Adaptive Neuro-Sliding Mode Control of FES-Cycling

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Abstract

To evaluate the physiological effects of FES-cycling, it is crucial that both cadence cycling and workrate are well controlled. However, the major impediment to the development of satisfactory control systems for FES has been the highly non-linear and time-varying properties of electrically stimulated muscle which make control very difficult to achieve and limit the utility of open-loop FES control system. In this paper, we propose a robust control methodology which is based on synergistic combination of an adaptive single-neuron controller with sliding mode control (SMC) for control of FES-cycling in paraplegic subjects. The results of experiments on three paraplegic subjects show that the neuro-SMC can produce a smooth and prolonged cycling movement.

1 Introduction

During several years, the beneficial effects of FES exercise have been demonstrated with the improvements in peripheral muscular fitness, central cardiovascular fitness, gas exchange kinetics and aerobic metabolism, reduce atrophy of skeletal muscle, increase lower limb circulation and improve immune system function, increase in bone density, and decrease in spasticity [1]-[4]. An important motivation in FES cycling is to take physiological advantage of functional electrical stimulation in combination with physiological incentive of cycling as an independent and safe locomotive activity.
Several factors could affect the FES-cycling efficacy. The mechanical configuration of ergometer, such as seat position, seat back angle, and cycling load [3], and stimulation patterns [4] contribute to the efficacy of FES cycling for subjects with paraplegia.
To evaluate the physiological effects of FES-cycling, it is crucial that both cadence cycling and workrate are well controlled. Daily changes in patients' physical condition, highly non-linear and time-varying properties of electrically stimulated muscle, muscle fatigue, and occasional occurrence of spasticity limit the utility of pre-specified stimulation pattern and open-loop FES-cycling control system. Moreover, the complexity of the interface between the ergometer and stimulated limb can make the design of a system controller even more complicated.
To deal with these problems, several control strategies for closed-loop control of FES-cycling movement have been reported in literature. In [6], a model-free fuzzy logic fixed-parameter feedback controller was adopted for control of the cycling speed powered by the stimulated quadriceps and hamstrings of both legs. The experiments on subjects with paraplegia confirm the jerky cycling movement and a sudden change in cranking speed.
Hunt *et al.* used an identified linear model to design a closed-loop speed controller using pole placement method [7]. However, pole placement controller design is a technique for LTI systems. The basic idea behind it is the design of state feedback such that all poles of the closed-loop system assume prescribed values. The success of the pole placement design is strongly dependent on the availability of an accurate model of the system under study. As modelling is a well-known bottleneck, there is a strong demand for robust control design that can take model uncertainty into account, while satisfying the closed-loop stability and performance specifications.
Sliding mode control (SMC) is a well-known and powerful control scheme to deal with the uncertainties, nonlinearities, and bounded external disturbances. Nevertheless, the conventional SMC suffers from the high frequency oscillations in the control input, which called "chattering". To solve this problem, we have already developed a novel control strategy which is based on combination of adaptive neural control and SMC (i.e., neuro-SMC) [8]. In this paper, we employed neuro-SMC for control of FES-cycling in paraplegic subjects.

2 Methods

2.1 Apparatus and System

We adapted a SCHWINN 233 recumbent bicycle for paraplegic FES cycling. The crank angle was measured by an absolute shaft encoder with a 360 pulses/turn resolution which was mounted on the chassis of the bike and driven by a belt attached to the pulley around the rod of the left crank (Fig 1). The cycling cadence was obtained by differentiation of the angle. Ankle-foot orthoses were designed and were fixed to the pedals. The measured signals were sampled at 2 kHz by a 12-bit analog-to-digital converter. The computer-based closed-loop FNS system uses Matlab Simulink under Windows 2000/XP for online data acquisition, processing, and controlling.

