Robust Cerebellar Controller Design for FES-Cycling Control Systems

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Abstract— **Current methods for automatic feedback control of functional electrical stimulation (FES) employ classical techniques, and require much trial-and-error calibration. Given the nonlinear and time-varying nature of the system, there is a need for more sophisticated control techniques. Cerebellar model articulation controller (CMAC) is the one that reflects most closely the behavior of the cerebellum, has shown great benefits for the control of complex nonlinear systems. This paper presents a robust proportional-integral-derivative (PID) based CMAC for FES cycling control systems. Successful on-line training and recalling process of CMAC accompanying the PID controller is developed. The advantage of the proposed method is mainly the ability to control sudden cycling velocity changes and robust tracking performance against external disturbances.**

Keywords- FES cycling, cerebellar model articulation controller, proportional-integral-derivative control, musculoskeletal model.

I. INTRODUCTION

Functional electrical stimulation (FES) has been explored as a means of restoring lost function in the spinal cord injured (SCI). Specific training with FES can cause significant improvements of the cardiovascular and pulmonary systems [1], reduce atrophy of skeletal muscle, increase lower limb circulation and improve immune system function, reduce edema, increase bone density and also lead to psychological benefits [1]. However, the control of multiple joints by FES is very complex, and effects such as muscle fatigue, spasticity, and limited force in the stimulated muscle further complicate the control task [2].

Cycling with FES may be a suitable and easy intervention for patients with cerebral palsy (CP) because the seated position decreases balance demands, and FES can create or augment pedaling forces [3]. Therefore, various control methods were investigated to make a robust, fast and stable cycling system. The prevailing control methods required the mathematical model of the FES cycling control system to determine the control law. These techniques have inherent limitations when applied to nonlinear, time-varying problems. PID control has been applied widely in industry because of its simple structure [4]. In general, PID control is used for steady-state tracking of step inputs or slow time-varying reference trajectories. However, PID control is not robust against system uncertainties and external disturbances because the proportional and derivative coefficients are usually fixed. To improve system performance and enhance system robustness of PID control, adaptive algorithms and self-learning rules need to be developed. CMAC is an iterative learning controller that imitates the human cerebellum through iterative weight updating [5-6]. Learning behaviors and the convergence of the iterative learning in a CMAC structure have been proved in [7], making it useful in many applications.

In this paper, we propose a PID-based CMAC strategy to achieve desired velocity control for FES cycling. At first, a normal PID controller is designed such that the error dynamics can be assigned in advance. Besides guaranteeing the stability and output accuracy, the PID controller also provides CMAC the training patterns. The CMAC is designed to enhance tracking ability and system robustness. These two controllers will compensate each other. We call this strategy "cerebellar FES cycling" (CFC).

II. DESCRIPTION OF THE MODEL

The use of models can significantly enhance the design and test of closed-loop control strategies applied to FES. Thus, trial-and-error adjustments during experiments that are very tiring for the patient can be avoided, or at least shortened. The musculoskeletal model to predict movements developed by nonlinear responses of electrically stimulated muscle is outlined in Figure 1(a). Muscle force produced by electrical stimulation (active force), F_A, was described by the Hill type muscle model, which consisted of muscle activation level determined by electrical stimulation a_m , length-force relationship $k(l)$, velocity-force relationship $h(v)$, and maximum isometric muscle force F_{max}[8]. That is,

$$F_A = a_m k(l) h(v) F_{max}, \tag{1}$$

Where l and v were muscle length and contraction velocity, respectively. F_A shows the force produced by contracted muscle fibers during electrical stimulation, which actively contributes to develop movements. Muscle activation a_m is computed considering the effect of spatial and temporal summation by a nonlinear recruitment curve, a nonlinear activation-frequency relationship, and calcium dynamics (Fig.1(b)). A fatigue/recovery model and an additional constant time delay have been incorporated [9]. The constant time delay is responsible for finite conduction velocities in the membrane

system and delays from the chemical reactions involved [9]. Recruitment characteristic describes the value of the recruited motor units in terms of the stimulation intensity applied. The recruitment depends on the amplitude and duration of the stimulation pulse [9,10].

