Intelligent Algorithm Tuning PID Method of Function Electrical Stimulation Using Knee Joint Angle

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***Abstract*-Functional electrical stimulation (FES) could restore motor functions for individuals with spinal cord injury (SCI). By applying electric current pulses, FES system could produce muscle contractions, generate joint torques, and thus, achieve joint movements automatically. Since the muscle system is highly nonlinear and time-varying, feedback control is quite necessary for precision control of the preset action. In the present study, we applied two methods (Proportional Integral Derivative (PID) controller based on Back Propagation (BP) neural network and that based on Genetic Algorithm (GA)), to control the knee joint angle for the FES system, while the traditional Ziegler-Nichols method was used in the control group for comparison. They were tested using a muscle model of the quadriceps. The results showed that intelligent algorithm tuning PID controller displayed superior performance than classic Ziegler-Nichols method with constant parameters. More particularly, PID controller tuned by BP neural network was superior on controlling precision to make the feedback signal track the desired trajectory whose error was less than 1.2°±0.16°, while GA-PID controller, seeking the optimal parameters from multipoint simultaneity, resulted in shortened delay in the response. Both strategies showed promise in application of intelligent algorithm tuning PID methods in FES system.**

I Introduction

Functional Electrical Stimulation (FES) has been widely used in the area of neural engineering, with the ability of restoring motor functions of paralyzed muscles caused by a spinal cord injury (SCI) or a stroke. FES uses electrical stimuli to induce muscle contractions to help the patients achieve the motion they want. Various FES systems have been developed with different functions. However, it is still a question regarding how to appropriately adjust the parameters of the FES system to make the patients achieve the desired motion. It is quite difficult to control limbs accurately and stably in the FES system, since musculoskeletal systems are always nonlinear. Many control strategies have been proposed in existing FES systems, including fuzzy controller [1-3], model based controller [4-5], rule based controller [6-7], and neural network-based electrical stimulation [7]. Proportional Integral Derivative (PID) controller, with a stable control loop feedback mechanism and generic application in industrial control systems, has been widely used in FES research studies for decades of years [9-10].

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Conventional PID (e.g., Ziegler-Nichols [11]), with fixed parameters, is based on the industrial experience and manual trial-and-error. However, such a fixed-parameter feedback control techniques cannot meet with dynamic characteristics of muscles. In order to enhance performance of the FES system, some improvements have been employed on the PID controllers. Gwo-Ching Chang et al [12] designed a neuro-PID controller system to control the movement of knee joint to track the desired trajectory of movement. Takashi Watanabe et al [13] in 2003 applied generalized inverse matrix and PID controller based on an expanded CHR method to track several trajectories of the wrist joint movement for neurologically intact subjects. Kenji Kurosawa et al, in 2005, investigated a Feedback Error Learning scheme by applying PID controller with fixed parameters in the FES system [14].

Most PID applications in FES system usually adopted fixed parameters controlling strategy. Their application yielded better tracking performance than the open-loop controlled FES devices, but still did not achieve very good performance and unable to guarantee stability. In the present study, PID controllers with adaptive parameters are designed to control the knee joint angle by adjusting the pulse intensity of FES stimulator. Two strategies, Back Propagation (BP) neural network with merits of self-learning and adaptive functions, and Genetic Algorithm (GA) with capability of locating high performance areas in complex domains, are used to modulate three parameters of the PID controller separately. Their performance will also be compared with that from the controller based on Ziegler-Nichols method.

II Methods

A. PID controller

PID controller attempts to correct the error between a measured variable and a desired setpoint P, I and D values, and then keeps the error minimal [15]. The discrete-form of the PID algorithm, with input *error(t)* and output *u(t)* is generally given as

$$u(t) = K_p error(t) + K_i \sum_{j=0}^{t} error(j) + K_d [error(t) - error(t-1)] \tag{1}$$

where, *Kp* is the proportional value, *Ki* is the integral value, *Kd* is the derivative value, *error(t)* means the difference between desired and measured output of controlled subject.

