Motor-Imagery EEG-based BCIs in Wheelchairs Movement and Control: A Systematic Literature Review

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Abstract—The pandemic emergency of the coronavirus disease 2019 (COVID-19) shed light on the need for innovative aids, devices and assistive technologies to enable people with severe disabilities to live their daily lives. EEG-based Brain-Computer Interfaces (BCIs) can lead individuals with significant health challenges to improve their independence, facilitate participation in activities, thus enhancing overall well-being and preventing impairments.

This systematic review provides state-of-the-art applications of EEG-based BCIs, particularly those using motor-imagery (MI) data, to wheelchair control and movement. It presents a thorough examination of the different studies conducted since 2010, focusing on the algorithm analysis, features extraction, features selection and classification techniques used, and wheelchair components and performance evaluation.

The results provided in this paper could highlight the limitations of current biomedical instrumentations applied to people with severe disabilities in the pandemic context of Covid-19 and bring focus to innovative research topics.

Index Terms—Motor-Imagery (MI), Brain-Computer Interface (BCI), Electroencephalography (EEG), Brain Controller Wheelchair (BCW)

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I. INTRODUCTION

THE epidemiological context of the coronavirus disease 2019 (COVID-19) pandemic has had wide-reaching impacts on all segments and sectors of society, imposing severe restrictions on the individuals' participation in daily living activities, mobility and transport, on access to education, services and healthcare. In this scenario, the pandemic emergency shed light on the need for innovative devices, biomedical solutions and assistive technologies (AT) to facilitate persons with severe disabilities regarding their participation in daily life [1].

In recent years, the Brain-Computer Interface (BCI) application has been growing rapidly, establishing itself as an emerging technology able to translate human intentions into control signals and allow disabled people to interact with the external environment without any kinaesthetic movement [1]. It has mainly targeted patients with neurological diseases such as amyotrophic lateral sclerosis (ALS), brainstem stroke, multiple sclerosis and high spinal cord injury.

ALS is a progressive neurodegenerative disease that mainly affects motor neurones in the cerebral cortex, brainstem, and spinal cord. As the disease progresses, it led to a condition characterised by loss of ability in controlling the voluntary muscles. Subjects are aware of everything going around (the brain works properly). Still, they show limited (LIS: locked-in syndrome) or no motor response (CLIS: completely locked-in syndrome), meaning that the movement commands are not transmitted through the body limbs.

In the pandemic context, ALS patients' management has become highly complicated [2] due to suspension or postponement of the outpatient follow-up visits.

Several innovative solutions of telehealth, telemedicine [2][3] and remote monitoring systems [4] have been proposed to allow patients' follow up in remote locations using telecommunications technology.

To complement the mentioned solutions, for these people unable to easily transmit their intentions to external devices using conventional interfaces such as a mouse or a keyboard, the development of brain-controlled systems could be the optimal solution to allow them to live their daily life [5][6].

Indeed, BCI is a useful tool to establish an additional communication channel between the subjects and external devices through users' cerebral patterns. Thus, this approach

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can be efficiently used to improve their independence and facilitate participation in activities, thus enhancing overall well-being, reducing marginalisation, and preventing impairments.

Specifically, electroencephalography (EEG)-based BCI has emerged as a technology with high translational potential owing to its desirable traits: direct measures of neural activity, portability, non-invasiveness and inexpensiveness [7].

EEG-based BCI technologies in controlling mobile robots, particularly wheelchair systems, have been the subject of recent research interest.

Several contributions have been published during the last decade to provide state-of-the-art wheelchairs driven by a brain-computer interface. Two of them [8][9] contain a survey, partially connected to this field, on brain-controlled mobile robots, describing the overall systems and the key techniques and the evaluation parameters of these robots. The other three articles [10][11][12] presented an extensive overview of current BCI-based wheelchair solutions. A recent paper [13] provides a detailed review of EEG signal processing in robot control (mobile robots and robotic arms), mainly based on non-invasive brain-computer interface systems.

Our paper aims to present the state-of-the-art applications of EEG-based BCIs, particularly those using motor-imagery (MI) data, to wheelchair movement and control in a real environment.

Focusing on the applicability and feasibility of brain-controlled wheelchair in the pandemic context and highlighting the need for easy usability required for disabled people, we considered studies that are based only on motor imagery EEG data and that tested the BCI approach on a real wheelchair, or at least a prototype, but not a simulator.

The review presents a thorough examination of the different studies conducted since 2010, focusing on the algorithm analysis, features extraction, features selection and classification techniques used, and wheelchair components and performance evaluation.

The rest of this paper is organised as follows: Section 2 describes more in details the methodology used for this review. Section 3 presents a synthetic overview of BCIs classifications and applications, identifying our area of interest more precisely.

Section 4 focuses on applying MI EEG-based BCIs in wheelchairs movement and control and summarises the different existing solutions.

Section 5 discusses algorithm analysis, features extraction, features selection, classification techniques and software used in the selected contributions. Finally, Section 6 presents the main conclusions of this study and focuses on the primary challenges of biomedical research applied to people with severe disabilities in the pandemic context of Covid-19.

II. METHODOLOGY FOR THIS REVIEW

A. Search Strategy

This systematic review was conducted following the preferred reporting items for systematic reviews and meta-analyses [14].

A comprehensive literature search was conducted on March 1, 2021. The most common engineering and medical databases (IEEE Xplore, Pubmed, Science Direct and Scopus) were selected for research.

The review was limited to texts published in English between 2010 and 2021, for which abstracts were available.

Considering the scope of the systematic review, the specific keywords were defined. This structured search string was used to organise this paper: “motor imagery” - AND - “EEG-based” OR “electroencephalography-based” - AND - “BCI” OR “Brain-Computer Interface” - AND - “Wheelchair movement” - AND - “control”.

