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DECODING GAIT INTENTION: MACHINE LEARNING AND NEUROPLASTICITY IN FNIRS BASED BRAIN-COMPUTER INTERFACES

Muhammad Khawar Abbas[*1], Muhammad Zulqarnain[2], Aisha Sethi[3], Farooq Bashir Butt[4], Muhammad Shahzad Khan[5], Abdul Wahab[6], Mudassar Mezher[7], Rida Sadiqque[8], Syed Fazil bin Farukh[9], Asif Mirza[10]

[*1,2,6]*Department of Physics, Government College University Faisalabad, Pakistan.*
[3]*Department of Pharmaceutics, Faculty of Pharmaceutical Sciences. Government College University Faisalabad, Pakistan.*
[4]*Khaldunia College of Pharmacy, Lahore, Pakistan.*
[5]*Abbas Institute of Medical Sciences, Layyah, Pakistan.*
[7]*Department of Pharmacy, The University of Chenab, Gujrat, Pakistan.*
[8]*Department of Pharmacology, Faculty of Pharmaceutical Sciences. Government College University, Faisalabad, Pakistan.*
[9]*Department of Physics, University of Agriculture Faisalabad, Pakistan.*
[10]*Department of Physical Sciences, The University of Chenab, Gujrat, Pakistan.*

[*1]khawar.abbas@gcuf.edu.com

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Corresponding Author: *
Muhammad Khawar Abbas

Abstract

Functional near-infrared spectroscopy (fNIRS) is non-invasive, lightweight, and portable, so it can be an ideal tool in the case of patients with less mobility. This review assesses the use of fNIRS-based brain-computer interfaces (BCIs) in the context of gait rehabilitation, with regard to their potential to decode motor intentions, and be used to drive lower limb exoskeletons. fNIRS-BCIs have demonstrated a high rate of classification accuracy when it comes to identifying the presence of a walking intention as opposed to resting states with a median range of 85-98 %. With machine learning algorithms like the k-nearest neighbor (kNN), gradient boosting decision trees (GBDT), and deep learning models, when combining it with other machine learning techniques, it increased its detection accuracy by as much as 15 % in comparison to traditional methods. In addition, there is even 10-20% increase in the detection of intent in unimodal systems with the use of hybrid Electroencephalography-functional near infrared spectroscopy (EEG-fNIRS) systems. Clinical trials have demonstrated the improvement in the gait speed and step symmetry ($p < 0.05$) between stroke and spinal cord injury patients who used fNIRS controlled exoskeletons. These outcomes indicate the possibilities of disposing Traumatic Brain Injury (TBI) related motor deficit using fNIRS-BCIs to facilitate mobility, neuroplasticity, and real-time adjustment rehabilitation interventions.

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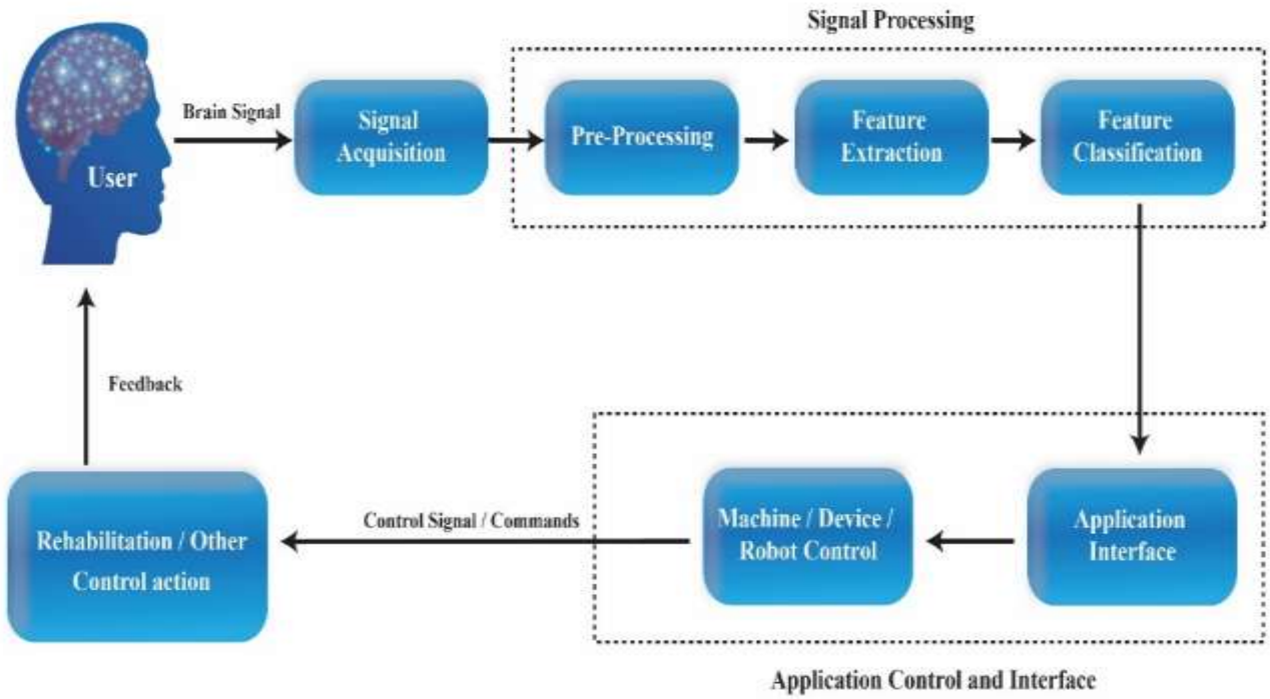

