v. 5, n. 18, 2025

International Journal of Health Science

Acceptance date: 24/04/2025

NEUROTECHNOLOGY AND REHABILITATION: ADVANCES IN NEURAL DEVICES AND BRAIN-MACHINE INTERFACES FOR POST-STROKE REHABILITATION

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Abstract: Brain-computer interfaces (BCI) that allow people with severe motor disabilities to use their brain signals to directly control objects have attracted growing interest in rehabilitation. BCIs have been used to help regain lost motor control in a limb after a stroke. While neuromorphic computing (NC) uses neural models in *hardware* and *software* to replicate brain-like behaviors, it could help usher in a new era of medicine by providing low-power, low-latency, small-size solutions that are significant for neurorehabilitation. Stroke is the most common severe manifestation of cerebrovascular disease, therefore characterized by a neurological deficit of sudden onset, stroke is predominantly caused by cerebral ischemia, due to atherosclerosis of large arteries, cardioembolism, or affection of small vessels and, less frequently, by intracerebral hemorrhage. The aim of the article is to carry out a literature review on updates in stroke rehabilitation and the association with BCI and NC and efficacy. This original article constitutes a bibliographic review, with several original articles, which were observed in scientific databases such as Latin American and Caribbean Literature in Health Sciences (LILACS), *Scientific Electronic Library Online* (SCIELO), *National Library of Medicine* (NIH), Nature, MEDLINE. Post-stroke cognitive impairment and dementia (PSCID) is a major source of morbidity and mortality after stroke worldwide. PSCID occurs as a consequence of ischemic stroke (ISC), intracerebral hemorrhage (ICH) or subarachnoid hemorrhage. Cognitive impairment and dementia that manifest after a clinical stroke are categorized as vascular. BCIs based on motor imagery are widely used in rehabilitation training for stroke patients. By using motor imagery, patients can be trained to gain control over their brain signals, allowing them to activate devices that assist movement. This training approach is believed to enhance sensory inputs, leading to brain plasticity that improves motor function. While NC presents a promising solution by mimicking biological synaptic activity, offering an alternative to conventional architectures. Unlike *von Neumann* computers, which operate in sequential execution, neuromorphic systems integrate processing and memory in networks of neurons and artificial synapses, allowing for efficient, event-driven computing. This architecture allows for lower power consumption, real-time adaptability and enhanced processing of neural signals, making it a strong candidate for improving BCIs. It can be concluded that despite these advantages, large-scale experimental validation of neuromorphic integrated BCIs remains limited, and further research is needed to address challenges such as *hardware* constraints, signal fidelity and real-world implementation.

Keywords: Brain-Computer Interfaces; Neuromorphic Computing; Stroke;

INTRODUCTION

It is understood that stroke is one of the leading causes of chronic disability worldwide, as well as being the second leading cause of death and the third leading cause of disability (Fanning *et al.*, 2024), while in 2016 the number of new incidents increased to 13.7 million (Tsao *et al.*, 2023). Therefore, it can be observed that the natural history of this pathology involves its classification as ischemic stroke (iStroke) or hemorrhagic stroke (chStroke), iStroke is responsible for approximately 75% of all stroke cases (Barkas *et al.*, 2023). This cerebrovascular condition can cause a considerable number of functional limitations and can lead to death in severe cases.

In the clinic, stroke treatment generally involves thrombolysis and surgical recanalization (Fanning *et al.*, 2024). The patient's symptoms vary according to the artery affected. Mechanical thrombectomy needs to be performed because of the 4.5 hour interval. Thrombolytic therapy includes drug thrombolysis and interventional thrombectomy. Currently, intravenous thrombolysis has certain limitations. For example, the classic treatment, i.e. intravenous injection of tissue plasminogen activator (rtPA), has a short treatment window and the risk of bleeding complications is high. etPA is also not suitable for patients with comorbidities such as bleeding, hypertension and those on anticoagulant therapy. The clinical application of the intervention is limited by technical challenges, equipment requirements and high cost. Therefore, research into new safe and effective treatment approaches to promote nerve recovery after stroke is of great importance (Tsao *et al.,*. 2023)

Brain-Computer *Interface* (BCI) technology represents a frontier in neurorehabilitation research. Early, coordinated and multidisciplinary rehabilitation plays an important role in motor recovery after stroke, in addition to other brain pathologies such as tumors. Conventional stroke rehabilitation mainly includes physiotherapy, occupational therapy and speech therapy. There is a notable gap in the literature on comprehensive studies that delve into the effects of tumor resection, post-stroke rehabilitation and the role of BCI technology in the rehabilitation process (Lin *et al*.., 2025)

Neuromorphic computing (NC), a computing paradigm inspired by the human brain, allows for fast and energy-efficient artificial neural networks. To process information, neuromorphic computing directly imitates the operation of biological neurons in a human brain, and therefore uses artificial neurons based on memristors (Schuman *et al*.., 2022)

The aim of this article is to carry out a literature review on updates in stroke rehabilitation and the association with BCI and NC, efficacy and the development of neural devices that can be used in the rehabilitation of these patients.

