
	ZO	ZE (0.42)	VL (0.49)	LO (0.33)	ME (0.25)	HI (0.59)
	PS	VL (0.76)	LO (0.53)	ME (0.82)	HI (0.82)	HI (0.47)
	PB	LO (0.79)	ME (0.22)	HI (0.42)	HI (0.64)	HI (0.46)

NB=Negative big, NS=Negative small, ZO=Zero, PS=Positive small, PB=Positive big, ZE=Zero, VL=Very Low, LO=Low, ME=Medium, HI=High
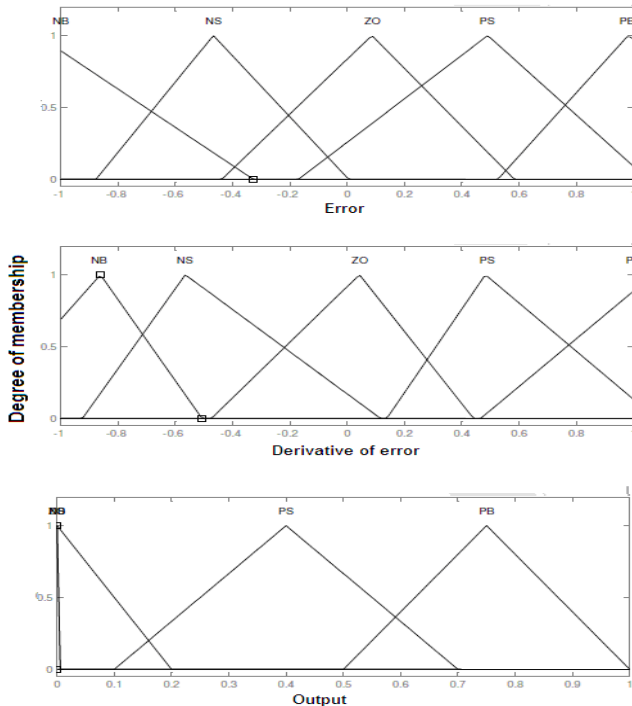

Fig.7 Optimised MFs of the fuzzy controller

3.1.2 Fuzzy Control Trajectory Tracking Performance

The computer simulation test of the designed swinging motion FLC was performed to track the desired trajectory. The test was initiated with 220μs amplitude with 0.15s burst durations of stimulation pulse for the first cycle of swing gait before controller took action. The simulation was carried out using Matlab/Simulink as a platform. The control was performed in stimulation course of 100 cycles. The first 10 cycles of the controller's performance can be seen in Figure 8. It can be noted that this fuzzy controller achieved the objective; to track the trajectory and thus maintain a steady swinging of the lower limb. The error between desired trajectory and actual response of the knee joint was less than 1º for the first 10 cycles.
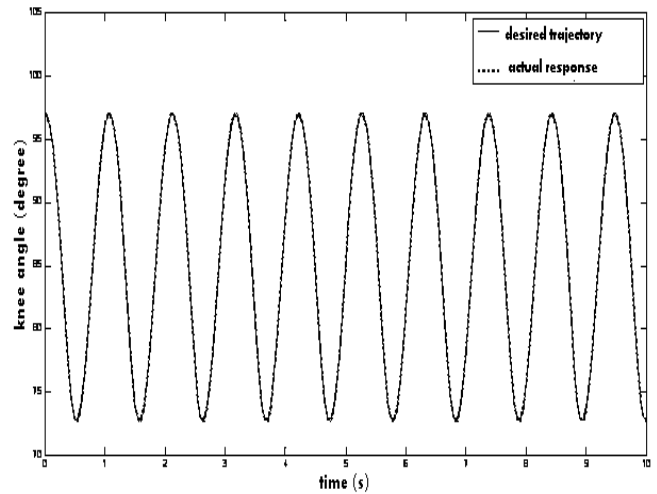

Fig.8 Controlled swinging leg (simulation study)

