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Electroencephalography-Based Brain-Computer Interfaces for Parkinson’s Motor Rehabilitation: A Review of Cognitive Fatigue Challenges

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Abstract: ***Parkinson’s disease (PD) is a progressive neurodegenerative disorder characterised by motor impairments such as tremor, rigidity, and bradykinesia, which reduces quality of life. EEG-based brain computer interfaces (BCIs) have emerged as a promising adjunct for motor rehabilitation by translating neural activity, including β and µ rhythms, into control signals that support neuroplasticity. This review examines key EEG signals used in BCI systems, including event-related desynchronization and synchronisation, and evaluates their reliability in PD. Particular attention is given to cognitive fatigue, which alters neural dynamics, reduces signal-to-noise ratio, and decreases classification accuracy across sessions. The review synthesises current BCI modalities and highlights challenges related to inter-session variability and sustained cognitive demand. Adaptive strategies such as fatigue-aware system design, AI-driven classifiers, hybrid EEG–EMG and EEG–VR systems, and wearable home-based platforms are discussed as potential solutions. Overall, EEG-based BCIs show strong potential for PD rehabilitation, but addressing cognitive fatigue and signal instability remains critical for long-term clinical application.***

Keywords: Parkinson’s disease, EEG, brain computer interface, cognitive fatigue, motor imagery, event-related desynchronization, neurorehabilitation, machine learning

Methodology

This study is a narrative review of the literature on electroencephalography (EEG)- based brain–computer interfaces (BCIs) for motor rehabilitation in Parkinson’s disease, with a particular focus on cognitive fatigue and its effects on neural signal reliability.

A literature search was conducted using electronic databases including Google Scholar, PubMed, and ScienceDirect. Keywords used in the search included “Parkinson’s disease”, “EEG”, “brain–computer interface”, “motor imagery”, “event-related desynchronization”, “cognitive fatigue”, and “neurorehabilitation”, as well as combinations of these terms. Studies were included if they focused on EEG-based BCI applications in Parkinson’s disease or related motor disorders, examined neural signal features such as β-band activity, µ rhythms, or ERD/ERS, or investigated cognitive fatigue and its effects on neural performance or BCI reliability. Both experimental and review studies were considered. Studies were excluded if they lacked sufficient methodological detail, did not include a detailed evaluation of experimental results, or focused mainly on invasive BCI systems.

The review primarily includes studies published between 2010 and 2025, with earlier foundational studies included where necessary.

Sources were selected based on relevance to the research aims, credibility of the publication, and contribution to understanding the interaction between cognitive fatigue and BCI performance.

1. Introduction

Parkinson's disease (PD) is a progressive neurodegenerative disorder that affects more than 12 million people worldwide, with prevalence increasing due to an increasingly ageing population [1]. The loss of control over motor skills significantly impacts daily living, causing difficulties with gait, balance, and fine motor tasks, often resulting in loss of independence, increased risk of injury, and decreased quality of life[2].

The progressive changes in the brain seen in PD are due to the loss of dopamine-producing neurons in the substantia nigra, the part of the brain which controls motor function, which disrupts normal movement control [3]. By the time motor symptoms appear, over 50–80% of these neurons may already be damaged. The disease is also associated with Lewy bodies, clumps of the protein alpha-synuclein, found in various brain regions[4], leading to the characteristic motor and non-motor symptoms of Parkinson's disease. PD is more common with increasing age, affecting 1–2% of people over 60 and up to 4% of those over 80[5]. While most cases have no clear genetic cause, around 10% are linked to mutations in genes such as LRRK2 or GBA[4,5]. Beyond movement difficulties, PD often causes non-motor symptoms like cognitive impairment, mood changes, sleep disturbances, and autonomic dysfunction, and can appear years before motor symptoms and significantly impact quality of life[2,4].

Pharmacological therapy, particularly levodopa and other dopaminergic agonists, remains the primary treatment for PD. Although these drugs initially improve motor symptoms, long-term use often leads to further complications such as motor fluctuations and dyskinesia[7,8]. Moreover, medications do not sufficiently address all aspects of motor impairment, including freezing of gait and postural instability[8].

Rehabilitation strategies, including physiotherapy and occupational therapy, have demonstrated benefits in enhancing mobility and reducing fall risk[9]. However, these interventions frequently require sustained attention, therapist supervision, and prolonged mental effort. They are often not intensive enough, and may limit their long-term effectiveness, particularly in advanced stages of PD[10].

