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Adaptive Sliding Mode Control of Functional Electrical Stimulation (FES) for Tracking Knee Joint Movement

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***Abstract*—Functional electrical stimulation (FES) has shown great potential in helping patients to achieve their joint movements. Since muscle system exists non-linear, time-varying and external disturbances, conventional controllers are difficult to achieve the precise control. In order to improve the accuracy of FES for knee joint movement, in this paper, a RBF neural network based sliding mode control method is designed. An electrical stimulation model of knee joint is first established, the nonlinear performance of RBF neural network is used to approximate the lower limb joint model uncertainties and external disturbances. To determine the width of hidden layer units and the architecture of the neural network, ~~the~~ genetic algorithm is introduced to optimize the network structure parameters. ~~The e~~Experimental results show that neural network sliding mode control based on genetic algorithm can accurately control the electrical stimulation to obtain the desired joint motion, and can be effectively compensated in the case of external disturbances.**

Keywords-functional electrical stimulation; knee movement tracking; neural network; sliding mode control

I. INTRODUCTION

Spinal cord injury (SCI) is the main type of central nervous system injury, often leading to motor disorders such as paralysis. SCI suffers from spinal cord nerve injury, so the brain control commands of limb movements can't be transmitted to the limb motor nerve, resulting in limb loss of motor function [1]. The rehabilitation of SCI has become a major social problem to be resolved [2], one of the most common technique to assist the patients with SCI is functional electrical stimulation (FES), using short electrical pulses is able to generate FES-induced contraction of muscle paralysis, and the FES can be adjusted to control the intensity of the contraction level [3].

A large number of FES control techniques have been applied to the lower limb [4], but few of them are capable of providing high accuracy with patients. Human body muscle is non-linear, volatile and the environment is complex [5], which makes it difficult to control FES to achieve the desired FES performance. When designing FES control system, it is the very important to improve the control precision accurately. Qiu et al [6] used PID algorithm to control the flexion and extension of the knee joint, but when external disturbances exist, it becomes difficult to achieve the desired performance. Kirsch N [7] presented a gradient projection based NMPC for regulating a limb joint angle through FES, the controller can follow step changes in desired angles and is robust to disturbances. However, the method is not robust to uncertain dynamics and other modeling uncertainties.

Sliding mode control is one of the effective nonlinear robust control approaches, since it provides matching conditions for system dynamics uncertainties and disturbances. In [8], a fuzzy sliding mode controller was proposed, through fuzzy control system to compensate for external error, but the fuzzy rule related parameters are difficult to determine. Nevertheless, the chattering problem of the sliding mode control affects the stability of the control to a certain extent [9]. Therefore, the neural network control is often combined to eliminate the sliding mode buffeting. Wu [10] proposed a neural network adaptive sliding mode control algorithm which can limit the chattering phenomena and approximate the un-modeled part of the system, but the relevant parameters of the neural network are obtained through experience.

Because of the network is hard to decided, it will constrain the training effects of neural networks if the parameter value is not appropriate [11]. In this paper, an adaptive RBF neural network based sliding mode control method is designed, then use genetic algorithm to optimize the network parameters, the nonlinear RBF is used to approximate the model uncertainties and disturbances, which has fast computation time in real-time implementation. The rest of this paper is arranged as follows: Section II and III presents the dynamic model of knee and the neural network sliding mode control based on genetic algorithm. The experiments and the results are shown in Section IV. Section V draws the conclusion of the paper.

II. DYNAMIC MODEL OF KNEE

This paper focuses on the knee extension movement with the assistance from FES system, as shown in Fig. 1. The dynamic model of the leg used in this paper was proposed in [12], the system equation is:

$$J\ddot{\theta}_v = -mgl\sin(\theta_v) - M_s - B\dot{\theta} + M_a \tag{1}$$

where~~:~~ J is the inertial moment of the shank; θ_v, θ are the knee angle as shown in ~~Figure~~ Fig. 1; $\dot{\theta}, \ddot{\theta}$ is the joint angular velocity, angular acceleration; m is the mass of the shank; l is the distance between the knee and the shank center; M_s is the torque due to the rigidity component; M_a is the knee torque due to the electrical stimulation;