To increase the likelihood that all the relevant studies were identified, additional articles identified through the reference list of previously retrieved articles were included.

B. Inclusion and exclusion criteria

Articles were considered for inclusion only if: (1) they described brain-computer interface systems based on motor imagery paradigms as mainly EEG acquisition modality; (2) they partially or totally demonstrate the feasibility, effectiveness and applicability of MI EEG-based BCIs for wheelchair movement or control in real-world settings; (3) they described completed research.

The articles were also screened for the following exclusion criteria: (1) contributions that described BCI systems mainly based on face gestures or intentional blinks to control wheelchair; (2) studies that described only a simulated system or virtual environment and in which there is no reference to real wheelchair (or prototype) movement and control; (3) studies that presented a hybrid-mental approach: wheelchairs that are based on more than one type of EEG signal (e.g. ERD/ERS and P300).

Exclusion criteria were also related to papers, books or book chapters, letters, review articles, editorials, and short communications.

C. Study selection

Our work aims to present state-of-the-art applications of EEG-based BCIs using motor-imagery data to wheelchair movement and control. Since these interfaces' target population are older people or patients with impaired motor abilities and considered our interest in assessing applicability in a daily context, only the studies that described a real wheelchair, or at least a prototype, but not a simulated system, are investigated and reported.

A particular emphasis was given to studies that performed experiment evaluation of wheelchair navigation in a real-world environment.

A total of 134 search results were identified through database searching and additional sources. After removing all duplicates, 117 studies underwent title, and abstract screening and the inclusion criteria were examined. The full texts of 22 papers assessed for eligibility were carefully analysed. Three articles [15][16][17] were excluded for exclusion criteria (1), one contribution [18] for exclusion criteria (2) and two scientific results [19][20] for exclusion criteria (3).

Finally, only 16 studies were included in the quantitative synthesis. The methodological approach is presented in Fig. 1.

For facilitating analysis and comparisons, we summarised all relevant BCI existing solutions and related system parameters in Table I. In Section 4, we discussed each study, contextualising the results in the BCI realm.

III. BRAIN-COMPUTER INTERFACES CLASSIFICATIONS AND APPLICATIONS: A SYNTHETIC OVERVIEW

Far from representing an exhaustive and detailed description of BCI systems' main characteristics and classifications, discussed in depth in several contributions [21][22], this section aims to frame the area of interest of our review more precisely.

According to their invasiveness, BCIs can be classified into invasive and non-invasive ones, depending on whether sensors used to measure brain activity penetrate the skin or not [23]. In invasive BCIs, cerebral signals are acquired inside the brain using electrodes located under the skull. The two invasive modalities mainly used in BCI research are intracortical recording and electrocorticography (ECoG).

We focused our research on the non-invasive BCIs in which brain signals are acquired using sensors placed on the scalp.

Among various non-invasive brain-imaging methods often used to implement BCI systems (EEG, Magnetoencephalography (MEG), Positron emission tomography (PET), functional magnetic resonance imaging (fMRI), and Functional Near-Infrared Spectroscopy (fNIRS)), over the last couple of decades, EEG has been the most widely employed due to its desirable traits, namely non-invasiveness, portability, high temporal resolution, and a relatively low cost compared to other neuroimaging methodologies [21][24].

In recent years, up-and-coming practical applications of EEG-based BCI with several elaborately designed paradigms [25] are being evaluated [26]–[31].

Within EEG-based BCI paradigms, two groups can be roughly identified: exogenous (or evoked), which use external triggers (flickering LEDs or auditory beeps) to evoke discriminative brain patterns, and endogenous (or spontaneous), which use self-regulation of brainwaves without external stimuli [24].

Typical examples of exogenous BCI paradigms are the steady-state visual evoked potential (SSVEP)[26][27] and the P300 signal [28][29].

P300 [32][33] is a localised brain pattern response to an external attended visual, auditory, or tactile stimulus and is mainly measured in the parietal lobe.

SSVEP [34][35] is a response to a visual stimulus at a frequency greater than 6 Hz, which can be primarily observed in the occipital area.

On the other hand, Event-Related Desynchronization/Synchronization (ERD/ERS) changes, elicited during the performance of mental tasks (e.g., motor imagery, mental arithmetic, and mental rotation) [30][31], are representative of endogenous BCIs paradigms, as they do not use any external stimuli.

Since controlling a wheelchair requires that the visual channel remains dedicated to the maintenance of visual attention on the environment, the endogenous signals, particularly those elicited by MI, are to be preferred.

Although learning to modulate endogenous signals requires

more time for the users, MI paradigms present significant advantages that should not be overlooked for this review's scope.

Indeed, they do not require any external stimulation. They can be operated via free self-control and, consequently, they are particularly suitable and advantageous for the patients suffering from motor neuron diseases [24].

In light of these observations, EEG-based BCIs, particularly those using motor image paradigms applied to wheelchair apparatus control, represent the sub-area of interest of our review (Fig. 2).

IV. MI EEG-BASED BCIS IN WHEELCHAIRS MOVEMENT AND CONTROL: LITERATURE RESULTS

In the context of the COVID-19 pandemic emergency, among various BCI applications, using the human brain in wheelchairs movement and control is attracting widespread attention in the scientific community due to its flexibility and potential to help old and paralysed individuals gain independence and potentially improve their quality of life.

Since the first demonstrations of feasibility that the "human mind can control a wheelchair" [36][37], several protocols have been proposed, and a sophisticated algorithm has been implemented to extend the applications of EEG-based BCIs to wheelchair movement and control [11].

