

Fuzzy Adaptive Proportional-Integral Control for Closed-Loop DBS in PD

Yi Chen^{1*}, Dechun Zhao¹, Yuan Zhang¹, Yuchen Shen¹, Yanghuazi Liu¹, You Lv¹, Siyu Chen¹

¹ School of Life Health Information Science and Engineering, Chongqing University of Posts and Telecommunications, Chongqing, China

Email Address

228757239@qq.com (Yi Chen)

*Correspondence: 228757239@qq.com

Received: 14 January 2026; **Accepted:** 10 February 2026; **Published:** 28 February 2026

Abstract:

Deep brain stimulation (DBS) has demonstrated significant efficacy in mitigating the motor impairments associated with Parkinson's disease (PD). The integration of real-time neural activity feedback into closed-loop DBS (CL-DBS) systems has opened new avenues for optimizing therapeutic outcomes. This study proposes a closed-loop control approach that dynamically adjusts stimulation parameters to restore physiological neuronal activity, utilizing a computational model of the neural circuitry. Traditional proportional-integral (PI) controllers are limited in their ability to cope with the nonlinear and time-varying nature of the PD condition. To address this limitation, a fuzzy logic-based adaptive mechanism was introduced to dynamically tune the controller parameters, thereby enabling adaptive control of nonlinear PD dynamics and time-varying targets. The control performance was also compared with conventional PI and fuzzy controllers. The performance evaluation indicates that the fuzzy adaptive PI (FAPI) controller is capable of accurately following both steady and dynamic beta-band oscillatory patterns, while ensuring low energy consumption for stimulation and achieving a reduced relative tracking error of 0.1824. These findings suggest that the proposed fuzzy adaptive PI-based CL-DBS strategy enhances control accuracy and provides a promising reference for the design of advanced CL-DBS systems.

Keywords:

Deep Brain Stimulation, Parkinson's Disease, Fuzzy Adaptive PI, Beta-band Oscillatory

1. Introduction

Parkinson's disease (PD) ranks as the second most widespread neurodegenerative illness and constitutes the leading cause of movement-related disorders. It manifests through motor symptoms such as bradykinesia and tremor, along with a range of non-motor symptoms, all of which collectively diminish the patient's quality of life [1,2,3]. Deep brain stimulation (DBS), a widely accepted treatment approach, operates by surgically placing electrodes into targeted regions of the basal ganglia to regulate

dysfunctional neural activity within the cortex-basal ganglia-thalamic (CBGT) circuitry [4,5]. However, current DBS predominantly uses open-loop high-frequency stimulation. While effective, it has limitations: stimulation parameters are determined by clinical experience, the energy delivery is fixed, and real-time neural state adaptation is lacking—leading to faster battery depletion and more frequent replacements [6,7]. Furthermore, extended exposure to high-frequency stimulation may induce adverse effects, including difficulties in articulation and compromised speech function [8,9]. Therefore, a closed-loop control system capable of automatically adjusting DBS parameters based on biomarkers that reflect the patient's clinical state is required.

Compared to continuous high-frequency stimulation, closed-loop deep brain stimulation (CL-DBS) has shown greater efficacy in alleviating motor symptoms while reducing side effects [10,11,12,13]. Yet challenges remain in controller design, including selecting appropriate feedback signals, adapting to dynamic reference targets, and limited access to experimental subjects. Direct patient testing is infeasible, and non-human primate studies are time-consuming and costly. Thus, computational models of PD-related basal ganglia circuits serve as critical tools to explore and validate CL-DBS strategies.

Beta-range (13–35 Hz) oscillations emerge prominently within the cortico-basal ganglia-thalamic circuitry during Parkinsonian conditions and are widely recognized as correlates of motor symptoms like slowness of movement and stiffness [14,15,16]. Therefore, detecting excessive beta oscillations is key to developing precise CL-DBS systems. Local field potentials (LFPs), directly recordable from implanted electrodes, are widely used as feedback signals due to their reliability in capturing pathological beta synchrony [17,18]. Studies by Peter Brown's team successfully recorded STN LFPs from multiple patients [19,20]. However, clinical implementation remains constrained due to insufficient baseline information from healthy subjects and the challenges involved in establishing reliable associations between LFP signals and clinical symptoms [21]. To address this, extracted LFP features such as beta-band power are used. For example, Fang et al. used beta power as a biomarker and implemented a robust adaptive controller to stimulate the STN, achieving improved regulation of Parkinsonian symptoms [22]. Still, beta power dynamically fluctuates during movement, making fixed reference values ineffective. Johnson et al. found that the reaching movement itself can suppress beta oscillations, causing CL-DBS to cease stimulation during critical motor phases, which may weaken its therapeutic efficacy [23]. Thus, designing CL-DBS controllers that adapt to time-varying beta targets is essential to enhance therapeutic outcomes.

In previous studies, methods such as proportional-integral-derivative (PID) control [9,10,24], fuzzy control [25,26], on-off control [27], and dual-threshold strategies [28] have been employed for closed-loop control of Parkinson's disease. These strategies modify stimulation variables, such as frequency and amplitude, in real time to optimize both treatment effectiveness and power consumption. However, they often lack robustness in tracking dynamically changing targets. References [29,30,31] utilized advanced optimization approaches—including reinforcement learning, machine learning, and deep learning—to enhance the efficiency and individualization of robust adaptive DBS systems. However, these optimization methods typically require large amounts of training data and substantial computational resources [9]. However, PID controllers are capable of regulating beta power toward a predefined target, rather than merely responding to neural activity. Moreover, due to their model-

free, data-driven, and user-friendly nature, PID controllers possess strong potential for clinical translation [32]. To address the limitations of PID controller in adapting to the highly nonlinear pathological changes and dynamically varying targets in PD, this study proposes the integration of fuzzy control into the PID control framework.

The present study proposes a CL-DBS controller for the subthalamic nucleus, designed to adapt to dynamically varying reference signals. Its performance is assessed through simulations based on a computational model of the CBGT circuit. Specifically, our contributions are as follows: (1) Fuzzy logic is integrated into the traditional PI controller, and a set of well-designed fuzzy rules is established to overcome the inherent limitations of conventional PI control; (2) A nonlinear and nonstationary computational model is constructed by modulating the synaptic strength between neurons, which is then used to evaluate the performance of the proposed fuzzy adaptive PI-based closed-loop DBS control strategy.