Brain–computer interfaces (BCIs) are emerging as innovative tools for motor rehabilitation in PD. BCIs utilise real-time neural signals to generate feedback or control external devices, by bypassing impaired basal ganglia circuits and facilitating voluntary movement[11]. By integrating immediate feedback with motor training, BCIs aim to enhance neuroplasticity and reinforce motor control through targeted interventions, potentially filling gaps in conventional rehabilitative approaches[12].

This review aims to summarise current EEG-based BCI approaches for motor rehabilitation in Parkinson's disease, examine commonly utilised neural signals, analyse the effect of cognitive fatigue on these signals and the BCI's reliability, and discuss emerging challenges related to cognitive fatigue that may affect long-term feasibility.

2. Neural Signals Relevant to BCI Control in PD

EEG-based BCIs for PD motor rehabilitation decode pathological oscillations and residual sensorimotor rhythm from scalp signals. β band activity reflects basal ganglia dysfunction while μ rhythms indicate neural plasticity, though both signals show variability across disease stages that challenge reliable BCI control[12].

2.1 β-Band Oscillations and Motor Control

β-band oscillations change during movement and normally show a clear decrease in power, known as β desynchronization, when a healthy person prepares for and performs a movement. This reduction reflects active motor engagement. In Parkinson's disease, however, this movement-related β suppression is weaker, causing hyperactive β band activity. This suggests that patients have difficulty reducing abnormal β activity due to dysfunction of the basal ganglia and loss of dopamine[13]. As a result, β signals become less stable and reliable for use as control features in brain–computer interface (BCI) systems. Because β modulation closely reflects motor state and responds to treatment, it is widely used as a marker of motor impairment[14].

2.2 Sensorimotor Rhythms (μ & Alpha Bands)

Sensorimotor rhythms in the μ (8–13 Hz) frequency band, recorded over the motor cortex, reflect the coordinated activity of cortical motor networks and decrease in amplitude during movement or its mental siμlation. Recent work has shown that μ rhythm desynchronization, a type of event-related desynchronization (ERD) can be reliably measured in people with Parkinson's disease. That modulation of these rhythms is responsive to motor experience and training, indicating that PD alters typical μ suppression patterns[15,16]. Furthermore, studies of event-related desynchronization during motor imagery and movement demonstrate that μ ERD occurs even in the absence of prevalent motor output. This preserved ability to modulate μ rhythms through imagined actions provides a rationale for using μ ERD in BCIs for individuals with movement-execution deficits, such as those with Parkinson's disease[15,16].

2.3 ERD/ERS Dynamics in Parkinson's Disease

Event-related desynchronization (ERD) occurs when brain activity in the sensorimotor cortex decreases during movement or even during imagined movement, reflecting active motor processing. Studies show that ERD appears during both executed and imagined movements, although it is generally stronger during real movement because actual μscle output provides additional sensory feedback[18,19]. In Parkinson's disease (PD), however, the amplitude of ERD is reduced, meaning the decrease in brainwave power is smaller than in healthy individuals. For example, one study reported an average β-band ERD of approximately −24 ± 13% in PD patients, compared with −42 ± 21% in healthy controls[12].

In addition to reduced strength, ERD and its opposite signal (event-related synchronisation, ERS) often show delayed timing in PD, meaning the brain responds more slowly when starting or stopping a movement. There is also significant variability within individuals, as seen by the percentage error of the values, with ERD magnitude and timing differing widely between patients depending on disease severity, medication state, and individual neural compensation. This variability makes ERD patterns less predictable across sessions and individuals.

Such inconsistency creates a challenge for brain–computer interface classifier training. BCI algorithms rely on stable and repeatable neural features to accurately decode motor intent. When ERD amplitude fluctuates or occurs at different times across trials, the classifier becomes less reliable, increasing misclassification and reducing overall system performance[29].

2.4 Signal Stability and Inter-Session Variability

EEG signals used for brain–computer interface control are known to change between recording sessions, leading to day-to-day variability in signal features and classifier performance. Large μlti-day motor imagery datasets have shown that classification accuracy can drop markedly when models trained within a single session are applied to data collected on different days, revealing the practical impact of signal variability across sessions[17]. In addition, the non-stationary nature of EEG signals across sessions, caused by changes in electrode positioning, user state, and neural dynamics, has triggered the creation of adaptation techniques that improve cross-session accuracy by reducing session-specific differences[18].