Graphical abstract

INTRODUCTION

Lack of movement can lead to many health complications such as deep vein thrombosis, pressure ulcers, muscles wastage, pulmonary embolism etc. For the elderly and patients with mobility disorders, it is of immense satisfaction to be able to walk. Studies have shown that mobility programs with well-defined pathways decrease re-admission rates and have generally promoted better patient's health by improving physical activities[1, 2].Functional near infrared spectroscopy (fNIRS) is a safer technique that captures changes in light absorption in the prefrontal cortex of the brain and reflects neuronal activity. The fNIRS is gaining importance in rehabilitation studies compared to other imaging technique such as fMRI and EEG due to its portability, cost effectiveness and safety[3]. The most significant feature of fNIRS is its application in assessing the brain's activity during motor activities. This has been applied in brain computer interface (BCI) systems used in gait rehabilitation[4].BCIs rely on the brain signals to control objects in environment, thereby helping individuals with impaired motor functions to communicate and move more easily. For gait rehabilitation fNIRS is used to provide immediate feedback on brain activity during motor tasks such as walking. This feedback enhance the control of assistive equipment like lower limb exoskeletons, which assist patients in movement[3, 5]. Thus, fNIRS provides insights into the brain mechanisms associated with walking and motor imagery, helps to establish effective rehabilitation strategies for patients with motor disabilities. Subsequent studies on hybrid systems and improvements in signal-processing algorithms will likely enhance its therapeutics applicability[4, 6].

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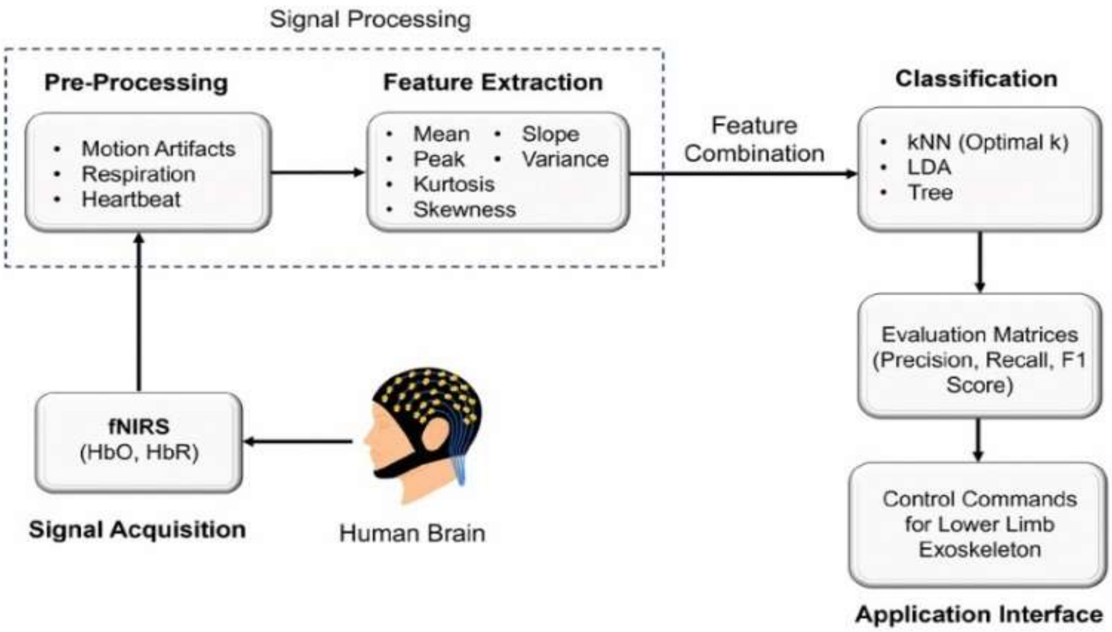

Figure1: A fNIRS-BCI methodology to develop control commands for a lower limb exoskeleton. It covers pre-processing, classification, feature extraction, and interface application[3].

The brain-computer interface system uses fNIRS to monitor brain signals that control a lower limb exoskeleton through pre-processing steps that eliminate motion artifacts and heartbeat artifacts as is indicated in **Figure 1.** Key features containing mean variance and skewness are extracted from cleaned data during analysis. Research methods including kNN, LDA and decision trees perform classification on these features. Control commands for the exoskeleton movement emerge from the final classification results.

In this review article we have discussed the applicability of fNIRS and BCI to enhance walking capacity of the several groups among which are the mobility impaired disabled. The purpose of this study is to determine whether fNIRS-BCI technology can be employed to decode intended walking and adapt gait characteristics in real time. This is particularly important to a large population of individuals with motor impediments as it may reflect a possible avenue through which their mobility could be boosted using technological aids. We have provided an overview of the methods applied in fNIRS-BCI studies; a special emphasis is made on the signal recording from the primary motor cortex during walking. It shows applicability of numerous approaches belonging to the machine learning, such as support vector machines (SVM) and k-nearest neighbors (k-NN), for categorizing the brain signals corresponding to the walking intention. The review also evaluates the filtering techniques that may be adopted to enhance signal quality and reduce noise which is very important in understanding the brain activities. The result obtained has revealed that fNIRS can accurately determine cerebral hemodynamic changes intending to walk. The review also mentions the progress of classifiers' accuracy through deep learning and how the proposed algorithms enhance the identification of intents to adjust gait. Incorporating fNIRS into robotic exoskeletons has also been explored and this has been found to have potential regarding maintenance of simpler user control interfacing. The paper also shows that fNIRS based BCIs holds a lot of potential for enhancing gait training and the use of a mobility assistance device. The review emphasizes that more investigations are required to fine-tune these systems for precise everyday applications in different environments.

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In this review, the criteria of systematic review were adhered to depicting transparency and rigor. It conducted a thorough search in messages, IEEE Xplore, Scopus, Web of Science, and Google scholar to find relevant studies that have been published between January 2010 and July 2025. The search terms were functional near-infrared spectroscopy, fNIRS, brain computer interface, gait rehabilitation, exoskeleton, motor intention and neuroplasticity. Abstracts and titles of articles retrieved were evaluated against their relevancy and evaluations of the full text were made on the studies that passed the initial evaluation. The focused studies were peer-revised, had human study objects, discussed fNIRS-based BCIs in gait rehabilitation or exoskeletons control, and provided quantitative results: classification rate and improvement of gait. The studies involving non-fNIRS modalities alone or not experimental validated were excluded. In each chosen research, the information on participants, modes of neuroimaging, research design, signal processing, machine learning methodologies, classification accuracy, and clinical rehabilitation data were retrieved. Qualitative and quantitative synthesis of the extracted data was done to deduce the trends, the recent progress, and research gaps in BCI implementation of fNIRS in gait rehabilitation.