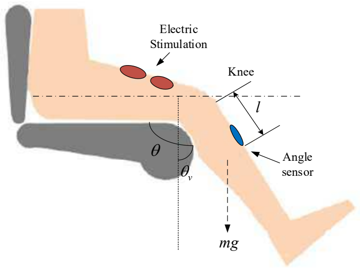


Figure 1. Experimental setup

With respect to the rigidity component, the following form was considered:

$$M_s = -\lambda e^{-E\theta}(\theta - \omega) \tag{2}$$

$$M_a = \varsigma(\theta, \dot{\theta})u(t) \tag{3}$$

λ, E are the coefficients of exponential terms ; ω is the resting knee angle; $u(t)$ is the electrical stimulation exerted on the muscles; $\varsigma(\theta, \dot{\theta})$ is the relationship between electrical stimulation intensity and muscle contraction torque, which is modeled by torque–length and torque–velocity, the passive and active knee joint torques are based on Hill-type muscle models, please refer to [13] for specific mathematical forms.

III. FES CONTROL STRATEGY

A. Sliding mode controller

Based on the kinematic equation of knee joint shown in (1), a sliding mode control system is designed. Define the desire knee joint angle and the actual joint angle θ_d , θ, then the joint position and velocity tracking error can be expressed as $e = \theta_d - \theta_v$ and $\dot{e} = \dot{\theta}_d - \dot{\theta}_v$, defined c as a sliding mode coefficient, the sliding surface is described as:

$$s = ce + \dot{e} \tag{4}$$

$$\dot{s} = c\dot{e} + \ddot{\theta}_d - \frac{1}{J}(-mgl\sin(\theta_v) - M_s - B\dot{\theta} + M_a) \tag{5}$$

Define:

$$f(\theta) = \frac{1}{J}(-mgl\sin(\theta_v) - M_s - B\dot{\theta} + \Delta f(\theta)) \tag{6}$$

$$Gu(t) = \frac{M_a}{J} \tag{7}$$

The nonlinear function $\Delta f(\theta)$ represents the system uncertainties including system parameter variations and disturbances. Generally, taking $\dot{s} = -\eta\,\mathrm{sgn}(s)$, the sliding mode control law is as follows:

$$u(t) = \frac{c\dot{e} + \ddot{\theta}_d + \eta\,\mathrm{sgn}(s) - f(\theta)}{G} \tag{8}$$

B. Genetic algorithm to optimize neural network weights

Because RBF neural network has universal approximation, RBF neural network approximation is used to compensate for the uncertainty of knee modeling and the external error $\Delta f(\theta)$, the network algorithm is:

$$h_j = \exp\left(\frac{\| x - c_j \|^2}{2b_j^2}\right),\ f = W^T h(x) + \varepsilon \tag{9}$$

c_j is the core function center, b_j is the width parameter of the function. The selection of the c_j and b_j have a great influence on the performance of the neural network.

Genetic algorithm is an optimized search algorithm, b and c in the neural network are encoded into binary code string representation, and the initial population of these strings is randomly grown, so that the conventional genetic algorithm can be optimized [14].

In this paper, the maximum number of iterations is 500, the population size is 30, the parameter binary coding length is 10, and the optimized value is:

$$c_j = [0.25\ \ {-2.15}\ \ 0.33\ \ 1.47\ \ 2.17;$$
$$0.26\ \ {-3.08}\ \ {-3.03}\ \ 3.45\ \ 0.36]$$
$$b_j = [2.73\ \ 4.88\ \ 1.19\ \ 3.14\ \ 0.55]$$

C. Adaptive sliding mode controller

The matrix $x = [e\ \dot{e}\ \theta_d\ \dot{\theta}_d\ \ddot{\theta}_d]$ of the ideal motion angle θ_d ,velocity $\dot{\theta}_v$,acceleration $\ddot{\theta}_v$,angle error $\dot{e}$ and error rate of change of the knee joint $\dot{e}$ is used as the input of the neural network.