METHODOLOGY

This original article is a bibliographic review, with several original articles, which were looked at in scientific databases such as Latin American and Caribbean Literature in Health Sciences (LILACS), *Scientific Electronic Library Online* (SCIELO), *National Library of Medicine* (NIH), Nature, MEDLINE. The descriptors used in this research were: "Stroke", "Brain--Computer Interface", "neuromorphic computing", "Deep-Learning". The Boolean operators used in this research were AND and OR.

The data collection was carried out between 2020 and 2025, over the last 5 years. the inclusion criteria were studies available in full and free online, the articles used were originals such as literature reviews, randomized and double-blind studies, systematic reviews, their technologies and the impact of their interventions, articles in Portuguese and English were used. while the exclusion criteria for this article were the exclusion of duplicate articles, incomplete works, paid works and articles that were not in English and Portuguese. 80 original articles were found, of which 43 were considered relevant and used in the preparation of the article.

RESULTS AND DISCUSSION

COMPUTER-BRAIN INTERFACE IN NEUROREHABILITATION

A brain-computer interface (BCI) structure uses computer algorithms to detect patterns of mental activity and manipulate external devices. BCI technology is an emerging field in neurotechnology. Applications for BCI have been used in a variety of settings to help people with neuromuscular conditions, such as stroke and spinal cord injuries, improve their overall quality of life, consequently BCI can also help restore motor skills present in various neurodegenerative pathologies (Samal; Hashmi, 2024).

In this context, BCI provides easy-to-use technological assistance and robotic prostheses that measure brain activity and translate it into commands for a computer or other device, allowing users to control machines and devices using only their thoughts (Peksa; Mamchur, 2023).). In addition, it is possible to observe in this method that there is direct transmission of neural signals to an external device or system. BCI algorithms look for patterns in brain waves and perform actions based on what they find. This method allows people to engage with the environment without using peripheral muscles (Stegman *et al*., 2020). According to Mdriha *et al*, (2021) the clinical context as an assessment and diagnosis is of importance, there are reports in the literature of its use in young patients with cerebral palsy (Perales *et al*., 2019), for diagnosis of schizophrenia (Jochumsen *et al*., 2021) and detection of brain tumors (Sharanreddy; Kulkarni, 2013).

It can therefore be seen that BCI comprises two categories, such as unidirectional and bidirectional devices based on the direction of their action. Unidirectional BCIs receive signals from the brain or send them to it, while bidirectional BCIs allow information to be exchanged in both directions, which allows external devices to be controlled by the brain (Elashmawi *et al*., 2024). Therefore, the BCI employs the user's brain activity signals as a means of communication between the person and the computer, translated into the output, this allows users to operate external devices that are not controlled by peripheral nerves or muscles through brain activity (Mridha *et al*., 2021). BCI can also be performed by an invasive method, referring to the neurosurgical execution and implantation of the electrodes in the gray matter, however, despite the higher incidence of the signals, the formation of scar tissue at the applied site can occur, while semi-invasive BCIs consist of electrodes located under the skull bone on the surface of the brain, such as electrocorticography (ECoG) (Singh *et al)*.., 2023)

Brain electrical activity can be measured using methods such as electroencephalography (EEG), ECoG, while magnetic activity can be measured by Magnetoencephalography (MEG), while brain metabolic activity can be measured using functional magnetic resonance imaging (fMRI), near infrared spectroscopy (NIRS), Positron Emission Tomography (PET), Computed Tomography (CT) (Samal; Hashmi, 2024). The operation of the interface is typically structured in this way: electrodes detect brain signals, which are then processed by a BCI microcontroller to remove any noise caused by external and device-specific factors. Subsequently, the signal obtained is analyzed to identify the corresponding command. In addition, it is important to use artificial neural networks, which are often used for this purpose due to their high data processing and adaptation capabilities. The command is then sent to an external device for further processing according to a pre-programmed algorithm (Singh *et al*.., 2023)