Following the definition given in [13], the wheelchair is classified as a mobile robot that can navigate two dimensions.

EEG-based wheelchair system refers to a type of brain-computer interfaces technology in which this specific mobile robot is controlled using electroencephalographic patterns collected from the human brain. This technological approach allows the subject to reach a particular target using only brain signals.

Despite the enormous interest in implementing a brain-controlled wheelchair (BCW) that can improve disabled people autonomy allowing them to move through a real environment [10], the number of scientific contributions in the field is not very high due to the complexity of developing such elaborate system [38].

In presenting the background of recent studies on wheelchair control through the acquisition of a user's brain activity, the groups of Al-qaysi [11] and Fernández-Rodríguez [10] analyzed several BCW existing solutions: MI-based BCW [39]–[41], P300-based BCW [42]–[46], SSVEP-based BCW [47]–[51] and hybrid-based BCW [52][53]. Hybrid-based BCW is commonly identified as a system based on one EEG input combined with one or more channels (e.g. EEG, electromyography (EMG), electrooculography (EOG) or movement detection).

All these studies present a standard signal acquisition methodology (EEG) to control the system, but different structural elements: the specific signals used to implement the BCI system, the tasks to be performed by users, the number and type of commands available on the device, the modality of navigation, etc.

As mentioned above, our interest is to prove the feasibility and applicability of a brain-controlled wheelchair in a real environment considering, as the target population, patients with impaired motor abilities.

For this reason, among the four EEG control signals models used to handle BCI wheelchairs, those based on motor-imagery task can be considered the most appropriate choice for achieving the intended purpose. Indeed, a motor-imagery paradigm does not rely on visual stimuli and does not interfere with navigation's visual task, allowing the user to control the wheelchair spontaneously. The subject is not exposed to any stimulation, and thus there is no risk of fatigue.

In addition, a brain-controlled wheelchair based on the motor imagery paradigm is more appropriate for use in an unknown environment, and several classes of identified motor imagery output can be directly transmitted into the directional control of a robotic wheelchair [54].

Finally, the use of MI when dealing with motor-disabled patients makes sense since this paradigm does not interfere with the patient's residual capabilities, involving a part of the cortex that may have effectively become redundant [55].

This systematic review focuses on key issues related to non-invasive EEG-based BCIs that use motor imagery as the main paradigm applied to wheelchair movement and control.

In this section, several existing applications of MI EEG-based BCIs for wheelchair movement and control are illustrated. These studies are carefully analysed, and the main characteristics in terms of signal acquisition, preprocessing, feature extraction and classifications methods, and wheelchair performances evaluation were summarised in Table I. The studies are tabulated in chronological order.

Tsui *et al.* [54] presented a simple 2-class self-paced MI-based BCI for wheelchair control. With this system, the user was able to make path planning and fully control the wheelchair. Based on a laser range finder, an automatic obstacle avoidance system is integrated with the robotic wheelchair's control mechanism.

The work of Carrino *et al.* [56] proposed a user-friendly, self-paced BCI system that, using a commercial EEG headset and a motor imagery approach, allows the user to drive an electric wheelchair. Although the low-cost EEG device provided interesting results, the authors stated that it could hardly be used for self-paced systems in error sensitive context. Indeed, the system was tested directly on the wheelchair, and several problems occurred. More specifically, the classification process's errors produced an unexpected behaviour of the wheelchair and, thus, a strong perturbation for the user, concentrated in motor imagery tasks. Since this problem does not allow any kind of navigation for non-trained subjects, the test was finally performed using real gestures, less sensitive to emotional perturbations.

A novel wheelchair system controlled by EEG signals was constructed by Choi *et al.* [57], using effective signal processing methods to allow people paralysed from the neck down to interact with society more freely. The authors confirmed that the proposed wheelchair system demonstrated almost the same performance as a wheelchair controlled by a joystick.

In Li *et al.* [39], authors evaluated the feasibility of BCI-based wheelchair, which users' thoughts can steer without any additional involvements. In practical driving testing in a real

environment, the system achieved a good performance, suggesting a potential application to people with disabilities in daily life.

The group of Carra [58] illustrated the development of a non-invasive experimental BCI system. The proposed approach generated commands to move a motorised wheelchair using portable and low-cost equipment and capturing the brain signals from the somatosensory cortex without the involvement of peripheral nerves and muscles. Experimental tests performed in an uncontrolled environment showed promising results, thus enabling a possible future interface with real-life situations.

For designing a BCI system, Reshmi *et al.* [59] introduced five-class motor imagery EEG-based approach. The patterns acquired from the sensory-motor cortex are translated into a control signal to manage the directional movement of a wheelchair. Indeed, users' movement intentions are classified according to the limb movements, and the results of patterns identification can be used as a command to move and stop the wheelchair.

Carlson *et al.* [55] proposed an asynchronous wheelchair system, integrated with robotics and computer vision techniques, that allows the subject to control the wheelchair by performing a motor-imagery task spontaneously. This group introduced the notion of shared control to integrate the user's intelligence with the precise capabilities of a robotic wheelchair given the context of the surroundings. The authors demonstrated that several types of BCI wheelchair operators (new and experienced ones) could complete a navigation task successfully. Moreover, compared with an alternative P300-based system, the asynchronous MI approach gives users greater flexibility and authority over the actual trajectories driven. More specifically, the users can interact with the wheelchair spontaneously and can voluntary control the motion at all times, rather than having to wait for external cues. Besides, they can dynamically produce intuitive and smooth trajectories rather than relying on predefined routes, thus reducing the inactivity navigation time.