2. Background and Fundamentals

Functional near-infrared spectroscopy (fNIRS) is a non-invasive and optical neuroimaging modality used in the study of cerebral hemodynamics by observing the increase or decrease in the concentration of oxygenated hemoglobin (HbO) and deoxygenated hemoglobin (HbR) in the brain. Near-infrared light (650-1000 nm) is used, which penetrates through the scalp and skull, reaches the cortical parts of the brain, and gets selectively absorbed in hemoglobin species. fNIRS is able to measure alterations in HbO and HbR through the Modified Beer Lambert Law (MBLL), provided by the resting brain activity linked to the neuronal firing and its use of oxygen[7-9]. fNIRS has numerous advantages over other neuroimaging methods due to being easily transported, cheap, hardy in the face of electrical interference, and safe since it is not invasive or makes use of any electrical or magnetic work, or any ionization radiation[10, 11]. Such properties give it great potential to be utilized in real-time detection of brain activity related to movement based activities, like gait training and rehabilitation. A brain-computer interface (BCI) is a technology that takes brainwave data in order to make usable commands to control exterior devices like exoskeletons. A typical BCI workflow can comprise the following phases; fNIRS is deployed to identify the cerebral hemodynamic responses, whereas EEG capacitates electrical activity monitoring. fNIRS has a better situation resolution and tolerance to electric interference than EEG[12]. This involves filtering methods such as band-pass, and artifact rejection method to clear raw data to improve the signal quality[13]. The features derived by the fNIRS signals include the mean, variance, skewness, and kurtosis that are used to represent hemodynamic responses to cerebral processing mechanisms of cognitive or motor intents[11, 14]. Support vector machines (SVM), k-nearest neighbors (kNN), decision trees, and deep learning models (e.g., CNNs) are machine learning algorithms applied to classify brain signals relevant to various motor states, i.e., walk or rest[15, 16].

The classifications of the outputs are translated to control commands that can initiate or end movement of the exoskeletons so that the subjects can restore useful mobility[17, 18]. The implementation of fNIRS into BCI systems has led to the development of effective decoding of motor intentions that have incorporated the assistance technology where lower limb exoskeletons have been analyzed to a range of 85-98% percent specificity in motor intent decoding[3, 4]. This is further enhanced by the incorporation of the hybrid systems that have a combination of fNIRS and EEG whose classification accuracies have been reported to be improved by 10-20%[19]. These integrated systems apply the technique of sliding window and also real-time machine learning to update the movement commands dynamically according to the intention by the user[20]. Also, fNIRS enables feedback speaking in favor of closed-loop rehabilitation, boosting neuroplasticity and motor recovery in SCI patients or after stroke[21]. The

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fNIRS has been described as a more feasible, portable, and accessible platform to carry out rehabilitation strategies compared to other neuroimaging devices, such as the fMRI, where the former is effective in applications relating to patients with limited mobility levels or requiring home-based therapy[11, 22].

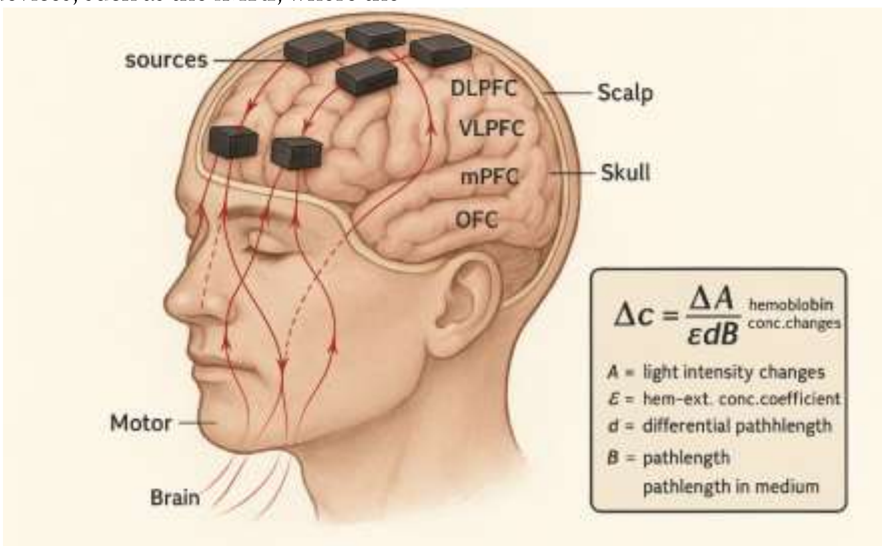

Figure 2. The illustration shows how fNIRS analyzes cortical brain activity by using near-infrared light combined with the Modified Beer-Lambert Law to determine hemoglobin concentration modifications.

The conceptual illustration from Figure 2 demonstrates how fNIRS provides brain activity measurement through scalp-mounted near-infrared light sources that pass through the skull to interact with cortical areas including the DLPFC, VLPFC, mPFC, and OFC. The returning light enables HbO and HbR concentration detection which follows the Modified Beer-Lambert Law (MBLL). The presented calculation uses light intensity measurements with extinction coefficients and tissue pathlength differences to determine changes in concentrations of HbO and HbR. Brain function monitoring that involves motor and cognitive processes becomes possible through this invasive-free measurement technique.

2.1. Investments of This Review

Despite a few studies in the use of brain-computer interfaces (BCIs) and neuroimaging modalities in motor rehabilitation, to the best of our knowledge, a study focuses specifically on functional near-infrared spectroscopy (fNIRS)-based brain-computer interface (BCIs) in gait rehabilitation and exoskeleton control does not exist. Such article is lacking and the present one addresses this gap by critically reviewing the recent developments in signal acquisition, preprocessing methods, machine learning models and hybrid neuroimaging (EEG-fNIRS). We have aggregated the results of several studies to emphasize the rates of classification reliability, better results compared to the control strategies, and those critically important effects in clinical practice, including gait rates and neuroplasticity. Also, it is possible to specify the ongoing challenges, technological limitations and prospective research areas, which make this review a consolidated source, so expect the researchers and clinicians to design next-gen fNIRS-based BCIs to use in real-time rehabilitation requirements.

