Design of BCI-Based Exoskeleton System for Knee Rehabilitation

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Abstract: Injuries of the lower limb, particularly the knee, usually require several months of rehabilitation. Exoskeletons are great tools supporting the rehabilitation process; their research and suitable practical use are at the center of interest of researchers and physiotherapists. This paper focuses on designing a brain-computer-interface (BCI)-controlled exoskeleton for knee rehabilitation. It includes reviewing and selecting electroencephalography (EEG) acquisition methods, BCI paradigms, current acquisition devices, signal classification methods and techniques, and the target group of people for whom the exoskeleton will be suitable. Finally, the preliminary proposal of the exoskeleton is provided.

1 INTRODUCTION

The number of people with lower limb movement disorders due to aging and paralysis is increasing. Exoskeletons can be a promising solution and a useful, practical medical device in these cases; Recently, exoskeletons have become a powerful tool for the clinical rehabilitation of people with impaired lower-limb function.

However, the proper design of exoskeletons is not easy; exoskeletons should be lightweight, enabling movements during rehabilitation on the one hand and preventing health-hazardous movements on the other. Another step in their improvements is introducing active exoskeletons, i.e., exoskeletons that can be controlled directly by impaired people and supported with pneumatic control. This direct control should be carried out remotely by using, for example, speech commands or the human brain itself.

To design and implement such controllers, researchers have recently used various biological signals to control exoskeletons and other neuroprosthetic devices. As one of the results, Brain-Computer Interface (BCI) controllers based on electroencephalographic (EEG) signals can potentially (among others) bridge users' need for control and related rehabilitation devices (exoskeletons), especially when the user needs to rehabilitate the motor functions and the brain parts responsible for movements in parallel.

BCIs are designed to decode intent by extracting it from the human brain and its neural activity (Lin & Lin, 2023). The main applications of BCIs have been in communication with people in locked-in states and just in rehabilitation, control of prosthetics, and neurofeedback.

Specific protocols and paradigms need to be chosen to implement an EEG-based BCI system for a particular application. First, the user performs a particular task (e.g., movement imagery or visual task) (to learn) to modulate their brain activity while EEG signals are recorded from the scalp. A neural decoder for the paradigm is designed using the recorded EEG as underlying (training) data. Afterward, the user performs the task again, and the neural decoder is used for BCI control (Orban et al., 2022).

There are various experimental methods, paradigms, and protocols for EEG data acquisition, such as motor imagery (MI), active movement, movement intention-active movements, assisted movements, and electrical lower limb stimulation (others are described later) to get suitable EEG data for the control of exoskeleton. For example, MI

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allows users to control systems by imagining the movements of their limbs, and the related EEG signal is collected when the person imagines the movement. The recorded EEG signal needs to be processed and classified before it is used to actuate the exoskeleton, i.e., the methods for lower limb movement detection and classification need to be proposed, applied, and validated.

This study investigates the experience and best practices used to design and operate a successful exoskeleton controlled by the human brain and to look for BCI-based exoskeleton systems for lower-limb and knee rehabilitation. Finally, the custom proposal for such a system is shortly presented.

The paper is organized as follows. Section 2 reviews scientific papers on EEG-based control to detect movement intention using various experimental approaches, BCI paradigms, and EEG signal classification methods. Also, current companies' products are shortly presented. Section 3 presents our design proposal for this purpose. The final section concludes the findings.