To overcome some of the limitations of several existing solutions, such as gaze dependence and unnecessary stops, Kim *et al.* [60] presented an MI-based brain-actuated wheelchair system using an extended five command protocol. The presented wheelchair could be driven by the user in both smooth and right-angled turns. The user could be integrated with various robotic and computer vision sensors via additional channels in the network module for safety improvement. This approach can allow the user to cope with various environments, reaching a goal point with lower execution time.

In the study of Varona-Moya *et al.* [40], the authors tested the feasibility of driving a customised robotic wheelchair with an MI-based BCI system and the auditory cues to inform the subject of the available navigation command at every moment. To enable effective and autonomous wheelchair navigation, this group proposed an application interface that, based on a two-class sensorimotor rhythms-BCI paradigm, provided the user with four navigation commands. The results suggested

that this system seems to be an effective way of driving a robotic wheelchair autonomously and could provide locked-in patients with a better quality of life.

Swee et al. [61] proposed developing an electric wheelchair that can be directly controlled by the brain and that does not require any physical feedback as controlling input from the user. The authors anticipated that this system could give a new contribution to physically disabled people to regain their mobility.

Zhang et al. [62] demonstrated the effectiveness of a brain-controlled intelligent wheelchair that combines an MI- (or P300-) based BCI and an automated navigation system. For the scope of this review, only the MI-based BCI solution was taken into account. The proposed wheelchair has several advantages: (i) it can adapt to changes in the environment; (ii) once the user selects a destination with the BCI, the system automatically navigates to it, allowing the workload reduction for the user; (iii) during the wheelchair navigation, the user can issue a stop command via the BCI.

To provide several navigation commands without worsening the system performance, a paradigm based on the discrimination of only two mental tasks to control the wheelchair is presented in the study of Ron-Angevin et al. [38]. Such a non-muscular control system has the peculiarity that it is embedded with an auditory interface that provides the user with four navigation commands. The authors suggested that this system could be an effective option to allow wheelchair displacement in a controlled environment for potential users with motor neuron diseases in the face of more extensive training.

The group of Al-Turabi [63] described the experience of developing a complete BCI system able to instruct a wheelchair to move to different directions using non-invasive EEG brain waves. In light of the experimental results, the authors proposed their system to control other devices and hypothesised, as future improvement, a cloud-based system to direct communication from the headset to the wheelchair.

In Yu et al. [64], the authors implemented an asynchronous control strategy in which the wheelchair commands are generated by a multi-step process based on sequential MI, without any external prompt information. Although the system was tested in healthy subjects, the preliminary experimental results demonstrated this navigation strategy's potential applicability in enhancing the mobility of people with physical disabilities in a real environment.

Permana's project purpose [65] was to control the wheelchair using a motor imagination-based BCI and a portable EEG device. In performing a preliminary experimental test using only MI patterns from a single data channel to trigger the wheelchair movement, the authors found some problems. Indeed, due to similarities in EEG patterns related to different motor paradigms, the classification for several wheelchair control signals failed. To overcome this limitation, they added a new variable (eyes motion) as a differentiator of similar data without obtaining evaluable results. In conclusions, our method needs to be developed and improved.

In a recent work of Xiong et al. [7], authors have made several important contributions to the state-of-the-art in BCIs. They proposed a wheelchair prototype that uses hand motor imagery and jaw clench data collected with a consumer-grade EEG system, bridging the gap between the real-time classification of motor imagery and the use of a low-cost apparatus. Although future experiments and a consistent neurofeedback training procedure are required to validate their prototype, this system seems to get closer to the actual context's needs and demands. Authors highlighted that this system's clinical applications would largely depend on the motor abilities of the user (EMG toggle would be inaccessible to patients with more severe disabilities such as CLIS) and proposed, as future work, other integrative non-muscular signals, such as electrooculography (EOG).

V. MI-BASED BCW ELEMENTS

In the design and implementation of a brain-based control wheelchair system, four stages are necessary to establish the communication between the human brain and the external device and to get a useful output to be used in controlling it: brain signals acquisition, preprocessing, features extraction from patterns and features classification. An example of brain-controlled wheelchair components and the system application in a real environment is illustrated in Fig. 3.

A successful BCI system must be characterised by the best accuracy in extracting EEG features and classifying them. Indeed, since the presence of errors can cause the initiation of a wrong command that can lead to dangerous situations, a high classification rate and accuracy are required [17]. For this reason, features extraction and classification processes play a significant role.

In this section, we discussed these four stages in more detail, together with published examples and in the light of summarised results. As integration, the software libraries primarily used in the collected studies were illustrated and analysed.

A. Signal acquisition

As mentioned above, this systematic review focuses on the non-invasive methods on which the applications of EEG-based brain-controlled wheelchair are based.

Many EEG data acquisition devices are available in commerce, which vary in the number of channels, sampling rate, electrode connection type, headset preparation time, and price [13][66][67].

Our review results revealed that, in MI-based brain-controlled wheelchair applications, the most used devices to capture EEG signals are Epoc [68], produced by Emotiv Systems Inc., and the g.tec medical engineering products, such as gUSBamp.

The Emotiv Epoc is a portable, high-resolution EEG system with 14 dry electrodes designed to be quick and easy to fit, taking practical applications measurements. Many BCI studies used EPOC to control or interact with machines in users' environment [69], although the validity of Emotiv products in

clinical research is still a matter of debate.

On the other hand, g.USBamp RESEARCH [70], a high-performance and high-accuracy 16 channels biosignal amplifier, was proposed by the g.tec medical engineering to acquire and process physiological signals.

g.USBamp has become a widely used standard for neurophysiological research, life sciences, neurofeedback and brain-computer interface approach.

Also, Brain Products EEG amplifiers [71], such as BrainAmp DC [64] and Acti-CHamp [40], were commonly used for a variety of practical uses in neurophysiological research.

