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A review of disability EEG based wheelchair control system: Coherent taxonomy, open challenges and recommendations

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ABSTRACT

Context: Intelligent wheelchair technology has recently been utilised to address several mobility problems. Techniques based on brain–computer interface (BCI) are currently used to develop electric wheelchairs. Using human brain control in wheelchairs for people with disability has elicited widespread attention due to its flexibility.
Objective: This study aims to determine the background of recent studies on wheelchair control based on BCI for disability and map the literature survey into a coherent taxonomy. The study intends to identify the most important aspects in this emerging field as an impetus for using BCI for disability in electric-powered wheelchair (EPW) control, which remains a challenge. The study also attempts to provide recommendations for solving other existing limitations and challenges.
Methods: We systematically searched all articles about EPW control based on BCI for disability in three popular databases: ScienceDirect, IEEE and Web of Science. These databases contain numerous articles that considerably influenced this field and cover most of the relevant theoretical and technical issues.
Results: We selected 100 articles on the basis of our inclusion and exclusion criteria. A large set of articles (55) discussed on developing real-time wheelchair control systems based on BCI for disability signals. Another set of articles (25) focused on analysing BCI for disability signals for wheelchair control. The third set of articles (14) considered the simulation of wheelchair control based on BCI for disability signals. Four articles designed a framework for wheelchair control based on BCI for disability signals. Finally, one article reviewed concerns regarding wheelchair control based on BCI for disability signals.
Discussion: Since 2007, researchers have pursued the possibility of using BCI for disability in EPW control through different approaches. Regardless of type, articles have focused on addressing limitations that impede the full efficiency of BCI for disability and recommended solutions for these limitations.
Conclusions: Studies on wheelchair control based on BCI for disability considerably influence society due to the large number of people with disability. Therefore, we aim to provide researchers and developers with a clear understanding of this platform and highlight the challenges and gaps in the current and future studies.

1. Introduction

Mobility is one of the challenges faced by stroke survivors. A wheelchair can assist these patients to become partially independent in performing certain daily activities [1,2]. At present, the need for wheelchairs has increased for paralysed patients and the elderly [3]. However, for physically challenged individuals, relying on a push wheelchair does not provide comfort and manoeuvrability. Therefore, electric-powered wheelchairs (EPWs) were invented to conserve the physical energy of users and provide them with increased manoeuvrability [4,5]. Robotic technologies are used to support people with disability through wheelchair robots, which consist of an intelligent control unit, actuated motors and environment recognition sensors [6]. These robots help people with disability perform their daily activities [6]. Considering their main objective of assisting people with disability, wheelchair robots aim to decrease or eliminate the need to drive a motor-powered wheelchair. In this regard, an intelligent mobile device called intelligent wheelchair was invented [7].

Considerable research on intelligent wheelchair technology has recently been conducted to address several mobility problems [9,10]. Techniques based on brain–computer interface (BCI) are currently used to develop electric wheelchairs [11–13]. Using human

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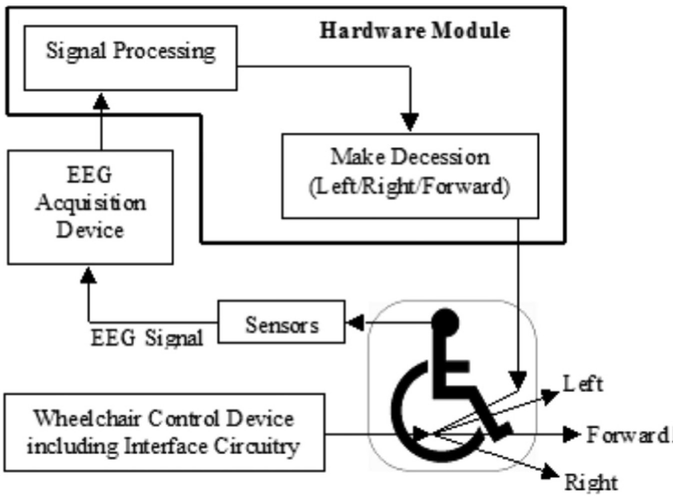

Fig. 1. Architecture of an intelligent wheelchair system adapted from [8].

brain control in wheelchairs for people with disability has elicited widespread attention due to its flexibility [14], convenience, relatively low cost, high mobility and easy setup [15]. Researchers have conducted numerous studies on the field of BCI, particularly on its application to wheelchair control. The articles identify the issues that motivating researchers to conduct their studies, the challenges that future researchers may encounter whilst performing similar investigations and recommendations to mitigate these problems. Studies on BCI-based wheelchair control cover a broad and dynamic spectrum. The current study aims to present insights into BCI technology and its applications to wheelchair control and provide researchers with multiple research options by highlighting the major challenges. Moreover, this study aims to (1) highlight the efforts of researchers in response to recent trends and new technologies, (2) map the background of recent studies in this area into a coherent taxonomy and (3) identify relevant topographies that describe this evolving field. Fig. 1 shows the general architecture of the smart wheelchair scheme.

2. Method

The scope of our study is specified by two keywords: 'EEG' and 'wheelchair'. We excluded any article about wheelchair control without electroencephalography (EEG) signals. Non-English articles were also excluded. The included articles are those related to wheelchair control using either EEG signals or hybrid BCI with EEG signals. The final articles are those on system development, brain-controlled wheelchair (BCW) signal analysis, proposals for BCW system frameworks, simulation of EPW control using brain signals and review or survey articles.

2.1. Information resources

Three relevant digital databases were selected for the targeted systematic review of articles: (1) Web of Science (WOS) indexing cross and multidisciplinary studies in engineering, sciences, arts, humanities and social sciences; (2) IEEE Explorer in engineering and technology and (3) ScienceDirect database offering access to journals regarding a wide range of research areas, including science, technical and medical. These digital databases were selected to cover technical and scientific studies in the literature and reflect a broad spectrum of researchers' influence on an extensive but related area.

2.2. Selection of studies

The strategy used to select articles comprised intensive search in the literature resources and tracking by two filtering processes. The first filter excluded irrelevant and duplicate articles by reading them briefly and focusing on their abstracts and titles. The second filter involved thorough and extensive reading of the full text. Both filtering processes applied the same criteria for article eligibility as surveyed by four authors who completed the selection and then revised by two other authors.

2.3. Search

The search covered the three databases and began in the midst of March 2017. The three databases (ScienceDirect, IEEE Explore and WOS) were explored via their search engines using two keywords: 'EEG' and 'wheelchair'. The 'AND' operator was applied to include any article related to the two keywords and exclude articles not related to the two keywords. Advance search options in each search engine were also used to disregard book chapters and other types of reports, journals and conference papers. We assumed that the two concepts most likely contained recent and appropriate methodical, technical and official works related to the field of BCI and its applications in mobility assistance and device control. Fig. 2 presents the complete text query used in this study.

2.4. Eligibility criteria

The research space includes articles with the topic 'EEG-based wheelchair control' . However, each article included in the research repository for the systematic review must satisfy all the inclusion criteria listed in Fig. 2.After identifying duplicate articles, the remaining articles were excluded by both filters if they did not satisfy the eligibility criteria. The exclusion criteria are as follows: (1) non-English articles and (2) articles that focus on using electrooculography (EOG) or electromyography (EMG) without EEG for wheelchair control.

2.5. Data collection

All the important data, which were highlighted during reading the full text to obtain the final set of articles, were compiled in a Microsoft Excel file for a simple and fast retrieval process. Many research areas are available, and each field has its own techniques, approaches and methodologies. Hence, the Microsoft Excel file has no standard categorisation. The categorisation adopted for this study includes many fields, such as type of EEG signal and device and number of samples, commands and classification techniques, given the focus on BCI signals used to control EPWs. This categorisation helped us build the taxonomy for the final set of papers. Other important data, including motivations, challenges and recommendations, were also highlighted and gathered during full text reading.

2.6. Statistical data analysis

Statistical analysis was performed on the collected data. The results were visualised using Microsoft Excel charts to help researchers and health and federation authorities/organisations. The statistics include academic, social and technical information. The statistics also provide the number and type of participants in the EEG experiments on wheelchair control, type of EEG signals used with their respective purpose, type of EEG device used in the studies, article distribution based on their databases and objectives and studies supported by financial grants with their distribution by country.

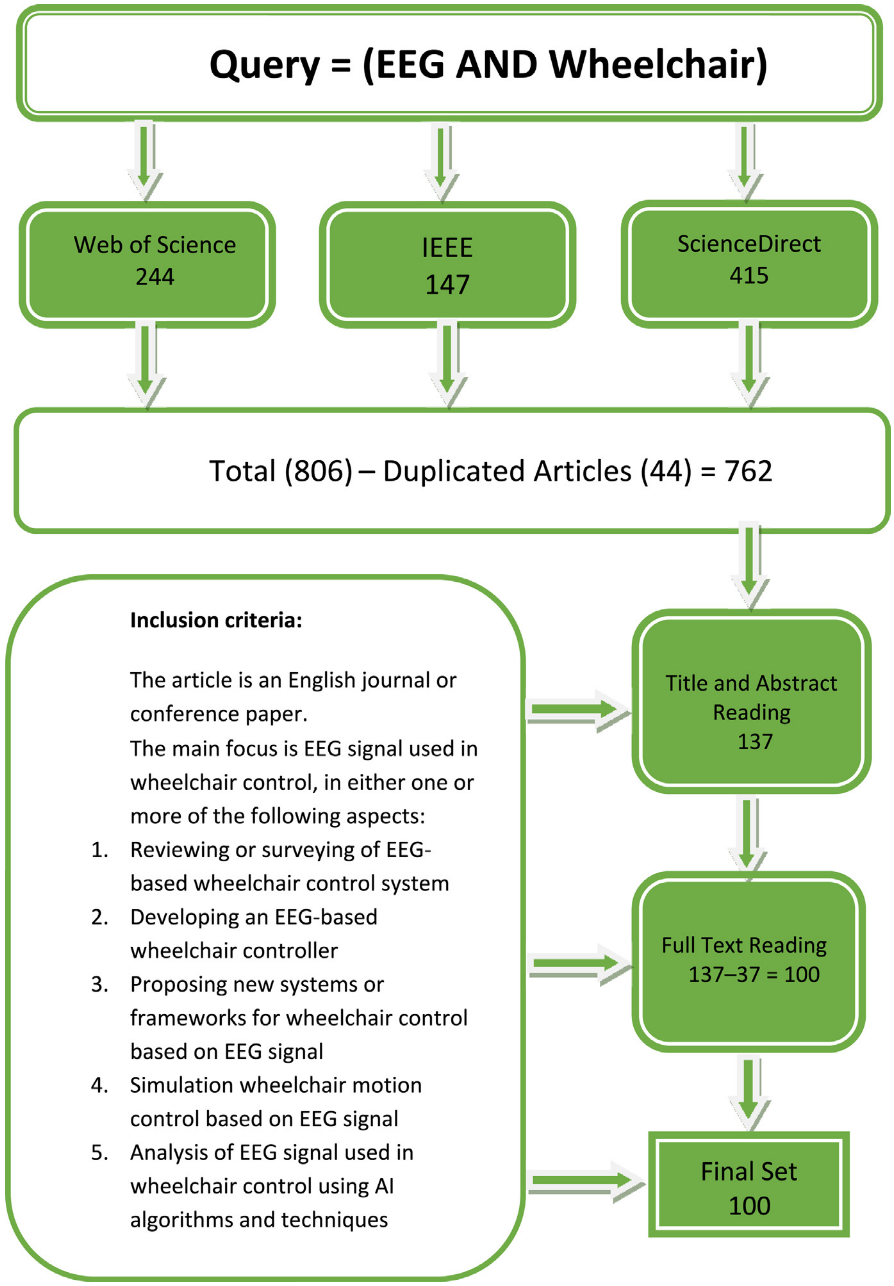

Fig. 2. Article collection.

3. Results

The first search query obtained 806 articles, which were categorised as follows: 244, 415 and 147 from WOS, ScienceDirect and IEEE, respectively. The search covered the period from 2007 to 2017. Forty-four articles were considered duplicates and consequently removed, leaving 762 articles. Numerous articles were excluded after scanning the titles and abstracts, thereby resulting in 137 papers. After reading the full text of the remaining articles, 37 were excluded. The final set of articles included 100. Our main objective is to develop the palaeography of the articles based on our research topic, so intensive reading and thorough analysis were conducted. Fig. 3 shows the taxonomy of articles on wheelchair control based on EEG signals which are divided as follows. A large set of articles (55) discussed developing real-time control systems for wheelchairs using BCI signals. Another set of articles (25) focused on the analysis of BCI signals for wheelchair control. The third set of articles (14) considered simulating wheelchair control based on BCI signals. Five articles proposed frameworks for wheelchair control based on BCI signals. The last paper is a review article about wheelchair control based on BCI signals. Fig. 4 presents the distribution of the articles according to their databases and research objective.