In terms of brain functions, electrical measurement techniques, despite having a high level of noise, provide a high temporal resolution, while metabolic signals, although providing a high spatial resolution, are resource--intensive, have a low temporal resolution and require a high level of computational complexity. Therefore, among these approaches, the association of EEG with BCI is the most widely used method, due to its portability and high temporal resolution. A BCI-based system consists of four components, namely signal acquisition, pre-processing, translation and *feedback* or output (Elashmawi *et al*., 2024). EEG-based BCI employs steady-state visual evoked potentials (SSVEPs), P300 event-related potentials, movement-related cortical potentials (MRCP) and sensorimotor rhythms (SMR) as different types of neurological mechanisms (Said *et al.)*.., 2022)

The evaluative method used to assess the output of an EEG-based BCI system is to classify EEG signals for specific applications. The growth of artificial intelligence technology has inspired researchers to use *machine learning* and *deep learning* to improve the use of EEG-based BCI. *Machine learning* techniques allow the brain- computer interface to learn from the subject's brain with each new session, adapting the rules generated to classify thoughts and thus improving the efficiency of the system (Gao; Mao, 2021). According to Lin *et al*,(2025) the deep learning method using EEG to identify the type of stroke, artery involved and stroke severity, demonstrated accuracy of the stroke type classification model of 97.74% and an F1 score of 0.9774 and correlation coefficient of 0.91.

Therefore, some *deep learning* models can be used to perform BCI, these can therefore present layers such as *Convolution Layer*, which performs the extraction of different features from input images, execution of mathematical action, *Pooling Layer*, characterized by minimizing the size of the feature map and reducing computational costs, *Activation Layer*, which evaluates any form of relationship of continuous and intricate network variables, *Fully Connected Layer*, used to link neurons from several layers, positioned before the output layer, *Batch Normalization Layer*, used to normalize the activations of a specific input volume before sending it to the next layer in the network, *Dropout Layer*, removes some neurons from the architecture during training and *Upsampling Layer* which makes spatial dimensions identical to the input image like the *Encoder-Decoder* network. (Chaki; Woźniak, 2024).

In addition to the above, some studies suggest that models with more convolutional layers have better performance, however, if EEG-related data is absent from the model, the accuracy of the model can drop to up to 59%, while according to Sign *et al*.,(2024) *deep learning* models to classify the affected artery in CVA used 33 features and gave an accuracy of 95.7%, while the classification between CVA and CVA showed classification accuracy ranging from 98.33% to 98.77%. BCI systems are based on motor imagination and provide real-time *feedback*, patients can see the intended movements and participate in their rehabilitation (Xu *et al*.., 2023)

In addition, according to Orban *et al*.,(2022) when performing the endogenous technique, which consists of RSM and slow cortical potentials, the EEG signal can be generated independently of external factors and controlled by the patient. In this way, it is understood that RSM show changes in their amplitude through the capture of motor images and cerebral motor executions, which is a good method for rehabilitating hand function in post-stroke patients (Fu; Chen; Jia, 2022). While MRCP are fundamental processes proportional to motor execution and are connected active and imagined motor tasks.

Therefore, for the detection and diagnosis of strokes, *deep learning* models need to make correct predictions about the targeted phenomena, correct metrics such as accuracy, precision and *recall*, and a confusion matrix (Chaki; Woźniak, 2024). For the rehabilitation of these patients, the application of BCI with *deep learning* is extremely important, as it mimics the functioning of the human brain, identifying patterns and making decisions through learning and training. In this sense, it becomes possible to interpret brain signals more precisely and achieve finer control. This paves the way for more personalized and precise rehabilitation strategies for stroke patients, allowing them to better rebuild damaged neural connections and regain functional independence (Cao *et al*., 2022). Meanwhile, functional electrical stimulation can be associated to provoke muscle contraction in the paretic arm, which would provide electrical stimulation, as well as promoting the efficacy of closed sensory-motor circuits and corticospinal excitability (Bai *et al.)*.., 2020)

In relation to stroke rehabilitation, motor imagery can be used, as this method induces and promotes rehabilitation of upper limb functions through an integrated process of mental practice, thus stimulating the neural pathways and facilitating brain processes in organization of remapping and motor control. Motor images include movements of the left hand, right hand, both feet and tongue. Similarly, the implementation of these systems is useful for people with spinal cord injuries, as mental practice helps to improve their motor function and quality of life (Subhi *et al*.., 2024)

According to Cao(2025), in order to carry out an upper limb rehabilitation project for post-stroke patients, it is important to design and develop neural network models, which can be the convolutional recurrent model, which consists of image recognition, associated with an attention model and electromyographic (EMG) matrix data, thus obtaining the recognition of relevant movements, however, adaptive transfer learning methods can also be used.