An overview of other used EEG signal recording devices is presented in Table I, together with examples of associated brain-controlled wheelchairs.

B. Pre-processing

Signal preprocessing is a non-trivial step required to clean data and remove any unwanted components (noise, artefacts or interference) embedded within the EEG signals [13][21]. A proper preprocessing procedure produces an improvement in the signal quality and results in better features separability and classification performance.

The most common methods applied in BCIs preprocessing and adopted in the summarised scientific contributions are frequency-domain filtering and spatial filtering. Bandpass filters [7][38][40][58][59][62][64], the primary attempts to attenuate artefacts in the measured EEG, and notch filters [57][64], used to remove the noise generated by the power line, are examples of frequency domain preprocessing solutions. However, only when the frequency bands of the signal do not overlap, these methods are effective.

A spatial filter is an alternative approach to increase the signal-to-noise ratio (SNR) of the brain signal. Typical examples of spatial filtering methods are Laplacian filtering [55][56], blind source separation (BSS)[57], common average reference (CAR) [39][60], autocorrelation (AC), canonical correlation analysis (CCA), independent component analysis (ICA), minimum energy combination (MEC), and principal component analysis (PCA). For real-time BCI applications, automatic methods and low computational cost are required. Recently emerging algorithms, such as independent vector analysis (IVA), a modified joint BSS approach (JBSS), a quadrature regression IVA (q-IVA) and the filter-bank-based supervised machine learning approach, introduced more effective artefact removal approaches, paving the way for innovative and helpful research in BCI field [72]. A detailed description of the mentioned methods out of this review's scope can be found in [13][21][22][73][74].

C. Feature extraction

Although the feature extraction methods used in the selected studies are quite heterogeneous, analysis in the spatial domain using Common Spectral Patterns (CSP) resulted in being the general approach [39][57][60][62][64].

Started to be employed since 2000 to detect event-related desynchronizations [75], CSP filter is mentioned as an effective way to discriminate classes and one of the most popular feature extraction methods in the BCI field [22]. This method aims to transform EEG data into a new space, maximising the variance of the (projected) signal from one class and minimise it for the other class.

It is considered a strong technique in MI EEG processing since it enables the extraction of signal information from particular frequency bands.

However, proper selection of the filtering frequency band dramatically affects the performance of CSP, and the optimal frequency band is typically subject-specific. Thus it is difficult to select manually.

The common spatial frequency subspace decomposition (CSFSD) method, adopted in Choi *et al.* [57], is a modified type of CSP [75].

In other summarised BCW systems, the power spectral density (PSD) method is also adopted. PSD is the measure of how the power of a signal is distributed over frequency.

It is an efficient frequency domain based feature widely used in motor imagery paradigms, but its performance may decrease seriously when applied to low SNR data.

D. Pattern classification

Implementing a successful BCI approach requires that the system identifies several user brain activity patterns, extract from them the most significant features, and classify them with the best accuracy. The classification step compares the user's intention into command signals for an output device (for example, a wheelchair).

Especially in third-party device control applications, where errors can lead to dangerous situations, high classification rate and accuracy are mandatory [17]. Although either regression or classification algorithms could be employed to achieve the goal above, the latter's use is considered to be the most popular approach [76]. Among the numerous classification algorithms commonly used in BCI's scientific context [21] and especially in brain-controlled mobile robots [13], the SVM-based and LDA-based approaches predominate in the studies of this review.

LDA is an effective statistical technique used as a well-known binary classification method for EEG data. It is employed to identify the linear combinations of feature vectors that characterise the corresponding signal. This method projects data in a new space and uses a hyperplane to distinguish different classes, minimizing the variance within a class and maximising the variance between classes [13].

Thanks to its satisfactory performance, very low computational cost, easy use and no requirement of extensive pretraining, an LDA classifier is to be preferred in various BCI systems, for example, in motor imagery-based approach. However, its linearity can cause performance degradation and poor results in a few circumstances containing complex large non-linear EEG data.

On the other hand, SVM, first proposed by Vapnik *et al.* [77], is a supervised learning algorithm used to solve binary

classification problems by creating a linear optimal hyperplane. To perform a classification process for a given set of training data, SVM constructs a hyperplane model in a multidimensional space that separates the patterns belonging to the different classes by the widest margin [13]. As reported in Padfield *et al.* [22], the SVM classifier resulted in higher performance when compared to LDA and regression algorithms.

In addition to LDA and SVM classification solutions, artificial neural network (ANN) and k-nearest neighbour (k-NN)[78] are also adopted.

The element that identifies the neural network (NN) is identifying trends challenging to find, either by humans or by computerised techniques. An ANN is a multi-class classifier, widely used in the BCI field, based on a brain-inspired information system that simulates and replicates the process of human cognition [13].

KNN is a supervised learning algorithm that can be used to classify between two or more patterns. It is based on the concept that features related to different patterns will result in different clusters in the features space, while similar patterns will form convergent or alike clusters. The BCI community doesn't seem to widely use this method due to its sensitivity to the curse-of-dimensionality, which causes it to fail in several experiments.

E. Software platforms

Several commercial software, toolbox and framework were adopted to implement the necessary steps for EEG signals processing, such as filtering, artefact correction, feature extraction, and classification.

An overview of the most widely-used BCI platforms is presented, together with examples of associated brain-controlled wheelchairs (Table I). Besides, several features that could be essential in wheelchair control application are highlighted for each of them.

OpenVibe [79], developed by the French National Institute for Research in Computer Science and Control (INRIA), is a free and open-source platform to design, test and use BCI systems in both real and virtual environments. Adopted in Carrino *et al.* [56], it can be used for real-time processing and analysis of brain signals (acquire, filter, process, classify and visualize data) due to its modularity features, portability and flexibility.