3.1. Development of wheelchair control system based on BCI

The first category in our taxonomy includes 55/100 articles, which concern the development of a wheelchair based on a BCI control system. These articles are classified into three groups based on the wheelchair platform (i.e. wheelchair, wheelchair with mounted arms and wheelchair integrated with a smart environment). The first group contains 51/55 articles, which are about wheelchairs without additions, as shown in Fig. 5. This group is divided into three subgroups based on the type of brain signals used

Fig. 3. Taxonomy of wheelchair control based on EEG signals.

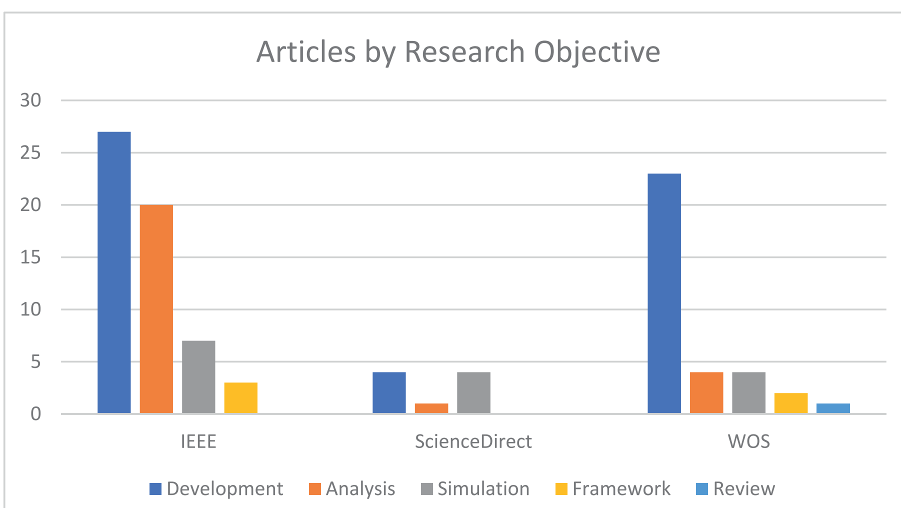

Fig. 4. Number of included articles according to databases and research objective.

to control the wheelchair, namely, evoked, hybrid and spontaneous. The first subgroup (evoked) includes 16/51 articles. This subgroup is further divided into three types: steady-state visual evoked potential (SSVEP) method, including those in [6,11,13,16–18] (which provide four commands to control a wheelchair), [19] (which provides five commands to control a wheelchair) and [4] (which provides six commands to control a wheelchair; the other evoked method (P300 method), such as those in [20] (which provides four commands to control a wheelchair), [21–23] (which provide five commands to control a wheelchair), [24] (which provides six commands to control a wheelchair) and [25] (which provides seven commands to control a wheelchair) and steady-state somatosensory evoked potential (SSSEP) method, such as those in [26,27] (which provide three commands to control a wheelchair).

The second subgroup comprises articles on brain signals (hybrid), which includes 20/51 articles. In [28], P300 and SSVEP were used to generate five commands. In [29,30], motor imagery (MI) and SSVEP were adopted to generate five and eight commands, respectively. In [31], MI and P300 were applied to produce 16 commands. In [32–35], MI and EMG were used to generate seven, five, five and six commands, respectively. [36] applied MI, P300 and EMG to generate five commands. In [37,38], EMG and EOG were adopted to generate five and four commands, respectively. In [39,40], mental cognitive and EMG generated five and four commands, respectively. In [7], head movements, mental cognitive and EMG were utilised. In [41–43], attention level and EMG were applied to generate four, three and four commands, respectively. In [44], head movements, mental cognitive, EMG and EOG generated 16 commands. In [45], SSVEP, MI and mental cognitive produced

Fig. 5. EEG-based SSVEP command for wheelchair control adapted from [13].

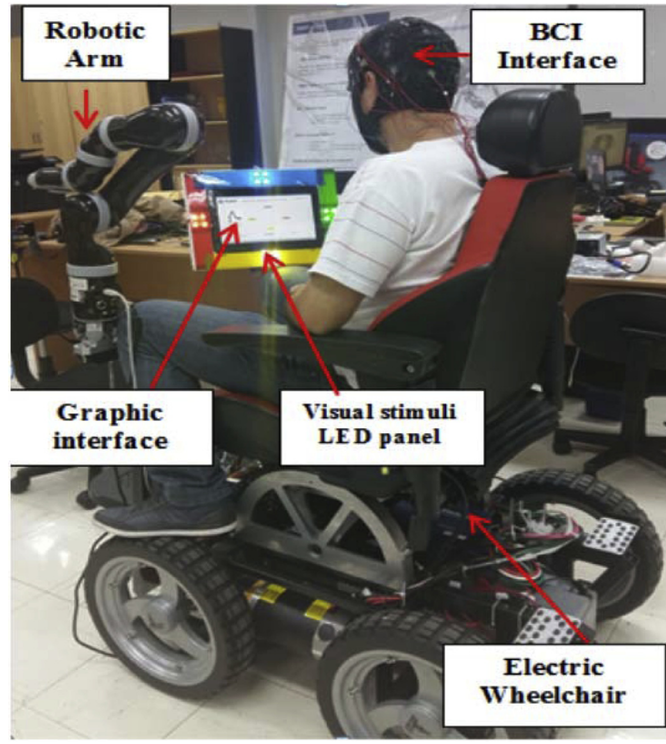

Fig. 6. Wheelchair with mounted arms adapted from [59].

four commands. In [46], P300 and EMG were adopted to generate seven commands. These studies aim to achieve specific goals, such as increasing the efficiency, accuracy and number of commands compared with the conventional methods by using hybrid BCI, wherein two or more types of mental activity modalities were combined or mental activities could be combined with non-brain signal-based systems, such as EOG or EMG signals. The third subgroup of articles on brain signals (spontaneous) includes 15/51 articles which are based on spontaneous signals. This group is subdivided into two types: articles based on non-motor cognitive functions, such as [47,48,5], and articles based on motor and sensorimotor rhythms. The latter includes [49] which used EOG signals based on EEG to generate six commands, [50] which used MI signals to generate brain switch command, [2,51] which used MI signals to generate two commands, [52,53] which used MI signals to generate three commands, [9,54] which used MI signals to generate four commands, [55–57] which used MI signals to generate five commands and [58] which used head movement signals to generate four commands.

The second category, which comprises wheelchairs with mounted arms, has 2/55 articles [59,60]. These articles address the problem of using biological signals to control a wheelchair with an embedded robotic arm, as shown in Fig. 6. This arm is used to assist people with disability in performing their daily activities and accomplishing essential tasks such as picking up a glass of water. The third category, which consists of wheelchairs integrated with a smart environment, has 2/55 articles [61,62]. These articles address the problem of integrating a smart environment into a wheelchair which can allow people with disability to control their wheelchair and essential home appliances, such as air conditioner, television, radio, light/lamp and electric fan using biological signals as a tool for human-computer interface (HCI), as shown in Fig. 7.

3.2. Proposed framework for a wheelchair control system based on BCI

The second category in this taxonomy includes 5/100 articles that cannot match the previous group of articles due to their approach. These studies did not develop a new wheelchair control system based on brain signals. Instead, the articles proposed overall frameworks or models. The first article in this category is [63] which intended to propose a research framework based on a two-tier architecture for a BCI control system to improve performance in terms of the overall efficiency, reusability, maintainability, interactivity and rehabilitation values of the BCI system. The second article in this category is [64] which aimed to cover the largest proportion of paralysed patients using a proposed wheelchair control system based on three BCI techniques: cognitive data, eye movements and head gestures.

The third article [65] proposed a research to discover new communication channels in a BCI-based wheelchair control system. The goal is to increase and facilitate interaction between patients with amyotrophic lateral sclerosis (ALS) and their environment using different strategies and techniques to satisfy their need for communication with the outside world, such as controlling a wheelchair. The fourth article [66] presented a wheelchair control system based on hybrid BCI and speech recognition sensors, which can be used by paralysed patients. When brain signals and voice recognition synchronise with each other, the system will minimise its effort to gain high attention power, increase its accuracy and provide a large number of commands, such as forward, left, right, accelerate and decelerate. The fifth article [8] suggested an approach for assisting people with severe disability by using discrete wavelet transform based on high-order statistical techniques to analyse EEG signals for controlling their intelligent wheelchair. To realise an optimal hardware platform, the proposed algorithms should be implemented on a field-programmable gate array board to obtain an efficient and accurate signal processing platform.

3.3. Simulation of a wheelchair motion control system based on BCI

The third category in our taxonomy includes 14/100 articles that do not belong to the previous group of articles. The reason is that the articles neither developed a new wheelchair control

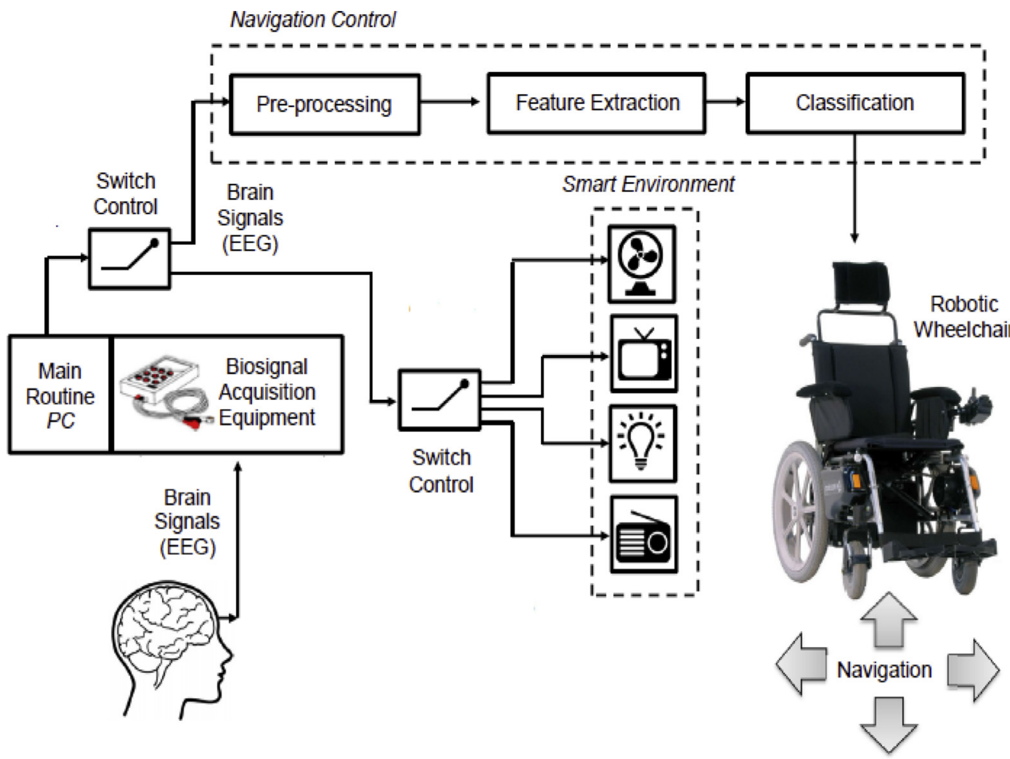

Fig. 7. Wheelchair integrated with a smart environment adapted from [62].

Fig. 8. 3D wheelchair simulator adapted from [72].

system nor proposed an overall framework or model. However, these studies used a simulated and virtual environment to control virtual wheelchairs via brain signals. The studies are further classified based on wheelchair and environmental modelling into either 2D or 3D, as shown in Fig. 8. In the 2D group, [67] used small screen images to demonstrate a sequence of wheelchair steps in one run, whereas [68] conducted virtual application tests to model positioning and pass door tests.