2 STATE-OF-THE-ART

We perform a search of articles in the field of BCI-based exoskeleton system for knee rehabilitation. In our search we used the general keywords such as "knee", "lower limb", "EEG", "exoskeleton", "motor imagery", "transfer learning", "deep learning". Brain-computer interface (BCI) is an emerging research field that creates a real-time bidirectional connection between the human brain and a computer/output device. It is a communication tool for patients with neuromotor disorders, spinal cord injuries, or amputations (Tariq et al., 2018) (Lebedev & Nicolelis, 2017). Among its various applications, the most popular one is neurorehabilitation, which involves sensory feedback and the use of brain-controlled biomedical devices, e.g. exoskeletons. Neurorehabilitation, a critical component of the recovery process for those with neurological impairments, is being revolutionized by integrating exoskeletons. These wearable robotic devices have shown significant potential in enhancing mobility, functional independence, and overall quality of life for people suffering, e.g., from spinal cord injury, stroke, and multiple sclerosis. Moreover, the lower limb exoskeletons are also effective tools for clinically rehabilitating people with impaired lower limb function due to injury.

In the BCI community, many BCI systems have utilized the classification of imaginary upper limb movements, e.g. (Paredes-Acuna et al., 2024) (Liao et al., 2014) to generate different commands for controlling devices, including robots (Jeon et al., 2024). Only a few studies addressed the MI problem of the lower limb, and these studies were all focused on the imagination of brisk foot movement (ankle dorsiflexion) (Xu et al., 2014). The main reason is that the left and right foot representation areas in the sensorimotor cortex are very close to each other and located deeply within the interhemispheric fissure.

The following parts review papers based on various experimental methodologies for data acquisition, BCI paradigms, products of BCI companies, and classification methods. Their interesting characteristics and results (such as used protocols, tasks, EEG channels, preprocessing and feature extraction methods, and accuracies) are summarized in Table 1 (EEG-based control for lower limb movements). The summary of investigations utilizing transfer learning is given in Table 2 (Summary of transfer learning for MI Classification using EEG signal).

2.1 Experimental Methodologies

We can classify all experimental methodologies used to record EEG signals for lower limbs into the following types:

In most cases, alpha power (8-13 Hz) is suppressed, while beta power (13-30 Hz) increases, when an individual is executing tasks that require concentration which is highly related to motor imagery.

Active movement-based (AcM) BCIs can work well for individuals with sufficient residual control over their knee joints. By using brain signals related to particular movements, AcM BCI allows users to manipulate external devices in real time. Tortora et al. (Tortora et al., 2023) recorded EEG and electromyographic (EMG) activity from ten healthy volunteers walking with an exoskeleton. Choi et al. (Choi et al., 2020) recorded EEG signals from 10 healthy volunteers. All volunteers were right-handed males with no history of neurological disorders. The volunteers had to sit and walk while making energetic movements. The patients were given visual cues when it was time to do the movement. Ten healthy subjects participated in the offline and online sessions, and the average classification accuracy was more than 80% for both sessions.

Motor imagery (MI) is viable if the user can imagine movements. It's a non-invasive approach that doesn't require physical movement, making it suitable for users with various mobility levels. Hsu et al. (Hsu et al., 2017) recorded EEG signals from eight healthy volunteers. The volunteers' tasks included both left and right stepping. Because a screen was used for visual stimulation, electrooculography (EOG) was employed as an extra sensor.

Event-related desynchronization (ERD) reflects a decrease in oscillatory activity related to internally or externally paced events. The increase in rhythmic activity is called event-related synchronization (ERS). Event-Related Desynchronization and Event-Related Synchronization (ERD/ERS) EEG signals were recorded from 14 healthy participants by Tariq et al. (Tariq et al., 2019). During the experiment, participants completed MI tasks while seated.

Jeong et al. (Jeong et al., 2022) recorded two lower-limb MIs (gait and sit-down) and resting EEG data from five healthy subjects. The subjects were asked to stand comfortably in front of the monitor and start the MI task when ready through a mouse click. Then, the subjects performed two MI tasks related to the lower limb and rested for five seconds according to the monitor's visual cues. Roy and Bhaumik (Roy & Bhaumik, 2022) recorded EEG signals from three participants. The protocol consisted of four MI-related tasks: the imagination of left hand (L), right hand (R), foot (F), and tongue (T) movement.