The ultimate outcomes of the FLC optimization effort, the resultant nonlinear control surface defined by plotting the output of the FLC against its inputs are shown in Figure 9. The control surfaces in these figures are plotted in normalized values.
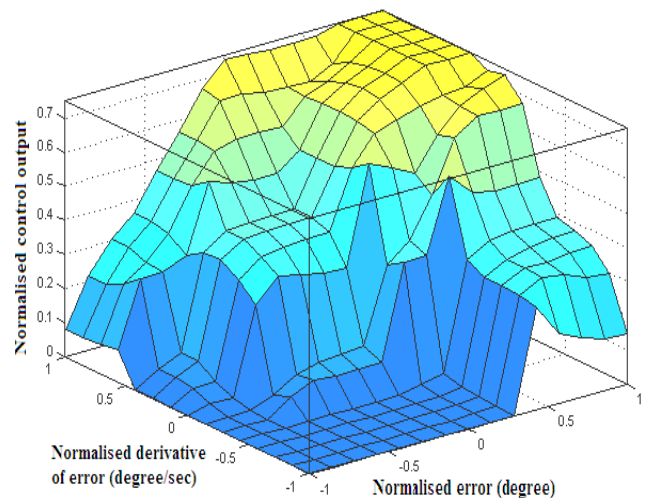

Fig. 9 Nonlinear control surfaces of the optimized FLC

3.2. Experimental Validation
3.2.1. Experimental Setup
The laboratory apparatus built to study the knee joint control by FES is shown in Fig.10. The subject sat on a chair, which allowed the lower leg to swing freely, while the ankle angle was fixed at 0°. The knee extensors (quadriceps muscle group) were stimulated by a pair of surface electrodes (2"x5"). The cathode was placed on the motor point of rectus femoris and the anode was placed distally at the quadriceps tendon. Knee angle was defined in Figure 2, with when the lower leg was at rest during knee flexion (i.e., 90).

The computer-controlled stimulator system consisted of a personal computer, computer-controlled interface (including analog-to-digital converter), current controlled stimulator and goniometer (see Figure 9). The system software was written in the Matlab and Simulink. The computer controlled the stimulator through the stimulator interface which performed all of the timing functions in generating either monophasic or biphasic stimulation patterns. The stimulation pulsewidth is generated by FLC based on the error by comparing the actual extension angle and the desired ones. All these operations were performed in the Simulink environment in the computer. The Hasomed stimulator device was connected to PC via USB interface port with sampling time of 0.05s. The knee joint angle was measured via the Biometric flexible electroganiometer mounted at approximate center of rotation of the knee joint. Stimulation pulsewidth ranged from 0 to 230μs and stimulation current was fixed to 40mA with a biphasic type pulse. The stimulation frequency was set to 25Hz and the knee joint angle sampling time was 0.05s. An intra-trial interval for 120 s was used to reduce the effects of fatigue.
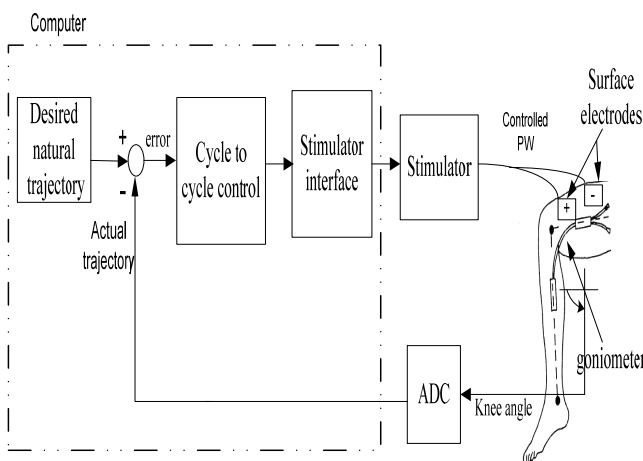

Fig.10 The equipment setup of this study

3.2.2. Fuzzy Control Trajectory Tracking Performance

The experimental test of the optimized FLC (based on simulation study) was carried out to assess the capability of the controllers to track the desired trajectory. The initial position was defined at the rest position (almost 90°). The same procedure as in the simulation work was applied with the test, initiated with 220μs amplitude with 0.15s burst durations of stimulation pulse. A controller was tested in stimulation course of 100 cycles. Only the first 10 cycles were considered for tracking performance test to avoid any fatigue influence due to intense stimulation.