For the 3D wheelchair modelling group, [69] used a rectangle as a simulated wheelchair displayed in a virtual environment, [70] utilised a virtual electric wheelchair in a realistic virtual world game environment created with the Unity 3D game engine, [10] used a 3D wheelchair simulator created by a graphic application programme interface of 3D max software and [71] used the BIBA robot and Morsel simulator. However, in the simulated environment, the robot starts from position (S) to goal location (G). The Marilou simulator was used in [72]. This simulator can model the robot environment and the robot with its physical components, such as motors, odometers, distance sensors (ultrasound, infrared and laser), bumpers, actuating cylinders, air pressure forces, cameras, global positioning system and accelerometers. In [73], a small wheelchair was supplied with two motors for control and to manoeuvre according to BCI control commands. In [74], a 3D simulator for driving EPWs was created by the French laboratory LCOMS using a virtual electric wheelchair. The goals of this simulator include learning safe driving, testing driving skills, aiding in the customisation process of a wheelchair and testing new functionalities and methods in a safe environment. In [75,76], a small robot was used with a maze environment that comprised a set of rooms labelled from A to H. The robot has to start from room A and follow a predefined path to reach the goal in room H. Meanwhile, [77] adopted the simulation software developed by a research group on urban simulators, which allowed the robot to penetrate gamifications. In [78], a blender was used to model a wheelchair and a virtual environment, such as rooms, corridor, table and checkpoint flags. Finally, wheelchair control was simulated in a virtual environment using Invacare-storm 3G-Ranger in [79].

3.4. Review of wheelchair control system based on BCI

The fourth category in our taxonomy contains only 1/100 review article, namely, [80]. This review article was classified based on wheelchair features, such as brain signals used for commanding the wheelchair, navigation system adopted by the wheelchair and metrics applied to evaluate wheelchair performance. In addition, these factors were compared according to the type of signal used in commanding the wheelchair to identify their differences. Finally, the authors addressed and discussed the trend in this field of study, along with the challenges that should be solved in the future.

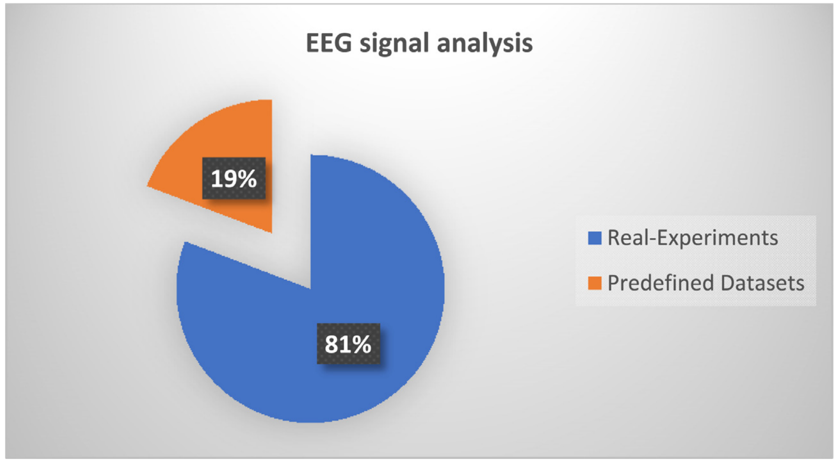

Fig. 9. Articles based on EEG signal analysis.

3.5. Analysis of BCI-based wheelchair control system

The last category in our taxonomy contains 25/100 articles. This category concerns the analysis of brain signals used in wheelchair control by performing only feature extraction and classification without developing a wheelchair. We classified the articles in this category into two groups based on the source of brain signal data as follows: based on offline analysis using standard predefined datasets or online analysis of EEG signals. The first group, which is based on standard predefined datasets, includes 5/25 articles which are either based on BCI competition datasets [81,82,14], the University of Alcala plus Graze University datasets [83] or the dataset of a previous research [84]. The second group includes 20/25 articles and is based on the online analysis of EEG signals. The online analysis of EEG signals motivated the researchers to analyse brain signals for increasing the accuracy of feature extraction and classifying wheelchair control systems based on brain signal controls. Hence, the researchers exerted their best effort to improve the performance and increase the number of commands in the navigation system, such as forward, right and left, amongst others.

The researchers used different methods and techniques for the command feature classification. For two commands, [85] used a neural network classifier, whereas [86] adopted linear discriminate analysis followed by a support vector machine classifier. For three commands, [87] applied fuzzy logic with an artificial neural network (ANN) based on particle swarm optimisation, whereas [88] [89] used a genetic algorithm-based neural network. For four commands, [90–92] used adaptive network fuzzy interference system, [93] applied multilayer perception, [1] adopted ANN, [94] used adaptive feed forward neural networks, [95] applied recurrent neural networks, [12,96] utilised a nonlinear adaptive filter, [3,97] adopted threshold-based method and [98,99] selected voting-based method. For five commands, [100] used an adaptive neural network. For six commands, [15] utilised fuzzy neural networks to classify signal features into six classes: switch on, switch off, forward, backward, left and right. Fig. 9 shows the number of articles (in percentage) based on EEG signal analysis.

4. Discussion

To highlight the research trends in the field of BCI and its applications to EPW control, studies relevant to the current state-of-the-art technologies were evaluated. The final set of articles in the derived taxonomy was developed and proposed. Taxonomising the literature considerably affects the researchers involved in this area. The derived taxonomy in this literature is useful for ordering diverse activities and works into a meaningful, manageable and concrete blueprint. Firstly, the taxonomy highlights the potential directions of research in this area. For example, the anatomy of classifying BCWs indicates that the researchers have addressed the problem of BCWs from at least four perspectives: (1) wheelchair platform, given that wheelchairs can either have mounted arms or integrated with a smart environment, (2) EEG signal analysis used in wheelchair control, (3) proposed framework and architecture of wheelchair control based on BCI signals or (4) wheelchair motion simulation using brain signals. Secondly, research gaps can be identified using taxonomy. Therefore, mapping the works in the current literature on BCWs into various categories will be useful in highlighting weak and strong points in terms of research boundary coverage.

For example, the taxonomy in this study reflected how sets of distinct studies were considered in the development of BCW and the analysis of EEG signals used in wheelchair control. The taxonomy could also highlight the lack of studies on BCW. Moreover, this study exposed three highlighted aspects that were quoted from the literature, namely, motivations in choosing this case study from a wheelchair, brain signals and human–machine interaction (HMI). The challenges to the effective deployment of these technologies from the BCI and intelligent wheelchair perspectives were identified. Recommendations to researchers and federation authorities/organisations were provided to overcome and solve the aforementioned challenges.

4.1. Motivation of using BCI-based EEG

The biomedical engineering and signal processing fields have recently been attracting the interest of researchers who have published several books and journals on these relevant fields [85]. The use of bio-signals generated from people with disability can contribute to improving their quality of life and providing augmentative communication capabilities and autonomy of movement [32,91]. In addition, the concept regarding measuring the number of electrical signals from muscle nerves was derived from the research of Emil Du Bois Reymond and Carlo Matteuci during the 19th century [7].Consequently, analysing and recognising bio-signals from the human brain significantly affect the understanding of brain operational functions and their structures [94]. Finally, in terms of assistive devices, biomedical engineering is rapidly evolving due to the high demand for valuable products from this emerging field [48]. Brain activity can be monitored using two acquisition techniques [36]: non-invasive and invasive approaches [88].

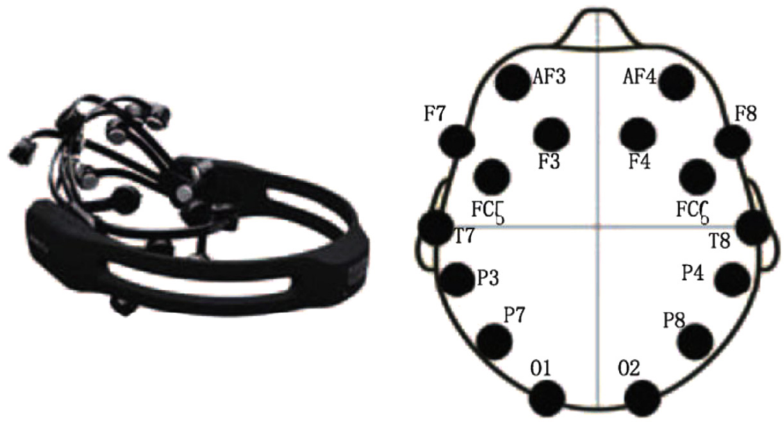

Fig. 10. Emotive wireless EEG device adapted from [60].

BCI schemes based on non-invasive techniques can be used in aiding patients with severe neuromuscular disorders to control devices and interact with their environment using brain signals obtained through the scalp [82]. In addition, a BCI-based non-invasive technique is highly recommended and desirable for many research areas due to its usability and efficiency in real applications [20].

Morever, brain signals can be obtained using EEG techniques. Such techniques measure the electrical potential amongst complex human brain activities by using a helmet with electrodes placed on the scalp [5].An EEG records the electrical potentials generated by the brain through the scalp [8,2]. EEG signals play a critical role by facilitating communication between a device and paralysed individuals without depending on the classical output of motor pathways [84,7,3]. Recent BCI-based EEG schemes have elicited considerable attention because they are non-invasive, portable, low cost, convenient and affordable [87,31,89,14,22]. However, EEG-based BCIs provide continuous time measurement and exhibit high performance [65]. In addition, recent schemes are compressed, portable and wireless [5].Consequently, an EEG helmet comprises a number of dry electrodes that are used to obtain brain signals by fixing the electrodes on the scalp.The wireless EEG device, Emotiv EPOC®, which is a comfortable, lightweight and user-friendly BCI platform, has recently been providing maximum mobility to system users [73,54]. Emotiv EPOC® became available in the market recently to support various applications in terms of HMI based on the BCI paradigm.

Moreover, the Emotiv EPOC® headset can measure various types of human brain features, such as mental cognition, emotions, facial expressions and head movements. Furthermore, the Emotiv EPOC® headset is powered by a lithium battery that allows continuous usage by providing approximately 12 h of operation [98,58]. Fig. 10 shows an overview of the Emotiv EPOC® headset and the arrangement of its electrodes.

Numerous types of EEG signals can be recorded, such as an endogenous and an exogenous signal, which is evoked at will by a participant and an external stimulus presentation, respectively [80]. However, the most frequently used EEG signals are P300, SSVEP and MI [30]. In addition, brain activities, attention level and emotional state are considered distinct patterns of EEG signals by using EEG technology [76,75]. Brain signals obtained from EEG measurement are directly used as control input for computer and automated devices [99]. The diversity of EEG applications have recently elicited the interest of researchers who conducted a wide spectrum of studies, such as rehabilitation technology [63], smart houses, Internet browsing, marketing, arm control and the memory status of individuals with mild cognitive impairment [94].

4.1.1. Using BCI-Based EEG in human-robot interaction (HRI)

The HRI research field aids people with severe disability, particularly quadriplegic patients, by promoting the use of controlling devices, such as a wheelchair, and complex and advance techniques of interface modalities which allow them to become independent [11]. Recently, various types of human features have been used as an input modal to facilitate HMI using modalities, such as eye blinking, speech, facial expression and body gesture [64]. At present, BCI technology has been evolving to enhance the utilisation of robotic wheelchairs by people with disability [81]. EOG and EEG models are well suited for patients suffering from locked-in syndrome or ALS. These models help the patients interact with their environment because they suffer from voluntary muscle movements [10,38]. Fig. 11 illustrates the HRI schemes. BCI techniques based on invasive and non-invasive schemes are organised in a manner that enables them to interpret human brain activities and map them into control commands [82] or machine instructions [30]. BCIs are tools that establish a real-time communication channel between the user and a particular device [34] through EEG or other brain signals [35,80,31,77], but avoid the neuromuscular scheme [55,78,86,22,73,75,99]. Therefore, these tools have been developed for people with impairment [97,6,76], such as patients with cerebral palsy, brain stroke, spinal cord damage and ALS [93,43]. These tools also help such patients to interact with their environment [84,2,36].