Combining both MI and AcMs can provide more flexibility. Users can imagine knee movements when their physical capabilities are limited or actively move when they can. Lins (Lin & Lin, 2023) recorded EEG signals from eight healthy subjects for MI tasks at rest and during walking. Gordleeva et al. (Gordleeva et al., 2020) recorded EEG signals from eight healthy volunteers. EEG and EMG signals for a leg lift movement were acquired. AcMs and MI were the tasks completed. EMG sensors were also employed to provide feedback to the exoskeleton control system for the lower limb. Li et al. (Li et al., 2022) recorded EEG signals and sEMG signals controlled by the participants' brains on the arms of two healthy subjects. The task performed was based on MI and AcM.

Another methodology is based on Motor imagery, Active movements, and Attempted movements (AtMs): Unlike active movement, which depends on utilizing brain signals connected to actual physical actions for real-time interaction, attempted movement focuses on interpreting neural signals related to individuals' intentions to move, allowing control of external devices without physical execution. Jochumsen et al. (Jochumsen et al., 2015) recorded EEG signals from twelve healthy subjects and six stroke patients with lower limb paresis. The subject was seated in a comfortable chair with the right foot (or the affected foot) attached to a foot pedal where a force transducer was set up. The healthy subjects performed the two tasks with Motor Execution (ME) and Motor Imagery (MI), while the stroke patients were asked to attempt the movements.

Movement intention - Active movements: Movement intention (like attempted movement) refers to the mental state in which an individual intends to carry out a specific action, even before the actual execution. Movement intention-based BCIs benefit users who want the exoskeleton to respond to their intentions even before visible movements occur. Rea et al. (Rea et al., 2014) recorded EEG signals from seven right-handed patients with chronic stroke. The subjects were seated during the experiment and performed movements with a foot pedal. The authors employed additional EMG sensors during the tasks.

Assisted movement benefits users with severe mobility impairments; an exoskeleton with BCI-controlled assisted movements can be the best option. This method involves integrating BCI technology to improve physical movements, providing people with assistance or control over external devices to augment their motor functions. Qiu et al. (Qiu et al., 2015) recorded Event-Related Desynchronization (ERD) EEG signals from 12 healthy volunteers and a stroke patient with hemiplegia. The tasks performed were right-leg lifts.

Electrical lower-limb stimulation is suitable if the user has complete paralysis but still wants to engage in knee movements; electrical lower-limb stimulation controlled by a BCI may be the most suitable option. Hauck et al. (Hauck et al., 2006) recorded EEG signals from six healthy right-handed volunteers. Furthermore, Magnetic Resonance Imaging (MRI) was obtained from five volunteers for data recording. Subjects were lying down, and low-amperage electrical stimulation was applied to the peroneal, proximal, and distal tibial nerves. Sensors for electrooculography (EOG) were also employed.

2.2 BCI Paradigms

BCIs can be divided into two main categories: invasive and non-invasive (Sitaram et al., 2007). Most of the EEG-based BCI systems rely on the following paradigms: ERD associated with motor imagery (MI), event-related potentials (ERPs) based on the P300 or other event-related components, steady-state visual evoked potentials (SSVEPs), auditory steady-state responses (ASSRs), slow cortical potentials (SCPs), sensorimotor rhythm (SMR), and various hybrid systems based on more than one input signal (Orban et al., 2022).

ERD is widely used in MI tasks for motor rehabilitation and control of prosthetic limbs, allowing users to control devices or perform actions by imagining specific movements. ERP BCIs are used for communication, cognitive, and clinical applications. SSVEP BCIs are often used in applications requiring high information transfer rates, such as gaming and spelling systems.

ASSRs are less common than visual-based BCIs but can be used for auditory communication and spatial tasks. SCPs are primarily used for neurofeedback and cognitive regulation, such as improving attention and relaxation.