OpenBCI GUI [80], used in Xiong *et al.* [7], is an OpenBCI's software that offers a powerful tool for visualizing, recording, and streaming data the OpenBCI Boards. Data can be transmitted in live-time to third-party software such as MATLAB.

Matlab is also a powerful tool for researchers to test models and algorithms in the BCI field, benefiting from resourceful toolboxes and easy implementation process [81]. It was adopted in most of the summarised studies.

LabVIEW (National Instruments, Inc.), a high-level multiplatform graphical development environment, was also used to implement a brain-controlled wheelchair [58].

Although not used in any of the studies summarised in this review, it is worth mentioning, within the brain-controlled wheelchair research, other open-source BCI platforms: Wyrn,

BCI2000, BCILAB and Gumpy.

Wyrn [82][83] is an open-source Python-based BCI package applicable to a broad range of neuroscientific problems. The toolbox offers several functionalities to analyse and visualise neurophysiological data in offline processing and real-time settings, like an online BCI application.

BCI2000 [84][85] is an open-source C++ based software developed in 2000 for real-time BCI systems application. It includes stimulus presentation functionality and provides the data acquisition and signal processing modules. Still, some important methods (e.g. discrete wavelet transform) and some classification techniques (e.g. deep learning) are not embedded. Since this software does not directly support other programming languages such as Matlab or Python, it is not easy to extend or integrate it with other toolboxes [86].

BCILAB [87][88], developed by "Swartz Center for Computational Neuroscience" (SCCN) and distributed free to help researchers in processing signal with Matlab, is among the earliest publicly available software packages for research purposes in the BCI community. The toolbox supports several feature extraction methods, experimental paradigms and classification approaches (LDA, Quadratic Discriminant Analysis (QDA) and SVM).

Gumpy [86][89] provides state-of-the-art algorithms, signal processing methods and classification approaches that the scientific community has employed over the last 20 years. Gumpy is designed for a hybrid brain-computer interface and is implemented to chart a route ahead for new BCI improvements [86]. It is an open-source Python toolbox suitable for EEG and EMG bio signal analysis, visualisation, real-time streaming and decoding. More importantly, in addition to classical machine learning algorithms, Gumpy includes different deep learning models such as deep convolutional neural networks (CNN)[90], recurrent convolutional neural networks (RCNN) and Long Short-Term Memory (LSTM)[91] which can be used to classify sensory-motor rhythms from EEG signals.

VI. CONCLUSIONS

Our scientific research group's interest has been focused for years on the development of innovative technological solutions and assistive systems designed to preserve communication and interaction with the external world in people with ALS [4][92]-[98].

The pandemic emergency of COVID-19 has shed light on the needs of people with severe disabilities regarding their participation in daily living activities, mobility and transport, on access to education, services and healthcare.

Therefore, in this context, it was necessary to highlight the limitations of current biomedical instrumentations applied to people with severe disabilities to pave the way for future and helpful research in the BCI field.

This systematic literature review aims to prove the feasibility and applicability of a brain-controlled wheelchair in a real environment considering, as the target population, patients with impaired motor abilities.

Wheelchairs are among the most appropriate equipment that can promote mobility and improve people autonomy,

providing valuable aid, particularly to the elderly and people with physical impairments, to move through a real environment and to do daily routines and tasks with ease.

In implementing an efficient brain-controlled wheelchair, three main challenges need to be considered: (i) system control is multi-objective, including numerous and different commands (start and stop, direction and speed). The system based on a navigation approach with a specific mental task can offer only a few navigation commands. On the other hand, an high number of cognitive tasks increases the number of navigations commands, but it can worsen the BCI system's performance. Producing numerous control signals is challenging for an EEG-based BCI, and making an accurate control command is a time-consuming process. (ii) The efficacy and the performance of a BCI system largely depend on the user who often fails to perform the MI required to produce direction control signals. (iii) Continuous control of wheelchair navigation may produce a large mental workload for the user, especially for disabled people.

Despite the enormous interest in implementing a brain-controlled wheelchair, the current solutions do not seem to fully satisfy the demands in today's pandemic context, mainly due to the complexity of developing such an elaborate system. Although innovative technological solutions of considerable importance have been implemented in MI-BCI research, some critical issues still need to be resolved [74].

Firstly, as most of the published studies are based on synchronised MI-BCI in offline modality, there is a need to give more prominence to online BCI studies.

In addition, the performance of a designed brain-controlled wheelchair should be quantified while navigating a predefined set of common obstacles.

Several performance evaluation metrics were used by researchers, as per their convenience. However, researchers have no standard performance metrics that could be widely adhered to facilitate comparisons between brain-computer systems. Improving the performance of BCW is still a critical issue even after two decades of research. Taking advantage of sophisticated algorithms availability, future research in MI-BCI should concentrate more on reducing long calibration, on increasing the number of commands without, however, producing a large mental workload for the user. BCI illiteracy, reported in [74] as the users' inability to produce required oscillatory pattern during motor imagery paradigm, leads to poor performance of MI-BCI. The current trend of researchers is to predict whether a user falls under BCI illiterate category or not and to use this information to improve the implementation of an optimal algorithm for decoding MI and design a better training protocol for enhancing user skills.

In conclusion, we hope the results provided in this paper will highlight the limitations of current biomedical instrumentations applied to people with severe disabilities in the pandemic context of Covid-19 and bring focus to innovative research topics.

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FIGURES AND TABLE

Fig. 1. Flow chart of the search strategy and study selection according to PRISMA guidelines.