3. fNIRS-BCI to Control Exoskeletons

3.1 Control methods of Exoskeletons

BCI refers to the potent method of brain-near-infrared spectroscopy (fNIRS) signals to binary responses to exert their control over exoskeletons, especially lower limb rehabilitation. The brain then determines the motor intention and a hemodynamic response is to be analyzed into

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acting instructions like start to walk or stop walking[23, 24]. The typical one is placing the fNIRS sensors on the brain areas that are motively relevant (e.g., primary motor cortex), measuring the cortical responses to imagined or attempted movements. These signals are preprocessed (e.g. artifacts are removed, band-passed filters) after which features are extracted and categorised using machine learning algorithms. The latter are then transduced into controllable two-state signals (e.g., may be active or rest), and can these be used to control the exoskeleton behavior[3]. A sliding window technique (data is transmitted in overlapping windows so that the user state of his or her motor can always be updated) is used in many systems to ensure responsive operation of any system[25, 26].

3.2. Adaptation procedures in real time

Contemporary fNIRS-BCI technologies are being developed that are asynchronous in nature, which can sense walking approaches in real time, without time-definitive signals. This is what is needed to rehabilitate natural and adaptive gait. The real-time control is carried out using a multi-step pipeline; Motion artifacts and physiological noise (e.g., heart rate, breathing) are suppressed with the help of advanced filters, Kalman, Wiener, wavelet denoising, adaptive filters and the like[27, 28]. The behavior of hemodynamic response parameters (mean, variance, skewness, kurtosis) is calculated based on the assured signals to describe hemodynamic response patterns in the brain[29]. Such features are classified by algorithms such as gradient boosting decision trees (GBDT), k-nearest neighbors (kNN), and convolutional neural networks (CNNs) into intention states. Such states are then cross-mapped with exoskeleton control commands[26, 30, 31]. The loops of feedback are incorporated to enable one to modulate their cortical activity with respect to the behaviour of the system, enhancing user engagement and neuroplasticity[32, 33]. Pseudo-online testing environments are frequently deployed to mimic continuous communication in real-time detection systems and limit the total amount of response latency. Amore robust and reliable execution of the commands is achieved by incorporating prediction smoothing[34, 35].

3.3 As compared to Other Modalities

fNIRS also presents some distinct benefits over the other ways of neuroimaging such as EEG and fMRI in controlling exoskeletons; fNIRS instruments are light, portable, and do not impede motion as fMRI does. They can be applied in the real-life and ambulatory environments[16, 36]. The fNIRS is less prone to influence by electromyographic and environmental electrical noise, a typical constraint in EEG technologies, and is thus more dependable in dynamics operation[8, 37]. fNIRS-BCIs provide naturalistic control of motor intentions as applied to walking to achieve neuroplastic adaptability to walking aids using real-time feedback and task-specific neuroadaptation schemes[19, 38]. fNIRS systems can be integrated By facilitating this natural and efficient process of interaction between people and robotic exoskeletons, fNIRS-BCIs are turning the context of gait rehabilitation and mobility-enhancing technologies on its head[38, 39].

4. Real-Time fNIRS-BCI Approaches to Gait Rehabilitation Using Machine Learning and Signal Processing

Use of machine learning (ML) and other related advanced algorithm-based signal processing has become the focus of improving the accuracy and reliability of fNIRS-based brain-computer interface (BCI) in gait rehabilitation. Such methods allow mapping of motor intentions out of hemodynamic activation in the brain and mapping them into real-time control signals used to manipulate existing assistive devices, including exoskeletons of the lower limbs. In recent years, researchers have shown that when high-quality signal collection, reduction of artifacts and extraction of features are used, followed by advanced ML techniques, the classification accuracy and responsiveness of BCI systems can also be greatly increased[3, 14]. One of the fundamental procedures in fNIRS-BCI implementation is feature extraction of statistical parameters of preprocessed hemodynamic signals which include the mean, variance, skewness and

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kurtosis. Mean gives a first-order estimate of cortical activation whereas variance measures dispersion of signal that is associated to variability of the neural activity. Skewness quantifies any bias in the distribution of signals and kurtosis picks up heavy tail of signals, which may be associated with the non-normal brain reactions. Experiments have indicated that pooling of these statistical attributes can increase classification accuracy by a maximum of 30 percent in comparison to that using raw signals[11, 40]. By coming up with these definitions in this section, it is possible to avoid repetition that has been present in the previous versions of this manuscript. Signal processing is also of equal importance in the preparation of fNIRS data in order to be classified. The physical activity has the potential to corrupt the signal because of the existence of motion artifacts and physiological noise when they appear on the basis of the walking activities. Kalman and Wiener filtering and wave-based artifact reduction are some advanced methods of filtering that have been found to be effective in averting these interferences[27, 41]. Also, vector based phase analysis has come to fore as another formidable technique in using more discriminative features to improve classification performance[40].

One of the most popular methods to decode gait intentions on the basis of fNIRS signals is machine learning algorithms. Simple and easy to apply methods such as k-nearest neighbors (kNN) are used in real time applications, where complex and non-linear insights are discovered using ensemble models like Gradient Boosting Decision Tree (GBDT) on high-dimensional data[42]. Most recently, deep learning methods, especially the convolutional neural networks (CNNs), proved to be better at temporal-spatial patterns of hemodynamic responses modeling with accuracies of above 95 percent in multi-class motor imagery tasks[15, 43]. The combination of such algorithms along with feature optimization methods has resulted to substantial increment in the detection of walking intentions in stroke patients as well as in spinal cord injury patients. Dynamic adaptation mechanisms are needed to achieve real-time control of exoskeletons. Sliding window methods enable the consistent observation of the brain functionality by dividing the data of fNIRS into the overlapping time portions to update the classification quickly. Low-latency processing pipelines and pseudo-online testing can be used so that motor intentions are detected early making the interaction fluid and natural with assistive devices[26, 30]. The user control is further optimized because, through additional feedback mechanism, the gait patterns can be reconfigured when provided, through visual or haptic methods of feedback. In general, the combination of signal processing and ML into a consolidated framework increases the power of fNIRS-based BCIs that can be used in a real clinical setting. Future systems may provide essentially perfect intent recognition via the continuous development of noise reduction, feature engineering, and deep learning, which will make more effective, personal gait rehabilitation solutions available.