SMR requires people to use mental strategies or MI to enable motor execution (ME). For subjects with motor disabilities, the thought of movement can suppress EEG rhythm, leading to desynchronization, resulting in movement initiation. By harnessing neuroplasticity, MI can enhance motor learning (Müller-Putz et al., 2005). With both MI and ME derived from sensorimotor areas such as the primary motor area, supplementary motor area, and premotor cortex, SMR can be manipulated to help disabled people towards rehabilitation. The SMR paradigm has been one of the most promising paradigms used by people with tetraplegia, spinal cord injury, and amyotrophic lateral sclerosis (ALS) (Kawala-Sterniuk et al., 2021).

Hybrid BCIs combine multiple input signals, such as EEG, ECoG, EMG, other physiological measurements, and various paradigms to enhance overall BCI performance and functionality. They are used in applications where high accuracy, versatility, and adaptability are needed, such as advanced prosthetic control and complex communication systems.

The primary EEG-based BCI paradigms for lower limb rehabilitation are ERD associated with MI, SMR, and Hybrid BCIs (combining EEG with other modalities).

2.3 BCI Products

EEG acquisition systems and related BCI systems have also become popular during the last few years; many companies were founded to produce simpler and cheaper BCI systems for ordinary users, but qualitatively compared to those intended for fundamental research on the brain's functioning.

The most frequently used EEG (BCI) headsets are delivered by the following companies: Emotiv Inc. (San Francisco, CA, USA), Ant Neuro (Hengelo, Netherlands), Cognionics (San Diego, CA, USA), Neurosky Inc. (San Jose, CA, USA), OpenBCI (Brooklyn, NY, USA), InteraXon (Toronto, Canada), g.tec (Schiedlberg, Austria), and CREmedical (Kingston, RI, USA). The products continuously improve signal acquisition quality, wearing comfort, raw EEG signal preprocessing, or accompanying software tools. The critical feature for further EEG signal processing is the accessibility of raw EEG data. In comparison, g.tec provided a stronger and cleaner signal than Emotiv Inc. The biggest advantage of Neurosky Inc. products is a low, competitive price and ease of use. The OpenBCI provided extremely similar EEG results to those obtained with the g.tec device, and the medical-grade equipment performed marginally better than the consumer-grade one and OpenBCI gave very close EEG readings to those obtained with the g.tec device (Kawala-Sterniuk et al., 2021). Most of the clinical-quality EEG data for the BCI applications are gathered using the following clinical-grade amplifiers which are popular mostly due to their price, availability, and the high quality-signals they provide: g.tec amplifiers, Porti7 (TMSI), Nuamp amplifier, BrainAmp128DC, and BioNomadix amplifier (Biopac).

Clinical-level (medical devices) EEG equipment is also popular in numerous BCI-related applications. In many cases, the g.tec (Kuś et al., 2013) amplifiers are used, e.g., BCI systems dedicated to controlling a neuroprosthesis (Tung et al., 2013). Another popular clinical-level device is Porti7 from the TMSI company, which was applied for an SSVEP-BCI system, where the authors tried to find the most appropriate SSVEP frequencies (Onose et al., 2012). The neuroscan device Nuamp was applied for BCI-based post-stroke patients' rehabilitation (Fazli et al., 2009). BrainAmp128DC was used in studies (Katona & Kovari, 2018) (Fazli et al., 2009) to gather EEG-based robotic arm control data. In (Katona & Kovari, 2018), the authors compared the inexpensive Neurosky's Mindwave device with Biopac's BioNomadix amplifier, and the obtained results proved the similar quality of the recorded data. Based on a new research, market leaders for medical exoskeletons included Ekso Bionics Holdings, Rewalk Robotics, Cyberdyne, Bionik Laboratories, Bioness Inc. (*Exoskeleton Market - Size, Growth & Trends*, n.d.).

In the next section devices related to the BCI companies and parameters for choosing suitable devices are discussed.