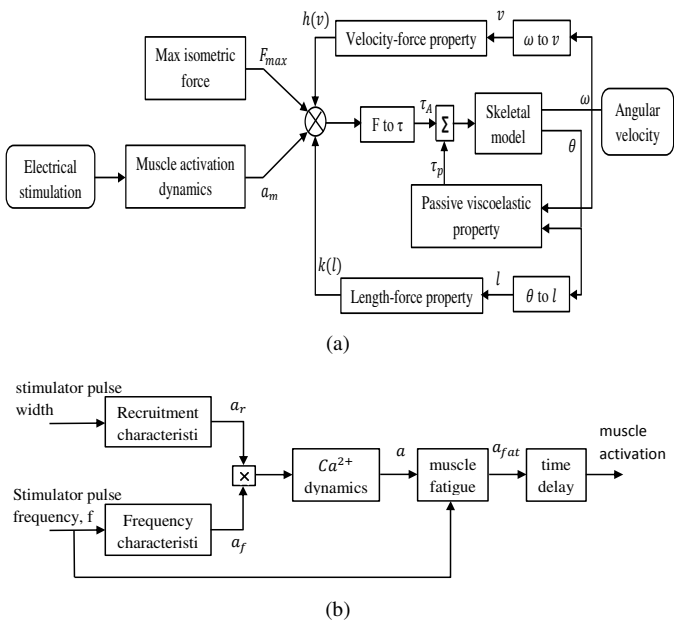

Fig. 1. (a) Outline of the musculoskeletal model for FES, (b) Activation dynamics. Each muscle group has its own activation and contraction dynamics.

The normalized portion of motor units recruited a_r is calculated as a nonlinear function of the pulse width PW, using [9,10]

$$a_r(pw) = c_1\{(pw - pw_{thr})\, tan^{-1}[k_{thr}(pw - pw_{thr})]\} \quad (2)$$

$$-c_1\{(pw - pw_{sat})tan^{-1}[k_{sat}(pw - pw_{sat})]\} + c_2$$

where pw_{thr} and pw_{sat} denote pulse width values corresponding to threshold and saturation, respectively. The curvatures of the recruitment curve in the area of threshold and saturation can be adjusted by changing k_{thr} and k_{sat}, respectively. The recruitment curve is scaled by the constants c_1 and c_2 in order to satisfy the conditions $a_r(0) = 0$ and $a_r(pw) = 1$ for $pw \to \infty$.

The normalized amount of activation in a single motor unit is expressed as a function of stimulation frequency f (Fig.1(b))

$$a_f(f) = \frac{(\alpha f)^2}{1+(\alpha f)^2} \quad (3)$$

where α is the shape factor [10].

Due to calcium ion function in muscle contraction, the muscle cannot be activated and relaxed instantly, and there is a so-called calcium dynamics which is modeled as a first order differential equation:

$$\dot{a} = \frac{1}{\tau_{ac}}(u^2 - ua) + \frac{1}{\tau_{ad}}(u - a) \quad (4)$$

where a is the muscle activation without fatigue, $u = a_r a_f$, τ_{ac} is activation time constant and τ_{ad} is de-activation time constant. These two time constants have been estimated to be 0.04 and 0.07 seconds respectively [10].

To describe the effect of muscle fatigue, a fitness function has been introduced, which can be expressed by a first-order relation:

$$\frac{dfit}{dt} = \frac{(fit_{min} - fit)a\lambda(f)}{\tau_{fat}} + \frac{(1-fit)(1-a\lambda(f))}{\tau_{rec}} \quad (5)$$

$$\lambda(f) = 1 - \beta + \beta(\frac{f}{100})^2 \qquad \text{for} \quad f < 100\ Hz.$$