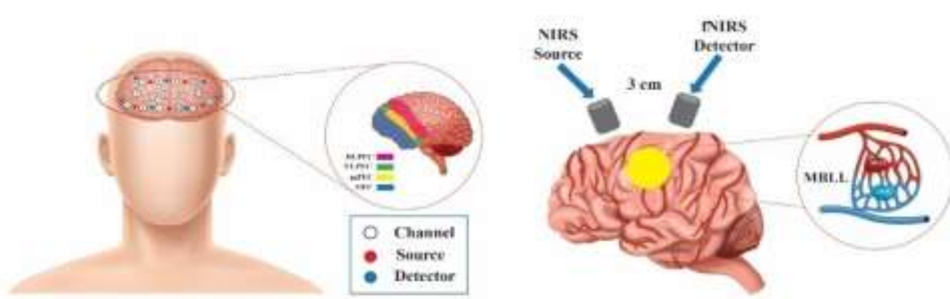

Figure 3: Modified Beer-Lambert Law (MBLL) is used to convert the changes in light intensity measured by the fNIRS device into changes in the concentration of oxygenated (HbO) and deoxygenated (HbR) hemoglobin in the brain[44].

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Figure 3 displays the fNIRS measurement technology which monitors prefrontal cortex brain function. Multiple measurement channels are located on the scalp to monitor specific brain regions such as DLPFC, VLPFC, mPFC, and OFC through sources (red) and detectors (blue). The detector positioned three centimeters from the sources measures reflected signals which change according to HbR and HbO concentration levels when near-infrared light transmits through the scalp and skull. Researchers use the Modified Beer-Lambert Law (MBLL) to evaluate the detected modifications which help determine brain hemodynamic changes throughout cognitive functions.

Table 1: Overview of Machine Learning Strategies to Employ in fNIRS-BCI in Gait Rehabilitation

ML method	Features used	Applications	Reported accuracy	References
k-Nearest Neighbors (kNN)	Mean, variance, skewness, kurtosis	Walking vs Rest state classification	85 to 95%	Minhas et al., 2024[3], Rattansak et al., 2022[45]
Gradient Boosting Decision Trees (GBDT)	Statistical features, vector based phase analysis	Multi class motor intention detection	90 to 96%	Zhang et al., 2019[42], Bremer et al., 2023[30]
Convolutional Neural Networks (CNN)	Raw fNIRS time series, kurtosis enhanced features	Walking tasks classification, asynchronous detection	92 to 98%	Ma et al., 2023[43], Milu et al., 2023[15]
Deep Neural Networks (DNN)	Mean, variance, Teager Kaiser energy, kurtosis	Hybrid EEG-fNIRS classification	90 to 97%	Shibu et al., 2023[11], Khan et al., 2024[14]
Vector-based Phase Analysis (Feature Optimization)	Phase shift features, standard statistics	Improved discrimination of walking intention	Accuracy improved from 68.7% to 98.7%	Nazeer et al., 2020[40]

5. Hybrid Systems

Hybrid Brain-Computer Interface (hBCI) devices are usually made by combining fNIRS with another available modality a technique that is used to take advantage of both methods. fNIRS has good spatial resolution as well as robustness to noise associated with electricity, whereas EEG has better temporal resolution, even to the rapid detection of neural activities. This multiple modality alignment overcomes the drawback of single modality systems, as classification accuracy, responsiveness, and artifact robustness is enhanced[5, 46, 47].The classification accuracies of typical Hybrid systems are higher by 10 to 20 percent compared to standalone methods because of the complementary information [4]. EEG provides a more extensive and consistent feature set to decode motor intentions by recording millisecond brain dynamics (fNIRS is more of a slowest hemodynamic signal) to a lesser degree[48, 49]. Also, a mixture of modalities can be utilized in the reduction of false positives generated by a muscular or aggressive motion movement typically observed in an EEG only system. The majority of hBCI deployments in use do not add electrical coupling to in-step-treated EEG and fNIRS signals. Classification is supposedly improved with feature-level fusion (such as multi-resolution singular value decomposition) which reduces noise maintaining discriminative features[46]. Mutual information or Pearson correlation for channel selection also provides an additional optimization of feature extraction[50].

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Table 2: Hybrid EEG-fNIRS vs. Single-Modality BCI systems comparison

Feature	**fNIRS only**	**EEG only**	**Hybrid EEG-fNIRS**	**References**
Temporal resolution	Moderate (0.5 to 1 s)	High (ms scale)	High (EEG dominates)	Khan et al., 2021[4], Jeong et al., 2024[49]
Spatial resolution	Moderate to high	Low	Improved (fNIRS adds spatial info)	Hasan et al., 2020[48], Gramigna et al., 2025[47]
Noise sensitivity	Low to motion artifacts	High (muscle & electrical interference)	Reduced artifacts (complementary noise tolerance)	Hasan et al., 2020[48], Schultz & Maedche, 2023[51]
Classification accuracy	80 to 90 %	75 to 85 %	90 to 98% (+10 to 20% improvement)	Khan & hasan 2020[46], Chen et al., 2023[5]
System complexity	Simple hardware	Simple hardware	Higher complexity, requires synchronization	Jeong et al., 2024[49]
Clinical applicability	Suitable for portable applications	Light weight and widely used	Best for rehabilitation	Gramigna et al., 2025[47]

