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Variable universe fuzzy closed-loop control of tremor predominant Parkinsonian state based on parameter estimation

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ABSTRACT

A variable universe fuzzy closed-loop control method based on parameter estimation is proposed for controlling tremor predominant Parkinsonian state. First, the computational model of thalamocortical relay neuron is established to characterize the cortico-basal ganglia-thalamocortical loop behavior in relation to Parkinsonian state. Then, in order to estimate critical parameter which exhibits the different levels of the tremor state, unscented Kalman filter is presented. Finally, an efficient control strategy on Parkinsonian state is designed by using variable universe fuzzy control theory. In the whole strategy, the slow variable that is easily reconstructed from the measured membrane potential is regarded as feedback variable, being vital to excellent control performance and low energy of the control signals. By comparing with simple proportional–integral control algorithm and ordinary fuzzy control method, it can be demonstrated that variable universe fuzzy control can avoid the repeated determinations of the controller's parameters, quicken the convergence speed, and improve the robustness of the controlled system, which may become a universal and valid method to alleviate any levels of the tremor state, and its control signals may apply to the current deep brain stimulation.

1. Introduction

Deep brain stimulation (DBS) is an effective therapy to alleviate the symptoms of movement disorders such as essential tremor (ET), dystonia and Parkinson's disease (PD) [1–3]. The research on optimization of DBS is of great significance, which has become a prevalent new trend [4–6]. Thus, DBS's rapid developments not only greatly enhance the control effects of the neuronal abnormal firing patterns, but aim to reveal remaining unknown mechanisms underlying [7]. Recently, Feng et al. explored a nonlinear closed-loop learning algorithm to identify effective DBS inputs, and thus, optimal DBS of the subthalamic nucleus (STN) has been further developed [7]. Moreover, Schiff et al. designed a model-based rational feedback controller, which applied to internal segment of the globus pallidus (GPi) to adjust the abnormal inhibitory synaptic currents into thalamus. They optimized the controller performance, which is obtained from an improved proportional–integral–derivative algorithm with amplitude proportional–derivative control and integral bias [8]. Furthermore, for the control of tremor-predominant Parkinsonian state, thalamic DBS plays a more significant role in debilitating tremor [9]. Although these expanding and in-depth explorations of the DBS optimization contribute to the treatments of the nervous system diseases, the control strategy still deserves a further investigation.

In a closed-loop scenario of the tremor-predominant Parkinsonian state, previous studies have proposed a slow variable feedback control to improve the relay functionality of the thalamocortical (TC) neuron [10,11]. It has been demonstrated that the loss of TC neuron's relay ability may result from its pathological rebound activities, whose fundamental cause is shown as the severe fluctuations of slow low-threshold T-type Ca^{2+} current [12]. This may be caused by the excessive inhibitory synaptic current from GPi nucleus [10,11]. Moreover, the different inhibitory synapses may induce the different degrees of the tremor behaviors. Considering that this significant slow variable information and the corresponding level of the synaptic current cannot be measured directly, unscented Kalman filter (UKF) can be used to achieve their tracks and estimations from the measurable TC's neuronal membrane potential [10,11]. However, when there exist the large external perturbations in the neuronal system and especially the model of the neuronal system is unknown, the property of the simple control strategies, such as proportional plus integral (PI) control algorithm, may be restricted [10]. Hence, this paper aims to design a closed-loop control strategy to cope with the difficulties involved in complexity and uncertainty of the neuronal model. For the existence of the unknown and time-varying parameters, several

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control techniques [13–20] such as variable universe fuzzy control scheme are more suitable to be proposed to fight against the challenge of the selection of controller's parameters, and to break the limitation of the customized parameters to the great extent.

Early, Takagi–Sugeno (TS) [21] fuzzy systems have been successfully used to approximate nonlinear systems, whose main feature is to express the local dynamics of each fuzzy implication (rule) [22–26]. Recently, it is shown that rapidly growing popularity of fuzzy control systems has been witnessed in engineering applications [27–29]. Moreover, in the neuroscience, fuzzy control has gradually applied to control neurons' firing patterns and synchronization of a coupled dynamical system with uncertain parameters [30]. Furthermore, Chen et al. proposed a robust observer-based tracking control of Hodgkin-Huxley (HH) neuron systems under environmental disturbances. In order to simplify the robust tracking control design of nonlinear stochastic HH neuron systems, they employed a fuzzy interpolation method to interpolate several linear stochastic systems to approximate a nonlinear stochastic HH neuron system, which solved the nonlinear robust tracking control problem [31]. Nonetheless, fuzzy control algorithm is failing in controlling the full dynamics of stochastic neuron model, whose control design procedure depends on the specified neuron model [30]. Thus, it is necessary and significant to propose an adaptive online closed-loop control method to improve the performance of the fuzzy controller [32] so as to alleviate the tremor-predominant Parkinsonian symptoms.

Accordingly, in order to optimize the previous closed-loop control strategy and further to improve the tremor-predominant Parkinsonian state, this paper aims to design a novel variable universe fuzzy closed-loop controller. By combining with the application of the UKF, the improvement of the slow variable feedback closed-loop control scheme can be achieved. The rest of this paper is organized as follows. Section 2 outlines computational model of the TC relay neuron and describes the design of the controller. Section 3 illustrates the implementation of fuzzy logic control strategy. In Section 4, qualitative and quantitative results of the variable universe fuzzy control system based on slow variables feedback are presented. Finally, the conclusions are given.