BCI systems are more accurate and efficient than other systems [4] and have received considerable attention in the last two decades [54,41]. BCI systems are being integrated into various research areas ranging from industrial, biomedicine [39], engineering, physiology, rehabilitation, neuroscience, psychology and healthcare, given that such systems belong to a multidisciplinary field [66]. Various BCI-based applications exist, such as mind-controlled wheelchairs and prosthesis, which monitor the state of the human operator, smart houses, targets, launch weapons, low-speed unmanned aerial vehicle control and military equipment [14]. The US Department of Defense has funded a considerable number of research on designing helmets that can extract mental activities and map them to control commands for military weapons and other devices [1]. In biomedical assistive technology research, BCI exhibits considerable potential given the large number of people with multiple degrees of disability. BCI mainly focuses on two essential areas: neuroprosthetics and brain-actuated wheelchairs [21]. For example, BCI helps paralysed patients drink from a cup of water by using a robotic manipulator, P300 speller and wheelchair robot [26,27]. The results indicate that a paralysed patient can effectively communicate using a BCI scheme-based EEG device to control the mouse cursor, wheelchair and prosthetic

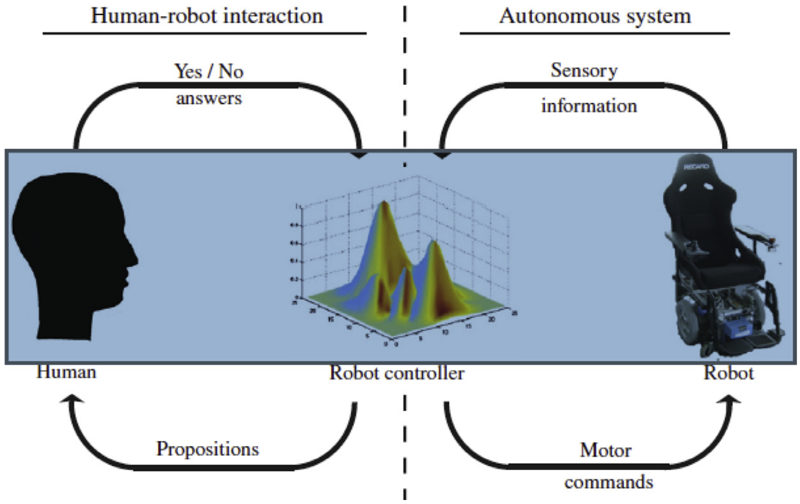

Fig. 11. HRI adapted from [71].

device [63]. This technique helps paralysed patients become independent in executing necessary daily tasks as well as reduces economic cost because the need for caregivers also declines [67].

4.1.2. Using BCI-based EEG in EPW control

In the field of BCI, the potential of wheelchair control-based BCI has recently been increasing [11–13]. Wheelchairs based on human brain control for people with physical disability have also elicited considerable attention due to their flexibility [14], convenience, low cost, high mobility and easy setup [15]. In addition, the integration of BCI into wheelchair control is an important method to aid severely paralysed patients improve their voluntarily movement control [34,9]. However, controlling an electrical wheelchair is a challenging task for people suffering from fatal diseases, such as spinal cord injury, multiple sclerosis and brainstem stroke, which result in loss of control of voluntary muscles [10,55]. Therefore, BCI is an alternative method for people with disability by providing hands-free wheelchair control [39,89,78,40,87,68,88,65,4]. Users with disability can control a wheelchair through their brain activity by using BCW [80]. Advances in biomedical signal processing and healthcare applications [85], particularly EEG devices and the intelligent control of mobile robot, have motivated researchers to develop wheelchairs controlled by brain signals [16]. At present, wheelchair control-based EEG signal is considered one of the important applications of BCI-based systems that can help people with physical impairment gain independence in their daily activities [27,31,64]. BCI-based systems are non-invasive [47], can deliver continuous commands and possess a portable essential hardware scheme [23]. Recent studies have shown that the integration of EEG signal processing, artificial intelligence and machine learning techniques is efficient and affordable, thereby allowing people with disability to continually control EPWs [52]. Patients with a healthy brain can voluntarily control external devices, such as robots and wheelchairs, by using various mental states measured using an EEG device [2]. These mental states include upper and lower body movements, mathematical operations and object visualisation [54].

4.1.3. Using motor Imagery, P300, SSVEP, SSSEP signal in EPW control

MI is one of the most common methods used in BCI-based EEG control systems [95,86]. MI does not require any voluntary muscle movement. Thus, MI is considered effective for people with severe disability [2]. Recently, EEG-based MI signals have been used in various types of applications, such as sports, psychology, neuroscience and rehabilitation technology, as well as wheelchair control [30,35]. This approach does not require gazing or focus. In addition, MI-based BCI signals provide a rapid response [28]. Therefore, these signals support the dynamic movements of an electrical wheelchair by turning over and crossing a path during navigation [52,31]. MI-based BCI signals will be of particular interest in shared and low navigation because they can offer continuous control of BCW with few low-level commands (e.g. forward, backward or stop and turn left and right) [80]. An EEG-based P300 signal can be recorded by monitoring the positive deflection in voltage at an approximate latency of 300 ms. Signal amplitude, time and structure are commonly used as metrics for mental tasks in decision-making [23]. Recently, the investigation of P300-based BCI has attracted the interest of researchers on BCI application to wheelchair control [20]. The activity of brain signals based on the P300 method can be translated into control commands [46]. The most motivating features of the P300 method are its high throughput [80], the possibility of interpreting a large number of commands and the reaction to the P300 oddball paradigm without training [84]. A user can relax and avoid the exhausting mental processes required in other devices. The reason is that an order is immediately given despite the low degree of data transmission (two orders per minute) because navigation is automated [21]. The challenges of other BCI-based systems can be addressed using the EEG-based SSSEP paradigm, which only depends on the somatosensory scheme that affects its potential in the nervous system and the human brain. In this BCI scheme, the control commands can be expanded using additional vibration stimuli without any restriction in the human eye gaze [26,27]. In addition, SSVEP is one of the critical brain signals that has been used to observe the activities of the human brain [94]. Obtaining special modulated frequencies from visual stimuli using common types of visually evoked potential signals is possible because they collect evoked potential signals without transition [59]. The EEG-based SSVEP signal has recently been considered an important tool for exploring cognitive activities in the human brain, which is studied in various types of research applications in the medical and scientific fields and other domains [91,90]. Consequently, many types of BCI-based SSVEP signals have been developed, such as the wheelchair-based control-based BCI signal and the BCI-based speller scheme, to help paralysed patients interact with their environment and overcome their disability [92]. Moreover, the efficiency of the EEG-based SSVEP-based signal has been proven in wheelchair control and in avoiding static and dynamic obstacles [30]. SSVEP achieves fast adaptation, high accuracy, short training time, high information transfer

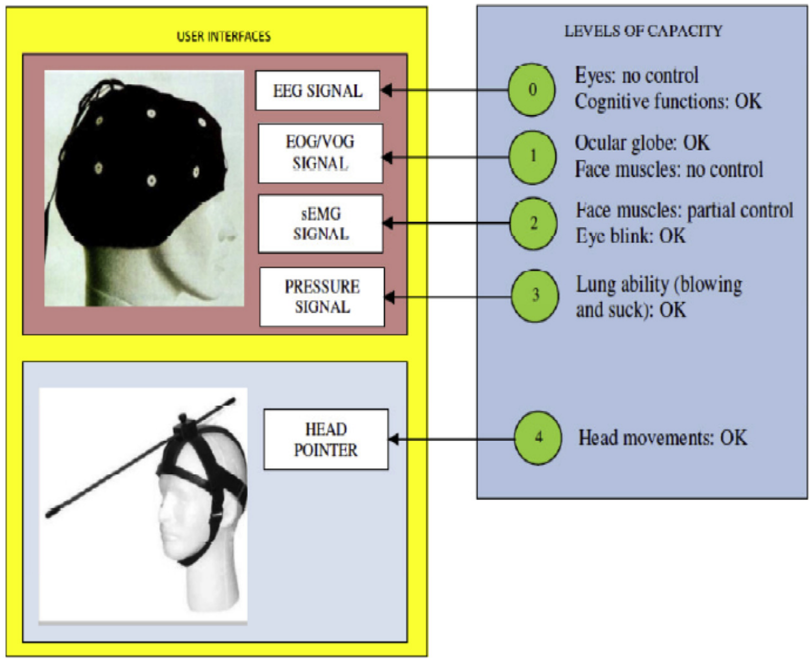

Fig. 12. Multi-modal interface adapted from [44].

rate and minimum EEG channel; therefore, it is more efficient and applicable than other BCI-based schemes [99,80,13,19,16]. Finally, EEG-based SSVEP is less vulnerable to EOG artefacts because this signal is commonly measured from the occipital region; hence, it is rarely affected by external artefacts [44].

4.2. Motivation of using other BCI axillary techniques in EPW control

Wheelchair control using only EEG signals is not always perfect in stopping wheelchair movement [53]. A more reliable channel, such as muscle-assisted signal recorded with either EMG, EOG or EEG, is selected to improve the safety and accuracy of BCW systems. The amplitude of EMG and EOG signals is higher than that of EEG signals, thereby allowing a more accurate control of BCI [80]. BCW systems can be useful for patients who still possess residual muscular mobility. EOG signal data can be collected using the minimum number of electrodes. Hence, the applications of EOG signal data on wheelchair control have been examined in a number of research [36]. Eye blinking and movement signals can be recorded using an EEG device, which is more efficient than taping an EOG electrode over the eyes [38]. Moreover , recording head movement is favourable for wheelchair control according to the health sciences group at the University of Technology Sydney due to its flexibility [100]. In addition ,research on the evolution and assessment of multi-modal HMI has recently been gaining attention [75]. However, multi-input modalities are considered more appropriate for people with a severe degree of disability. These modalities can help them adapt to their disability level [76]. In addition, communication via multi-modal paradigms significantly influences the quality of life of people with impairment by deploying signals to control applications. Available paradigms in multi-modal techniques include EOG, EMG, sucking from a straw, body gesture and EEG-based brain signals [44]. Fig. 12 shows that various modalities are integrated into one HCI scheme.

Multi-modal BCI is a technique that combines various sources of signals to construct a hybrid BCI by considering the advantages of different schemes [10]. In a hybrid BCI scheme, examining the mental activity of multiple types of brain signals and combining brain signals with non-brain signals, such as EOG and EMG [36], are necessary to proficiently execute specific tasks compared with using traditional BCI paradigms [28]. Consequently, a number of studies have reported that combining EMG with EEG signals is affordable, which improves the performance of the hybrid scheme-based BCI [59]. The hybrid scheme-based BCI provides a BCI user with a high degree of usability and a large number of control commands [31]. The hybrid scheme-based BCI aids in the development of a wheelchair control system with multiple degrees of freedom, parallel control [30] and high safety transportation for paralysed patients [34].

4.3. Motivation of using electrical powered wheelchair

Wheelchairs allow stroke survivors to become independent in at least one of their daily activities, i.e. mobility [1,2]. At present, the need for wheelchairs has rapidly increased for paralysed patients and for the elderly due to the aging of the current population [3]. For physically challenged individuals, relying on a push wheelchair is uncomfortable and cannot provide manoeuvrability; therefore, EPWs have been invented for people with disability to conserve energy and increase manoeuvrability [4]. In addition, a large proportion of patients with spinal cord injuries and neuromuscular disorders mainly rely on EPWs to gain mobility [39]. Moreover, healthcare costs from existing healthcare organisations are gradually increasing as baby boomers near the age of retirement over the next few years. EPWs are necessary for such situations [86]. Universal statistical data indicate that roughly 650 million people, which is approximately 10% of the global population, suffer from motor disability, with nearly 7% in need of an electrical wheelchair [79]. According to the Department of Social Welfare statistical data [47], the number of paralysed patients has recently been increasing exponentially in Malaysia. Consequently, electrical wheelchairs are considered useful devices for paralysed patients for them to gain mobility [40].

4.3.1. Using intelligent wheelchairs

The manoeuvrability of mechanical wheelchairs is a challenging task for the elderly and people with disability. Hence, designing an

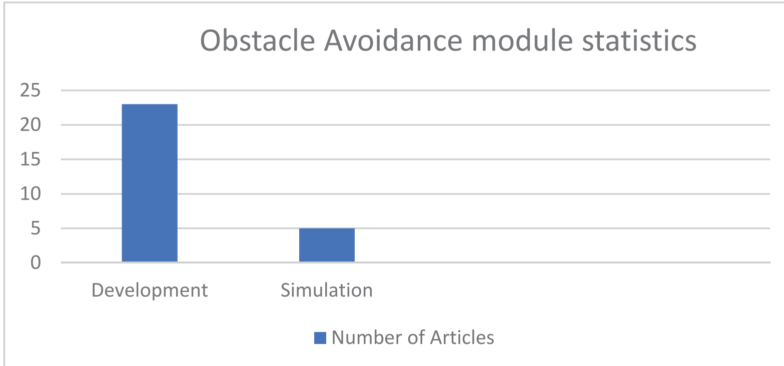

Fig. 13. Number of studies that considered an obstacle avoidance module.

intelligent wheelchair that provides easy manoeuvrability is necessary [5]. To help people with disability perform their daily activities, robotics has been working on intelligent wheelchairs equipped with a smart control unit, environment recognition proximity sensors and actuated motors [6]. Considerable attention has been afforded to the invention of intelligent wheelchairs in the scientific and general communities [7]. The main objective is to help users by decreasing or eliminating the need to drive a motor-powered wheelchair. A wide spectrum of studies on intelligent wheelchair technology have recently been conducted, which aim to adapt this device to individuals with severe mobility problems [9,10].