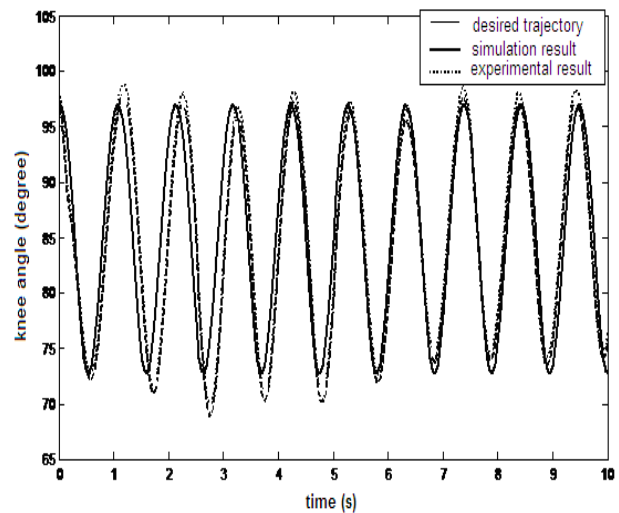## 3.2.3. Result Comparison between simulation and experimental work

Fig.11 Controlled swinging leg (simulation and experimental results)

Figure 11 shows the comparison between simulation and experimental results with respect to desired trajectory. As can be seen in this figure, the simulation result follows exactly as the desired trajectory while the experimental knee joint angle lagged behind the desired trajectory at the beginning of the test. This might be due to time-delay in muscle response in the early stage of the stimulation. Time delay is the time loss from muscle activation to active torque generation due to the neuro-musculoskeletal (NMS) dynamics [21]. However, the controller was able to follow the trajectory after 5s. Hence these fuzzy controllers achieve the main objective; to track the trajectory but the controller need more time to track and maintain a steady swinging of the lower limb. The error between the actual angle and the desired trajectory was slightly higher than in the simulation study. These might happen due to optimisation of both controllers performed in off-line mode rather than on-line optimisation since genetic algorithm can only be applied in the off-line mode.

4. Conclusion

FES induced movement control is a difficult task due to the highly time-variant and nonlinear nature of the muscle and segmental dynamics. The great merit of a musculoskeletal model of knee joint is to help understand how the muscle works and serves for control development. In this control design approach, fuzzy logic controller has been optimized using genetic optimization technique to track the trajectory based on natural dynamics of the paraplegic's leg segment. In principle, this control scheme is based on 'natural dynamics' of the leg segment and are applicable to control any FES induced movement of periodic nature. The performance of the controller in terms of tracking has been assessed through simulation and experimental study. This study of knee joint swinging control provides valuable insight into the control of FES-induced paraplegic walking and cycling.

References

[1]   M. Levy, J. Mizrahi, and Z. Susak, "Recruitment force and fatigue characteristicsof quadriceps muscles of paraplegics isometrically activated by surface functional electrical stimulation," J. Biomed. Eng., vol. 12, pp. 150–156, 1990.

[2]   P.E. Crago,N. Lan, P. H. Veltink, J.J. Abbas and C.Kantor. New control strategies for neuroprosthetic systems, Journal Rehabilitation Res Device 33(2):158-72,1996.

[3]   M.S.Huq, Analysis and control of hybrid orthosis in therapeutic treadmill locomotion for paraplegia, PhD Thesis. The University of Sheffield, Sheffield, UK, 2009.