2. Model and methods

In order to restore the relay ability of TC neuron, the control strategy of this study is realized by simulating a computational model of TC relay neuron. It is shown that, a closed-loop control strategy can be designed to modulate the firing patterns of the TC relay neuron [10,11], in which the slow variable of TC relay neuron is regarded as a commendable feedback signal. It can be seen that, contrast to the membrane potential feedback, using slow variable as feedback not only has an advantage of smooth control input signals with a smaller standard deviation of the control signals, but also can effectively shorten the adjusting time. Thus, the closed-loop control strategy based on slow variable exhibits a better performance. However, traditional PI control algorithm [10] carries limitations. For instance, the controller parameters such as proportional gain and integral gain are always set to the constants via trial-and-error method, which may ignore the uncertainty of the model and limit controller configuration to auto-update. To cope with this difficulty of the controller's parameters tuning, iterative learning control (ILC) scheme is further explored [11]. In the design of the ILC algorithm, it does not require any particular knowledge on the detailed physiological. In addition, since ILC is able to reduce the tracking error of the TC model to zero as the iterations increase toward infinity, it can improve the control performance by a simple self-tuning process. Only it has own limitation and disadvantage. On one hand, repetitive iterative learning process lengthens the control period; on the other hand, repetitiveness in the controlled objects is essential to design of ILC strategy. Thus, considering that these limitations of previous work, it is vital to develop a novel control strategy to solve the difficulties involved in unsatisfactory circumstances.

2.1. Overview of the TC neuron model and application of the UKF

The corresponding details of the TC relay neuron model under the external electric field have been given in the previous work [10,11,33]. On the basis of the establishment of the TC neuron model, the evolution of the TC neuronal membrane potential can be described as follows:

$$C_m(d\,v_{Th}/d\,t) = -I_L - I_{Na} - I_K - I_T - I_{Gi\rightarrow Th} + I_{SM} \tag{1}$$

where I_L, I_{Na}, I_K and I_T represent passive leak current, Na^+ current, K^+ current and low-threshold T-type Ca^{2+} current across the membrane, respectively. $I_{Gi\rightarrow Th}$, the inhibitory synaptic inputs from GPi neuronal population, represents a critical factor which can induce the various firing patterns of the TC relay neuron, especially, the emergence of the tremor predominant Parkinsonian state. However, since $I_{Gi\rightarrow Th}$ is an unobservable parameter, it is difficult to be measured directly, which brings us great challenges to identify the level of the inhibitory currents corresponding to tremor behavior. Moreover, the excitatory input from sensorimotor cortex is described by I_{SM} with the term of pulse sequences as follows:

$$I_{SM} = A_{SM} H\left(\sin\left(\frac{2\pi t}{\rho_{SM}}\right)\right)\left(1 - H\left(\sin\left(\frac{2\pi t + D_{SM}}{\rho_{SM}}\right)\right)\right) \tag{2}$$

where A_{SM}, ρ_{SM} and D_{SM} are amplitude, period and pulse width of the pulse sequences respectively. H represents a Heaviside step function, which has the value 0 for $x<0$, 1 for $x>0$, and 0.5 for $x=0$.

The currents are given by the following equations:

$$\begin{aligned}
I_L &= g_L(v_{Th} + V_e - E_L)\\
I_{Na} &= g_{Na} m_\infty^3(v_{Th}) h_{Th}(v_{Th} + V_e - E_{Na})\\
I_K &= g_K\left[0.75(1-h_{Th})^4\right](v_{Th} + V_e - E_K)\\
I_T &= g_T p_\infty^2(v_{Th})\omega_{Th}(v_{Th} + V_e - E_T)
\end{aligned} \tag{3}$$

where g_i and E_i, with $i \in \{Na, K, L, T\}$, represent the maximum ionic conductance expressed in $nS/\mu m^2$ and equilibrium reversal potentials expressed in mV, respectively. $m_\infty(v_{Th})$ is the asymptotic value of the gating variable m_{Th} in the Na^+ channel and $p_\infty(v_{Th})$ is the maximum permeability of the membrane for T-type Ca^{2+} channel. V_e represents an external electric field on the TC relay neuron. The gating variables h_{Th} and ω_{Th} are satisfied with first-order dynamics defined by Hodgkin and Huxley as follows:

$$\begin{aligned}
dh_{Th}/dt &= (h_\infty(v_{Th}) - h_{Th})/\tau_h(v_{Th})\\
d\omega_{Th}/dt &= (\omega_\infty(v_{Th}) - \omega_{Th})/\tau_\omega(v_{Th})
\end{aligned} \tag{4}$$

where $X_\infty \in \{h_\infty, \omega_\infty\}$ represents the voltage-sensitive steady-state function and $\tau_x \in \{\tau_h, \tau_\omega\}$ is the time constant of each channel.

Additionally, $\{m_\infty, h_\infty, \omega_\infty, p_\infty\}$ and $\{\tau_h, \tau_\omega\}$ are defined as follows:

$$\begin{aligned}
h_\infty(v_{Th}) &= 1/\left(1 + \exp((v_{Th}+41)/4)\right)\\
\omega_\infty(v_{Th}) &= 1/\left(1 + \exp((v_{Th}+84)/4)\right)\\
m_\infty(v_{Th}) &= 1/\left(1 + \exp(-(v_{Th}+37)/7)\right)\\
p_\infty(v_{Th}) &= 1/\left(1 + \exp(-(v_{Th}+60)/6.2)\right)
\end{aligned} \tag{5}$$

$$\begin{aligned}
\tau_h(v_{Th}) &= \left(1 + \exp(-(v_{Th}+23)/5)\right)/\left(4 + 0.128\exp(-(v_{Th}+46)/18)\right.\\
&\quad \left. + 0.128\exp(-(23v_{Th}+644)/90)\right)\\
\tau_\omega(v_{Th}) &= 28 + \exp(-(v_{Th}+25)/10.5)
\end{aligned} \tag{6}$$