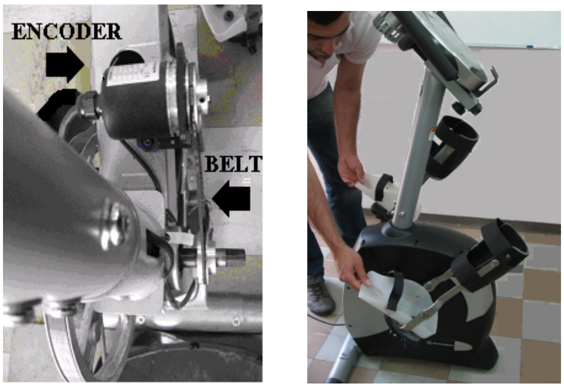

Fig.1 Shaft encoder and ankle-foot orthoses arrangement.

Four muscle groups, i.e. the left and right quadriceps and hamstrings were stimulated using adhesive surface elliptical electrodes. Pulse width modulation (from 0 to 700 µsec) with balanced bipolar stimulation pulses, at a constant frequency (25 Hz) and constant amplitude was used. The measured crank angle was used to switch on and off the stimulation according to a predefined pattern [6].

2.2 Design of Adaptive Neuro-SMC

2.2.1 Sliding Mode Control

Consider the following nonlinear system

$$\ddot{\theta} = f(\theta,\dot{\theta}) + b(t)\cdot u \tag{1}$$

Where $\ddot{\theta}$ and u of the system, and $f(\theta,\dot{\theta})$ and control gain $b(t)$ are unknown nonlinear functions. The objective of the controller is to design a control law to force the system state vector to track a desired state vector in the presence of model uncertainties and external disturbances. We first define a sliding surface as follows

$$s(e,t) = \left(\frac{d}{dt}+\lambda\right)^2 \left(\int_0^t e\,dr\right) = 0 \tag{2}$$

where e is the state error and λ is a positive constant. By solving the above equation for the control input using (1), we obtain the following expression for u which is called equivalent control:

$$u_{eq} = \frac{1}{\hat{b}}\cdot(-\hat{f} + \ddot{\theta}_d - 2\lambda\dot{e} - \lambda^2 e) \tag{3}$$

where $\hat{f}$ and $\hat{b}$ are estimations of nonlinear functions f and b, respectively. $\ddot{\theta}_d$ is the second derivative of reference state. The estimation error on f is assumed to be bounded by some known function F :

$$\left|f-\hat{f}\right| \le F \tag{4}$$

The equivalent control keeps the system states in the sliding surface if the dynamics were exactly known. If the state is outside the sliding surface, to drive the state to the sliding surface, the control law is chosen such that

$$\frac{1}{2}\frac{d}{dt}s^2 \le -\eta|s| \tag{5}$$

where η is a positive constant. By choosing the following control input, u_1 ensures the satisfaction of condition (5).

$$\begin{aligned} u_1 &= \frac{1}{\hat{b}}\cdot\left[u_{eq} - k\,\mathrm{sgn}(s)\right] \\ k &= F+\eta \end{aligned} \tag{6}$$

where $k>0$ and $\mathrm{sgn}(s)$ is a sign function. This control law leads to high-frequency control switching and chattering across sliding surface. In this paper, we used a linear dynamic first-order model to describe the system (1).

2.2.2 Adaptive Neural Control

A single-neuron controller is used here. The output of the neuron is given by

$$u_2 = h(net) = a\frac{[1-\exp(-b\cdot net)]}{[1+\exp(-b\cdot net)]} \tag{7}$$

$$net = e + \dot{e} - \varphi \tag{8}$$

where e is the state error, φ is the threshold, and net denotes neuron input. The parameters $\rho = (a,b,\varphi)$ are adapted using the following adaptation rule:

$$\dot{\rho} = -\delta\cdot e\cdot\frac{\partial u_2}{\partial\rho}\cdot\mathrm{sgn}(\frac{\partial\theta}{\partial u}) \tag{9}$$

where $\delta > 0$, is learning rate parameter.