2. Methods

2.1. Cortex-Basal Ganglia-Thalamic circuit model

Abnormal activity within the CBGT circuit is closely linked to the onset and progression of PD. Therefore, this study adopts the conductance-based CBGT model proposed by Kumaravelu et al. to develop and evaluate the proposed control strategy [16]. The model comprises the cerebral cortex (CTx), basal ganglia (BG), and thalamus (Th). The basal ganglia include the subthalamic nucleus (STN), globus pallidus internus (GPi), globus pallidus externus (GPe), and the striatum (Str). As illustrated in Fig. 1, the circuit includes three major pathways: the direct pathway, the indirect pathway, and the hyperdirect pathway. Each nucleus consists of one or two neuronal populations, with each population containing 10 neurons. As illustrated in Fig. 2, the network consists of 80 neurons interconnected by excitatory and inhibitory synapses, forming the underlying structural framework.

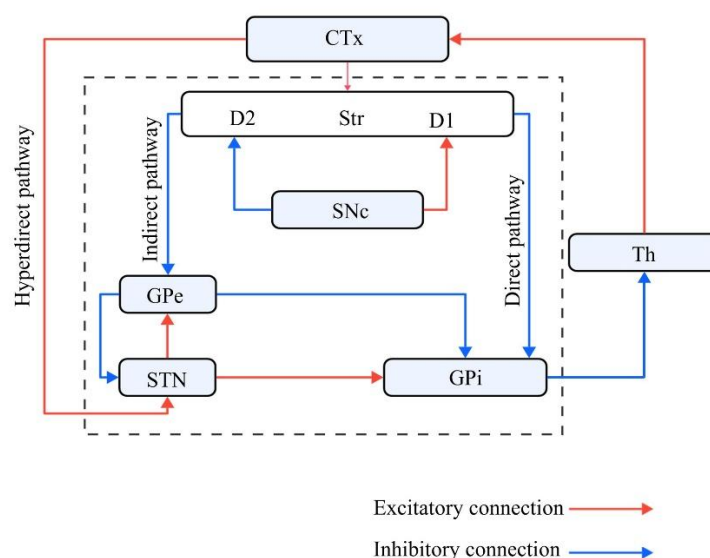


Figure 1. Connectivity among neuronal populations. Red arrows indicate excitatory connections, while blue arrows represent inhibitory connections. The black dashed box in the figure denotes the basal ganglia.

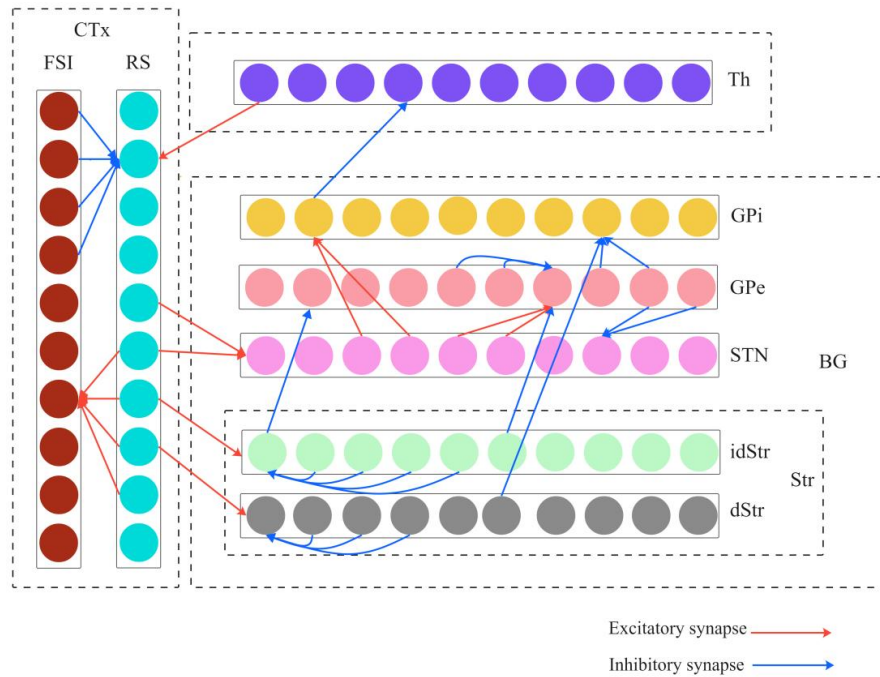


Figure 2. Prominent connections in the CBGT model. Red arrows indicate excitatory connections, while blue arrows represent inhibitory connections.

The STN, GPi, GPe, and Str neurons are modeled using conductance-based Hodgkin-Huxley (HH)-type equations, as shown in Equation (1).

$$C_m \frac{dv_i}{dt} = -\sum I_a - \sum I_{syn} + I_{app} \quad (1)$$

In Equations (1), C_m represents the membrane capacitance, which is set to $1\mu F/cm^2$ for all nuclei in this study. I_a denotes the ionic currents specific to each neuron type, I_{syn} represents synaptic currents arising from neuronal connections, and I_{app} corresponds to external input currents, referring to inputs from other nuclei not explicitly modeled in this study. Table 1 summarizes the types of ionic currents and external inputs for different neuron types. Here, Na , K , and Ca represent sodium, potassium, and calcium ionic currents, respectively; CaK denotes calcium-dependent potassium current; l indicates a nonspecific leak current; A , T and L refer to A -type potassium currents, T -type currents, and L -type currents, respectively; AHP and M represent afterhyperpolarization potassium current and M -type potassium current, respectively.

Table 1. Ionic current types and external current amplitudes for each nucleus in the model.

Nucleus	Types of ion channels	External current
STN	Na, K, CaK, T, L, A, l	$0 \mu A/cm^2$
GPi	Na, K, Ca, T, AHP, l	$3 \mu A/cm^2$
GPe	Na, K, Ca, T, AHP, l	$3 \mu A/cm^2$
Str	Na, K, M, l	$0 \mu A/cm^2$
Th	Na, K, T, l	$1.2 \mu A/cm^2$

The cortical network comprised reciprocally connected regular spiking (RS) excitatory neurons and fast-spiking inhibitory interneurons (FSI), both based on the model developed by Izhikevich [33]. The membrane potentials v_{rs} and v_{fsi} of RS and FSI neurons, respectively, are computed as shown in Equation (2).

$$\left\{ \begin{array}{l} \dot{v}_{rs} = 0.04v_{rs}^2 + 5v_{rs} + 140 - u_{rs} - I_{ie} - I_{thco} \\ \dot{u}_{rs} = a_{rs}(b_{rs}v_{rs} - u_{rs}) \\ \text{if } v_{rs} \geq 30\text{mV, then } v_{rs} \leftarrow c_{rs}, u_{rs} \leftarrow u_{rs} + d_{rs} \\ \dot{v}_{fsi} = 0.04v_{fsi}^2 + 5v_{fsi} + 140 - u_{fsi} - I_{ei} \\ \dot{u}_{fsi} = a_{fsi}(b_{fsi}v_{fsi} - u_{fsi}) \\ \text{if } v_{fsi} \geq 30\text{mV, then } v_{fsi} \leftarrow c_{fsi}, u_{fsi} \leftarrow u_{fsi} + d_{fsi} \end{array} \right. \quad (2)$$

In Equations (2), u represents the membrane potential recovery variable. I_{ie} , I_{ei} , I_{thco} denote the synaptic currents from fast-spiking interneurons (FSI) to regular spiking (RS) neurons, from RS to FSI neurons, and from the thalamus (Th) to RS neurons, respectively. The parameters a , b , c and d correspond to the time constant of u , the sensitivity of u to the membrane potential v , the reset value of v following a spike, and the post-spike increment of u . For RS neurons, these parameters are set to (0.02, 0.2, -65, 8), and for FSI neurons, they are set to (0.1, 0.2, -65, 2).