6. Clinical Applications of fNIRS and Hybrid EEG-fNIRS Systems

There is great potential of combining fNIRS and hybrid EEG-fNIRS systems in clinical practice, particularly in neurorehabilitation. The fact that they can be integrated into brain-computer interface (BCI) systems allows real-time decoding of motor intent, which may be useful in operating assistive technologies, such as robotic exoskeletons. The patients who had motor impairment as a result of stroke, or spinal cord injury, or any other neurological diseases are given the opportunity by these systems to restore functional mobility and independence after being affected by the stroke. Research has shown that fNIRS- or hybrid-based BCIs have the potential to increase gait duration, step symmetry, and more efficient rehabilitation protocols[3, 5]. In combination with the high specificity of an EEG signal, the hybrid BCIs appear to offer accurate brain activity that can be evaluated spatially and hemodynamically, as well. This multimodal technique helps to monitor the cortical signals continuously even when one is in motion and the device responds accordingly to the intentions of the walking pattern of the user. The aspect of real-time systems is essential towards attaining dynamic adaptation of assistive devices in the course of rehabilitation. Studies have demonstrated that hybrid systems can perform better than unimodal BCIs with the accuracy of classification performed as much as 10% to 20% higher than that of unimodal BCIs as they take advantage of the complementary nature of the signals[4, 23].

Besides the motor control, the systems also have a critical role in the assessment and facilitation of neuroplasticity. Neuroplasticity is used to define the capacity of the brain to remodel its neural pathways when there is training or damage. BCIs aid neuroplasticity through repetitive task performance and by utilizing Hebbian learning (which makes neurons that fire together to wire together), and making closed feedforward loops. Such forms of learning involving the provision of feedback, particularly in the context of additions of haptic or proprioceptive or functional electrical stimulation feedback, mediate motor learning and reinforce the intention-movement linkage[19, 43].

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These mechanisms have produced measurable improvements in cortical activity and motor improvement in the course of BCI-based rehabilitation. Clinically, there is more and growing use of fNIRS-based BCIs in rehabilitation. This is great because they have a non-invasive character, are portable and can be easily integrated into a clinical setting to do continuous monitoring and therapy. Not only are these systems used to read motor intention, but the results can deliver objective data used by therapists when programming rehabilitation plans. Moreover, the application of such technologies reaches beyond in-home rehabilitation because further advancement and research have trended towards in-home rehabilitation involving wireless, ergonomic design of sensor devices enabling full-time movement during therapy.

Hybrid BCIs using a combination of EEG and fNIRS also have excellent advantages in terms of artifact rejection, system robustness and responsiveness of the user. fNIRS is not as prone to electrical or muscle artifacts as EEG and in combination with the EEG, signals are improved and system responsiveness to the user is enabled. Accuracy of detecting walking intentions based on brain signals has been increased with the usage of fusion techniques of detection, which include multi-resolution singular value decomposition (MSVD). These methodological updates, in conjunction with deep learning and machine learning allow real-time feedback in system that closely measures the intention of the user and adjusts accordingly[43, 52]. Lastly, these systems must be fully integrated in clinical practice which is only possible upon establishment of standard calibration procedures, longitudinal evaluation of outcomes, and the customization of these systems to the specific user. Continued advances in sensor designs and signal processing algorithms, as well as adaptive software interfaces will only enhance the clinical relevance of fNIRS and hybrid BCIs. The technologies have a bright future of utilization in the personalized, customized rehabilitation approaches where they are going to be responsive and will greatly enhance the quality of life of the persons with motor related disability.

7. Neuroplasticity Mechanisms

Neuroplasticity, or the capacity of the brain to rearrange itself to meet task demands, experience, injury or training, is perhaps the touchstone of contemporary neurorehabilitation. In regard to brain-computer interface (BCI) devices, and more specifically ones that integrate both functional near-infrared spectroscopy (fNIRS) and EEG, neuroplasticity allows a person to recover previously lost motor capabilities with a strengthening of the neural pathways associated with movement compensation. The combination of the fNIRS-based BCIs and the assistive device like a robotic exoskeleton can induce neuroplastic change due to a variety of major mechanisms[19, 43]. Among these, repetitive engagement is one such of its main mechanisms, when the patients repeat or imagine motor acts (e.g. walking), stimulating related cortical motor zones. This repetitive activation strengthens already existing synapses and facilitates development of new ones forming further neural pathways, which in the long term translates to the strengthening of motor pathways[43, 53]. This process is tightly associated with Hebbian learning in its catchphrase form Hebbian learning: The neurons that fire together, wire together. As cortical activity and motor output are being matched during BCI therapy, this builds pairing between the two processes when a motor intention (e.g., imagining a step) yields suitable sensory feedback (e.g., the exoskeleton moving or haptic stimulation)[54, 55]. As well, some BCIs create closed loop sensorimotor channels, with cortical activity observed in real-time and converted into immediate physical actions through robots or functional electrical stimulation (FES). By allowing patients to experience what this means to their movement, this loop promotes motor learning and motor adaptation[56, 57]. This circuitry shortens the time delay between what the patient may wish to do and what he or she feels happening and this is vital in the coordination of movements [43]. Proprioceptive and haptic feedback in particular have demonstrated increasing neuroplastic effect when there is the use of multimodal feedback BCIs over visual or auditory feedback. Inputs provided by proprioception, which includes

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muscle contractions that have as a source FES, or movements by robotic limbs, are more similar to those that are natural to movement and as such, trigger somatosensory regions of the brain and strengthen motor circuits[58]. It results in more purposeful and lasting adjustments to the brain cells. The empirical evidence has shown that the functional reorganization of brain networks involved in motor control is not only associated with temporary motor improvement in BCI-based rehabilitation, but also with long-term plastic reorganization of such networks, especially with a functional near-infrared spectroscopy (fNIRS) or electroencephalography-fNIRS systems. Improved corticospinal tract connections and corpus callosum and better upper and lower limbs outcomes have been specified in meta-analyses and clinical trials[53]. These observations remind of the necessity that the rehabilitation BCI systems should be targeted at neuroplasticity design and application. Overall, fNIRS-BCI systems would trigger neuroplasticity by using repetitive mental training, repetitive training, Hebbian learning, and multimodal sensory input. The combination of such mechanisms can boost motor recovery, therefore, BCI guided neurorehabilitation is a potentially viable therapy in neurologically compromising patients.

