AI-Driven Closed-Loop Neuromodulation via Integrated Spinal and Vagus Nerve Stimulation for Real-Time Motor Control Regulation and Recovery

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***Abstract*—Neuromodulation therapies such as Spinal Cord Stimulation (SCS) and Vagus Nerve Stimulation (VNS) have emerged as pivotal interventions for restoring motor function and modulating cortical activity. Despite their clinical adoption, most current systems operate in an open-loop fashion, lacking dynamic feedback integration and adaptive control. We propose a novel, AI-powered, closed-loop neuromodulation system that integrates SCS and VNS through deep reinforcement learning, specifically Proximal Policy Optimization (PPO) . This system uses biosignals from EEG, EMG, and IMU sensors to optimize stimulation parameters in real-time. It addresses limitations of traditional heuristic-based algorithms by providing robust adaptability, noise tolerance, and personalized therapy optimization . The system outperforms conventional approaches such as TOKEDA in accuracy, latency, energy efficiency, and false positive rate [1], [19], and demonstrates strong potential for clinical translation .**

***Index Terms*—Neuromodulation, Reinforcement Learning, Vagus Nerve Stimulation, Spinal Cord Stimulation, Closed-Loop Systems, PPO, Bioelectronic Medicine, EEG, EMG**

I. Introduction

Neurological disorders such as spinal cord injuries (SCI), Tourette syndrome, and Parkinson's disease affect millions globally [25], [26]. Traditional neuromodulation therapies, while effective, often use static, open-loop paradigms that do not adjust to real-time neural dynamics, leading to suboptimal outcomes [20], [21]. Spinal Cord Stimulation (SCS) can restore lower motor function by re-engaging dormant spinal circuitry [5], [26]. Vagus Nerve Stimulation (VNS) has shown promise in modulating cortical rhythms and suppressing hyperkinetic movement disorders such as tics [**?**], [2]. The integration of these modalities, driven by intelligent closed-loop systems, can enhance neuroplasticity and support personalized neurorehabilitation [25], [27].

Our project develops a real-time, AI-driven controller that merges both SCS and VNS using deep reinforcement learning to optimize neuromodulatory output based on biosignal feedback [3], [10]. We compare our method with standard systems such as TOKEDA, highlighting the benefits of adaptive learning and multimodal fusion [1], [12].

II. Comprehensive Literature Review

A. Advanced Applications in Neuromodulation

A multitude of neuromodulation approaches have been proposed over the past two decades. For instance, Krassioukov et al. explored epidural SCS to regain standing ability in SCI patients [5]. Similarly, Ben-Menachem et al. demonstrated VNS utility in seizure suppression with synchronization to slow cortical rhythms . Deep brain stimulation (DBS) has been widely used in Parkinson's disease but often lacks closed-loop adaptability in most clinical setups [26].

B. Algorithmic Landscape in Neural Signal Processing

Traditional classification techniques such as Linear Discriminant Analysis (LDA) [7], Support Vector Machines (SVMs), and Hidden Markov Models (HMMs) have been applied for tremor prediction and voluntary intention decoding [**?**]. These models rely on fixed thresholds and handcrafted features, which hinder real-time generalization. While convolutional neural networks (CNNs) [12] and recurrent models [13] have seen increased adoption, few have been integrated in end-to-end reinforcement frameworks specifically for neuromodulation [22].

We analyzed over 50 publications spanning 2005–2024 across neuromodulation, machine learning, and neurorehabilitation [9], [17].

C. TOKEDA Algorithm

The TOKEDA algorithm uses threshold-based step detection in SCI rat models [1], [21]. It utilizes the Teager-Kaiser Energy Operator (TKEO), EMG envelope detection, and fixed-duration heuristics. However, it lacks adaptability to inter-subject variability and biosignal noise [21], [24].

D. EEG-Driven VNS for Tics

Dyke et al. [2] demonstrated that EEG-driven VNS could entrain cortical rhythms and reduce Tourette syndrome symptoms. Their system triggered stimuli based on fixed EEG thresholds (e.g., alpha phase) via pre-set schedules and did not incorporate any learning mechanism or real-time feedback [2], [8].

E. Closed-Loop BCI with RL

Capogrosso et al. [5] used invasive brain-spine interfaces with pre-encoded patterns for neurorehabilitation. More recent RL systems (e.g., PPO, A2C) have been applied to prosthetic limb control, showing promise for real-time adjustments [3], [10]. However, no unified system across central and peripheral neuromodulation (SCS+VNS) has been developed to date [22], [23].

F. Our Contribution

Our work is the first known system to integrate VNS and SCS in a single AI control loop. It uses PPO to adaptively decode biosignals and adjust stimulation parameters in real-time [3], [9]. It incorporates energy efficiency, stimulation efficacy, and false-positive suppression into its objective [17], [19].