A number of advanced research in the field of biomedical engineering for the development of assistive devices have also been conducted, including the use of bio-signals, voice and touchscreen as device input to improve the motor ability of paralysed patients [14]. BCW is the appropriate device for completely paralysed patients with a healthy brain to navigate their environment [48].In recent years, intelligent wheelchairs have improved with regard to their attributes, such as low cost and high performance, and navigation components, such as autonomous mobility, obstacle avoidance, safety, flexibility, HMI modalities and adaptation to the degree of disability [64].

4.3.2. Using EPW with a robotic manipulator

Statistical results obtained from studies on people with disability indicate that the movements of the human upper limbs, such as pointing and picking objects, are the most dominant in daily life activities. Therefore, integrating a robotic manipulator into an electric wheelchair can assist the elderly and paralysed patients to interact with their environment. Moreover, several types of robotic manipulators have been developed, including Victoria, Raptor, FRIEND, MANUS and Rancho Golden, to provide mobility assistance [60]. The results acquired from experiments prove the possibility of using and selecting a number of movement commands to drive a wheelchair with a robotic manipulator. In particular, a wheelchair platform integrated with a robotic manipulator can help paralysed patients with low and advanced levels of spinal cord injury [59].

4.3.3. Using EPW integrated with a smart environment

A wide range of assistive devices have recently been presented to improve the quality of life of people with impairment, particularly mobility impairment, to help them become independent in performing their daily activities. Therefore, having an integrated control scheme with multi-modal control interfaces (e.g. speech, stick and EEG) is valuable to control single- or multi-assistive devices (e.g. television, air conditioner and robotic wheelchair) [61]. HCI based on various biological signals are used to control an integrated robotic wheelchair under a smart environment which can allow people with disability to control essential home appliances as well as their EPW [62].

4.3.4. Using EPW with obstacle avoidance

Safety is crucial in intelligent wheelchair navigation systems. However, studies on the wheelchair usability of people with disability have estimated that approximately millions of individuals can utilise these systems with the presence of an autonomous navigation system and an obstacle avoidance module [68]. In the past years, numerous navigation systems with intelligent features for robotic wheelchairs have been utilised [19]. In addition, intelligent features have been developed to minimise possible collision risks during wheelchair navigation. On-board ultrasound sensors dynamically measure proximity towards objects within a particular environment. A sense of dependability and safety can be observed with such systems due to the availability of an obstacle avoidance module [39,51]. Fig. 13 shows the number of available studies that considered an obstacle avoidance module.

4.4. Challenges concerns on BCI techniques

Studies on a wheelchair control-based BCI have motivated scholars and companies to conduct research and develop intelligent wheelchairs that can help people with various mobility problems. However, challenges and limitations have been observed during their research. In the current review, key challenges that have been highlighted and quoted from the literature were classified into groups along with their citations. Thus, readers can refer to these references to see the original proposals and additional discussion regarding such challenges. Invasive and partially invasive BCI techniques remain risky. Therefore, the techniques require medical and surgical interventions, although BCI research has concentrated mostly on non-invasive techniques for monitoring brain activities [23,7]. By contrast, several studies with invasive-based BCI systems have used recording techniques from the local field potential of neuronal events. Potentials placed directly in the cerebral cortex remain impractical for humans and limited to monkeys [82]. In recent years, the key challenge in using non-invasive BCI is the limited bandwidth of communication channels and limitations in the extraction process of robust feature characteristics from signals with poor spatial resolution and minimum signal-to-noise ratio. In particular, controlling and communicating with assistive devices, such as an intelligent wheelchair or a telepresence robot, involve various options for motion command, such as forward, left, right, backward and start/stop [52,57,86,84,75,76,67]. These autonomous control signals are essential for a fast, complex and multi-degree continuous controller of EPWs [31].The control of EPWs using brain signals is the best solution for patients who have completely lost control of their upper and lower limbs and are unable to move on their own.

However, a high-quality EEG device remains expensive at present [47]. Moreover, signals from the human brain are combined with other sets of signals from different sources which may overlay one another in time and space. Hence, signals are typically unstable and may also be affected by artefacts, such as EOG or EMG signals and other biological signals. Furthermore, the users may become anxious when facing an obstacle. In such situation, the recognition of BCI signals may potentially deteriorate [66,19,48,8]. These problems can be reduced by using an efficient signal processing algorithm [40] Using efficient signal processing and machine learning techniques in feature extraction and classification can also improve the accuracy of extracting high-dimensional EEG features [89].Recent applications in the field of EEG-based BCI systems have limitations, such as the lack of complex configuration during EEG measurement that uses a large number of electrodes and the amount of time used for the arrangement and setup of electrodes [73,99]. However, a high-performance EEG device system that does not require an EEG gel should be developed [53].

EEG-based BCI is improving in terms of speed, precision and dependability. However, EEG-based BCI can experience a considerable challenge if an individual is required to directly control a certain device for a long period [51]. Furthermore, an EEG headset also presents considerable challenges, such as its bulkiness and lack of maturity [10]. Individual differences in EEG signals can also affect the stability of a control system, given that the signals are not ideal [9]. Finally, navigating a wheelchair-based BCI control is challenging and risky because a human will use it; thus, the behaviour of the wheelchair should be continuously monitored [20]. A BCI system can pose a threat to the user or to nearby people due to unwanted navigation controls of the wheelchair resulting from using the wrong commands or being unfamiliar with the machine interface. The machine can misunderstand the gesture of the user [39]. Consequently, a number of attempts have been made to build an efficient and flexible wheelchair control system by using hybrid BCI signals. However, these systems still lack efficiency and flexibility [30].

4.2.1. Concerns on P300 signal for EPW control

The effectiveness of using P300 has several limitations, such as when the patient is suffering from a neurological illness, particularly ALS [65]. A P300 system typically has a limited ITR. A number of works have also pointed out that performance may deteriorate after a long period because the P300 brain wave amplitude produced by the rare stimulus is reduced due to familiarisation to personal property [80,21,24,53,21]. Another weakness of these schemes is that the user has to be continuously focused on the mission when the process is synchronous [24]. Users may become exhausted or suffer from sore eyes if exposed to a visual stimulus for a long time. Therefore, such type of brain signals is unsuitable and ineffective for wheelchair control. In addition, people with disability easily become exhausted [26,87,46,88]. Moreover, the use of this synchronous procedure does not allow the user to change the track or path of his/her wheelchair as it travels towards its target [31]. The EEG-based P300 signal is considered inefficient for developing high-response stop commands due to their low response speed [28,20]. Another limitation of using P300 signal is the appearance of target visual patterns, and, thus, users have to wait for the appearance of the preferred target. Furthermore, attention at a specific time to the special visual patterns is decided by the user based on the occurrence of visual stimuli at a certain interval [84].

4.4.2. Concerns on SSVEP signal for EPW control

Numerous methods have been used to explore the research field and resolve the limitations of EEG particularly in obtaining the maximum amplitude of SSVEP, which are inadequately uniform [94,96,91,12]. However, small square blinking stimuli can influence exhaustion if BCI is used for a long period. These stimuli can result in epileptic annexations. Similarly, EEG-based SSVEP relies on certain motor movement control, which is ineffective for patients with severe motor disabilities. Moreover, a limited number of commands exists due to harmonic frequencies [45,13,78,46,80,6]. Finally, studies have shown that visual exhaustion is increased with low-frequency values, whereas high-frequency values decrease recognition accuracy [59,53].

4.4.3. Concerns on hybrid BCI signals

HMI potentially dominates the efficiency of assistive devices for paralysed patients [8]. Hence, most innovative HCI approaches are merely established. Recently, a few works have been conducted to combine these techniques with a multi-modal interface for a group of people with disability [76]. The use of hybrid systems that mix exogenous and endogenous signals appears to be a trend. However, the use of two exogenous signals remains uncommon. The lack of such combination of exogenous systems is due to the failure of executing parallel tasks, given that both tasks require selective attention and the user can attend to only one stimulus [80]. In addition, this model can effectively offer equal speed control and direction commands by using a hybrid MI and P300 BCI scheme. However, this model may not be an excellent and optimal choice in terms of influencing the multi-degree control of a wheelchair. This hybrid scheme does not allow the user to simultaneously regulate speed and direction, for example, slackening and making a turnover [30].

4.4.4. Concerns on motor imagery signal for EPW control

In the case of using the MI model, a substantial amount of time and work are essential to train the user. In addition, the accuracy of the MI model is less than those of other models, such as SSVEP and P300. Furthermore, users with severe mental disability cannot control the system appropriately [30,9,78,46,26,53,65,80]. Many MI-based devices are expensive and massive due to their dependency on the complex detecting scheme of EEG devices [35]. By contrast, for patients with an impaired motor cortex due to a brain stroke, using the MI signal will be difficult. Therefore, paralysed patients rely on non-MI signals, which are more beneficial and applicable to provide choices for the control platform. The user must possess appropriate emotions and attentiveness for an optimal device control. Finally, no clear rule on an ideal attention scheme is available, which can be applied to wheelchair control platforms [3].

4.5. Challenges concerns on classification accuracy and system response

A fast decision making is required in a wheelchair control system-based BCI signal because of the amplified communication in the BCI channel [52]. However, achieving high classification accuracy is challenging in a BCI-based system due to the complexity of brain signals [48].In addition ,Feature vectors must be given additional attention during the classification phase of a brain signal. Hence, the selection of excellent feature extraction techniques exerts a positive impact and considered essential for achieving an accurate pattern classifier [66]. Therefore, rapidly and efficiently extracting features from various signals are necessary to realise BCI systems [14]. In addition, studies have indicated that the prototype of wheelchair-based BCI systems exhibits limitations in performing the stop command because of the inefficient classification accuracy of the idle and stop states. Therefore, these systems remain unsafe and impractical for real wheelchairs [73]. A stop

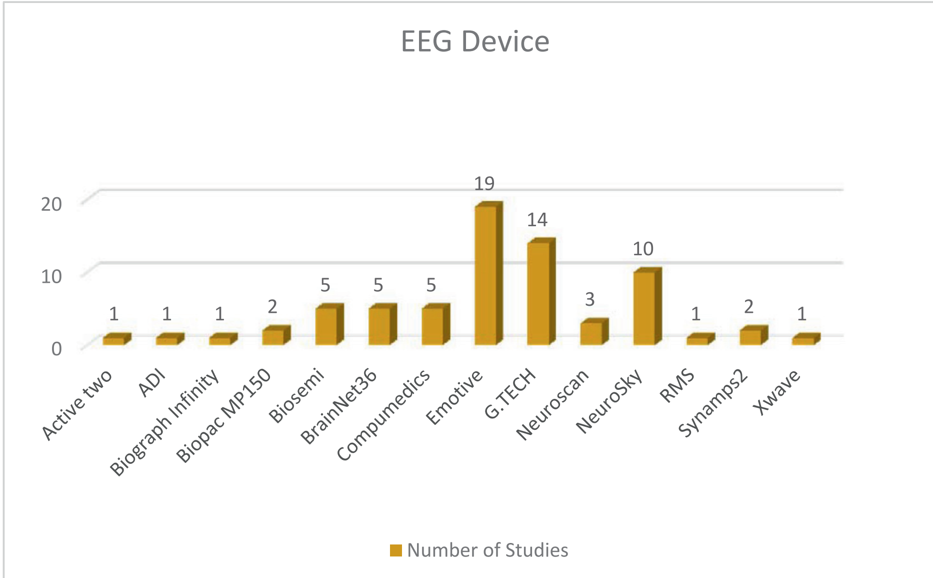

Fig. 14. BCI works conducted based on EEG device type.

command is vital in a BCI-based real-time wheelchair control system. However, designing an accurate and fast-response stop command is challenging [31,28]. Furthermore, the weakness of existing smart wheelchair systems is the unavailability of fast-response stop/go control commands, which must be accomplished by an asynchronous brain signal. Therefore, a smart wheelchair can only work in synchronous mode without an asynchronous brain signal. That is, the wheelchair cannot be intentionally stopped by the user throughout its operation and cannot be triggered using EEG [22].