In the PD state, the M-type potassium current in Str neurons is reduced, reflected by a decrease in its maximal conductance, modeled as $g_m = 2.6 - 0.9 \times pd$. The coupling strength between the cortex and the striatum is also weakened, represented by a decrease in the cortical-to-striatal synaptic conductance $g_{ctx-str} = 0.07 - 0.044 \times pd$. In contrast, the internal coupling strength within the GPe increases, modeled as $g_{gpe-gpe} = 0.0125 + 0.0375 \times pd$. The variable pd is employed to simulate the progression from a normal to a PD state within the model, where $pd=0$ denotes normal physiological conditions and $pd=1$ indicates an advanced stage of Parkinson's disease. Values between 0 and 1 represent intermediate stages, allowing the simulation of varying degrees of Parkinsonian pathology. Figure 3 shows the raster plots of neuronal firing in the GPi, GPe, and STN under both normal and PD states.

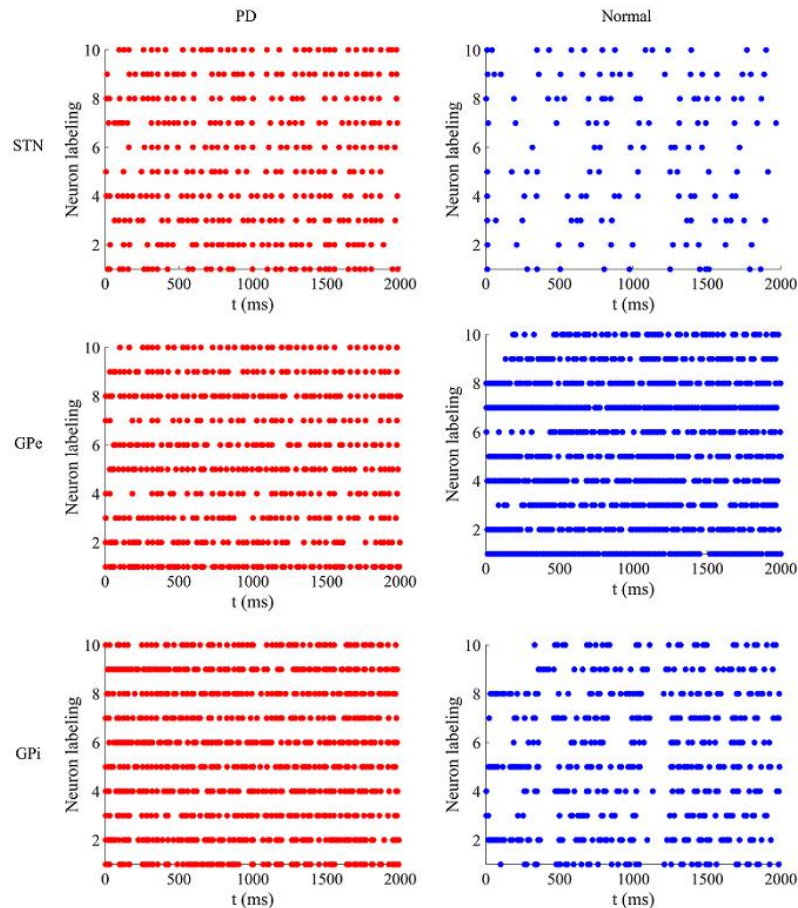


Figure 3. Comparison of spike firing patterns in the membrane potentials of STN, GPe, and GPi neurons in the CBGT model under normal and PD states. Red dots represent model neuronal activity in the PD state, while blue dots represent activity in the healthy state.

The Parkinsonian condition alters both the discharge rates and firing dynamics across multiple nuclei. Specifically, enhanced activity in the hyperdirect and indirect pathways, coupled with suppression of the direct pathway, contributes to elevated neuronal activity in the GPi and STN, whereas the GPe exhibits decreased firing rates. These findings, illustrated in Figure 4, align well with previously reported results [34,35]. The above experimental results represent the average of 50 simulation trials. The differences in firing rates between normal and Parkinsonian conditions were statistically assessed using a one-way analysis of variance (ANOVA). The results revealed notable variations in the firing rates of neurons in the STN, GPe, and GPi under normal and Parkinsonian conditions (GPe: $F = 3503$, $P < 0.001$; GPi: $F = 3905$, $P < 0.001$; STN: $F = 697$, $P < 0.001$).

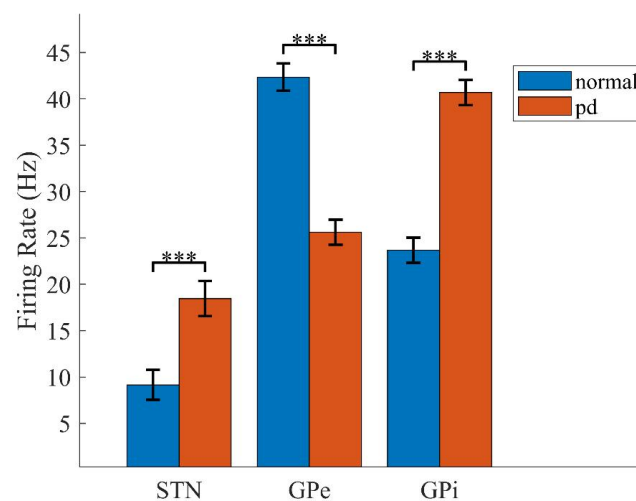


Figure 4. Firing rates of model neurons under normal and PD states (mean $\pm$ standard error). Asterisks indicate statistical significance (***) indicates $p < 0.001$.

In the PD state, GPi neurons exhibit accelerated and more synchronized firing compared to the normal state. As illustrated in Figure 5, the power spectral density (PSD) analysis reveals markedly elevated oscillatory components in the beta frequency range.