Ziegler–Nichols, a popular PID tuning method in current FES application, confirms the PID parameters by escalating the Kp until the system starts to oscillate, while $Ki=0$, $Kd=0$, and then calculates the PID parameters by following formulas:

$$K_d = \frac{K_p \pi}{4\omega}, \quad K_p = 0.6K_p^{'}, \quad K_i = \frac{K_p \omega}{\pi} \tag{2}$$

where Kp is the proportional value when the oscillation appearances and ω is the circular frequency gotten from $\omega=\theta/T$ (θ is the position of the pole in the unit circle and $1/T$ is the sampling rate).

B. BP tuning PID

The structure of PID base on the BP neural network is that the *rin* is the desired trajectory and *yout* means measured output. The *rin*, *yout* and their error, as the input of the BP neural network, were used to optimize the parameters of the PID through training and adjusting the weighting coefficient adaptively. Here, a 3-5-3 structure is adopted in the BP neural network.

The inputs and outputs of the output layer are:

$$net_l^{(3)}(k) = \sum_{i=1}^{5} w_{li}^{(3)} O_i^{(2)}(k) \tag{3}$$

$$O_l^{(3)}(k) = g(net_l^3(k)) \qquad (l=1, 2, 3 \text{ and } i=1, 2, 3, 4, 5)$$

There among:

$$O_1^{(3)}(k) = K_p, \; O_2^{(3)}(k) = K_i, \; O_3^{(3)}(k) = K_d$$

where g(x) is the activation function of neurons located in the output layer.

The Performance Function is defined as

$$E(k) = \frac{1}{2} error^2(k) \tag{4}$$

The correction $\Delta w_{li}^{(3)}(k)$ applied to $w_{li}^{(3)}(k)$ is defined by

$$\Delta w_{li}^{(3)}(k) = -\eta \frac{\partial E(k)}{\partial w_{li}^{(3)}} \tag{5}$$

where η is the learning-rate parameter of the BP algorithm.

The learning algorithm of the weight in the output layer is given as,

$$w_{ij}^{(2)}(k) = w_{ij}^{(2)}(k-1) + \Delta w_{ij}^{(2)}(k) \tag{6}$$

$$\Delta w_{ij}^{(2)}(k) = \eta f'(net_i^{(2)}(k)) O_j^{(1)} \sum_{l=1}^{3} \delta w_{li}^{(3)}(k) \tag{7}$$

$$\delta = error(k)\,\mathrm{sgn}\left(\frac{\partial y(k)}{\partial \Delta u(t)}\right) \frac{\partial \Delta u(t)}{\partial O_l^{(3)}(k)} g'(net_l^{(3)}(k)) \tag{8}$$

The learning algorithm of the weight in the hidden layer is

$$w_{li}^{(3)}(k) = w_{li}^{(3)}(k-1) + \Delta w_{li}^{(3)}(k) \tag{9}$$

$$\Delta w_{li}^{(3)}(k) = \eta \delta O_i^{(2)}(k) \tag{10}$$

C. Genetic Algorithm

GA is a search technique used in computing to find exact or approximate solutions to optimization and search problems. It maintains a population of the individuals Ki $(i=1, 2\ldots N)$, where N demotes the population size. Each individual represent a potential solution of the problem.

Selection operation: this is a processing that stochastically selects the individuals from the population according to their fitness. The individuals with high fitness are selected and then reproduce new individuals to form the next generation for further genetic processing.

Crossover operation: this operator combines character of the two or more parents together to create new individuals. In this paper, we use arithmetical crossover, viz., two new individuals in the second generation $K_3(t+1)$ and $K_4(t+1)$ are produced as a linear combination of their parents $K_1(t)$ and $K_2(t)$.

$$\begin{aligned} K_3(t+1) &= \alpha K_1(t) + (1-\alpha)K_2(t) \\ K_4(t+1) &= (1-\alpha)K_1(t) + \alpha K_2(t) \end{aligned} \tag{11}$$

where $\alpha \in (0,1)$, the crossover operator is applied with a probability p_c.

Mutation operation: Mutation randomly alters a variable with an appropriate probability and entire new individuals were injected to the population with which Genetic Algorithm may be able to approach a better performance. In this paper, a variable mutation probability is adopted that an individual with higher fitness would be provided with a smaller mutation probability.