8. Challenges and Future Directions

Another constructive approach to consider, is the near infrared spectroscopy/ functional near infrared spectroscopy (NIRS/ fNIRS) when the studied person engages in dynamic movements such as walking. Nevertheless, motion artifacts as well as physiological noise seriously affect the quality of fNIRS data. A knowledge of these issues is necessary for enhancing the capability of this technology in providing accurate fNIRS measurement in natural condition[59]. Swinging the head could jeopardize the connection between the light source and detector; produce high frequency interruptions or shifts of baseline in the recorded signals. This decoupling alters the path length of near infra-red light and so impacts the measurement of hemodynamics response accuracies[41, 60].Swinging motions of the limbs during walking can also introduce artifacts, particularly where the device is poorly fixed on the scalp. These movements can produce slow oscillations or constantly varying off-baseline changes that can be likened to physiological noise[60, 61]. Such speaking may create motion artifact peculiar to hemodynamics changes needed to perform talking or eating[61]. Oxygenation and deoxygenation of blood flow due to pulsatility of heartbeat can superimpose phasic variation which is similar to brain activity on the fNIRS signal. Breathing activity and changes in the concentration of oxygen in blood are known to affect signals during fNIRS especially during session containing physical movements[62]. Excluding trials based on motion artifacts, as is common in practice, reduces the number of allowable points of comparison, compromising statistical potential and result accuracy[41, 62]. Some strategies have been established with an aim of minimizing the motion artifacts and physiological noise in fNIRS data[63].

Albeit hybrid systems offer better performance, these come with concerns of increased computational complexity. Due to the requirement of processing big datasets in real-time from numerous sources, algorithms as well as technologies required for computation are raising up[64]. Variations in the data features, sampling frequency and noise characteristics may hinder the possibility of achieving effective integration of different bio-signals. Signal synchronization and alignment are good in the accurate interpretation of a signal[65]. Above all, it is necessary to develop new algorithms of machine learning, allowing to effectively working with fused data. Although there is a great use of basic classifier like kNN and decision trees, there is growing literature in proposed deep learning models which can extract complex feature representation from multivariate data[66]. The fusion of different bio-signals in BCIs significantly enhances the classification accuracy and time response, making the approach a potential avenue for enhancing augmented devices and rehabilitation practices. It will be useful for researchers to apply signal processing and machine learning approaches to combine the advantages of EEG and fNIRS brain imaging and create more complex systems that are able to

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directly capture user intentions and change their functioning correspondingly. Further advancements in fusion methods are going to be important to remove current drawbacks and optimize the utility of hybrid BCI systems[67].To enhance the reliability of the fNIRS data especially during dynamic actions, there is a lack of standardization on the methods of correction. More specific, for research, standardized methodologies are needed for the assessment of and the implementation of motion artifact reduction techniques in order to guarantee comparability and replicability[62]. Cortical activation can be conceived with fNIRS combined with other non-invasive neuroimaging (like EEG) for higher degrees of data refinement and analysis[68]. Movement blurs and fluctuation noises are likely limitations to obtaining excellent fNIRS data when the individual is inactivity such as while strolling. To enhance the reliability of the fNIRS readings, elaboration of these difficulties, as well as advancement of the correct procedure of corrections are important and essential with regard to the accurate interpretation of the brain activity or even in real life conditions [69].Flexibility of BCI systems is paramount since users in clinical and rehabilitative environment may have diverse patterns and needs[70]. Standard BCIs often need tuning for improved performance for every user, the process of which may be lengthy and limits its use. For making the use of BCIs more flexible, strong algorithm needs to be developed which should work on all types of users well. This discussion only revolves around critical strategies and considerations for achieving this goal[71].

Every user has their own patterns of brain signals that depend on the age, the general intellect, type and degree of motor disabilities. These differences can limit the portability of the BCI systems since a model established on a specific user results in reduced effectiveness when used on another subject[72]. Conventional BCIs often demand a long period aligning the system with a user's brain signals. This process is time consuming and may require some experience and hence implementing the changes as and when may be needed in clinical areas can be quite a challenge[73].

Work in the last two decades has meant developing algorithms which can learn fast enough so that they can be used immediately while previously, they required a lot of formation. For instance, a BCI was shown in a study conducted at the University of Texas at Austin that did not require users to be calibrated even when they needed to switch between subjects. The system made use of an ML model trained by data from a single power user, and refined based on new users through repeated interaction, essentially learning on the job. There is always reliability to transfer learning approaches where models learned from one data set are fine tuned to another data set possibly reducing the need to be realigned. This method of performance can be used in combination with other data culled from other users to enhance performance amongst different populations[74].

BCIs are therefore best viewed as applications that constantly learn from their interaction with the user and from the user's interaction with the application. Researchers noted that users are trained to generate specific patterns of signals detectable by the system and the BCI modifies the algorithms based on user output and effectiveness. It also increases the dependability and usefulness of the overall system as both parties teach themselves new approaches[75]. The feedback must be given in real-time since it helps the users to optimize their mental tasks in making the BCI function well. In addition, haptic feedback systems allow users to modify their cortical activations with regard to the corresponding input brought into the interface. For example, the self-organizing maps SOM can display the neural signals online so the participants can see how the signals correspond to the BCI inputs[76].