2.4 EEG-Related Devices

Several important parameters should be considered when choosing EEG devices for MI in rehabilitation to ensure that the chosen device fits the unique

requirements and objectives of the rehabilitation program. Some crucial selection standards involve wireless connectivity; devices with wireless capabilities increase the mobility and flexibility of users during rehabilitation exercises. The placement and number of electrodes ensure the device captures relevant brain activity associated with MI and accurate monitoring. Researchers frequently place electrodes over the sensorimotor cortex (C3 and C4) in the context of motor imagery BCIs because these regions are directly involved in the mental simulation of movement. There are equivalent changes in brain activity in the sensorimotor cortex when an individual performs motor imagery, such as imagining moving their left hand. These electrical potential changes corresponding to motor imagery can be recorded by EEG electrodes located at C3, C4 and Cz.
Higher sampling rate and data resolution help to provide more precise and thorough brain activity tracking if necessary. Lightweight and portable devices are ideal for rehabilitation environments where people must move freely. Long battery life is essential for continuous monitoring sessions without frequent interruptions for recharging. The overall cost of the EEG device, including any additional accessories, software licenses, or maintenance fees, should be balanced with the available budget for the rehabilitation program.

Emotiv company offers solutions for BCI applications, including MI tasks. It is well-known for its Emotiv EPOC+ and Emotiv Insight EEG headsets. The Emotiv EPOC headset is straightforward to use and does not require any particular scalp preparation. NeuroSky provides a small wireless MindWave Mobile EEG headset, which can be used for BCI and neurofeedback applications. The biggest advantage of NeuroSky products is a low, competitive price. g.tec is known for its excellent data resolution and adaptable features. One of the most popular clinically-approved professional EEG systems is g.USBAMP from the g.tec company. It is a cheap device (ca. 25 USD), providing excellent data quality. OpenBCI is renowned for offering configurable and open-source EEG platforms. OpenBCI Cyton and Ganglion are two of their popular offerings among developers and researchers.

2.5 Deep Learning-Based Approaches Applied in MI Classification

Several lower limb movement classification models have recently emerged, utilizing machine learning (ML) and deep learning (DL) techniques for EEG data processing. Hsu et al. (Hsu et al., 2017) employed a Fuzzy SVM (FSVM) approach to classify imagined lower-limb stepping movements and create a resilient MI classifier. They utilized data from nine EEG channels and electrooculography (EOG) signals. The highest performance, with a high average classification accuracy across eight subjects (86.25% in single-trial analysis), was attained using a filter bank common spatial pattern (FBCSP) and FSVMb combination.

Gordleeva et al. (Gordleeva et al., 2020) proposed a multimodal human-machine interface (mHMI) that integrates EEG and EMG modalities for real-time control of a lower-limb exoskeleton. The classification and control system based on linear discriminant analysis (LDA) achieved successful movement prediction and differentiation (81.5% ± 14.9%) using the combined EEG and EMG signals.

In another study by Roy et al. (Roy et al., 2022), LDA was utilized to classify the walking MI task, achieving an accuracy of 98.67%. This investigation involved data from a dataset comprising 32 EEG channels collected from five healthy subjects.

Similarly, Roy & Bhaumik (Roy & Bhaumik, 2022) employed LDA to classify four MI tasks, including left hand (L), right hand (R), foot (F), and tongue (T) movements, using data from 3 EEG channels (C3, Cz, C4). Their study demonstrated a classification accuracy of 88.89%.

Tortora et al. (Tortora et al., 2023) employed a Convolutional Neural Network-Long Short-Term Memory (CNN-LSTM) hybrid model to classify the walking MI task. They utilized data from 38 EEG channels in conjunction with EMG and inertial measurement unit (IMU) information gathered from 10 healthy subjects. Their approach achieved a classification accuracy of 89.32% ± 4.65%. Table 1 shows EEG-based control for lower limb movements with MI and Active Movement using ML and DL for classification.

Deep Neural Networks (DNNs) have emerged as game changers in ML and DL, capable of tackling complex tasks with remarkable accuracy. However, training DNNs from scratch can be computationally intensive and data-hungry, limiting their practical utility. This is where transfer learning (TL), especially using pre-trained networks, comes into play.