3. Overview of Brain Computer Interfaces

3.1 What is a BCI?

A Brain–Computer Interface (BCI) is a technology that enables the brain to control external devices by interpreting neural signals and translating them into control commands. Typically, BCIs function as closed-loop systems in which neural activity is recorded, processed, and converted into feedback that users can understand and adapt to[9]. This feedback may be visual, auditory, or haptic, and is designed to reinforce voluntary control over motor functions. The central principle is that repeated engagement with the system can promote neuroplastic changes in the motor cortex and associated pathways, enhancing functional recovery in undamaged neurons even when some neural circuitry is compromised by disease[10].

BCIs primarily rely on non-invasive methods of signal acquisition, such as electroencephalography (EEG), to detect patterns including μ and β frequency waves and event-related desynchronizations/synchronisations (ERD/ERS). These signals reflect motor imagery, even in the absence of voluntary movement, enabling patients with impaired motor output to control external devices or receive feedback to guide rehabilitation[11]. The closed-loop design of BCIs allows patients to adapt their learning in real time.

3.2 BCIs in Movement Disorders

BCIs have been extensively investigated in post-stroke motor rehabilitation, where cortical damage impairs voluntary movement pathways. In such cases, BCIs strengthen the remaining cortical networks and provide sensory feedback to facilitate the relearning of lost motor skills. Parkinson's disease (PD), however, presents a unique challenge, as motor impairment primarily results from basal ganglia dysfunction and pathological β-band synchrony (when neurons in this area start firing at the same time and in a rigid rhythm, rather than firing independently) [13]. This dysfunction leads to bradykinesia in the limbs, face and voice (slowed speech), rigidity, and tremor, which often persist despite optimised dopaminergic therapy. EEG-based BCIs in PD are designed to bypass dysfunctional basal ganglia circuits by decoding cortical motor signals and providing real-time feedback to enhance voluntary movement initiation[19].

BCIs in Parkinson's disease work to enhance and strengthen existing cortical control while reducing the effects of pathological oscillatory activity. By reinforcing cortical activity and providing real-time closed-loop feedback, these systems have the potential to improve motor function, reduce reliance on high-dose pharmacological therapy, and alleviate motor fluctuations in PD patients[13,20].

4. EEG-Based BCIS used in Parkinson's Disease

Several types of EEG-based BCIs have been explored, including motor imagery-based BCIs, event-related potential (ERP) systems, and hybrid approaches that combine μltiple signal types. Each method focuses on the plasticity of cortical networks while targeting specific deficits in PD motor control.

4.1 Motor Imagery-Based BCIs

Motor imagery (MI)-based BCIs, a type of EEG-based BCI, enable users to generate neural activity patterns similar to actual movement, even when actual motor execution is impaired. These systems typically rely on the detection of event-related desynchronization (ERD) and event-related synchronisation (ERS) in sensorimotor rhythms (SMR), neural oscillations detected over the motor cortex, particularly in the alpha (8–13 Hz) and β (13–30 Hz) frequency bands[15]. Consistent engagement with MI-BCIs facilitates reinforcement of motor cortical networks, which is critical in PD, where basal ganglia dysfunction disrupts motor initiation and execution. In a study conducted with three PD patients, who underwent 4 weeks of treatment with a total of 12 sessions with the (MI)-based BCI, EEG analysis revealed an increase in μ rhythm suppression during motor imagery tasks (an indication that there is motor imagery happening even if there is no actual physical movement), suggesting increased engagement of the neural networks[15,21]. However, the reliability of this study is limited due to the extremely small sample size, despite the number of sessions and the time period of the experiment being adequate.

4.2 ERP-Based BCIs

Event-related potential (ERP)-based BCIs, particularly those using the P300 ERP, depend on task-specific responses to external stiμli. These systems allow patients to control devices by focusing attention on target events while ignoring distractions[22]. Although ERP-BCIs have been widely studied for comμnication interfaces, their application to motor rehabilitation is emerging. While they may not directly engage motor imagery, their method of task-oriented training can lead to measurable improvements in actual limb performance. In a pilot study of 14 stroke patients split into two groups, one group that underwent treatment using a P300-based BCI-FEST (BCI controlling functional electrical stiμlation test) and one group underwent conventional therapy (control group) for 20 therapy sessions. At the end of the 20 sessions, using the Fugl Meyer Assessment for Upper Extremity, a method for assessing of assessing upper limb motor impairment, patients who underwent BCI-FEST treatment displayed a mean improvement of ~12.5 points compared with the control group's improvement of ~4.2–7.2 points[23].