Developing individual BCI interfaces therefore requires the construction of interfaces that will reflect specific user characteristics. This includes creating particular strategies for acquiring brain signals, handling of collected data, feature extraction techniques, as well as classification techniques for different users. Individualized BCIs may enhance the efficacy and satisfaction of a user since the system is tailored to individuals[77]. Thus, assessment of task fit is essential, as

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necessary for guaranteeing that users engage in mental tasks achievable by them. Individualised mental job paradigms can help identify optimal jobs that cause clean mind signal patterns in this way boosting the results of categorisation[78]. It is thus key to enhance how BCI systems differentiate between diverse users to enhance the success of rehabilitation and assistive technology[79]. When grouping advanced machine learning methods, co-adaptive training, and fit paradigms, researchers can then design powerful algorithms that adapt well across various populations. As these technologies develop further still, they offer a great possibility of improving the attainability and effectiveness in helping people with motor dysfunctions regain the ability to perform self-care[80]. Subsequent fNIRS systems will be expected to employ more advanced sensor configurations in terms of spatial sampling density and area. It may also cause the development of smaller and more elastic sensors which a person can wear during any activity including walking and exercising without worrying about being constrained by a clumsy bulky device tracking the vital signs all along[69].

The market of wireless fNIRS systems will shift towards this development because it offers users more mobility during rehabilitation activities. To achieve organism and response integration, cordless systems that can easily connect with exoskeletons or other adaptive clothing will enable real time user-response feedback to be most effective.

Optical/neural interfaces will be applied integrally with other hybrid systems like fNIRS and other techniques like EEG or electromyography. This integration can provide complementary information enhancing the general performance of brain state categorization and the stability of BCI applications in complex environments[81].

It is also forecasted that deep learning models are essential to enhance machine learning techniques leading to the higher categorization of the fNIRS signal[82]. So, CNNs and RNNs can learn characteristics directly from the data and reconsider motor intentions during the gait rehabilitation tasks more effectively than before[83]. Optimization of the applied software algorithms for the near real-time analysis of fNIRS data will be critical. It also encompasses improved noise reduction and motion artifacts that are most effective during motion such as walking[69]. Some learning-based methods, like deep neural networks (DNNs), have demonstrated ability in using them just to cancel motion artifacts without erasing signals[62]. If explainable artificial intelligence is adopted into fNIRS-BCI systems, the clinicians assisting the patients will be able to understand how the algorithms arrived at the decision on the patient. This transparency may lead to increase the trust in the system and make the therapeutic decision better since the relationship between different brain signals and movements or intentions can be explained[84]. Thus, further developments will probably exclusively concentrate on enhancing the individual BCI experience. This could include learning algorithms which modify the system's answers based on user preferences thereby enhancing the usefulness and reliability of the system in rehabilitation organizations[85]. The development of canonical operating surfaces that don't merely map brain activity and movement intentions but also give feedback in real time as regards the workings of the brain will be important. These interfaces should be designed to engage the users especially during rehabilitation exercises and hence gain their needed compliance to therapeutic routines[86].

Detecting gaps and carrying out direction into future studies

Even though there are advances with a positive outlook, there are still some major gaps in the existing literature. To begin with, there exist no general conventions of hybrid EEG-fNIRS incorporation researchers tend to have various preprocessing pipelines, feature extraction and classification algorithms, which is why they cannot rather easily compare their findings across the studies. Secondly, although numerous clinical techniques work in the laboratory conditions, they are not sufficiently assessed with large-scale clinical trials or rehabilitation practice conditions, which creates some questions of generalization and long-term efficiency. There is also a lack of studies

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comparing hybrid systems to unimodal BCIs in gait rehabilitation, specifically analyzing their effect longitudinally, on markers of neuroplasticity, and functional independence. There also exists lack of consistency in the method used to measure neuroplastic changes, some of them are based on measured behavioral outcome and others on patterns of cortical activation impinges on agreement of which are effective biomarkers. In addition, the majority of the studies are conducted either on stroke or spinal cord injury cohorts, excluding other neurological diseases, in which gait deficiency is equally characteristic, such as Parkinson disease or multiple sclerosis. Lastly, the issues were scarcely discussed in the reviewed articles as some have indirectly mentioned, or provided a detailed plan on how hybrid BCIs should be incorporated into the clinical environment. In putting light on these neglected aspects, this review was not only able to abstract the existing knowledge on that topic, it also pinpointed how future research should be conducted, with the necessity of a unifying data processing system and providing infallible multimodal fusion methodologies, validating between different populations and assessing affordable and yet user-friendly designs.

Conclusion:

This is the first synthesis of existing literature on hybrid fNIRS-EEG brain-computer interface (BCI) systems with respect to gait rehabilitation. Although different observational theories have previously investigated the EEG or fNIRS modality separately, the present review is the first study to comprehensively survey and synthesize the improvements, the underlying working mechanism, and clinical usage of hybrid EEG-fNIRS BCIs with particular reference to gait-related motor rehabilitation. Combined temporal (EEG) and hemodynamic (fNIRS) data is reflected as a stronger decoding of motor intentions and better comprehension of cortical dynamics when requesting an individual to perform a task related to walking. The main limitations of the review consist of the detailed actual analysis of signal processing, neuro plasticity mechanisms, methods of multimodal feature extraction, and clinical outcomes. It is important to note that hybrid BCIs have achieved better classification accuracies with some reports suggesting that 90 to 98% accuracy is achieved which is way much higher than unimodal EEG (75 to 85%) or with the use of fNIRS system (80 to 90%). That is a 10 to 20% increase in the ability to decode motor produce and use assistive devices. Further, real-time sensorimotor loops and proprioceptive feedback has proven to facilitate faster neuroplastic reorganization, properties that can allow improved rehabilitation results. This review also discusses the translational opportunities of hybrid BCI systems, in particular, its use in exoskeleton-walking, stroke therapy, and medical planning of personalized rehabilitation. These systems have been used in clinical trials and pilot studies to produce measurable improvement in gait parameter outcomes, including step symmetry, stride length, and gait speed with improvements in cortical connectivity as observed using longitudinal fNIRS measurements. Summing it all up, hybrid EEG-fNIRS BCIs appear to be a viable and non-invasive method providing real-time and adaptive gait rehabilitation. The possibility to improve diagnosis evaluation and medication therapy preconditions the emergence of the next generation of neurorehabilitation systems. In the future, studies directed to enhancing signal integration algorithms and to simplify the hardware, and testing in large population clinical studies to garner broader clinical acceptance, would be important.

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