TL is a technique that leverages the knowledge gained from one task and applies it to a different, often related task. TL is a promising approach to address these challenges by transferring knowledge from related tasks to improve learning ability. TL can help improve the performance of decoding models across subjects/sessions and reduce the calibration time of BCI systems.

Table 1: EEG-based control for lower limb movements.

Study	Subjects	Protocol	Task	EEG channel	Pre Processing	Feature extraction	Method	Accuracy (%)
(Hsu et al., 2017)	8 healthy subjects	MI - Active Movement	Left/Right stepping	9 channels (FC3, FC4, FCz, C3, C4, Cz, CP3, CP4, and CPz)	Filter-bank common spatial Pattern (FB-CSP)		Fuzzy SVM (FSVM)	86.25
(Tariq et al., 2019)	5 healthy subjects	Kinaesthetic Motor Imagery (KMI)	left/right knee extension	19 channels	FB-CSP		Logistic Regression (Logreg)	70.0 ± 2.85
(Gordleeva et al., 2020)	8 healthy subjects	MI - Active Movement	Leg lift	7 channels (C5, C3, C1, Cz, C2, C4, C6)	Bandpass filters	CSP	LDA	81.5 ± 14.9
(Roy et al., 2022)	5 healthy subjects	MI	Walk	32 channels	Band pass filter	Cross-correlation and Spectral entropy	LDA	98.67
(Jeong et al., 2022)	5 healthy subjects	MI	gait and sit-down	31 channels	Band pass filter	Dual-domain CNN	Dual-domain CNN based subject-transfer approach	66.57 ± 7.33
(Roy & Bhaumik, 2022)	3 subjects	MI	left hand (L), right hand (R), foot (F) and tongue (T) movement	3 channels (C3, Cz, C4)	Band pass filter	Cross-correlation and Wavelet Energy	LDA	88.89
(Tortora et al., 2023)	10 healthy subjects	Active Movement	Walk	38 channels	High-pass, notch and low-pass filtered	PSD	CNN-LSTM	89.32 ± 4.65
(Lin & Lin, 2023)	8 healthy subjects	MI-ME (motor execution)	Walk & Stand	8 Channels (FP1, FP2, C3, Cz, C4, CP3, CPz, CP4)	Band pass filter	**CSP**, PSD, DWT+AR	SVM	83.09
(Li et al., 2022)	2 healthy subjects	Active Movement	Walk & Stand	32 Channels of EEG	Fifth-order Butterworth filter and Notch filter	CSP	ICA	99.0

Table 2: Summary of transfer learning for MI Classification using EEG signal.

Study	Subjects	Protocol	Task	EEG channel	Pre Processing	Feature extraction	Method	Accuracy (%)
(Zheng et al. 2020)	10 healthy subjects	MI	Left/right hand	8 channels (Cz, C3, C4, CP1, CP2, Pz, P3, and P4)	-	CSP, PSD	classical transfer learning algorithm	91.6 ± 2.8
(Liang., & Ma, Y. (2020).	12 subjects	MI	right hand and both feet	13 channels	band-pass filtered	balanced distribution adaptation (BDA)	multi-source fusion transfer learning (MFTL)	71.89
(Kant et al., 2020)	a healthy female	MI	left/right hand movement	3 channels (C3, Cz and C4)	band-pass filtered	Continuous Wavelet Transform (CWT)	VGG19	95.71
(Zhang et al., 2021)	9 healthy subjects	MI	left hand, right hand, feet, and tongue	22 channels	OVR-FBCSP		HDNN-TL	81
(Zhang et al., 2021)	54 healthy subjects	MI	grasping with the hand	62 channels	Chebyshev type-I filter	-	Deep CNN	84.19 ± 9.98
(Mattioli et al., 2021)	109 participants	MI	4 tasks and 14 experimental runs	64 channels	-	-	1D CNN	99.46
(Cai et al., 2022)	- Dataset 1 - Dataset 2a	MI	left hand, right hand, foot	- 59 channels - 22 channels	band-pass filter	symmetric positive definite (SPD) and Grassmann	manifold embedded transfer learning (METL)	- 83.14 - 76.00
(Khademi et al., 2022)	9 healthy subjects	MI	left hand, right hand, feet, and tongue	22 channels	spatial and frequency domains	CWT	Inception-v3 and LSTM	92