Patients who have suffered a stroke have an interruption in the sensorimotor circuit and consequently a loss of voluntary movements, but the capacity for motor planning may still be preserved, and the application of BCI in these patients also promotes Hebbian plasticity. According to Revill *et al*,(2020) Hebbian stimulation can result in improved coding of motor memories, motor training can lead to neuroplasticity and kinematic coding of movements practiced by patients, which would directly involve stimulation of N-methyl-D-aspartate (NMDA) and gabaergic receptors, similar to long-term potentiation in post-stroke patients. Therefore, the improvement in upper limb motor function associated with BCI training and the induction of Hebbian plasticity can only be seen after 4 weeks.

Complementarily, according to Tennant *et al*.,(2015) the effect of ipsilesional Hebbian-type motor cortex (M1) stimulation on motor training-related improvement in affected hand function and M1 plasticity was determined in a double-blind, randomized, placebo-controlled study of chronic stroke patients. M1 plasticity was defined as increases in the blood oxygen level dependent (BOLD) response to hand movements.

In addition to disabling pathologies such as stroke, the BCI method can be used in a variety of pathologies, according to Ma *et al*.,(2024) BCI technology can be applied to support or restore visual function. This technology has shown promise in allowing visually impaired individuals to interact with their environment in new ways, such as controlling assistive devices or navigating computer interfaces.

The integration of BCI with visual rehabilitation protocols offers a new approach to improving the quality of life of individuals with occipital lobe tumors, marking a significant advance in neurorehabilitation. According to Duan *et al*.,(2019) the application of BCI combined with proprioceptive *feedback*, increased SMR, in a short training session, however it was observed that visual stimuli alone are not able to alter the function of the motor cortex during BCI training. However, there is a need for more studies related to the application of visual stimulation, as visual impulses are called visual evoked potentials (VEPs), they can occur as transient VEPs, smaller than 6Hz and generated from changes in the optical field and steady-state VEPs due to a high-frequency optical stimulus, they can also be full-field, half-field and partial-field (Gao *et al*., 2022). While according to Mudgal *et al*.,(2020) the use of BCI technology in visual enhancement can be applied in models such as time-modulated by flashing at different targets orthogonal in time, frequency-modulated, in which each target is flashed at a specific frequency and pseudo-random code-modulated BCIs with flashing performed in random order.

Therefore, the application of BCI technology reduces neurological deficits and restores the damaged sensorimotor circuit. After treatment, patients with stroke and acute spinal cord injury showed great functional and neurological recovery (Curt *et al.*., 2008). BCI can also serve as an assistive therapy for children with neurodevelopmental problems, such as autism spectrum disorder (ASD) and attention deficit hyperactivity disorder (ADHD) (Lim *et al.*, 2019) by reducing beta and theta rhythms in the EEG. In addition, the BCI system has shown progress in the treatment of Alzheimer's disease (AD), facilitating neural stimulation techniques aimed at modulating pathological neural circuits and promoting neuroplasticity, improving cognitive function (Raikar *et al.*., 2024)

NEURAL DEVICES AND UPDATES

NC is a promising computational structure for surpassing the processing speed and energy efficiency of classical *Von Neumann* computing architecture in learning, recognition, optimization and classification applications. In such bio-inspired neural networks, neurons play the role of integrator and information processor. The synapses, which are the connection between the neurons, transmit and store the processed information. Therefore, the first NC systems are mainly based on conventional complementary metal oxide semiconductor technology (Liu *et al.*., 2023)

Neuromorphic *software* uses a range of algorithms designed to replicate the functionality of neurons and synapses in the brain, including spiking neural networks and spike-time dependent plasticity, which model the dynamic interactions between neurons. These algorithms are event-driven, which means that they process information in discrete values, but continuously in time, making them biologically inspired and compatible with neuromorphic *hardware* (Pisarchik *et al.*., 2024)

In addition to the biologically inspired models, the neuromorphic *software* incorporates adapted conventional machine learning algorithms commonly used in traditional computing. This includes *deep learning* architectures such as convolutional neural networks. Consequently, it can be used to restore somatosensory functions by translating sensory data from wearable sensors embedded in prosthetic limbs into biomimetic neural stimulation patterns. Specifically, convolutional neural networks have been used to predict electrode activation patterns required to generate desired visual stimuli (Sharma *et al.*., 2025)

Biologically inspired spiking neural networks (SNNs), which stand out as the most demonstrative form of NC approaches today, have shown advantages in energy efficiency and performance in classification tasks and should be the next generation of artificial intelligence (AI). To detect the onset of epileptic seizures based on EEG, Guo *et al.*,(2017) designed an ANN using supervised training methods and achieved an accuracy of 92.67%.