Fig. 2. A synthetic overview of Brain-Computer Interface typologies and of biometric signals generally used in BCI systems. The path connecting the opaque coloured blocks defines the sub-area of interest of the systematic review.

Fig. 3. The general architecture of a brain-controlled wheelchair system and application example in a real environment. Reproduced with permission [97, 98].

TABLE I BRAIN-CONTROLLED INTERFACE STUDIES IN WHEELCHAIR MOVEMENT AND CONTROL APPLICATIONS

Reference	MI Paradigm	Types of control command	EEG system	Addition al biosignals acquisition	n° of EEG Electrodes	EEG Sample frequency (Hz)	EEG features extraction	Classification algorithm	Performance	Wheelchair type and components	Obstacle avoidance system	Software
Xiong et al. 2019 ^[7]	LH, RH & Jaw Clench	Left, Right, Forward, Stop	OpenBCI's Cyton Biosensing 32-bit board (also used for EMG signal), (OpenBCI, New York, NY, USA)	EMG ECG US Location	4: C1, C2, C3, C4	250	PSD	Logistic Regression	Mean subject accuracy: 60±5%	Modified version of commercially available Orthofab Oasis 2008 wheelchair (Orthofab, Anjou, QC, Canada) with components: - n° 2 commercial-grade 40A, 12V PWM controllers connected to an Arduino Uno. Project: MILO: Mind Controlled Locomotive	- 4 consumer-grade ultrasonic sensors	OpenBCI Graphical User Interface (GUI) Python Javascript
Permana et al. 2019 ^[65]	MI and eye motion -Think moving forward -Think moving backward -Think moving backward while continually move the eyes -Think moving forward while continually move the eyes -Default (motionless)	Move forward Move backward Turn left Turn right Default (motionless)	Neurosky Mindwave Mobile2	NO	1: Fp1	512	For MI: eSense score For eyes-motion: high alpha	n.d.	Success rate range: (46, 67-82.22)%	Modified version of JRWD 501 electric wheelchair	NO	Matlab
Yu et al. 2018 ^[64]	LH RH IDLE STATE	Move forward Turn left Turn right Accelerate Decelerating Stopping	BrainAmp DC, (Brain Products, GmbH, Germany)	NO	31: F3, F1, Fz, F2, F4, FC5, FC3, FC1, FCz, FC2, FC4, FC6, C5, C3, C1, Cz, C2, C4, C6, CP5, CP3, CP1, CPz, CP2, CP4, CP6, P3, P1, Pz, P2,	250	Multi CSP	LDA	Accuracy: >85% Success rate: 94,2%	Wheelchair prototype: a chair and an omnidirectional moving vehicle	NO	n.d.

Al-Turabi et al. 2018 ^[63]	Imagine visually moving a pen	Forward, Backward, Right, left	Emotiv Epoc	NO	P4	128	PSD	SVM KNN ANN	Accuracy: 70.8-79.2%	Wheelchair prototype	Ultrasonic sensor	Matlab
Ron-Angevin et al. 2017 ^[38]	RH IDLE STATE	Move forward, move backward, turn right, turn left	ActiChamp amplifier (Brain Products GmbH, Munich, Germany)	NO	9: C3, F3, P3, T7, Cz, C4, F4, P4, T8. (+CMS and DRL)	200	Average signal power	LDA	Medium accuracy: 83%	Customized Invacare Mistral3 electric wheelchair	-n° 11 ultrasonic rangefinders SRF08 -n° 2 magnetic rotary encoders AS5048	Matlab
Zhang et al. 2016 ^{*(62)}	RH LH	Turn right, turn left, stop	EEG-cap (Compumedics, Neuroscan Inc., Abbotstford, Australia) EEG-amplified (NuAmps, Neuroscan)	NO	15: FC3, FCz, FC4, C3, Cz, C4, CP3, CPz, CP4, P3, Pz, P4, O1, Oz, O2	250	CSP	SVM	Success rate: 94.7 ± 2.3%	Mid-wheel drive model 888WNLL, Pihsiang Machinery MFG. Co. Ltd., Taiwan, with sensors: - n° 1 laser range finder (SICK LMS 111) - n° 2 encoders, which are attached to the central driving wheels	-n° 2 webcams -n° 3 ultrasonic sensors	GUI
Swee et al. 2016 ^[61]	PUSH, PULL, LEFT, RIGHT	Forward, backward, left, right	Emotiv Epoc	NO	14 (+2 ref): AF3; F7; F3; FC5; T7; P7; O1; O2; P8; T8; FC6; F4; F8; AF4 (+CMS and DRL)	128	n.d.	n.d.	Accuracy: <90%	Wheelchair Prototype with components: -Scooter motors DC 24 V -ATmega328P microcontroller -Arduino Uno microcontroller board -Bluetooth Hc-06 module	NO	Emotiv API Arduino IDE
Varona-Moya et al. 2015 ^{*(40)}	RH, RELAX	Move forward, turn right, move backward and turn left	actiChamp amplifier (Brain Products GmbH, Munich, Germany)	NO	9: F3, F4, T7, T8, C3, C4, P3, P4, Cz	200	PSD	LDA	n.d.	Customized Invacare "Mistral" ³⁸ electric wheelchair	-n° 11 SRF08 ultrasonic range finders (i.e., sonars) allowed to create a real-time discrete grid map of the area surrounding the	Matlab