Pre-trained CNN networks, such as VGGNet, AlexNet, ResNet, Inception, and GoogleNet, among others, represent the cornerstone of transfer learning. These networks are initially trained on extensive datasets for general tasks and serve as the foundation for our research, which focuses on classifying lower-limb MI using EEG signals. Utilizing pre-trained CNN networks, a form of TL based on model parameters, for lower limb movement classification using EEG signal offers several significant advantages and compelling reasons, such as complexity of EEG data, data efficiency, generalization, model performance, reduction in overfitting, knowledge transfer, reduced computational resource, and robustness to noise. Table 2 provides a comprehensive summary of recent research that has successfully harnessed the power of TL to achieve high-performance MI classification.

Kant et al. (Kant et al., 2020) proposed a combination of Continuous Wavelet Transform (CWT) along with deep learning-based transfer learning (pre-trained CNN like VGG19) using three EEG channels (C3, Cz, C4) for MI Classification for BCI. The results of the method have been compared to earlier works on the same dataset, and a promising validation accuracy of 95.71% is achieved in their investigation.

Khademi et al. (Khademi et al., 2022) employed a transfer learning-based CNN (ResNet-50 and Inception-v3) and LSTM hybrid deep learning model to classify MI EEG signals. Their model produced impressive results, achieving the highest accuracy of 92% and a Kappa value of 88% for the hybrid neural network featuring Inception-v3.

3 BCI-CONTROLLED EXOSKELETON FOR KNEE REHABILITATION

Summarizing the literature, BCI paradigms, EEG acquisition methods, current BCI products, classification and transfer learning methods, and approaches, the general usefulness of the BCI exoskeleton and possible target groups, we have decided to propose the BCI-controlled exoskeleton for knee rehabilitation.

This exoskeleton emerges as a promising solution for post-knee injury rehabilitation, particularly in cases without neurological diseases. Its lightweight design facilitates permissible movements during rehabilitation, and its active functionality, driven by both brain-controlled and pneumatic systems, positions it as an effective tool, particularly for bed-based rehabilitation scenarios. The BCI system will be based on two paradigms: processing and evaluating basic brain frequencies (distinguishing between attention and relaxation states) and motor imagery. As we move forward, it is crucial for individuals to recognize the significance of rehabilitation, emphasizing the role of attention and motor imagery in optimizing the efficacy of the exoskeleton and the overall recovery process.

The basic EEG acquisition device used will be based on Neurosky technology. We also aim to define MI tasks with the SMR paradigm for implementing experiments on healthy subjects using the OpenBCI Cyton device available in our laboratory. Regarding the classification method, we intend to use pre-trained CNN networks (such as VGG19) to classify lower limb movements. This interface leverages pre-trained CNN networks to extract shared features from EEG signals, thus enhancing the performance of lower limb movement classification in the human-exoskeleton interface. The benefits of transfer learning will be also utilized. Currently, the microcontroller for running the BCI part (i.e. collecting the EEG signal from the EEG acquisition device and running the classification methods) is designed, created, and tested in the laboratory.

4 CONCLUSION

This paper reviewed EEG current literature, acquisition methods, BCI paradigms, current EEG acquisition devices, and EEG signal classification methods and techniques to design and implement a BCI-controlled exoskeleton for knee rehabilitation. This preliminary design of such a system was presented. When the BCI part is ready for lab testing, the future work involves mainly building the interface for the exoskeleton and performing experiments when the BCI system and exoskeleton are integrated.

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