where fit_{min}, τ_{fat} and τ_{rec} are the minimum fitness, fatigue time constant and recovery time constant respectively. The minimum fitness is given by fit_{min}. The time constants for fatigue (τ_{fat}), and recovery (τ_{rec}), can be estimated from stimulation experiments. The term $\lambda(f)$ is a function of stimulation frequency and accounts for the fact that muscle fatigue rate strongly depends on stimulation frequency. The parameter β is a shape factor [9]. This equation considers fitness changes on the basis of both fatigue and recovery effects. The parameters τ_{fat}, τ_{rec}, β and fit_{min} are assumed 20 and 30 seconds, 0.6 and 0.2 [9] respectively and the frequency is 50Hz. Finally, the activation of fatiguing muscle is given by

$$a_{fat} = a(t)fit(t). \quad (6)$$

(The difference between muscle fatigue values of CFC control method with conventional PID will be used as a performance criterion in next section.)

The length-force and velocity-force relationships ($k(l)$, $h(v)$) that used for active force calculation in (1), were described by (7,8). The peak force occurs at the optimal muscle length and it is reduced in either eccentric or concentric contraction. A Gaussian-like function is used to model the relationship between the muscle force and length.

$$k(l) = \exp[-(\frac{\bar{l}-1}{\varepsilon})^2] \quad (7)$$

$$h(v) = 0.54tan^{-1}(5.69\bar{v} + 0.51) + 0.745 \quad (8)$$

where $\bar{l}$ is the muscle length normalized with respect to the optimal muscle length l_{opt} and ε is a shape factor, $\bar{v}$ is the muscle velocity normalized with respect to the maximum contraction velocity v_m of the muscle ($\bar{v} = v/|v_m|$, where $v = dl/dt$and $v < 0$ for muscle contraction).

The maximum muscle force produced by electrical stimulation F_{max} was determined by PCSA (physiological cross sectional area) as follows [11]:

$$F_{max} = 2.2\ \text{PCSA}. \quad (9)$$

Value of PCSA was determined from [11].

The passive viscoelastic element developed passive torque τ_p calculated by (10) for each joint movement [12]. The range of motion was also represented by

$$\tau_p = k_0\theta + b_0\dot{\theta} + k_1\{\exp(k_2\theta) - 1\}, \qquad (10)$$

Where θ and $\dot{\theta}$ were joint angle and angular velocity, respectively. Constants k_0, b_0, k_1 and k_2 were determined for each joint movement.

Considering function and geometry, the following pair of muscles were selected to make the active force for the pedaling movement: Hamstrings (HAM) and Vastii(VAS) (Fig.2). The ankle joint presumed to be fixed by an orthosis for paraplegics for stability.

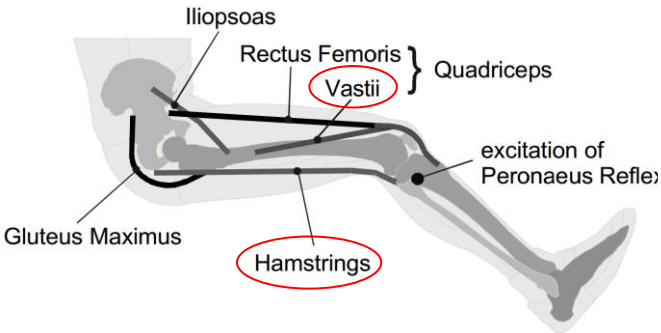

Fig. 2. Geometrical position of muscle groups on the leg.

A Model of rider-cycle system developed in [13] is used here as a virtual patient for evaluating the control strategy. The model consists of two double pendulums, each consisting of a thigh and a shank and attached to a fixed point at the hip (Fig. 3). Both pendulums have two degrees of freedom, which can be expressed as the hip and knee angles, but the endpoints are constrained to move on a circle around the center of the crank.