The network output is: $\hat{f}(x) = \hat{W}^T h(x)$

$$\Delta f(x) - \hat{f}(x) = W^{*T} h(x) + \varepsilon - \hat{W}^T h(x) = -\tilde{W}^T h(x) + \varepsilon \tag{10}$$

The Lyapunov function is defined by:

$$\dot{V} = s\dot{s} + \frac{1}{\gamma}\tilde{W}^T \dot{\hat{W}} \tag{11}$$

Then

$$\dot{V} = \varepsilon s - \eta|s| + \tilde{W}^T\left(\frac{1}{\gamma}\dot{\hat{W}} - sh(x)\right) \tag{12}$$

Take $\eta > |\varepsilon|_{\max}$,the adaptive law is $\dot{\hat{W}} = \gamma sh(x)$,the relevant parameters of the control system are described as: $c = 5,\ \eta = 10,\ \gamma = 1500$

IV. EXPERIMENTS AND RESULTS

Based on the experiment of genetic algorithm RBF sliding mode control, two healthy participants were tested. The participants sat on the chair, and they were instructed to remain relaxed to prevent muscle contraction, and influence in the measurements experiments. The experiment setup is shown in Fig. 2, the experiment uses the electrical stimulation device (Motionstim8, MEDEL, Germany) to stimulate the thigh quadriceps, and uses the angle sensor to measure the angle during the swing of the calf. The intensity of electrical stimulation is changed by adjusting the pulse width, and the electric stimulation frequency is 25Hz, the current is 25mA. The results of the identification parameters for one subject are shown in Table I, the body weight and centroid position of the calf were estimated by the binary regression equation [15], and the parameters such as the station elasticity of the knee joint model were identified by the least squares method, the specific parameter identification process refers to the literature [12].

The experimental results are shown in Fig. 3. The controller was given a reference of 30° for 10s, followed by a reference of 45° for 10s. A comparison has been drawn in terms of tracking the angles of between the performances of two controllers GA-RBF-SMC and RBF-SMC. It can be seen from the Fig. 3 (a), when it reaches 30°, the subject takes 3s to reach steady state, because it must achieve a certain intensity of electrical stimulation to induce calf movement. When it reaches 45°, unlike the RBF-SMC controller which takes a 4s to converge, the optimized algorithm only takes 2s, it has fast response. Fig. 3 (b) shows the pulse width, it can be

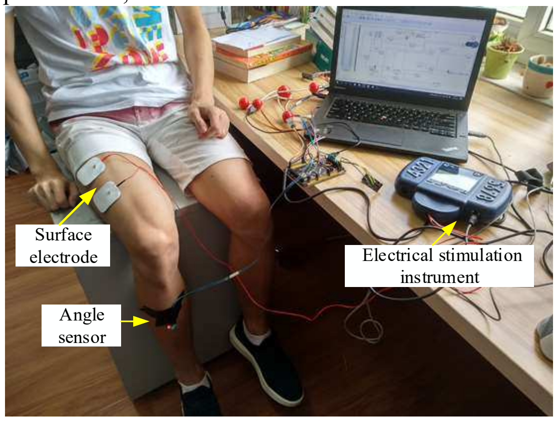
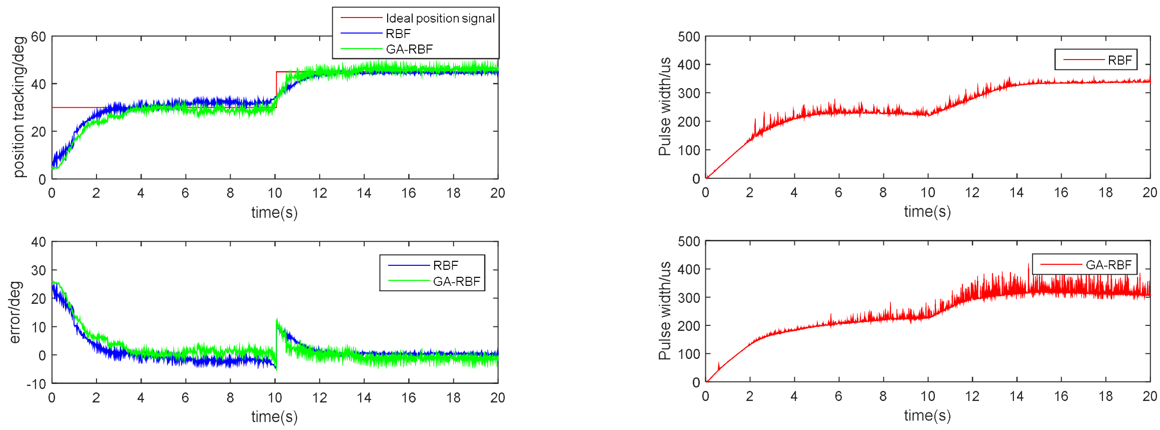