Fitness function: Genetic algorithm searches for the optimal solution by maximizing a given fitness function. In this study, we define the fitness function as:

$$fitness(n) = \frac{1}{(yout(n) - y_m(n))^2} \tag{12}$$

where y_m is the desired output and *yout* is its measured value of the plant. A lower error between desired output and measured value can result in a higher fitness.

GA-based PID controller optimizes the PID parameters through evolutionary computation techniques. Several indispensable elements need to be initialized: the reproduction probability Pr, crossover probability Pc, mutation probability Pm, and the number of generations G. Then calculating each individual's fitness in the population and selecting the top n individuals to generate the next generation through reproduction, crossover and mutation operation. The best individual with the highest fitness after G generations was used as the final *P, I,* and *D* parameters of PID controller. Muscle mathematical model is employed here in parameter optimization.

A second order deterministic autoregressive moving average (DARMA) model is adequate to describe the dynamics of electrically stimulated muscle. As shown below:

$$Y_k = a_1 * Y_{k-1} + a_2 * Y_{k-2} + b_1 * U_{k-1} \tag{13}$$

The input to the muscle U is the pulse amplitude and the output Y is the knee joint angle. The coefficient a_1, a_2 and b_1 were estimated through system identification according to the dynamic experimental data.

C. Experiment disign

Five healthy subjects, three males and two females, participated in this experiment. All experiments were carried out subjected to the regulations and approval of the appropriate Institutional Review Board, and after obtaining informed consent. In this study, the subject was seated on the platform with the un-loaded shank free to swing, the knee extensors (quadriceps muscle group) were stimulated by a pair of surface electrodes (Sigmedics, US). The knee joint angle was controlled by changing the amplitude of the stimulation pulse.

An electronic goniometer was attached on the surface of skin and through the knee section to monitor the knee angle. The lower leg was as rest during knee flexion, while the right rectus femora muscle was stimulated during the experiment, with original knee angle was defined as 90.

Stimulation trains were applied to relaxed quadriceps femoris muscles from the first level to the level at which the leg was straight. The highest level was recorded as the upper critical strength while the level of the knee beginning to move was the lower critical strength. Then, the lower critical strength-the upper critical strength-the lower critical strength was seen as an entire process and duration time was 4s during every level. At the same time the knee angle signal was always recorded in real time. This process is repeated for several cycles, and the maximum level of every cycle maintained the initial highest maximum.

III RESULTS

Three tuning modes for controller, Ziegler-Nichols, BP neural network and GA, were applied to five healthy subjects separately in this experiment. Fig.1 (a) show typical tracking results of the knee angle controlled by three methods respectively. The real line indicates the preset-trajectory and dashed line represents the measured output. The PID controller tuned by GA or BP Neural Network, which adopted adjustable and auto-adaptive P, I, and D values, has significantly better performance than Ziegler-Nichols method with constant parameters. Adaptive parameters for the PID controller have the advantages of suppressing the oscillation and reducing the error effectively in tracking process. Fig. 1 (b) recorded the errors controlled by these three methods during the whole trials. Comparatively, GA-PID which seek the optimal parameters from multi points simultaneously was superior in responding speed, while BP-Neural-Network-PID was able to give a more precise tracking performance than GA-PID ultimately.

The mean error of tracking trajectory at the first 10 seconds and that at after 20s based on the three control methods was calculated separately for the five subjects, showed in Fig. 2. Fig. 2a shows an obvious advantage of GA-PID on the responding speed for all the five subjects and Fig.2b presents BP-PID controller does the best performance on precision controlling in these three methods.