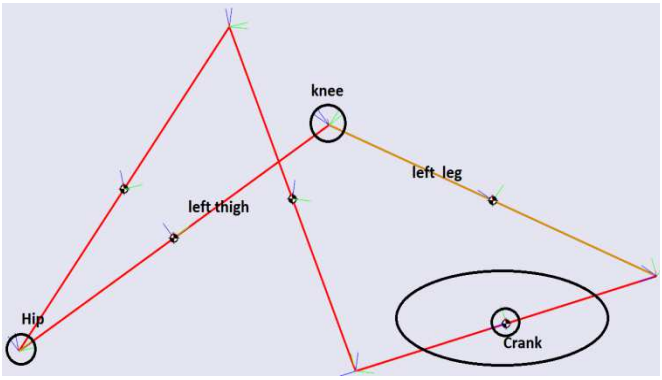

Fig. 3. Simmechanics model representation of rider-cycle system. Legs and crank shown by linked rigid bodies..

III. CEREBELLAR FES CYCLING CONTROL SYSTEM

The configuration of the proposed control scheme is shown in Fig. 4. The control law is defined as follows:

$$u = u_{PID} + u_{cmac} \qquad (11)$$

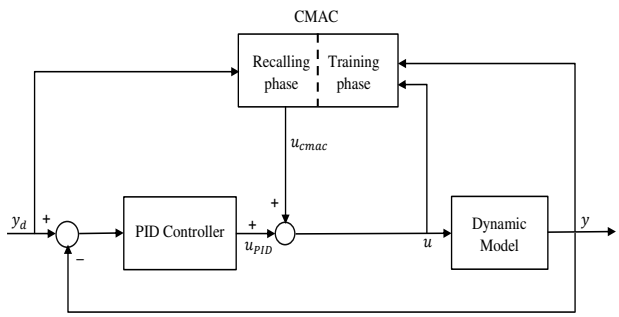

Fig. 4. FES cycling control system

where u_{PID} is the PID control input and u_{cmac} is the CMAC control input. The PID controller is designed to first stabilize the states of the FES cycling control system. In this stage, the robustness and tracking capability are not sufficiently satisfied. We further introduce u_{cmac} to complete satisfactory tracking performance and system robustness. Adequate training patterns and training time in the learning process required by the CMAC will be provided by the PID controller. Consequently, the PID controller and the CMAC are in a harmonizing status during learning and controlling cycles. y_d denote the desired angular velocity, respectively. The tracking error is defined as $e = y_d - y$, the aim is to develop a high performance cycling control system with low sensitivity to plant parametric variation and external disturbances, and with a tracking error approaching zero.

A. PID control

A PID controller consists of proportional, integral and derivative control factors. Define the PID controller as

$$u_{PID} = k_p e + k_i \int e + k_d \dot{e} \qquad (12)$$

Properly chosen, a simple PID controller is capable of improving damping and reduces maximum overshoot, rising time, and settling time. However, the proportional, integral and derivative gains are fixed in general. Low sensitivity to parametric variations and external disturbances cannot be guaranteed if a proper PID controller is used for FES cycling. In the following section, an intelligent CMAC approach is developed to incorporate the PID controller and bolster strong system robustness and stability.

B. CMAC design

1) Recalling phase

CMAC performs like an on-line tuning look-up table. This method imitates the model of the human memory, and has a fast learning capability. Typically, CMAC includes recalling and training procedures. Figure 5 shows the structure of CMAC. The whole input space is quantized by the discrete reference states, z_1, z_2, …, z_{40}. Every reference state z_j is mapped into the output y_{z_j}. Let the output of the CMAC be defined a

$$y_{z_j} = a_{z_j} w \qquad (13)$$

Where $w = [w_1, w_2, \dots, w_{42}]^T$ is the memory weighting vector and $a_{z_j} = \lfloor a_{j,1}, a_{j,2}, \dots, a_{j,42} \rfloor$ is the associated memory row vector of z_j. The number of memory is 42 in the CMAC. For each state, the number of referred memory (the number of layers) is 3. Thus, three elements in a_{z_j} are 1, and all else are 0. Figure 6 shows the memory allocation of the CMAC with reference states and referred memories. For example, the reference state z_1 :

- maps three memory addresses: $m_1 \sim m_3$
- memory row vectors: $a_{z_1} = [1, 1, 1, 0, \dots, 0] \in R^{42}$
- corresponding memory weights: $w_1 \sim w_3$

Referring to Fig. 6, every two adjacent reference states overlap two memory addresses. Because two same memory addresses are activated, the outputs of two adjacent reference states will not differ much. In other words, the input quantization affects the learning accuracy. More reference states imply more accurate learning. Accordingly, more memory addresses will be required.