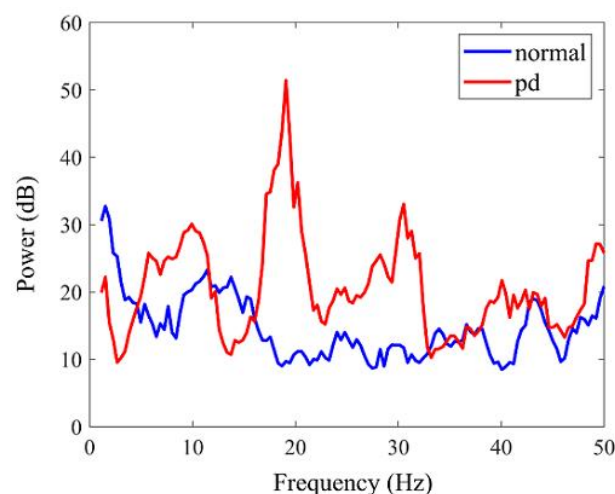


Figure 5. Comparison of Power Spectra of the GPi Nucleus Between Normal and PD Conditions.

These pathological beta-band rhythms serve as informative biomarkers and are utilized as reference inputs in closed-loop deep brain stimulation (DBS) frameworks, enabling modulation of aberrant neural activity and supporting the development of control strategies to mitigate excessive beta oscillations.

3. Closed-loop DBS system

The CL-DBS control block diagram based on fuzzy adaptive PI controller is shown in Fig. 6. It primarily consists of a dual-input dual-output fuzzy controller and a PI controller. The controller selects the beta power $y(k)$ of the GPi nucleus as the feedback signal for control. The error between the desired beta power $y_p(k)$ and the actual beta power, denoted as e , along with the rate of change of the error de/dt , serve as the inputs to the fuzzy controller. The outputs of the fuzzy controller are the incremental adjustments to the proportional gain k_p and integral gain k_i , which are then used by the PI controller to compute the stimulation frequency $u(k)$ in real time. This frequency is used to construct the stimulation current signal I_{dbs} , which is delivered to the CBGT network. The resulting beta power is then fed back into the system, repeating the process to achieve closed-loop control. This study primarily investigates three types of closed-loop controllers: PI fuzzy and FAPI control.

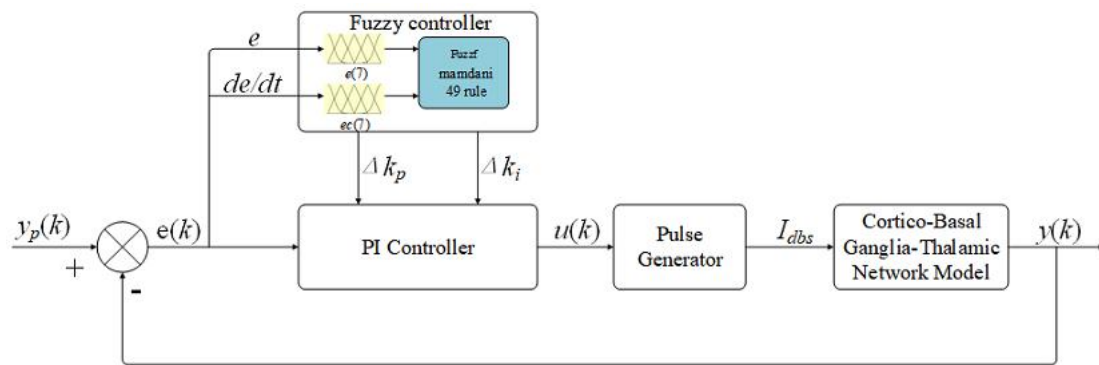


Figure 6. Block diagram of the closed-loop DBS control system.

3.1. Design of the Closed-loop DBS controller

The traditional PID control scheme incorporates three distinct elements: a proportional component to address present errors, an integral term to eliminate steady-state errors, and a derivative element to predict future trends based on error rate. However, in this study, only the P and I terms are used because neural signals are typically noisy, and the D term is highly sensitive to small, high-frequency disturbances, which can lead to excessive fluctuations in the output [10]. The configuration of the incremental discrete PI controller is presented in Equation (3).

$$u(k+1) = u(k) + k_p[e(k) - e(k-1)] + k_i e(k) \quad (3)$$

Where $e(k)$ denotes the current error, and k_p and k_i represent the proportional and integral gains, respectively.

Because of its minimal computational complexity and ease of deployment, the traditional PI controller has been commonly adopted in the regulation of neuronal dynamics. However, it exhibits certain limitations when dealing with practical challenges such as model parameter variations, strong nonlinearity, and high levels of noise in physiological signals [10,36]. To address these issues, a fuzzy logic controller (FLC) cascaded with a PI controller—referred to as a fuzzy adaptive PI (FAPI)

controller—is employed. This approach enhances performance in handling nonlinearities and uncertainties compared to the conventional PI controller. The design of FLC primarily involves the following components: (1) selecting appropriate input and output variables; (2) designing the fuzzy controller, including fuzzification, fuzzy rule base, inference mechanism, and defuzzification; and (3) determining suitable fuzzy control parameters [37]. By applying domain transformation and fuzzification to the input variables, the input values are converted into fuzzy quantities. These are then processed through fuzzy inference, and subsequently defuzzified to obtain the incremental adjustments to the proportional and integral gains, denoted as Δk_p and Δk_i . In this study, the fuzzy sets are defined as Z (Zero), PB (Positive Big), PM (Positive Medium), PS (Positive Small), NS (Negative Small), NM (Negative Medium), NB (Negative Big). The initial universes of discourse for the input and output variables are defined in Equation (4).

$$\begin{cases} X_{input1} = [-E_0, E_0] = [-3, 3] \\ X_{input2} = [-EC_0, EC_0] = [-3, 3] \\ U_{output1} = [-\Delta k_p, \Delta k_p] = [-1, 1] \\ U_{output2} = [-\Delta k_i, \Delta k_i] = [-1, 1] \end{cases} \quad (4)$$

Their scaled universes of discourse are defined in Equation (5).

$$\begin{cases} X_{input1}(E) = [-f_1 E_0, f_1 E_0] \\ X_{input2}(EC) = [-f_2 EC_0, f_2 EC_0] \\ U_{output1}(\Delta k_p) = [-f_3 \Delta k_p, f_3 \Delta k_p] \\ U_{output2}(\Delta k_i) = [-f_4 \Delta k_i, f_4 \Delta k_i] \end{cases} \quad (5)$$

Here, f_1, f_2, f_3 , and f_4 are referred to as scaling factors for the universes of discourse X_{input1} , X_{input2} , $U_{output1}$, and $U_{output2}$, respectively. By adjusting f_1 and f_2 , the input variables are mapped appropriately within their defined universes of discourse, with their values depending on the actual error and error rate. f_3 and f_4 are used to tune the effective output range of the fuzzy controller to ensure consistency with the practical requirements or physical constraints of the controlled system.