Figure 2. Experiment setup for knee extension

TABLE I. The parameters of knee joint model

Parameter	Value	Parameter	Value
Height	178 cm	B	0.35 $Nm \cdot s / rad$
Weight	64 kg	λ	3.58 Nm / rad
J	0.323 $kg.m^2$	w	0.17 rad
m	2.653 kg	E	0.041 Nm / us
l	0.25 m	G	0.06 Nm / us

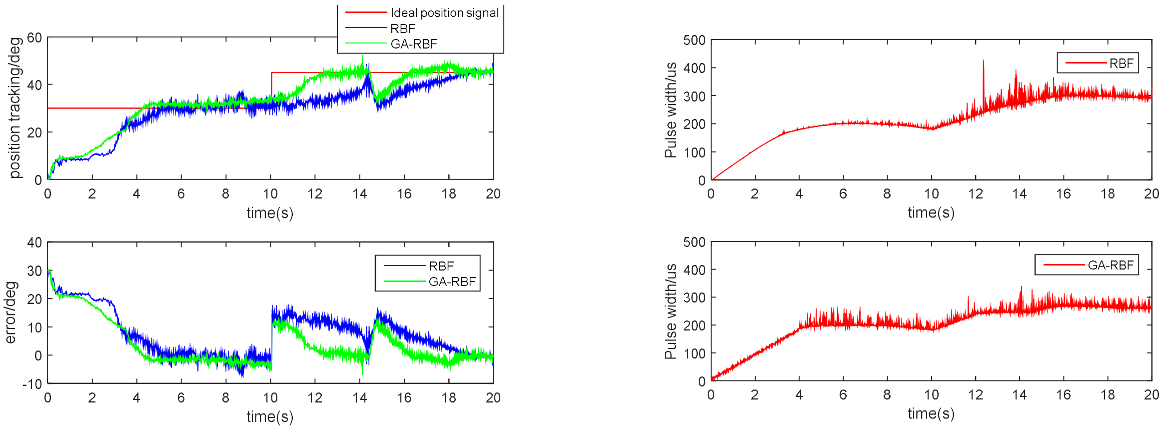


(a) (b)

Figure 3. Experimental results for tracking the references angels

seen that the pulse width changes automatically with the angle changes. The square root error of the steady-state angle at 10-20s is approximately 0.0872. The results show that the optimized algorithm has the advantages of better tracking performance and faster convergence.

In order to validate the robustness of the control algorithm to the disturbance, a certain torque was applied to the subject during the experiment, a load of 1kg is attached to the angle during the extension movements at 14s. The results of this robustness test are plotted in Fig.4. Hanging heavy objects, it can be noticed that the GA-RBF is very sensitive to the disturbance and it only takes 2s to reach steady state, the real angles deviated only slightly from the desired angles. The electrical stimulation of the pulse width is also adaptive adjustment as shown in Fig. 4 (b). The root mean square error for optimized algorithm in 45° increases to 0.3786 but remains acceptable. The experimental results show that the proposed algorithm performs better in robust to disturbance.



(a) (b)

Figure 4. Experimental results for tracking the references angels with disturbance

V. CONCLUSION

In this paper, a RBF sliding mode control based on genetic algorithm is proposed for FES assisted knee joint movement tracking. Genetic algorithm is used to optimize the RBF network parameters. The nonlinearity of RBF is used to approximate the uncertainty of lower limb joint model. The effect of the control algorithm on two healthy subjects was verified by knee extension experiment. Results show that the proposed algorithm can control the FES to adjust the joint angle more accurately than the unmodulated RBF-SMC, and the steady-state RMS error is no more than 2°. Even in the presence of disturbance, the control system can adjust the stimulus intensity adaptively so as to achieve accurate movement. Future work will combine the FES with rehabilitation robot to help patients to do more supple movement.

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