4.6. Challenge concerns on navigation safety and reliability of BCW

The financial costs and reliability limitations of BCI-based wheelchair control systems are a result of the numerous models of smart wheelchairs that have been developed using high-tech assistive solutions, but are not yet marketed [98,60]. In such situations, for example, placing the user in an unsafe condition, the wheelchair control system must be sensitive to checking if the extracted commands from the BCI system is accurate and will place the user in a safe zone [6]. People with disability and the elderly will find steering and driving a wheelchair with electrical and mechanical schemes challenging. Therefore, various technologies that aid people with disability have been recently proposed [5]. Moreover, In complex and real environments, driving a wheelchair safely is essential and recommended for people with disability due to the requirement of sending commands on time [51]. In addition, the safety criteria in designing a wheelchair system for people with a physical impairment must be given more importance [4].Furthermore, dependable navigation control systems are required for the wheelchair user to comfortably and freely navigate around and ensure his/her safety [78]. Another challenge is the adaptation of pathways is time-consuming and slightly difficult for a wheelchair navigation system. However, this process must be achieved once the configuration of the surrounding has been changed. In particular, certain problems may occur, such as a pet blocking the predefined pathway (in case the user owns a pet) [2]. However, the estimation of distances appears more difficult in a simulated environment than in a real one. Therefore, the advantages of position and perspective tracking may be insignificant compared with that of a real environment [78].Moreover, navigating through an ideal path is considered impossible by using an intelligent wheelchair due to the recognition errors of the navigation commands of the system. For example, the user not proficiently controlling the switch of the control commands and system time delay in response to the control commands [9].

4.7. Recommendations to developers/researchers

To depict the complete scenario in the research scope, the important recommendations that address the challenges of researchers, developers and health and federation authorities/organisations are summarised, facilitating the construction of wheelchairs based on BCI for paralysed patients.

These recommendations regarding EEG devices and signals, wheelchair navigation systems, use of hybrid signals in wheelchair control and samples that will be used in BCI experiments are for developers and researchers.

4.7.1. Concerns on EEG device

Attention must be given to the development of EEG, particularly in obtaining an affordable and appropriate EEG device. Hence, high-quality EEG devices remain expensive at present [15]. Moreover, numerous up-to-date enhancements must be completed. For example, present systems consider the degree of attention level to control a device, which is slightly limited to a number of control commands. Furthermore, studies must be conducted on the events and auditory stimuli of the human brain. The P300 evoked signal can be obtained using eye stimuli, which are mapped onto the brain signal. At present, a number of games use EEG-based MI for control; using a similar method and a portable scheme is probable [97]. Fig. 14 shows the numbers and types of EEG devices used in research based on the literature survey.

4.7.2. Concerns on wheelchair navigation

A wheelchair navigation system is commonly consistent despite the friction and bearing between the ground surface and the wheels of the wheelchair. However, additional improvements must be provided for a wheelchair to execute advanced tasks, such as when the wheelchair is not located in the corridor area and dynamic obstacles in a free and unknown space. In such cases, a complete wheelchair control system with main navigation components, such as mapping, localisation, path planning and obstacle avoidance, is highly recommended [6].

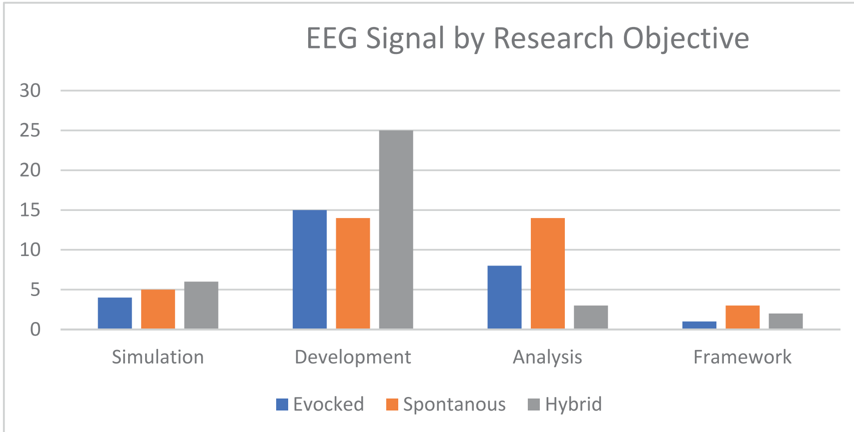

Fig. 15. Type of brain signal based on research objective.

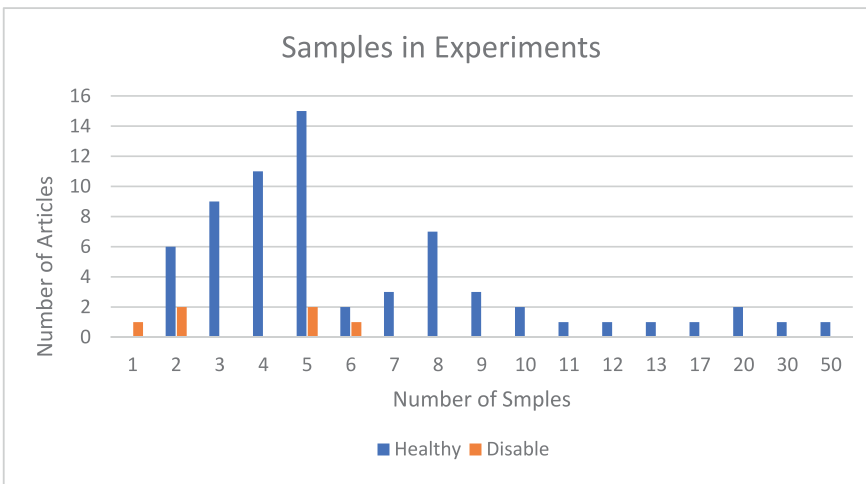

Fig. 16. Sample participants in the EEG experiments.

4.7.3. *Concerns on using hybrid BCI signal for EPW control*

An EEG headset has limited power capacity; therefore, using the headset with another input device is highly recommended [10]. In addition, a cervical gesture mechanism is more accurate compared with an evoked SSVEP brain signal. However, using the mechanism may result in a negative outcome due to ordinary head movements. Therefore, using more than a single-input device support on/off wheelchair control commands is highly recommended [59]. Hence, additional studies must be conducted to examine hybrid BCI signals [89]. Fig. 15 shows the type of brain signal based on the statistical result of our systematic review.

4.7.4. *Concerns on samples*

The large number of participants used with the previous experience in BCI systems and subjects that satisfied certain criteria before handling BCW should be noted. However, the present study aims to show that a proposed device is capable of running BCW with adequate performance and also intends to determine systems that any user can manage, and not just by users with excellent skills [80]. Therefore, increasing the total number of participants in the studies is recommended. Moreover, paralysed patients have different responses compared with healthy individuals. Therefore, experimental studies must be conducted with people with disability who actually need wheelchairs [65]. Furthermore, increasing attention towards the differences in brain signal patterns across various people is highly recommended [89]. Fig. 16 presents the statistical results based on the sample number and type used in the systematic review due to such an important area of study.

4.8. *Recommendations to federation and health authorities/governments*

Population aging is gradually becoming a challenge in many nations worldwide as the quality of healthcare and living standard improve. In addition, a serious demand for a smart life exists amongst young people as attention towards supporting the elderly increases. Brain signals can be used to help the elderly who are suffering from lower limb problems to adapt to their daily lives. Finally, the innovation of smart wheelchairs for the modern generation must be considered [43]. Fig. 17 shows the number of studies on wheelchair control system-based BCI that was supported by grants from various countries worldwide.

5. Limitations

The first and most prominent limitation in this literature review is the variety of databases used, although the articles are obtained from trusted databases. Secondly, allowing a timeline in a survey is a challenging task due to the rapid progress in this emerging field of study. Thirdly, a number of researchers believe that the

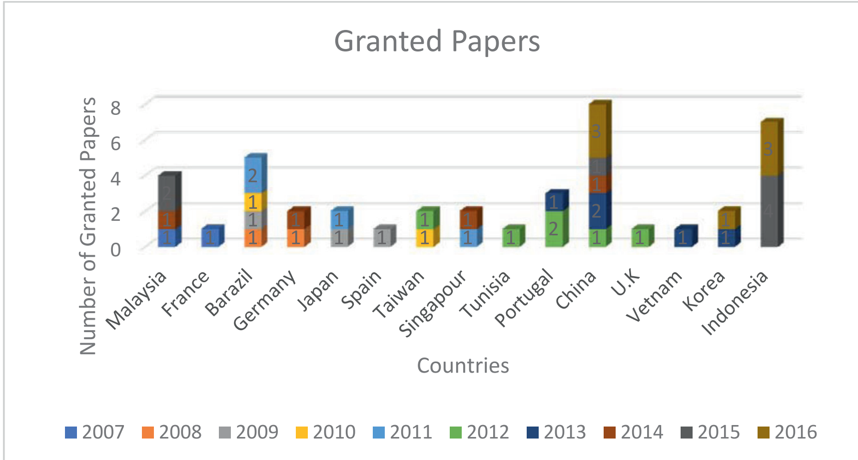

Fig. 17. Number of studies supported by grants distributed by countries.

usability of BCI research and its positive impact on real life cannot be measured with snapshots of research activities in this relevant biomedical engineering field. Hence, this type of research reflects its tendency and response to the hot topics in this emerging field.

6. Conclusions

Trends in the use of BCI and its applications to EPW control techniques are currently emerging. Studies in this research area are being conducted through related reports. However, challenges in using BCI remain unresolved. Therefore, formulating better BCI in such an evolving field is important. This review aims to classify and analyse relevant studies by examining a number of works on wheelchair control-based BCI techniques. These works are categorised into five classes: development of EPW control-based BCI, frameworks of EPW control-based BCI, simulation, reviews or surveys of EPW control-based BCI and analysis of brain signals used in EPW control. An intensive analysis of the articles facilitates the categorising and describing of motivations, addressing challenges and recommending solutions for BCI and its applications to wheelchair control. The results indicate the types of available brain signals used in wheelchair control applications and the current gaps in the use of such technology. Researchers have mentioned factors that motivated them to focus on a particular field of study. These issues have been organised and grouped into topics that consist of similar issues, such as HRI, bio-signals and intelligent wheelchair. Moreover, the researchers have identified issues on and provided recommendations for EEG device technology, type and number of samples used in the experiments, wheelchair navigation and the utilisation of hybrid BCI techniques to researchers, developers and organisations. These recommendations may help researchers/developers and organisations address challenges that they may encounter with using BCI signals and their applications to electrical wheelchair control systems, such as BCI techniques and intelligent wheelchair control issues. An insight is provided in the current systematic review. Furthermore, a summary of the recently published studies in wheelchair control-based BCI techniques is presented. This study may serve as a reference for researchers in the current field of study and for individuals who will continue to adopt these useful techniques.

Conflict of interest

None

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.cmpb.2018.06.012.