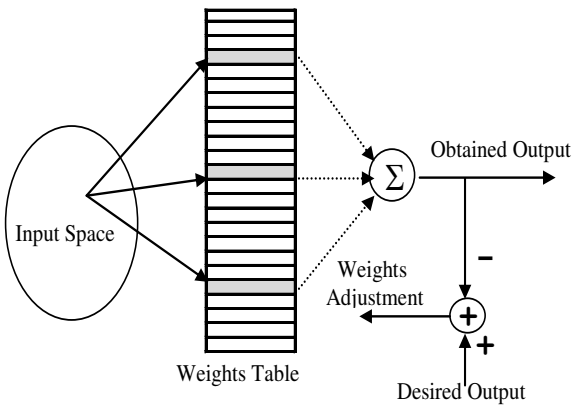

Fig. 5. Structure of the CMAC

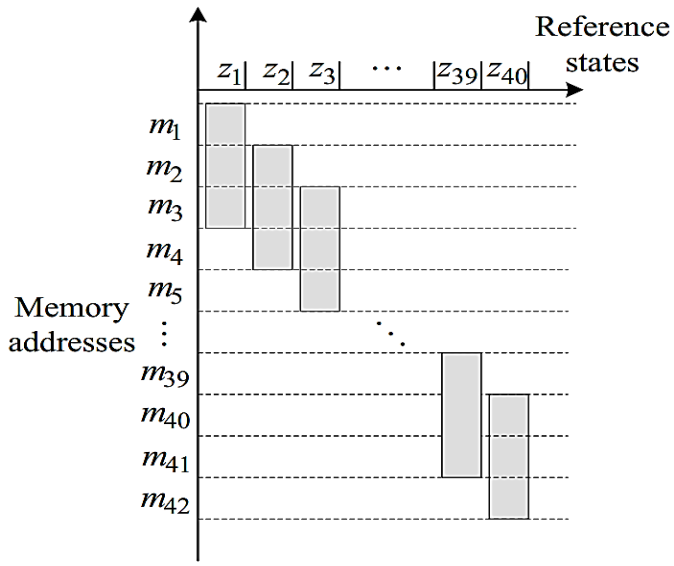

Fig. 6. Memory allocation of the CMAC

2) Training phase

Referring to Fig. 5, the training object of the CMAC is to construct a learning process for mapping from velocities to control inputs to the plant. The CMAC controller was first trained offline using the data from the plant identification surface for different pedal resistant torques (fig.7). 450 training patterns were used, resulting from uniform sampling of the PID plant identification surface. This initial offline training will impressively help to reduce transient time of reaching the desired velocity. Responding to the desired velocity y_d, the CMAC output will approach the desired control input. Then, in online training, the memory weighting vector w is adjusted iteratively according to the training error. The on-line updating law is chosen to be

$$w(k+1) = w(k) + \Delta w(k) = w(k) + \frac{\emptyset}{3} a^T(k)(u(k) - u(k)_{cmac\_training}) \quad (14)$$

where $a(k)$ denotes the associate memory row vector of the kth training pattern for CMAC. The constant $\emptyset$ is the learning rate, and satisfies $0 < \emptyset < 1$. Generally, learning accuracy will be enhanced with a large number of training patterns.