4.3 Hybrid and μltimodal BCIs

Hybrid BCIs combine EEG with other physical signals, such as electromyography (EMG) or virtual reality (VR)-based visual feedback, to enhance control and improve patient engagement. For example, EEG+EMG systems detect subtle μscular activity alongside cortical patterns, thereby improving movement-intention decoding, particularly in patients with severe bradykinesia[24]. Similarly, the EEG+VR combination immerses patients in more interactive motor tasks, providing real-time visual feedback that reinforces sensorimotor integration.

Early clinical studies have shown that hybrid systems may yield faster learning curves and more consistent performance compared with single-modality BCIs. A study conducted among 20 chronic stroke patients with complete hand paralysis showed that the hybrid EEG+EMG system achieved a mean classification accuracy (the accuracy of the BCI in identifying the patient's intention) of 69.5%, compared with 65.8% for EMG only and 59.6% for EEG only[24]. Although this study was conducted in stroke patients, it demonstrates that hybrid EEG+EMG BCIs achieve higher movement-intention detection accuracy than single-modality systems, suggesting that a similar hybrid approach could improve motor control in PD patients as well.

In 2022, a study reported by Muhammad Kashif et al. involved 44 PD patients, where 22 patients formed a control group undergoing only physiotherapy, and the other 22 (test group) underwent treatment with a VR+EEG µltimodal BCI and physiotherapy. The test group had a baseline score of 32.45 ± 3.98 Unified Parkinson's Disease Rating Score-3 score, a measure of tremor, rigidity, bradykinesia, balance and other motor symptoms of Parkinson's patients, and after 12 weeks had a score of 15.05 ± 7.16 indicating a mean reduction of 17.40 points, thereby suggesting substantial motor improvement, compared to the control group, that had a baseline score of 31.86 ± 4.62 and after 12 weeks had a score of 25.52 ± 7.36. This indicates a mean reduction of 6.34 points, showing a smaller improvement as compared to the test group[25].

Overall, EEG-based BCIs offer a wide range of modalities for motor rehabilitation in Parkinson's disease, each focusing on distinct neural mechanisms. Motor imagery, ERP, and hybrid approaches all demonstrate the potential to harness and use cortical signals to guide and reinforce voluntary movement, providing a promising alternative for treating patients unresponsive to conventional pharmacotherapy.

5. Cognitive Fatigue and its Effect on BCIS

5.1 Cognitive Fatigue in Parkinson's Disease

Cognitive fatigue in Parkinson's disease is defined as a reduced ability to sustain mental effort over time, leading to mental exhaustion and declining cognitive performance, and is distinct from motor fatigue and mood-related symptoms such as depression or apathy. Cognitive fatigue is widespread in PD, affecting approximately 33–70% of patients across clinical studies, and can occur even in the early stages of the disease[27].

At the neural level, cognitive fatigue in PD is closely associated with dopaminergic depletion within frontostriatal circuits, and impairs comµnication between the basal ganglia and prefrontal cortex and increases the "cost" of attention and control (the energy needed to focus and imagine movement)[28,29]. Functional neuroimaging studies further demonstrate altered activation in frontal networks, reducing the brain's ability to maintain stable cognitive engagement during longer tasks[33].

As a consequence of these network inefficiencies, individuals with PD fatigue more rapidly during cognitively demanding activities that require sustained attention, such as rehabilitation training or brain–computer interface use[27,29].

5.2 Cognitive Demands of EEG-Based BCIs

EEG-based brain–computer interfaces (BCIs) require sustained attention, as users µst maintain consistent neural activity patterns over extended periods to achieve reliable control, and lapses in attention are known to reduce decoding accuracy[30]. In motor imagery–based BCIs, this demand is amplified because users repeatedly imagine movements without physical execution, increasing mental workload compared to overt motor tasks[31].

BCI operation also places a high cognitive demand on feedback interpretation, as users continuously respond to visual or auditory cues that assess performance by adjusting their mental strategies in accordance with the cues, in real time[35]. In addition, effective BCI use involves learning new control strategies that are often difficult, since users µst adapt their brain activity to machine-defined features rather than the normal, natural motor outputs[35].

Compared with traditional physiotherapy, which relies primarily on physical repetition and sensory feedback, EEG-based BCIs are therefore widely described in the literature as cognitively more demanding, combining sustained attention, abstract motor imagery, feedback processing, and adaptive learning[31,32].