[4]   J. Quintern, P. Minwegen, and K. H. Mauritz, "Control mechanisms for restoring posture and movements in paraplegics," Prog. Brain Res., vol. 80, pp. 489–502, 1989.

[5]   J. J. Abbas, "Feedback control of coronal plane hip angle in paraplegic subjects using functional neuromuscular stimulation," IEEE Trans. Biomed. Eng., vol. 38, pp. 687–698, 1991.

[6]   J. Allin and G. F. Inbar, "FNS control schemes for the upper body," IEEE Trans. Biomed. Eng., vol. 33, pp. 818–828, 1986.

[7]   L. A. Bernotas, P. E. Crago, and H. J. Chizeck, "Adaptive control of electrically stimulated muscle," IEEE Trans. Biomed. Eng., vol. 34, pp. 140–147, 1987.

[8]   S. Jezernik, R.G. Wasink, and T. Keller, Sliding mode closed-loop control of FES: controlling the shank movement. IEEE Transaction Biomedical Engineering 51(2):263-72,2004.

[9]   G.C. Chang, Jer-Junn Luh, Gon-Der Liao, Jin-Shin Lai, Cheng-Kung Cheng, IEEE, Bor-Lin Kuo, and Te-Son Kuo, Senior Member, IEEE A Neuro-Control System for the Knee Joint PositionControl with Quadriceps Stimulation IEEE Transactions on Rehabilitation Engineering, Vol. 5, No. 1, March,1997

[10]   M. S. Hatwell, B. J. Oderkerk, C. A. Sacher, and G. F. Inbar, "The development of a model reference adaptive controller to control the knee joint of paraplegics," IEEE Trans. Automat. Contr., vol. 36, pp.683–691, June 1991.

[11]   B.S. K. K. Ibrahim, M.O. Tokhi, M.S. Huq, R. Jailani and S.C. Gharooni, Fuzzy modelling of knee joint with genetic optimization, Journal of Applied Bionics and Biomechanics, Vol. 8, pp. 85–99, 2011.

[12]   M. Ferrarin, and A. Pedotti. The relationship between electrical stimulus and joint torque: a dynamic model. IEEE Transactions on Rehabilitation Engineering, vol. 8 (3), pp. 342-352, 2000.

[13]   N.C. Singer and W.P.Seering, Preshaping command inputs to reduce system vibration. ASME Journal of Dynamic Systems Measurement and Control, 112(1), pp. 76–82, 1990.

[14]   M. M. Williamson Exploiting natural dynamics in robot control. MIT AI Lab, 545 Technology Square Rm 828, Cambridge, MA 02139.,1998.

[15]   Y.Uno, M.Kawato, R.Suzuki, Formation and control of optimal trajectory in human multijoint arm movement - minimum torque-change model. Biol. Cybern. 61:89-101. 1989

[16]   C. Fonseca, and P. Fleming, "Genetic algorithms for multiobjective optimization: formulation, discussion and generalization," Genetic Algoritms: Proceeding of the Fifth International Conference, San Mateo, CA, pp. 416-423,1993.

[17]   L Reznik, Fuzzy Controllers, Newnes-Butterworth-Heinemann, Oxford, 1997.

[18]   D. E. Goldberg, Genetic algorithms in search, optimization and machine learning. Reading, MA: Addison-Wesley, 1989.

[19]   H.N. Teodorescu, A. Kandel, L.C. Jain, editors, Fuzzy and Neuro-Fuzzy Systems in Medicine, CRC Press LLC, Boca Raton, Florida. 1999.

[20]   M. Levin, Use of Genetic Algorithms to solve biomedical Problems, M.D. Computing, 12(3), pp. 193-198, 1995.

[21]   Vette, A. H., Masani, K., and Popovic, M. R. (2008). Time delay from muscle activation to torque generation during quiet stance: Implications for closed-loop control via FES. Biomedizinische Technik. 53: 423-425.