According to Raikar *et al*,(2024) NC technology can be utilized through neuromorphic sensors, which offer a valuable approach to exploiting the memory and computational capabilities of the nervous system. These brain-inspired sensors leverage visible qualities to emulate the operational efficiency of biological sensing organs, which significantly outperform contemporary electromechanical sensors, so they can simulate characteristics of certain organs, as well as retinas, related to the input light. In this context, neuromorphic sensors can also improve neural prostheses by rectifying deficits associated with perception, generating physiologically more accurate representations of external inputs.

Implementations of neuromorphic systems such as neural networks are therefore important and involve complex activities such as prediction, classification and data filtering. The nervous system has a frequency of 10^1Hz compared to computer systems of 10^9Hz (Smol; Hamer; Hills, 2023)), so memory cells present in the *hardware* can simulate synapses, through SRAM and DRAM memory, as well as memristor devices.

As previously mentioned, memristor devices can play the role of artificial synapses, which would offer a new approach to modeling the complex neural networks involved in the pathogenesis of AD, through the use of *machine learning* algorithms and disease biomarkers, NC systems can analyze patterns of neural activity and identify early indicators of AD progression, allowing timely intervention and personalized treatment strategies (Raikar *et al*., 2024). Memristor devices have been widely used in brain-inspired circuits and systems, offering transformative potential in neuromorphic engineering, consisting of two terminals whose resistance corresponds to the applied electrical stimuli (Pisarchik et al.., 2024)

According to Jaga and Rama Devi(2024), the aforementioned method is relevant for the classification of brain tumors. The work was developed by applying the *Hopfield* Triple Memristor Neural Network optimized with the *Northern Goshawk* Optimization with neuroimaging methods such as Magnetic Resonance Imaging (MRI), the images collected are pre-processed, and found to be 13.88% more accurate than traditional methods for detecting these tumors.

In relation to the rehabilitation of post-stroke patients, through the application of NC models one study has replicated the time and amplitude characteristics demonstrated in the spasticity of these patients, Yan *et al*.,(2024) developed a neural network with alpha motor commands from electromyography to generate spasticity stretching responses, which demonstrates an innovative method that could be integrated into the rehabilitation of patients affected in this way.

According to Guimarães *et al*.,(2024) *Motor Imagery* (MI) is a technique consisting of the use of BCI, a neural network model and *deep learning*. The study carried out obtained an accuracy of 67.95% in the model without extraction, while the neural network model with extraction showed an accuracy of 100% of left and right hand movements, therefore, the neural network model with extraction could be a model that could be implemented in rehabilitation platforms for recovering movements for patients who have developed stroke episodes.

Models based on neural networks excel at the automated generation of features within the latent space, which explains their superior performance compared to conventional approaches. However, these rely on analysis based on time points, ignoring the internal configurations within a movement. This limitation hampers their ability to effectively capture intricate temporal relationships without the incorporation of clinical knowledge associated with the natural history and disability associated with the disease (Wang *et al*.., 2024)

FINAL CONSIDERATIONS

Overall, motor imagery-based BCI systems have enormous potential in the field of rehabilitation, with ongoing further research into exploiting the full potential of the systems in the context of advancing neurorehabilitation. The article established the usefulness of using EEG-based BCI as a diagnostic tool for individuals with stroke, in the rehabilitation of these individuals, in addition to the use of NC. Therefore, the portability of the EEG system can be used for better and faster diagnosis. *Machine learning* and *deep learning* techniques and their applications in the field of stroke rehabilitation have presented studies more focused on predicting the prognosis of motor function in stroke patients using clinical data and MRI images as input data, and it is essential to carry out more precise studies, as such studies are important bases for the development of more valuable and precise AI algorithms, and the development of more models for application in patients, despite demonstrating high levels of precision. Therefore, the results of the studies suggest that these methods could be useful in clinical environments.

However, the majority of BCI, *deep learning* and *machine learning* research has focused on internal validation of retrospective data, with insufficient research carrying out external validation. Therefore, practical AI algorithms can be developed for healthcare professionals and patients, such as predicting and providing rehabilitation treatment periods and costs, as well as being the main object of assistance in the rehabilitation of these patients, also due to the low cost of applying these models.

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