References

[1] W. Caesarendra, M. Ariyanto, S.U. Lexon, E.D. Pasmanasari, C.R. Chang, J.D. Setiawan, in: EEG based pattern recognition method for classification of four mental tasking Preliminary study for stroke survivors in Indonesia, International Conference on Automation, Cognitive Science, Optics, Micro Electro-Mechanical System, and Information Technology (ICACOMIT) (2015) 1–15.
[2] J. Li, J. Liang, Q. Zhao, J. Li, K. Hong, L. Zhang, Design of assistive wheelchair system directly steered by human thoughts, Int. J. Neur. Syst. 23 (3) (2013) 1–12.
[3] R. Tomari, R.R.A. Hassan, W.N.W. Zakaria, R. Ngadengon, Analysis of optimal brainwave concentration model for wheelchair input interface, Proc. Comput. Sci. 76 (Iris) (2015) 336–341.
[4] G.N. Jayabhavani, N.R. Raajan, R. Rubini, Brain mobile interfacing (BMI) system embedded with wheelchair, in: Proceedings of the 2013 IEEE Information and Communication Technologies, ICT 2013, 2013, pp. 1129–1133. no. Ict.
[5] I.A. Mirza, et al., Mind-controlled wheelchair using an EEG headset and arduino microcontroller, in: Proceedings of the International Conference on Technology for Sustainable Development, ICTSD 2015, 2015, pp. 2–6.
[6] A. Widyotriatmo, Suprijanto, S. Andronicus, A collaborative control of brain computer interface and robotic wheelchair, in: Proceedings of the 10th Asian Control Conference on Emerging Control Techniques for a Sustainable World, ASCC 2015, 2015.
[7] B.M. Faria, L.P. Reis, N. Lau, Cerebral Palsy EEG signals classification: facial expressions and thoughts for driving an intelligent wheelchair, in: Proceedings of the IEEE International Conference on Data Mining Workshops ICDMW 2012, 2012, pp. 33–40.
[8] M.B. Reaz, M.S. Hussain, M.I. Ibrahimy, F. Mohd-Yasin, EEG signal analysis and characterization for the aid of disabled people, Model. Med. Biol. Vii 12 (2007) 287–294\r332.
[9] M. Li, Y. Zhang, H. Zhang, H.S. Hu, An EEG based control system for intelligent wheelchair, Appl. Mech. Mater. 300–301 (2013) 1540–1545.
[10] F. Ben Taher, N. Ben Amor, M. Jallouli, A multimodal wheelchair control system based on EEG signals and eye tracking fusion, in: Proceedings of the INISTA 2015 International Symposium on Innovations in Intelligent Systems and Applications, 2015.
[11] C. Mandel, T. Lüth, T. Laue, T. Röfer, A. Gräser, B. Krieg-Brückner, Navigating a smart wheelchair with a brain-computer interface interpreting steady-state visual evoked potentials, in: Proceedings of the 2009 IEEE/RSJ International Conference on Intelligent Robots and Systems 2009, 2009, pp. 1118–1125.
[12] A. Turnip, M.A. Suhendra, W.S. Mada Sanjaya, Brain-controlled wheelchair based EEG-SSVEP signals classified by nonlinear adaptive filter, in: Proceedings of the IEEE International Conference on Rehabilitation Robotics, 2015, pp. 905–908. vol. 2015–Septe.
[13] S.M.T. Müller, T.F. Bastos-Filho, M. Sarcinelli-Filho, Using a SSVEP-BCI to command a robotic wheelchair, in: 2011 IEEE International Symposium on Industrial Electronics, 2011, pp. 957–962.
[14] Y. Xie, X. Li, A brain controlled wheelchair based on common spatial pattern, in: Proceedings of the Fourth International Symposium bioelectronic Bioinformatics, ISBB 2015, 2015, pp. 19–22.
[15] R.H. Abiyev, N. Akkaya, E. Aytac, A. Artificial, Brain-computer interface for control of wheelchair using fuzzy neural networks, Biomed Res. Int. 2016 (2016) 1–9.

[16] S.M.T. Müller, W.C. Celeste, T.F. Bastos-Filho, M. Sarcinelli-Filho, Brain-computer interface based on visual evoked potentials to command autonomous robotic wheelchair, J. Med. Biol. Eng. 30 (6) (2010) 407–416.
[17] P.F. Diez, et al., Commanding a robotic wheelchair with a high-frequency steady-state visual evoked potential based brain-computer interface, Med. Eng. Phys. 35 (8) (2013) 1155–1164.
[18] Z. Li, S. Zhao, C.Y. Su, C. Yang, J. Duan, X. Zhao, Human cooperative wheelchair with brain machine interaction based on shared control strategy, IEEE/ASME Trans. Mechatron. PP (99) (2016) 1–11.
[19] J. Duan, Z. Li, C. Yang, P. Xu, Shared control of a brain-actuated intelligent wheelchair, Proc. World Congr. Intell. Control Autom. 2015 (2015) 341–346 vol.March, no. March.
[20] B.-G. Shin, T. Kim, S. Jo, Non-invasive brain signal interface for a wheelchair navigation, in: Proceedings of the 2010 International Conference on Control, Automation, and Systems (ICCAS), 2010, pp. 2257–2260.
[21] I. Iturrate, J.M. Antelis, A. Kübler, J. Minguez, A noninvasive brain-actuated wheelchair based on a P300 neurophysiological protocol and automated navigation, IEEE Trans. Robot. 25 (3) (2009) 614–627.
[22] S. He, et al., A P300-based threshold-free brain switch and its application in wheelchair control, IEEE Trans. Neural Syst. Rehabil. Eng. 25 (6) (2017) 715–725.
[23] V. Venkatasubramanian, R.K. Balaji, Non invasive brain computer interface for movement control, in: Proceedings of the World Congress on Engineering and Computer Science, WCECS 2009, vol. I, 2009, pp. 275–279. Vols I Ii.
[24] I. Iturrate, J. Antelis, J. Minguez, Synchronous EEG brain-actuated wheelchair with automated navigation, in: Proceedings of the IEEE International Conference on Robotics and Automation, 2009, pp. 2318–2325.
[25] A.C. Lopes, G. Pires, U. Nunes, Assisted navigation for a brain-actuated intelligent wheelchair, Robot. Auton. Syst. 61 (3) (2013) 245–258.
[26] K.-T. Kim, H.-I. Suk, S.-W. Lee, Commanding a brain-controlled wheelchair using steady-state somatosensory evoked potentials, IEEE Trans. Neural Syst. Rehabil. Eng. X (X) (2016) 1–1.
[27] K.T. Kim, S.W. Lee, Towards an EEG-based intelligent wheelchair driving system with vibro-tactile stimuli, in: Proceedings of the 2016 IEEE International Conference on Systems, Man, and Cybernetics SMC 2016, 2017, pp. 2382–2385.
[28] Y. Li, J. Pan, F. Wang, Z. Yu, A hybrid BCI system combining P300 and SSVEP and its application to wheelchair control, IEEE Trans. Biomed. Eng. 60 (11) (2013) 3156–3166.
[29] L. Cao, J. Li, H. Ji, C. Jiang, A hybrid brain computer interface system based on the neurophysiological protocol and brain-actuated switch for wheelchair control, J. Neurosci. Methods 229 (2014) 33–43.
[30] J. LI, et al., Evaluation and application of a hybrid brain computer interface for real wheelchair parallel control with multi-degree of freedom, Int. J. Neural Syst. 24 (4) (2014) 1450014.
[31] J. Long, Y. Li, H. Wang, T. Yu, J. Pan, F. Li, A hybrid brain computer interface to control the direction and speed of a simulated or real wheelchair, IEEE Trans. Neural Syst. Rehabil. Eng. 20 (5) (2012) 720–729.
[32] D.C. Cavalieri, R.L. Silva, A versatile robotic wheelchair commanded by brain signals or eye blinks, in: Proceedings of the First International Conference on Biomedical Electronics and Devices, 2008, pp. 62–67.
[33] K. Choi, A. Cichocki, Control of a wheelchair by motor imagery in real time, in: Proceedings of the Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 5326, LNCS, 2008, pp. 330–337.
[34] Z. Li, S. Lei, C.-Y. Su, G. Li, Hybrid brain/muscle-actuated control of an intelligent wheelchair, in: Proceedings of the IEEE International Conference on Robotics and Biomimetics, (ROBIO), 2013, pp. 19–25.
[35] L. Jiang, E. Tham, M. Yeo, Z. Wang, B. Jiang, Motor imagery controlled wheelchair system, in: Proceedings of the 2014 Ninth IEEE Industrial Electronics and Applications, ICIEA 2014, 2014, pp. 532–535.
[36] H. Wang, Y. Li, J. Long, T. Yu, Z. Gu, An asynchronous wheelchair control by hybrid EEG-EOG brain-computer interface, Cogn. Neurodyn. 8 (5) (2014) 399–409.
[37] H.T. Nguyen, N. Trung, V. Toi, V.S. Tran, An autoregressive neural network for recognition of eye commands in an EEG-controlled wheelchair, in: Proceedings of the International Conference on Advanced Technologies for Communications, 2013, pp. 333–338.
[38] F. Aziz, H. Arof, N. Mokhtar, M. Mubin, HMM based automated wheelchair navigation using EOG traces in EEG, J. Neural Eng. 11 (5) (2014).
[39] N. Shinde, K. George, Brain-controlled driving aid for electric wheelchairs, in: Proceedings of the BSN 2016–13th Body Sensor Networks Conference, 2016, pp. 115–118.
[40] S.K. Swee, L.Z. You, Fast fourier analysis and EEG classification brainwave controlled wheelchair, in: Proceedings of the 2016 2nd International Conference on Control Science and Systems Engineering, 2016, pp. 20–23.
[41] J.-S.L.J.-S. Lin, K.-C.C.K.-C. Chen, W.-C.Y.W.-C. Yang, EEG and eye-blinking signals through a brain-computer interface based control for electric wheelchairs with wireless scheme, in: Proceedings of the 4th International Conference on New Trends Information Science and Service Science, 2010, 2010, pp. 731–734.
[42] J.S. Lin, W.C. Yang, Wireless brain-computer interface for electric wheelchairs with EEG and eye-blinking signals, Int. J. Innov. Comput. Inf. Control 8 (9) (2012) 6011–6024.
[43] Z. Su, X. Xu, J. Ding, Intelligent wheelchair control system based on BCI and the image display of EEG, in: IEEE Advanced Information Management, Communicates, Electronic and Automation Control Conference (IMCEC), 2016, pp. 1350–1354.
[44] T. Bastos-Filho, A. Ferreira, D. Cavalieri, R. Silva, S. Muller, E. Perez, Multi–modal interface for communication operated by eye blinks, eye movements, head movements, blowing/sucking and brain waves, in: Proceedings of the ISSNIP Biosignals Biorobotics Conference on BRC, 2013.
[45] T.F. Bastos, S.M.T. Muller, A.B. Benevides, M. Sarcinelli-Filho, Robotic wheelchair commanded by SSVEP, motor imagery and word generation, in: Proceedings of the Annual International Conference on IEEE Engineering in Medicine and Biology Society, EMBS, 2011, pp. 4753–4756.
[46] D. Puanhvuan, Y. Wongsawat, Semi-Automatic P300-Based Brain-Controlled Wheelchair, in: ICME International Conference on Complex Medical Engineering (CME), 2012, pp. 455–460.
[47] S.K. Swee, L.Z. You, and K.T. Kiang, "Brainwave controlled electrical wheelchair", vol. 5, pp. 3–6, 2016.
[48] I.H. Parmonangan, J. Santoso, W. Budiharto, and A.A. Santoso Gunawan, "Fast brain control systems for electric wheelchair using support vector machine", vol. 10011, p. 100111N, 2016.
[49] R. Ramli, H. Arof, F. Ibrahim, N. Mokhtar, M.Y. Idna, Using finite state machine and a hybrid of EEG signal and EOG artifacts for an asynchronous wheelchair navigation, Expert Syst. Appl. (2014).
[50] T.L. Fan, C.S. Ng, J.Q. Ng, S.Y. Goh, A brain-computer interface with intelligent distributed controller for wheelchair, IFMBE Proc. 21 (1) (2008) 641–644 IFMBE.
[51] T. Carlson, R. Leeb, R. Chavarriaga, R. Mill, The Birth of the Brain–Controlled Wheelchair, in: Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems, 2012, pp. 5444–5445.
[52] J.D.R. Millán, F. Galán, D. Vanhooydonck, E. Lew, J. Philips, M. Nuttin, Asynchronous non-invasive brain-actuated control of an intelligent wheelchair, in: Proceedings of the IEEE 31st Annual International Conference on Engineering in Medicine and Biology Society Engineering in Future in Biomedical Engineering EMBC 2009, 2009, pp. 3361–3364.
[53] K. Choi, Control of a vehicle with EEG signals in real-time and system evaluation, Eur. J. Appl. Physiol. 112 (2) (2012) 755–766.
[54] Z. Bahri, S. Abdulaal, M. Buallay, Sub-band-power-based efficient brain computer interface for wheelchair control, in: Proceedings of the World Symposium on Computer Applications & Research (WSCAR), 2014, pp. 1–5.
[55] G. Reshmi, A. Amal, Design of a BCI system for piloting a wheelchair using five class MI Based EEG, in: Proceedings of the Third International Conference on Advanced Computing and Communication ICACC 2013, 2013, pp. 25–28.
[56] K.-T. Kim, T. Carlson, S.-W. Lee, Design of a robotic wheelchair with a motor imagery based brain-computer interface, in: Proceedings of the 2013 International Winter Working Brain-Computer Interface, 2013, pp. 46–48.
[57] V. Gandhi, G. Prasad, D. Coyle, L. Behera, T.M. Mcginnity, EEG-based mobile robot control through an adaptive brain-robot interface, IEEE Transactions on Systems, Man, and Cybernetics: Systems 9 (44) (2014) 1–8.
[58] E.J. Rechy-Ramirez, H. Hu, K. McDonald-Maier, Head movements based control of an intelligent wheelchair in an indoor environment, in: Proceedings of the 2012 IEEE International Conference on Robotics Biomimetics, 2012, pp. 1464–1469.
[59] F. Achic, J. Montero, C. Penaloza, F. Cuellar, Hybrid BCI system to operate an electric wheelchair and a robotic arm for navigation and manipulation tasks, in: Proceedings of the IEEE Working Advanced Robotics and its Social Impacts , ARSO, vol. 2016–Novem, 2016, pp. 249–254.
[60] C. Naijian, H. Xiangdong, W. Yantao, C. Xinglai, C. Hui, Coordination control strategy between human vision and wheelchair manipulator based on BCI, in: Proceedings of the 2016 IEEE 11th Conference on Industrial Electronics and Applications, 2016, pp. 1872–1875.
[61] U. Qidwai, E.M. Hassan, R.M.A. Halabi, M. Shakir, Device interface for people with mobility impairment, in: Proceedings of the 2013 Seventh IEEE GCC Conference Exhibition GCC 2013, 2013, pp. 177–181.
[62] R.J.M.G. Tello, A.L.C. Bissoli, F. Ferrara, S. Müller, A. Ferreira, T.F. Bastos-Filho, Development of a human machine interface for control of robotic wheelchair and smart environment, IFAC-PapersOnLine 48 (19) (2015) 136–141.
[63] S.-Y. Cho, a.P. Winod, K.W.E. Cheng, Towards a brain-computer interface based control for next generation electric wheelchairs, in: Proceedings of the 2009 Third International Conference on Power Electronic System Appliances, 2009, pp. 1–5.
[64] F. Ben Taher, N. Ben Amor, M. Jallouli, EEG control of an electric wheelchair for disabled persons, in: Proceedings of the 2013 International Conference on Individual Collective Behaviour Robotics, ICBR 2013, 2013, pp. 27–32.
[65] A. Kodi, D. Kumar, D. Coyle, D. Kodali, EEG-controlled wheelchair for als patients, in: International Conference on Communication Systems and Network Technologies, 2013, pp. 879–883.
[66] M. Anousouya Devi, R. Sharmila, V. Saranya, Hybrid brain computer interface in wheelchair using voice recognition sensors, in: Proceedings of the 2014 International Conference on Computer Communications Informatics Ushering Technology Tomorrow, Today, ICCCI 2014, 2014, pp. 1–5.
[67] D. Huang, K. Qian, D.-Y. Fei, W. Jia, X. Chen, O. Bai, Electroencephalography (EEG)-based brain-computer interface (BCI): A 2-D virtual wheelchair control based on event-related desynchronization/synchronization and state control, IEEE Trans. Neural Syst. Rehabil. Eng. 20 (3) (2012) 379–388.
[68] W. Jia, D. Huang, O. Bai, H. Pu, X. Luo, X. Chen, Reliable planning and execution of a human-robot cooperative system based on noninvasive brain–computer interface with uncertainty, in: Proceedings of the IEEE International Conference on Intelligent Robots and Systems, 2012, pp. 3798–3805.