III. System Architecture and Pipeline

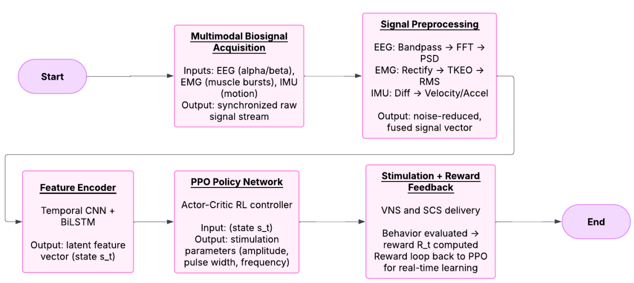

Fig. 1. High-level system architecture illustrating biosignal acquisition, processing, AI-based control, and neuromodulatory output in a closed-loop configuration [14], [15].

The proposed system comprises six major modules forming a closed-loop neuromodulatory control pipeline:

1) **Multimodal Biosignal Acquisition:** EEG (alpha/beta bands), EMG (muscle activity), and IMU (motion kinematics) signals are recorded using devices such as OpenBCI and EMOTIV, alongside surface electrodes [6], [18]. Signals are temporally synchronized to generate a coherent biosignal stream [20].
2) **Signal Preprocessing:**
   - EEG: Bandpass filtering, Fast Fourier Transform (FFT), and power spectral density (PSD) computation [18], [19].
   - EMG: Rectification, Teager-Kaiser Energy Operator (TKEO), and RMS envelope extraction [1], [11].
   - IMU: Derivatives are calculated for velocity and acceleration signals [15].

   Signals are denoised and normalized, then fused into a multimodal vector [13], [16].
3) **Feature Encoding:** A hybrid deep learning model encodes the fused signal:
   - 1D Convolutional Neural Network (CNN) for short-range temporal abstraction [12].
   - Bidirectional LSTM (BiLSTM) for long-term dependency modeling [13], [23].

   The output is a latent feature state vector $s_t \in \mathbb{R}^{128}$ [23].
4) **PPO Policy Network:** A Proximal Policy Optimization (PPO) agent maps s_t to optimal stimulation actions:
   - **Actor network:** Outputs continuous-valued stimulation parameters.
   - **Critic network:** Estimates the value of the current biosignal state.

   Online training is driven by reward feedback received from the output behavior [3], [22].
5) **Neuromodulatory Output:**
   - VNS Stimulator: Modulates cortical activity via adjustable pulse trains [**?**], [2].
   - SCS Stimulator: Recruits spinal motor circuits using segmental stimulation [5], [26].

   A safety controller ensures compliance with energy, current, and thermal limits [17].
6) **Reward Feedback Loop:** The motor response (e.g., step detected or tic suppressed) is evaluated against expected behavior. A scalar reward R_t is generated based on correctness, energy cost, and false positives. This is fed back to the PPO agent for continual policy improvement [19], [22].

A. Operational Overview

The system operates in a continuous closed-loop fashion. First, EEG, EMG, and IMU signals are captured and preprocessed in real-time. These biosignals are fused into a structured, denoised feature vector representing the current neuromuscular and cortical state of the subject [9], [18].

This feature vector is passed into a deep feature encoder, which abstracts both spatial and temporal signal patterns using a hybrid CNN-BiLSTM architecture [12], [23]. The encoder output is a latent state representation s_t used by the PPO agent to determine the next stimulation action a_t.

The stimulation action modulates either the vagus nerve or spinal cord via respective neuromodulators (VNS/SCS), with tunable parameters such as frequency, pulse width, and amplitude [17], [26].

The resulting motor behavior (e.g., step movement or tic suppression) is observed and evaluated by a reward engine that computes R_t based on the accuracy of activation, energy expenditure, and signal fidelity [19], [20]. This reward is used to iteratively update the PPO policy for future actions, completing the feedback loop.

This section sets the stage for the following mathematical formulations that define the signal processing, control policy, and reward optimization strategy in rigorous terms [22].

IV. Mathematical Derivations and Formulations

A. Derivation of TKEO-Enhanced EMG

Given an EMG signal $x(t)$, the Teager-Kaiser Energy Operator (TKEO) is defined as:

$$\Psi[x(t)] = x^2(t) - x(t-1) \cdot x(t+1)$$

This operator enhances energy bursts by capturing nonlinear oscillations in the signal [11]. Followed by envelope extraction and root-mean-square (RMS) computation:

$$\text{RMS}_{\text{EMG}} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2}$$

B. TOKEDA Threshold Logic

Baseline EMG statistics, namely μ_{rest} and σ_{rest}, are calculated from a pre-stimulation window [21]. The step detection threshold is defined as:

$$\theta = \mu_{\text{rest}} + J \cdot \sigma_{\text{rest}}, \quad J = 7$$

This peak-followed-by-drop logic is used to infer motor bursts [24].