Triangular membership functions are commonly employed in fuzzy logic controllers (FLCs) owing to their advantages in real-time implementation, computational simplicity, and effectiveness in enhancing control performance. In this study, the fuzzy controller incorporates a combination of S-shaped, Z-shaped, and triangular membership functions (MFs) to enhance the flexibility and precision of the control system. Specifically, PB and NB are represented using S-type and Z-type MFs, respectively, while the remaining fuzzy sets are modeled using triangular MFs. The membership function curves for the inputs and outputs are shown in Fig. 7(a) and Fig. 7(b). The fuzzy controller utilizes the current error (E) and its rate of variation (EC) to determine the appropriate control action through a rule-based inference mechanism. Table 2 presents the full set of fuzzy control rules, with column and row labels representing the fuzzy partitions of E and EC, respectively, and each cell specifying the associated output fuzzy subset. The value outside the parentheses indicates the fuzzy subset of Δk_p , and the value inside the parentheses denotes the fuzzy subset of Δk_i . Fig. 7(c) and 7(d) illustrate the output surfaces of Δk_p and Δk_i , respectively, derived from the fuzzy rules based on E and EC.

This work implements a Mamdani-type fuzzy logic controller, in which the fuzzy reasoning outcomes are translated into discrete values through the maximum membership-minimum inference technique.

Table 2. Fuzzy rule table.

	NB	NM	NS	Z	PS	PM	PB
NB	PB(NB)	PB(NB)	PM(NB)	PM(NM)	PS(NM)	PS(Z)	Z(Z)
NM	PB(NB)	PB(NB)	PM(NM)	PS(NM)	PS(NS)	Z(Z)	Z(Z)
NS	PM(NM)	PM(NM)	PM(NS)	PS(NS)	Z(Z)	NS(PS)	NS(PS)
Z	PM(NM)	PS(NS)	PS(NS)	Z(Z)	NS(PS)	NM(PS)	NS(PM)
PS	PS(NS)	PS(NS)	Z(Z)	NS(PS)	NS(PS)	NM(PM)	NS(PM)
PM	Z(Z)	Z(Z)	NS(PS)	NM(PM)	NM(PM)	NM(PB)	NB(PB)
PB	Z(Z)	NS(Z)	NS(PM)	NM(PM)	NM(PB)	NB(PB)	NB(PB)

Note: The table columns represent the fuzzy subsets of E , and the rows represent the fuzzy subsets of EC . Each cell displays the fuzzy subset for Δk_p (outside the parentheses) and Δk_i (inside the parentheses).

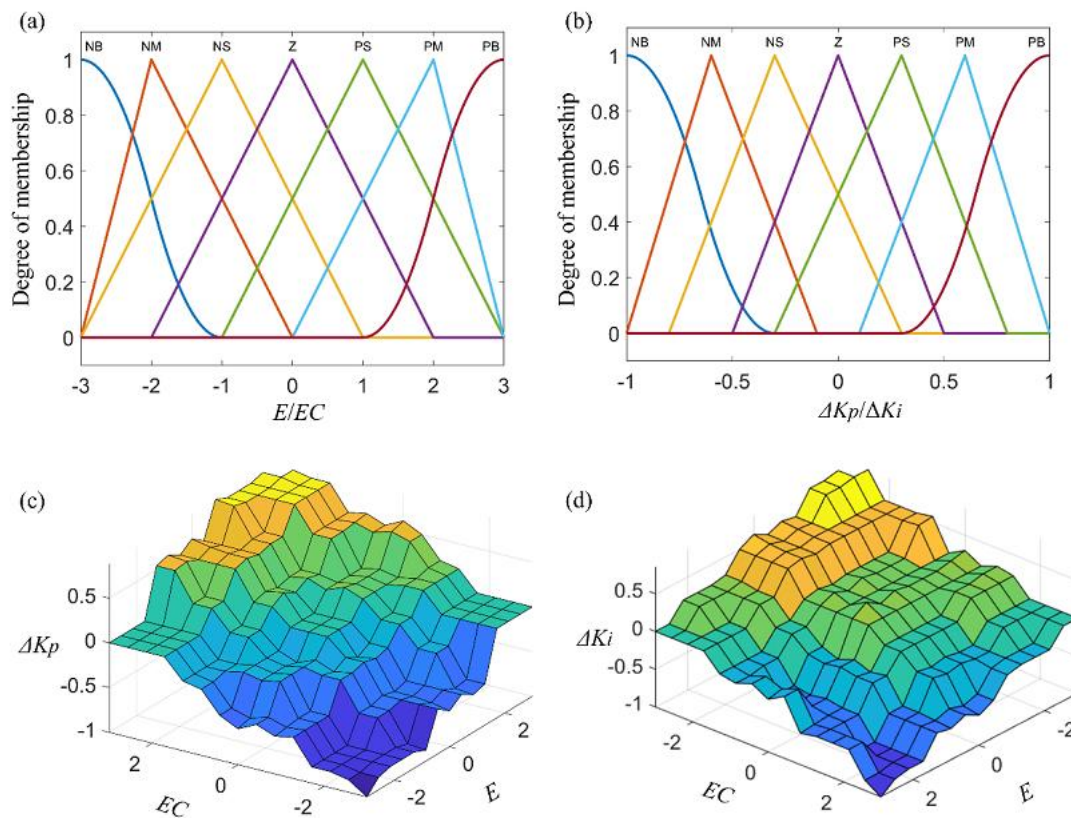


Figure 7. Membership function curves of the fuzzy controller inputs (a) and outputs (b). (c) and (d) represent the input–output surface plots for k_p and k_i , respectively.

3.2. Performance Evaluation Metrics

(1) Mean Beta-Band Oscillatory Power

Simulations were conducted using MATLAB R2022a, and the computation of beta-band power was performed with the aid of the Chronux signal processing toolbox (chronux.org), developed by Andrews et al. The mean beta-band oscillatory power is defined as follows:

$$\bar{\beta}_{av} = \frac{1}{N} \sum_{i=1}^N \beta_i \quad (6)$$

In Equation (6), β_i represents the beta-band power at each time step, and N is the total number of time steps.

(2) Mean Stimulation Frequency

$$\bar{f}_{av} = \frac{1}{(t/n)} \quad (7)$$

In Equation (7), $\bar{f}_{av}$ denotes the average frequency at which stimulation occurs, t is the total stimulation time, and n represents the number of stimulation events accumulated over that duration.