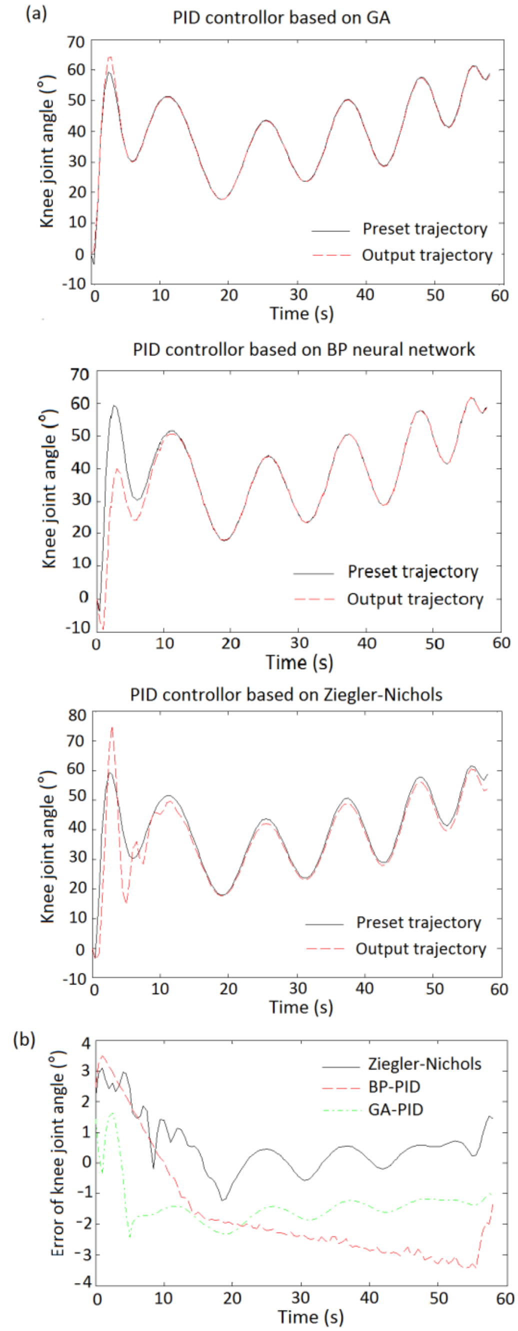

Figure 1. An example of the performance of the three controllers for a 60s segment of a knee joint movement. Panel a illustrates the knee angle for the three controller configuration and panel b shows the error of three controllers.

IV DISCUSSION

In previous work, some robust control strategies were designed which was based on the synergistic combination of artificial neural networks with sliding mode control for controlling the knee-joint movement, which provides an excellent tracking performance. However, the online computation burden to update the parameters of neural networks is a major problem. The method proposed in the current study was designed for the single muscle group stimulation, and it was a simpler design whereas the controller performance was not degraded.

In this study, two strategies, PID controller based on BP neural network as well as GA were designed to control knee joint position during stimulation. Both represented approaches with adaptive PID have better performance than traditional PID whose parameters were confirmed by Ziegler-Nichols formula. BP neural network, with advantage of self-learning, was able to get a better precision against others in the knee joint angle tracking experiment. Genetic Algorithm, utilizing the evolutionary ideas of natural selection and genetic to locating high performance areas in complex domains from multipoint, was superior on its response speed that the measured output approach the preset-trajectory rapidly.

Based on our current results, the following issues should be noticed: (1) an appropriate learning rate η is important for BP neural network algorithm, and an exorbitant η would result in output signal's overshoot while an insufficient would be slowed its responding speed; (2) the GA required suitable probability for selection operation, crossover operation and mutation operation that may affect the quality of the optimization directly; (3) the muscle mathematic model was the bottleneck for the controllers to enhance its precision in this study, and an excellent model that was able to simulate muscle characteristics perfectly would improve the control system significantly.

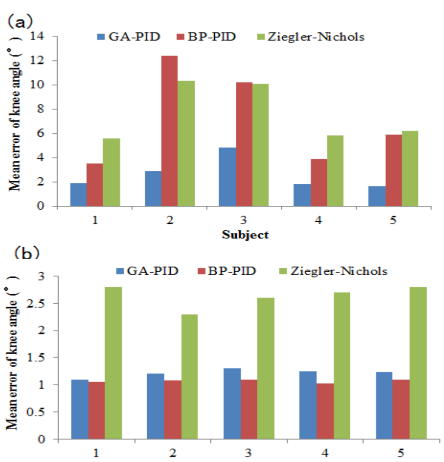

Figure 2. Mean error between the desired knee joint angle and the controller output for the three mehods. (a) Mean error at the frist 10 seconds, (b) Mean error after 20s.

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