											wheelchair. -n° 2 AS5048 magnetic rotary encoders were attached to the wheelchair's driving wheels to carry out the odometry and thus compute the wheelchair's heading at every moment.	
Kim et. al 2013 ^[60]	LH, RH, F, F-LH, F-RH	Left, right, forward, left-diagonal, right- diagonal	g.tec system (an EEG cap and a gUSBamp amplifier)	NO	16	256	OVR CSP	LDA OVR LDA	n.d.	Electric wheelchair (K2 POWER model of WHEELOPTIA), with components: - n° 2 permanent magnet DC brushed motors (pMDC motors: 24V at 320W) - n° 1 micro controller unit (MCV, Atmega128).	NO NO	Simulink Matlab
Carlson et al. 2013 ^[55]	RH, LH, F	Turn right, turn left, keep going straight	EEG device (model n.d.)	NO	16: Fz, FC3, FC1, FCz, FC2, FC4, C3, C1, Cz, C2, C4, CP3, CP1, CPz, CP2, CP4	512	PSD	Gaussian classifier	Average accuracy: 95%	Modified version of commercial mid-wheel drive model by Invacare Corporation (TDX SP2)	- n° 10 close- range sonar sensors - n° 2 webcams to provide environmental feedback to the controller.	n.d.
Reshmi, et al. 2013 ^[59]	LH, RH RLH, RLF, RELAX	Move left, move right, go forward, go backward, stop	RMS EEG machine	NO	3: C3,C4, Cz	256	PSD	SVM	n.d.	Wheelchair Prototype with components -ATMEGA 328 microcontroller -L293 motor driving circuit	NO	Matlab
Carra et al. 2013 ^[58]	RH , F	Forward, turn right	EEG device (model n.d.)	NO	6: F3, P3, Fz, Pz, F4, P4	256	BPM	LDA	Average hit rate: 65.7%	Motorized wheelchair (model n.d.)	NO	LabView 9.0 Matlab
Li et al. 2013 ^[59]	RH LH RLF	Turn right, turn left, go forward	g.tec amplifier (Guger Technologies, Austria)	NO	14: C5, C3, C1, Cz, C2, C4, C6, CP5, CP3, CP1, CPz, CP2, CP4, CP6	256	CSP	SVM	Average trial accuracy: 82.56%	Wheelchair system (model n.d.)	NO	Provided GUI
Choi et	LH	Turns left,	g.tec	EMG	5: C3, C4,	256	CSFS	SVM	Success rate:	Rear-wheel drive type	NO	Matlab

al 2012 ^[57]	(imagine clenching the left hand) RH (imagine squeezing the right hand) RLF	turns right Moves forward	system: an EEG cap and a gUSBamp amplifier (Guger Technologies, Austria)	NO	14 (+2 ref): AF3; F7; F3; FC5; T7; P7; O1; O2; P8; T8; FC6; F4; F8; AF4 (+CMS and DRL)	128	n.d.	LDA	Classification rate: 67,5-91%	Wheelchair prototype	wheelchair: JW active model of Yamaha Motor Co	NO	- n° 6 ultrasonic range sensors for obstacle avoidance; - n° 1 Hokuyo URG-04LX laser range finder to scan the environment.	Developed application GERBIL. OpenVibe
Carrino et al. 2012 ^[56]	STOP: EMG RH LH	Turn right Turn left	Emotiv Epoc	NO	10 (5 bipolar EEG channels): C3 (FC3 vs. CP3), C1 (FC1 vs. CP1), Cz (FCz vs. CPz), C2 (FC2 vs. CP2), and C4 (FC4 vs. CP4)	250	n.d.	LDA	n.d.	Electric-powered wheelchair (<i>RoboChair</i>) with components: -An on-board DSP TMS320LF2407-based controller for motion control of 2 differentially- driven wheels; -An on-board embedded PC connected to the DSP motion controller via a USB link -A 24-volt battery providing power for the DSP controller, the PC and drive motors -A local joystick controller connected to an A/D converter of the DSP-based controller	Wheelchair prototype	NO	- n° 6 ultrasonic range sensors for obstacle avoidance; - n° 1 Hokuyo URG-04LX laser range finder to scan the environment.	Developed application GERBIL. OpenVibe
Tsui, et al. 2011 ^[54]	RH LH IDLE STATE	Turn right Turn left	g-tec amplifier (Guger Technologies s OEG Austria)		10 (5 bipolar EEG channels): C3 (FC3 vs. CP3), C1 (FC1 vs. CP1), Cz (FCz vs. CPz), C2 (FC2 vs. CP2), and C4 (FC4 vs. CP4)	250	n.d.	LDA	n.d.	Electric-powered wheelchair (<i>RoboChair</i>) with components: -An on-board DSP TMS320LF2407-based controller for motion control of 2 differentially- driven wheels; -An on-board embedded PC connected to the DSP motion controller via a USB link -A 24-volt battery providing power for the DSP controller, the PC and drive motors -A local joystick controller connected to an A/D converter of the DSP-based controller	Wheelchair prototype	NO	- n° 6 ultrasonic range sensors for obstacle avoidance; - n° 1 Hokuyo URG-04LX laser range finder to scan the environment.	Developed application GERBIL. OpenVibe

Associated acronyms: RH: Right Hand; LH: Left Hand; RF: Right Foot; LF: Left Foot; RLF: Right and Left Foot; F: Foot; EMG: Electromyography; ECG: Electrocardiography; US: Ultrasound; LDA: Linear Discriminant Analysis; OVR: one versus rest; PSD: power spectral density; KNN: K-nearest neighbour; ANN: Artificial Neural Network; CSFSD: common spatial frequency subspace decomposition; WT: Wavelet Transform; FFT: Fourier Transform; BPM: Band Power Method; GUI: Graphical User Interface; IDE: Integrated Development Environment; ref: reference; n.d: not defined;

*In this paper, author presented an intelligent wheelchair that combines an MI- (or, alternatively, P300-) based BCI and an automated navigation system. Only the MI- based BCI solution is taken into account for the scope of the review.

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