(3) Mean Relative Tracking Error

$$e_{av} = \frac{\sum_1^N \frac{|y(k) - y_p(k)|}{y_p(k)}}{N} \quad (8)$$

Equation (8) defines $y(k)$ as the instantaneous beta-band spectral magnitude, $y_p(k)$ as the reference trajectory, and N as the overall number of temporal iterations involved in the computation.

3.3. Parameter Selection of the Fuzzy Adaptive PI Controller

In closed-loop DBS control for PD, setting an appropriate tracking target is critical for effective regulation of the Parkinsonian state. To determine the appropriate target value, this study investigates the association between deep brain stimulation (DBS) frequency and the beta-band spectral power of GPi neuronal activity within the CBGT computational framework, as illustrated in Fig. 8. Under the condition where $f=0$ (no DBS applied), the model exhibits Parkinsonian characteristics, and the beta-band oscillatory power demonstrates a consistent decline with increasing stimulation frequencies beyond 50 Hz. The beta power of 110 dB, calculated under open-loop stimulation at 130 Hz, is selected as the reference target for the controller. The initial PI controller parameters are set to $k_i=0.05$ and $k_p=0.8$. To ensure system stability, k_i and k_p are constrained within the ranges of $[0.01, 0.1]$ and $[0.3, 1]$, respectively.

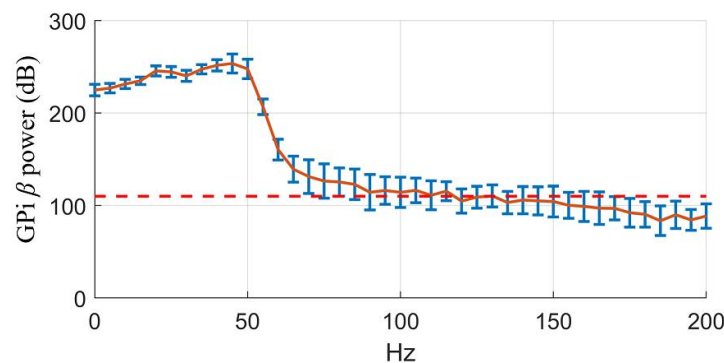


Figure 8. Variation of beta-band power with respect to stimulation frequency, with values reported as mean $\pm$ standard deviations. The red dashed line indicates the beta power value of 110 corresponding to a stimulation frequency of 130 Hz.

Based on statistical analysis of the pre-experimental data, the basic universes of discourse for E and EC are defined as $[-135, 135]$ and $[-1350, 1350]$, respectively. By adjusting the scaling factors, the input variables can be mapped within their respective

universes. Accordingly, the scaling factors f_1 , f_2 , f_3 , and f_4 are set to 45, 4500, 1, and 0.1, respectively. As shown in the Fig. 6, the inhibitory effect of stimulation saturates gradually when the frequency exceeds 130 Hz. Therefore, the stimulation frequency is constrained within the range of 5 to 150 Hz, with values below 5 Hz clipped to 5 Hz and those above 150 Hz clipped to 150 Hz.

4. Closed-Loop Control Experiments

In this study, simulation experiments were conducted using MATLAB. First, the proposed method was evaluated against open-loop DBS, PI control, and fuzzy control in terms of its performance in tracking a constant beta power level, with key metrics used to assess its effectiveness. Second, the robustness of the closed-loop controller was tested by tracking beta power signals of varying amplitudes. Finally, dynamic tracking performance was assessed by applying time-varying beta power inputs, and the relative error and mean stimulation frequency of the three control strategies were compared to draw conclusions from the study.

4.1. Tracking of Constant GPi Beta Power

To evaluate the basic control performance of the proposed method, a constant beta power target of 110 dB was set, and the fuzzy adaptive PI controller was compared with open-loop 130 Hz High-frequency stimulation, fuzzy logic controller, and PI controller. Stimulation was initiated at 2 seconds, with the initial stimulation frequency set to 5 Hz. The variations in frequency of stimulation and power of beta oscillations are shown in Figure 9.

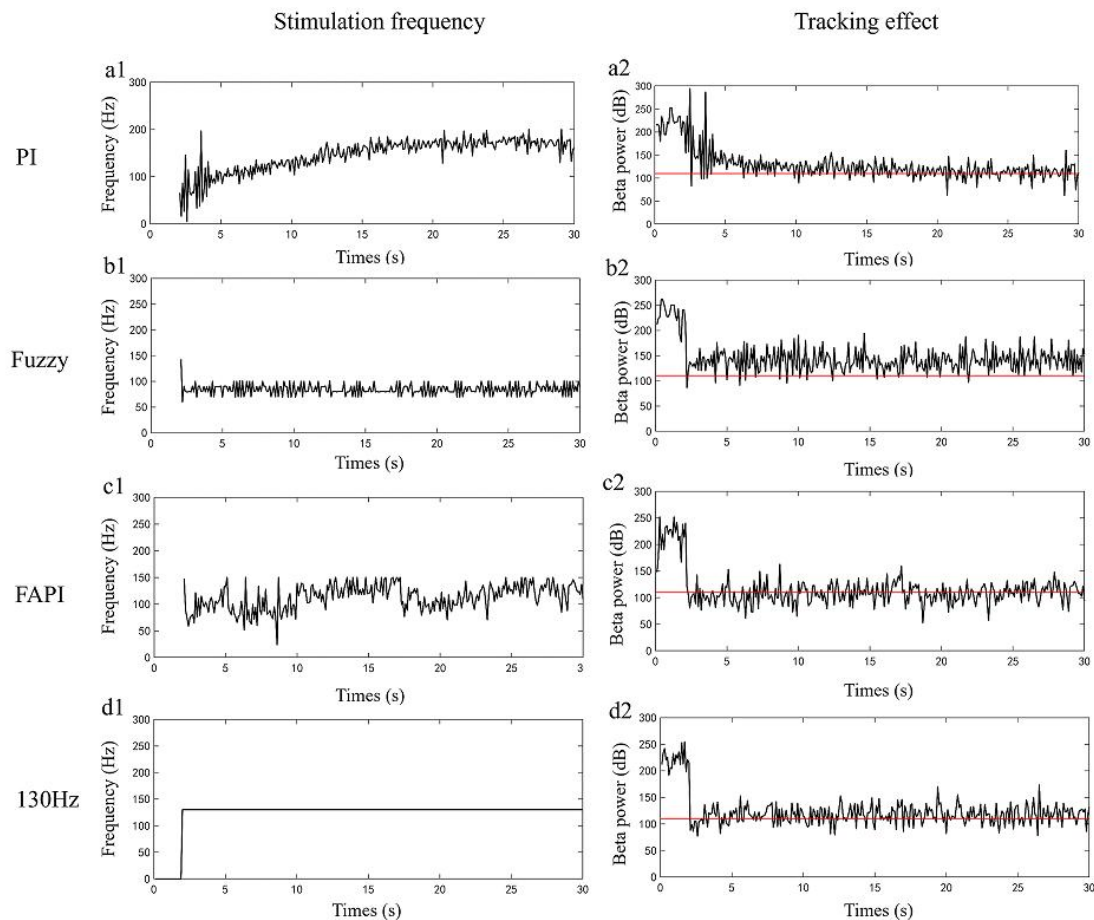


Figure 9. Comparison of stimulation frequency (a1, b1, c1, d1) and tracking performance (a2, b2, c2, d2) among three closed-loop control methods—PI control, fuzzy control, and fuzzy adaptive PI control—and open-loop 130 Hz stimulation, targeting a beta power of 110.