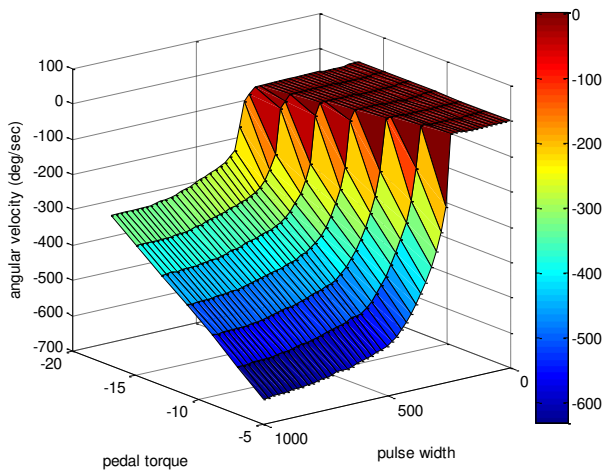

Fig. 7. Plant identification surface that provides training patterns for CMAC.

C. Control system performance

Referring to Fig. 4, the PID controller is first designed to stabilize the FES cycling control system. In fact, PID controller is used to provide nominal system control, and thus generate initial training data for the CMAC network. The initial memory weights of the CMAC are zero, i.e., u_{cmac} is zero. The control input comes only from the PID controller. Once the PID controller begins to work, a series of training patterns for the CMAC will be obtained, and the CMAC begins learning and merging the control. The CMAC recalls the corresponding memories to determine the control input u_{cmac}. With feedback of the tracking error, the PID controller determines the control

input u_{PID}. The control input vector u is used as the desired output of the CMAC. Through the weights updating law (14), the updated memory weights of the CMAC will be applied in the next sampling cycle. If the learning result of the CMAC is accurate, the CMAC will support the PID controller to ensure system robustness as well as stability. Two cases are investigated as follow.

case I. PID ability to control fixed and variable cycling velocity.

case II. CFC ability to control sudden velocity changes.

The initial desired velocity is assumed to be 440 deg/sec or 73 rpm. The PID controller is chosen to have k_p=10, k_I=3 and k_D=2. The weights updating law (14) is applied, in which the learning rate is chosen as $\emptyset = 0.8$.

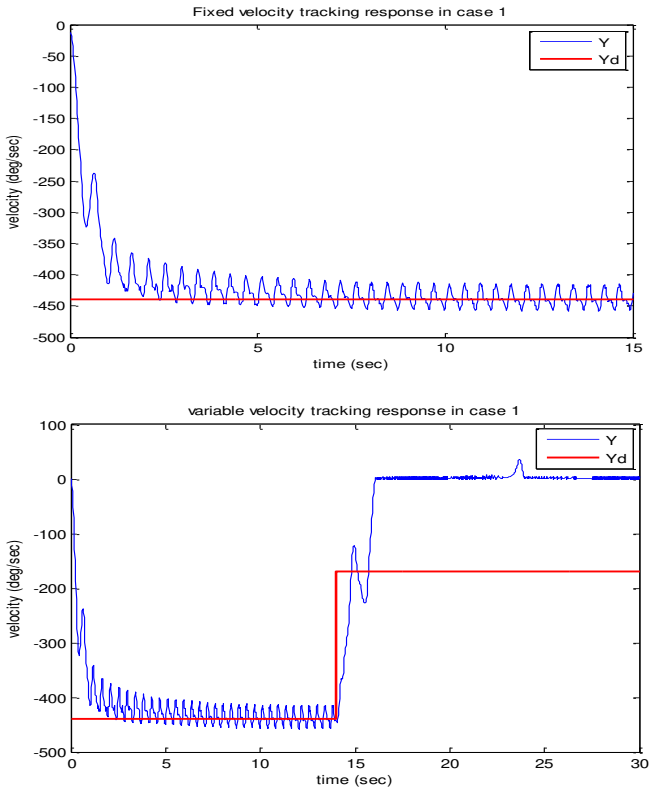

Fig. 8. Tracking responses in case 1. Negative velocity implies a clockwise motion.

Figure 8 shows the tracking response and performance of PID for controlling fixed and variable velocities. PID is a case study controller that works for fixed coefficients. Therefore, it doesn't have the capability of controlling sudden changes. Using the proposed control method that CMAC and PID cooperate with each other, the tracking improved and the system robustness is ensured (fig.9). Because the training process of the CMAC is successfully completed, u_{cmac} dominates the control action, and u_{PID} converges to zero. The proposed CMAC is capable of taking over most of the control need. Therefore, the PID controller can abdicate quickly. This implies that the control system will be stable and robust even when the PID controller is not well designed.