[69] F. Galán, et al., A brain-actuated wheelchair: Asynchronous and non-invasive Brain-computer interfaces for continuous control of robots, Clin. Neurophysiol. 119 (9) (2008) 2159–2169.
[70] by R.-M. Hjorungdal, F. Sanfilippo, O.L. Osen, A. Rutle, R.T. Bye, A game-based learning framework for controlling brain-actuated wheelchairs, in: Thorsten Claus, Frank Herrmann, Michael Manitz, Oliver Rose (Eds.), ECMS 2016 Proceedings, vol. 2, 2016, pp. 554–563. byno. Cd.
[71] X. Perrin, R. Chavarriaga, F. Colas, R. Siegwart, R. Millán, Brain-coupled interaction for semi-autonomous navigation of an assistive robot, Rob. Auton. Syst. 58 (12) (2010) 1246–1255.
[72] G.G. Gentiletti, J.G. Gebhart, R.C. Acevedo, O. Yáñez-Suárez, V. Medina-Bañuelos, Command of a simulated wheelchair on a virtual environment using a brain-computer interface, IRBM 30 (5–6) (2009) 218–225.
[73] W.A. Kaysa, S. Suprijanto, A. Widyotriatmo, Design of Brain-computer interface platform for semi real-time commanding electrical wheelchair simulator movement, in: Proceedings of the Third International Conference Instrumentation, Control Automation ICA 2013, 2013, pp. 39–44.
[74] F.R. Martins, ScienceDirect multimodal system for training at distance in a virtual or augmented reality multimodal system for training at distance in a virtual or augmented reality system distance in or environment multimodal system for for training training distance, IFAC-PapersOnLine vol. 49 (30) (2016) 156–160.
[75] H.A. Lamti, M.M. Ben Khelifa, P. Gorce, A.M. Alimi, The use of brain and thought in service of handicap assistance: wheelchair navigation, in: Proceedings of the 2013 International Conference on Individual Collection Behaviour Robotics, ICBR 2013, 2013, pp. 80–85.
[76] H.A. Lamti, M.M. Ben Khelifa, P. Gorce, A.M. Alimi, The command of a wheelchair using thoughts and gaze, in: Proceedings of the Mediterranean Electro technical Conference on MELECON, 2012, pp. 161–166.
[77] G. Valsan, B. Grychtol, H. Lakany, B.A. Conway, The Strathclyde brain computer interface, in: Proceedings of the 31st Annual International Conference on IEEE Engineering in Medicine and Biology Society Future in Biomedical Engineering, EMBC 2009, 2009, pp. 606–609.
[78] T. Kaufmann, A. Herweg, A. Kübler, Toward brain-computer interface based wheelchair control utilizing tactually-evoked event-related potentials, J. Neuroeng. Rehabil. 11 (1) (2014) 1–17.
[79] H.A. Lamti, P. Gorce, M.M. Ben Khelifa, A.M. Alimi, When mental fatigue maybe characterized by Event Related Potential (P300) during virtual wheelchair navigation, Comput. Methods Biomech. Biomed. Engin. 19 (16) (2016) 1749–1759.
[80] Á. Fernández-Rodríguez, F. Velasco-Álvarez, R. Ron-Angevin, Review of real brain-controlled wheelchairs, J Neural Eng. 13 (6) (2016) 061001.
[81] A.B. Benevides, T.F. Bastos, M. Sarcinelli Filho, Proposal of brain-computer interface architecture to command a robotic wheelchair, in: Proceedings of the IEEE International Symposium on Industrial Electronics, ISIE 2011, 2011, pp. 2249–2254.
[82] M. Carra, A. Balbinot, Evaluation of Sensorimotor Rhythms to Control a Wheelchair, in: ISSNIP Biosignals and Biorobotics Conference: Biosignals and Robotics for Better and Safer Living (BRC), 2013, pp. 3–6.
[83] A. Ferreira, T.F. Bastos, M. Sarcinelli, J.L.M. Sanchez, J.C.G. Garcia, M.M. Quintas, Evaluation of PSD components and AAR parameters as input features for a SVM classifier applied to a robotic wheelchair, In terface (2009) 7–12 466.
[84] G. Pires, U. Nunes, A brain computer interface methodology based on a visual P300 paradigm, in: Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems IROS 2009, 2009, pp. 4193–4198.
[85] T.A. Izzuddin, M.A. Ariffin, Z.H. Bohari, R. Ghazali, M.H. Jali, Movement intention detection using neural network for quadriplegic assistive machine, in: Proceedings of the 5th IEEE International Conference on Control System Computer Eng. ICCSCE 2015, 2016, pp. 275–280. no. November.
[86] K. Kaneswaran, K. Arshak, E. Burke, J. Condron, Towards a Brain controlled assistive technology for powered mobility, in: Proceedings of the 2010 Annual International Conference on IEEE Engineering in Medicine and Biology Society EMBC'10, 2010, pp. 4176–4180.
[87] R. Chai, S.H. Ling, G.P. Hunter, Y. Tran, H.T. Nguyen, Brain-computer interface classifier for wheelchair commands using neural network with fuzzy particle swarm optimization, IEEE J. Biomed. Heal. Informatics 18 (5) (2014) 1614–1624.
[88] R. Chai, S.H. Ling, G.P. Hunter, H.T. Nguyen, Mental non-motor imagery tasks classifications of brain computer interface for wheelchair commands using genetic algorithm-based neural network, in: Proceedings of the International Joint Conference on Neural Networks, 2012, pp. 10–15.
[89] R. Chai, S.H. Ling, G.P. Hunter, H.T. Nguyen, Toward fewer EEG channels and better feature extractor of non-motor imagery mental tasks classification for a wheelchair thought controller, in: Proceedings of the International Conference on IEEE Engineering in Medicine and Biology Society EMBS, 2012, pp. 5266–5269.
[90] M. Turnip, et al., An application of online ANFIS classifier for wheelchair based brain computer interface, in: Proceedings of the 2015 International Conference on Automation, Cognitive Science, Optics, Micro Electro-Mechanical System, and Information Technology, ICACOMIT 2015, 2016, pp. 134–137.
[91] A. Turnip, D. Soetraprawata, M. Turnip, E. Joelianto, EEG-based brain-controlled wheelchair with four different stimuli frequencies, Internet work. Indones. J. 8 (1) (2016) 65–69.
[92] A. Turnip, A.I. Simbolon, M.F. Amri, M.A. Suhendra, Utilization of EEG-SSVEP method and ANFIS classifier for controlling electronic wheelchair, in: Proceedings of the 2015 International Conference on Technology, Informatics, Management, Engineering, and Environment TIME-E 2015, 2016, pp. 143–146.
[93] E. Abdalsalam M., M.Z. Yusoff, N. Kamel, A. Malik, M. Meselhy, Mental task motor imagery classifications for noninvasive brain computer interface, in: Proceedings of the 2014 5th International Conference on Advances in Intelligent Systems Technological Convergence for Sustainable Future ICIAS 2014, 2014.
[94] A. Turnip, M.I. Rizgyawan, K.D. Esti, S. Yanyoan, E. Mulyana, Real time classification of SSVEP brain activity with adaptive feedforward neural networks, in: Proceedings of the Third International Conference on Information Technology, Computer and Electrical Engineering 2016, 2017, pp. 1–5.
[95] C.R. Hema, M.P. Paulraj, S. Yaacob, A.H. Adom, R. Nagarajan, Single trial motor imagery classification for a four state brain machine interface, in: Proceedings of the 5th International Colloquium Signal Process. Its Applications, CSPA 2009, 2009, pp. 39–41.
[96] A. Turnip, D. Soetraprawata, T.A. Tamba, EEG-SSVEP signals extraction with nonlinear adaptive filter for brain-controlled wheelchair, in: Proceedings of the 15th International Conference on Control, Automation, and Systems, ICCAS, 2015, 2015, pp. 1870–1873. no. Iccas.
[97] L. Jiang, E. Tham, M. Yeo, O.G. Phu, iPhone-based portable brain control wheelchair, in: Proceedings of the 2012 Seventh International Conference on Industrial Electronics and Applications 2012, 2012, pp. 1592–1594.
[98] F. Ben Taher, N. Ben Amor, M. Jallouli, A self configured and hybrid fusion approach for an electric wheelchair control, in: Proceedings of the 2016 IEEE 8th International Conference on Intelligent Systems IS 2016, 2016, pp. 729–734.
[99] S. Andronicus, N.C. Harjanto, Suprijanto, A. Widyotriatmo, Heuristic Steady State Visual Evoked Potential based Brain Computer Interface system for robotic wheelchair application, in: Proceedings of the 2015 Fourth International Conference on Instrumentation, Communications, Information Technology, and Biomedical Engineering, 2015, pp. 94–97.
[100] D.A. Craig, H.T. Nguyen, Adaptive EEG thought pattern classifier for advanced wheelchair control, in: Proceedings of the Annual International Conference on IEEE Engineering Medical Biology, 2007, pp. 2544–2547.