The average value of stimulation frequency and relative tracking error are summarized in Table 3, while Figure 10 illustrates the mean error and standard error over 50 simulation trials of 30 seconds each. The average stimulation frequencies for PI control, fuzzy control, and fuzzy adaptive PI control were 109.7881 Hz, 82.2847 Hz, and 117.9783 Hz, respectively, all consuming less energy compared to open-loop DBS. Although the fuzzy adaptive PI controller operated at a higher stimulation frequency than the other two closed-loop methods, it achieved the lowest relative tracking error of 0.1824. In terms of suppressing abnormal beta oscillatory activity, the fuzzy adaptive PI controller yielded a mean beta power of 109.5861 dB, which is closer to the target value of 110 dB compared to both PI and fuzzy control.

Table 3. Performance metrics of closed-loop and open-loop DBS in tracking constant beta power.

	130Hz	PI controller	Fuzzy controller	FAPI controller
f_{av} (Hz)	130	109.7881	82.2847	117.9783
e_{av}	0.2027	0.2521	0.2167	0.1824
β_{av} (dB)	110	121.8010	123.4593	109.5861

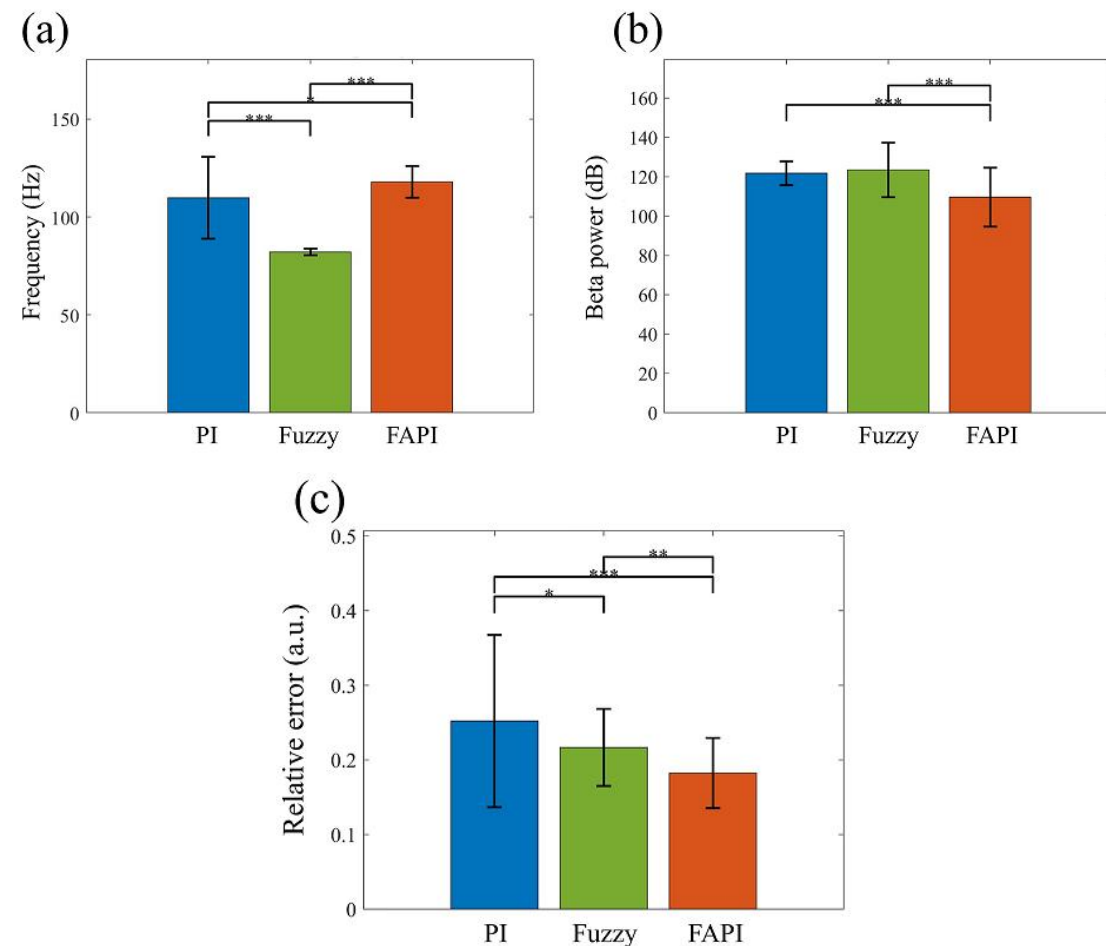


Figure 10. Comparison of the performance of the three controllers. PI, fuzzy control, and fuzzy adaptive PI (FAPI) are evaluated in terms of (a) mean firing rate, (b) beta-band power, and (c) relative error. Error bars indicate standard deviation, and asterisks denote statistical significance (* ** * indicates $p < 0.001$).

4.2. Robustness Testing

The closed-loop PI controller integrated with fuzzy logic demonstrated robust performance in sustaining a stable beta power level; however, several issues still warrant further exploration. First, Parkinson's disease (PD) is a chronic, progressive disorder characterized by gradually worsening symptoms and marked inter-individual variability. Thus, subject-specific differences should be incorporated into model-based evaluations of Parkinsonian states. Second, PD patients exhibit a substantial discrepancy in beta power between motor and resting states, underscoring the need to monitor time-varying beta power to better support desired motor functions.

To assess the controller's performance in addressing the time-varying beta power scenario (noted above), a targeted testing protocol was designed: A time-varying beta power reference signal was implemented to mimic the natural fluctuations in beta activity during transitions between motor and resting states, thereby verifying the controller's capacity to track dynamic reference signals.

For this scenario, the target beta power was set to vary sequentially as $110 \rightarrow 150 \rightarrow 120 \rightarrow 160 \rightarrow 130$, with changes initiated at 10 seconds and occurring every 5 seconds. Tracking results are presented in Figure 11, while Table 4 summarizes the mean stimulation frequency and relative tracking error. The average stimulation frequencies for the PI, fuzzy, and fuzzy adaptive PI controllers were 93.1250, 81.5108, and 109.5422, respectively. Notably, the fuzzy adaptive PI controller achieved the lowest mean relative tracking error (0.1427).