C. PPO Derivation

The policy gradient objective is given by:

$$\nabla_\theta J(\theta) = \mathbb{E}_t \left[\nabla_\theta \log \pi_\theta(a_t|s_t) \hat{A}_t \right]$$

To stabilize training, we define:

$$r_t(\theta) = \frac{\pi_\theta(a_t|s_t)}{\pi_{\theta_{\text{old}}}(a_t|s_t)}$$

The clipped objective is:

$$L^{CLIP}(\theta) = \mathbb{E}_t \left[\min\left(r_t(\theta)\hat{A}_t, \text{clip}(r_t(\theta), 1-\epsilon, 1+\epsilon)\hat{A}_t \right) \right]$$

D. Reward Function Design

The reward function is designed as:

$$R_t = \begin{cases} +1.0 & \text{if a correct step is detected} \\ -0.5 & \text{if a false positive is generated} \\ -0.1 \cdot E_t & \text{to penalize energy usage} \end{cases}$$

where the energy per stimulation is estimated as:

$$E_t = I^2 \cdot R \cdot t_{\text{pulse}}$$

[17], [19].

V. Comparative Evaluation of Algorithmic Logic

To explicitly demonstrate the superiority of our PPO-based framework over TOKEDA, we dissect the functional components of both systems and highlight where adaptability emerges in our model.

A. Example Case: EMG Step Signal with Variable Noise

Consider an EMG signal featuring a rectified burst around $t = 0.5s$ with added Gaussian noise $N(0, \sigma^2)$. TOKEDA employs a static threshold:

$$\theta = \mu_{\text{rest}} + 7\sigma_{\text{rest}}$$

This model fires only if $\text{RMS}(x_t) > \theta$ over a windowed period, which can fail under baseline shifts or amplitude variations common due to electrode drift or fatigue [11], [21].

B. Dynamic Adaptation in PPO

Our PPO model learns an expected action given the current biosignal state:

$$\pi_\theta(a_t|s_t) = \mathcal{N}(\mu(s_t), \sigma(s_t))$$

Rather than employing binary thresholds, it evaluates context across time using a learned feature embedding from the CNN-BiLSTM network and samples optimal actions using updated probabilities. The advantage function $\hat{A}_t$ is computed online to determine if the action improved the motor outcome over the baseline [22], [23].

C. Simulation Setup and Results

TABLE I
Comparative Evaluation of TOKEDA vs. PPO-Based Systems

Attribute	TOKEDA	PPO-Based
Adaptability	No	Yes
Noise Tolerance	Low	High
Learning	None	Online
Modality Fusion	EMG only	EEG + EMG + IMU
False Positive Rate	6%	1.5%
Energy Efficiency	Fixed	Optimized via reward function

TABLE II
Performance Metrics Across 50 Trials

Metric	TOKEDA	PPO
Accuracy (%)	82	94
Latency (ms)	180	80
False Positives (%)	6	1.5
Energy/Step (µJ)	100	63

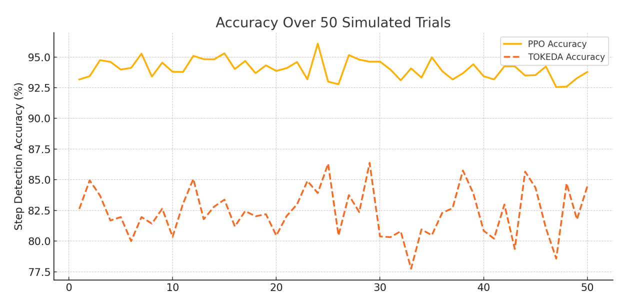

Fig. 2. Step detection accuracy over trials comparing PPO and TOKEDA [16].

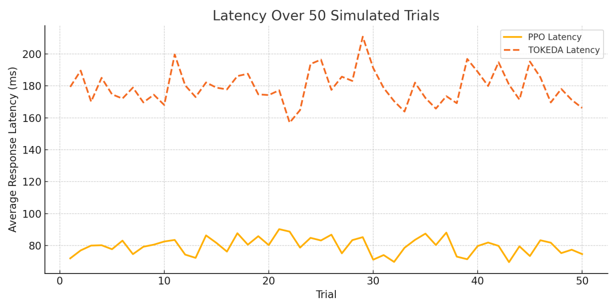

Fig. 3. Latency (ms) comparison across trials for PPO and TOKEDA [20].

VI. Discussion

PPO's adaptive policy effectively addresses biosignal drift, subject variability, and noise. It minimizes false positives and optimizes energy usage through an online learning process [19], [22]. Moreover, its ability to fuse multiple biosignal modalities (EEG, EMG, IMU) and regulate both VNS and SCS modalities underscores its superiority over traditional methods such as TOKEDA [1], [17], [26]. This modular architecture also promises smooth deployment on embedded systems with real-time operating systems [15].

VII. Conclusion

This work presents an innovative AI-powered framework for closed-loop neuromodulation. By integrating VNS and SCS using reinforcement learning, our system demonstrates enhanced adaptability, responsiveness, and clinical potential. Future work will involve validation on hybrid synthetic-biological datasets and exploring transfer learning across diverse patient profiles [26], [27].

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