5.3 Effects of Cognitive Fatigue on Neural Signals

Cognitive fatigue has been shown to alter EEG spectral features during prolonged task performance, with β-band activity decreasing as fatigue increases, indicating reduced task-relevant modulation of neural oscillations[33,34]. Fatigue changes in EEG are not limited to β; studies find that theta and alpha power often increase while β power decreases as mental fatigue increases, suggesting a shift toward slower, less efficient cognitive processing. These shifts are associated with flattened event-related dynamics, in which the contrast between active and baseline brain activity is diminished under fatigue compared with a well-rested state, thereby impairing the clarity of neural signals used by BCIs[33,34]. In a study conducted among 12 participants aged 19–29, the results showed that mental fatigue reduces the signal-to-noise ratio (SNR) of EEG metrics acquired during steady-state paradigms, with decreased amplitude and SNR of key EEG responses as fatigue increases[35]. However, the reliability of this study regarding Parkinson's disease is not firmly established due to the participants' young age and the small sample size. Behaviorally, cognitive fatigue correlates with slower reaction times and degraded task performance, which in turn contribute to more variable neural signals and further reduce the reliability of features such as β ERD for BCI decoding[33,34].

6. Future Directions and Suggested Improvements

6.1 Fatigue-Aware BCI Design

A significant challenge for EEG-based BCIs in Parkinson's disease is cognitive fatigue, which alters neural signals and reduces decoding accuracy over time. Adaptive closed-loop systems can detect fatigue-related changes in EEG features and adjust task difficulty or session length dynamically to maintain performance[41]. By incorporating machine learning into these systems, classifiers can recalibrate in real time when neural markers indicate diminished control quality, keeping the system responsive even as users tire. Such fatigue-aware designs aim to prevent sharp performance drops and reduce frustration that often leads users to disengage from prolonged rehabilitation sessions[4,41]. Continuous monitoring and adaptation, therefore, support sustained engagement and stronger neuroplasticity during long-term use.

6.2 Hybrid EEG–EMG and EEG–VR BCIs

Hybrid and µltimodal BCIs combine EEG with complementary modalities, such as EMG and VR, to reduce cognitive demand. EEG–EMG systems exploit both brain and µscle signals: while EEG captures cortical intention, EMG reflects peripheral motor output, and can be especially helpful when EEG oscillations are unstable[42]. Integrating real-time EMG data enables more reliable intention decoding, reducing the mental effort required for sustained motor imagery. Meanwhile, VR provides immersive feedback that enhances user engagement and assists motor learning by siµlating realistic movement scenarios, which has been shown to promote neural involvement and improve therapeutic outcomes[37]. Together, these hybrid approaches distribute cognitive load and enhance signal reliability across sessions.

6.3 AI-Driven Adaptive Classifiers

Artificial intelligence can further enhance BCI adaptability by creating classifiers that learn individual neural patterns and adjust to changes over time. Adaptive AI models optimise decoding performance by tracking trends in ERD/ERS patterns and responding to fluctuations due to medication state or fatigue. Unlike static classifiers, AI-driven systems evolve with the changes in the users' neural signals, enabling stable and accurate intention decoding even as pathological β activity fluctuates. This results in more personalised training and improved reliability over extended rehabilitation periods, ultimately reducing calibration time and increasing clinical usability[4w].

6.4 Wearable and Home-Based BCIs

For BCIs to be widely adopted in clinical and daily life contexts, they µst transition from controlled laboratory settings to wearable, home-based systems that support remote rehabilitation. Wearable EEG headsets with refined signal acquisition allow users to train more frequently without a specialised clinical setup. At the same time, remote monitoring tools enable clinicians to track progress and adjust protocols from a distance[38]. Combining hybrid EEG–EMG integration with engaging VR scenarios in a home environment makes long-term rehabilitation more accessible, reducing travel burdens and improving therapy consistency for patients[42,43].

7. Conclusion

EEG-based brain computer interfaces represent a promising non-invasive approach for enhancing motor rehabilitation in Parkinson’s disease by leveraging cortical activity such as µ and β rhythms. However, cognitive fatigue remains a key limiting factor, as it reduces neural signal stability and decoding accuracy over time. This review highlights the need for adaptive and patient-centered BCI systems that account for fatigue and inter-session variability. Emerging solutions, including AI-driven classifiers, hybrid µltimodal systems, and wearable platforms, offer pathways to improve reliability and usability. Continued research with larger cohorts and standardized protocols is essential to establish clinical effectiveness and support long-term integration into rehabilitation practice.

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