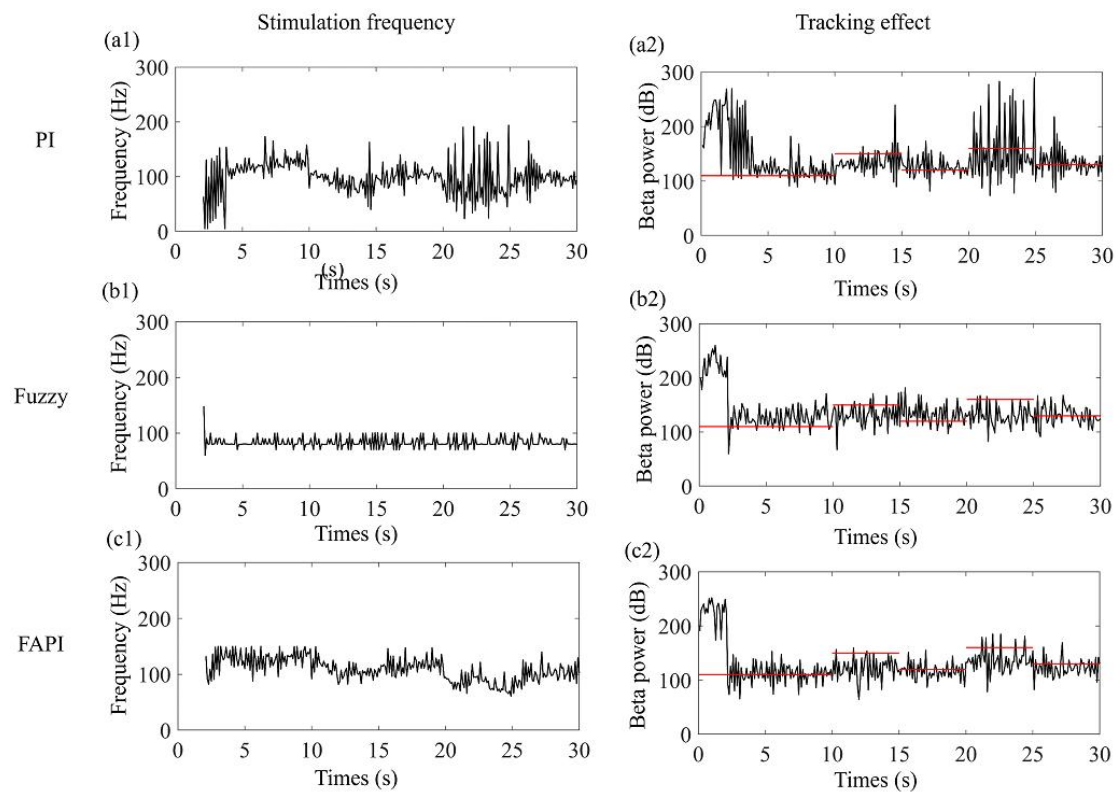


Figure 11. Comparison of the three controllers in tracking a time-varying beta power target. The red line indicates the changes in the target beta power to be tracked.

Table 4. Performance metrics of the three controllers in tracking time-varying beta power.

	PI controller	Fuzzy controller	FAPI controller
f_{av} (Hz)	93.1250	81.5108	109.5422

e_{av}	0.2521	0.1628	0.1427
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5. Results and Discussion

The present study proposes a closed-loop control framework aimed at attenuating abnormal neural oscillations characteristic of Parkinson's disease. To validate the reliability of the proposed approach, a CBGT circuit model was constructed based on Hodgkin–Huxley-type equations, incorporating cortical, STN, GPe, GPi, striatal, and thalamic neurons. The simulation results demonstrate that neuronal firing in the GPi exhibits pronounced beta-band oscillations under PD conditions, which is consistent with previous findings [34,35,38]. A fuzzy adaptive PI controller was developed for a closed-loop DBS system targeting PD, with the beta oscillatory power of GPi neuronal activity employed as the feedback signal. This control strategy demonstrated superior performance compared to traditional PI and fuzzy controllers, particularly in modeling nonlinear pathological states and tracking time-varying targets. By dynamically adjusting the PI parameters via fuzzy logic, the FAPI controller effectively mitigates nonlinear disturbances caused by synaptic plasticity and changes in neuronal firing patterns under PD conditions. It reduced the tracking error to 0.1824 under constant targets and maintained the lowest error (0.1427) under time-varying targets without significantly increasing stimulation energy consumption, indicating a favorable balance between control accuracy and energy efficiency. Furthermore, the FAPI controller robustly regulated GPi beta-band power within the desired range even under dynamic variations of the PD state variable (pd), demonstrating strong adaptability to disease progression and individual variability. In contrast, conventional PI controllers tend to exhibit oscillations or overshoot in the presence of nonlinear disturbances, while fuzzy controllers fall slightly short in terms of steady-state precision.

The results of this study align with recent trends in closed-loop DBS control research, which emphasize the use of biomarkers—such as beta-band oscillatory power—as feedback signals and the integration of intelligent control strategies to enhance system adaptability. The Fuzzy Adaptive PI (FAPI) controller proposed in this study integrates the model-free advantages of PID control with the nonlinear adaptability of fuzzy logic. Without increasing computational complexity, it significantly improves tracking accuracy, reducing the error to 0.1824. Compared to intelligent methods such as reinforcement learning, FAPI requires no offline training and is more suitable for integration into existing DBS hardware. Unlike conventional PI control, its parameters can be dynamically adjusted based on real-time error, achieving a balance between robustness and responsiveness. Therefore, FAPI offers an improved trade-off between clinical feasibility and control performance.

Although this study demonstrates the effectiveness of the FAPI controller at the computational model level, several limitations remain:

- (1) The CBGT model does not incorporate dopamine dynamics, glial modulation, or neurotransmitter diffusion, which may underestimate the complexity of the real neural system;
- (2) This study uses only GPi beta-band power as the feedback signal. Future work could incorporate multi-channel LFP recordings (e.g., combined STN and cortical signals) or multi-frequency features to enhance control accuracy.

(3) The current approach adjusts only the stimulation frequency. Future research may extend this to include joint control over multiple stimulation parameters such as pulse width, amplitude, and closed-loop phase-locked stimulation.

Future work could focus on building more refined multi-scale PD models that integrate neurotransmitter dynamics and synaptic plasticity, as well as developing hardware prototypes of the FAPI-based system to evaluate long-term stability through animal experiments.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this article.

Funding

This research received no specific grant from any funding agency in the public, commercial or not-for-profit sectors.

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