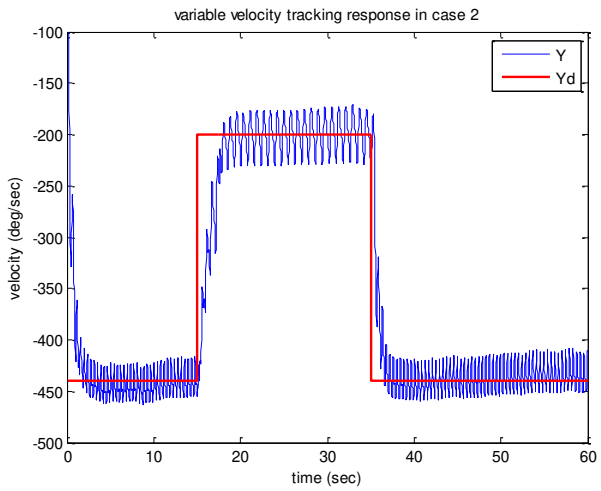

Fig. 9. Tracking responses in case 2.

Fatigue was included in the virtual patient to evaluate the capability of the control strategy to compensate for it. According to (6), activation of fatiguing muscles (a_{fat}) is related to muscle fitness that has an inverse relation with fatigue effect. The muscle fatigue effect impressively compensated when the CFC control method applied (Fig. 10).

$$a_{fat} \propto fitness \propto \frac{1}{fatigue} \tag{12}$$

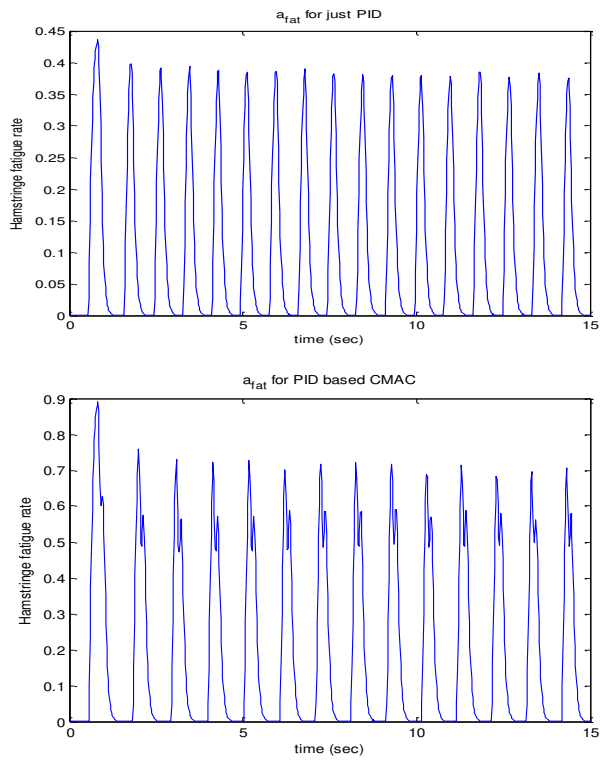

Fig. 10. Hamstrings fatigue rate shows fatigue compensation for CFC method.

IV. CONCLUSION

PID control is a simple and effective control method. However, it does not ensure the robustness if used alone for uncertain systems. CMAC can be used for robust control. However, it requires training patterns for tuning some weighting factors. A novel CMAC used together with a PID controller design is proposed in this paper. CFC is an iterative learning controller that imitates the human cerebellum through iterative weight updating in a feedback error learning algorithm. The inverse dynamic of the musculoskeletal model is produced with CMAC to handle the motor units input command. The PID controller provides the CMAC training patterns. The CMAC assists the PID controller to ensure the robustness. Even when the PID controller is not designed well, the CMAC is capable of doing a good job of robust control through on-line recalling and training procedures. Surely experimental researches and clinical trials are needed to validate the effectiveness of the proposed control method.

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