2.2.3 Structure of Neuro-SMC

The structure of neural sliding mode control which is based on the combination of neural network and sliding mode is schematically shown in Fig. 3, where u_1 is, SMC output defined in (6) and u_2 is the neuron output defined in (7). Controller output is a function of u_1 and u_2 defined by

$$u = \begin{cases} u_1 & if\,|s(e)| > \phi+\xi \\ \alpha(e)u_1 + (1-\alpha(e))u_2 & if\,\phi < |s(e)| \le \phi+\xi \\ u_2 & if\,|s(e)| \le \phi \end{cases} \tag{10}$$

where $s(e)$ is a scalar function described in (2), ϕ and $\xi > 0$ are the boundary layer thicknesses, and $\alpha(e)$ is a function of error and is adapted by

$$\alpha(e) = \frac{|s(e)|-\phi}{\xi} \tag{11}$$

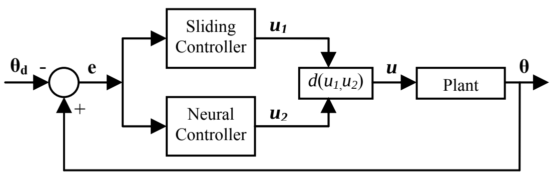

Fig. 3 Neuro-sliding mode control.

3 Results

The experiments were conducted on three complete paraplegics using an eight-channel computer-based closed-loop FNS system [9]. The paraplegic subjects were active participants in a rehabilitation research program involving daily electrically stimulated exercise of their lower limbs (either seated or during standing and walking). Typical results of control of cycling cadence for three paraplegic subjects were shown in Fig. 4. It should be noted that the model was identified during the first day on one subject and the identified parameters were used for all subjects during different sessions of experiment. An interesting observation is that the control method could generate control signals to compensate the muscle fatigue [Fig. 4(a)] during FES-cycling. The results of about 50 experimental trials on three paraplegic subjects show that the neuro-SMC can produce a smooth and prolonged cycling movement.

4 References

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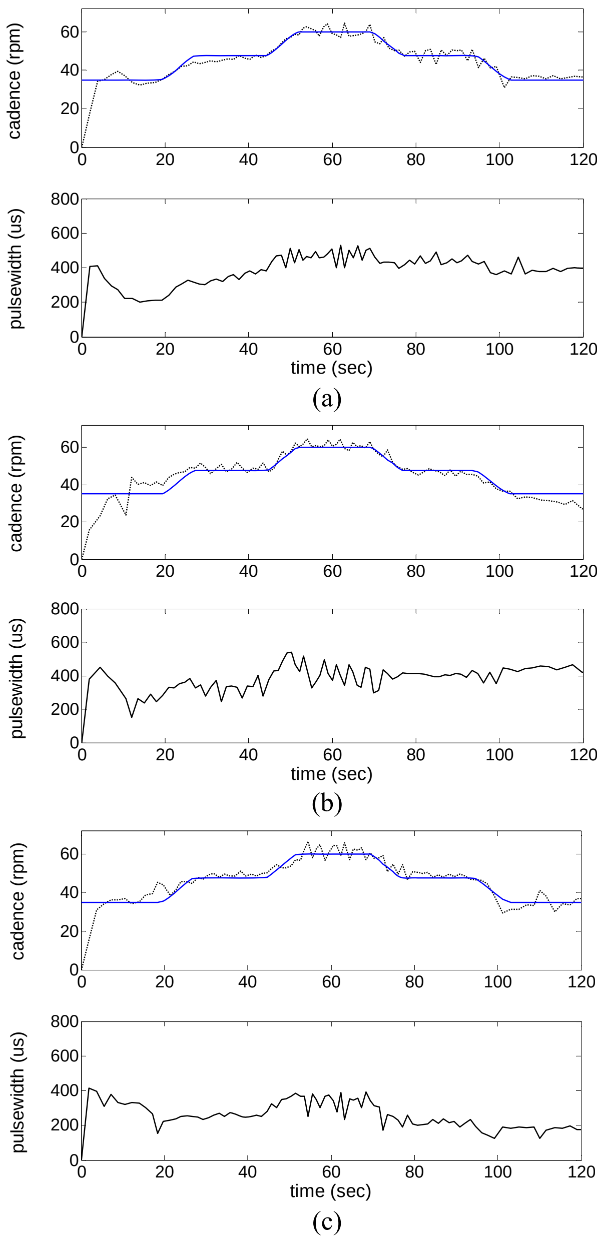

Fig. 4 Neuro-SMC of FES-cycling in paraplegic subjects RR (a), HA (b), and MS (c).