EEG-Based Brain-Controlled Mobile Robots: A Survey

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***Abstract*—EEG-based brain-controlled mobile robots can serve as powerful aids for severely disabled people in their daily life, especially to help them move voluntarily. In this paper, we provide a comprehensive review of the complete systems, key techniques, and evaluation issues of brain-controlled mobile robots along with some insights into related future research and development issues. We first review and classify various complete systems of brain-controlled mobile robots into two categories from the perspective of their operational modes. We then describe key techniques that are used in these brain-controlled mobile robots including the brain-computer interface techniques and shared control techniques. This description is followed by an analysis of the evaluation issues of brain-controlled mobile robots including participants, tasks and environments, and evaluation metrics. We conclude this paper with a discussion of the current challenges and future research directions.**

***Index Terms*—Brain-computer interface (BCI), brain-controlled mobile robot, EEG, human factors, performance evaluation, shared control.**

I. Introduction

ROBOTS have been not only widely used in industry, but also gradually entering into human life. Assistive robots can provide support for disabled people in daily and professional life, thus creating a growing demand for them. In general, healthy users can operate the robots with a conventional input device such as a keyboard, a mouse, or a joystick. These devices are, however, difficult to use for elderly or disabled individuals. For this reason, some special interfaces like sip-and-puff systems, single switches, and eye-tracking systems have been proposed [1]. However, these special interfaces do not work for some severely disabled people with illnesses such as the amyotrophic lateral sclerosis (ALS), multiple sclerosis (MS), or strokes. These severely disable individuals cannot convey their intentions or operations to robots with these interfaces. As a result, even autonomous robots are not yet able to transport severely disabled users to desired locations. Furthermore, people want to be in charge of their motion as much as possible even if they have lost most of their voluntary muscle control; decisions that are made by autonomous systems can cause awkward feeling and stress to the users [2]. Therefore, although autonomous systems exist, it is still necessary to develop alternative interfaces that can be used by the severely disabled population for communication with autonomous systems.

Brain–computer interfaces (BCIs) have been developed to address this challenge. BCIs are systems that can bypass conventional channels of communication (i.e., muscles and speech) to provide direct communication and control between the human brain and physical devices by translating different patterns of brain activity into commands in real time [3]. Signal recordings of brain activity used by BCIs can be either invasive or noninvasive. Invasive BCIs require surgery to implant electrodes directly on or inside the cortex, whereas noninvasive BCIs do not do so. Noninvasive BCIs can use various brain signals as inputs, such as electroencephalograms (EEG), magnetoencephalograms (MEG), blood-oxygen-level-dependent (BOLD) signals, and (de) oxyhemoglobin concentrations [4]. Due to the low cost and convenient use in practice, EEG has been the most popular signal that is used to develop BCI systems. To make this paper manageable, we focus here on EEG-based BCIs. Although the domain of EEG-based BCIs is broad and includes various applications such as controlling a cursor on the screen [5], [6], selecting letters from a virtual keyboard [7]–[13], browsing internet [14]–[16], and playing games [17]–[19], for the remainder of this paper, we will focus on the topic of EEG-based brain-controlled robots.

An EEG-based brain-controlled robot is a robot that uses EEG-based BCIs to receive human control (hereafter, brain-controlled robots refer to EEG-based brain-controlled robots only). Two main classes of brain-controlled robots to assist disabilities are brain-controlled manipulators and mobile robots. One representative work of brain-controlled manipulators is the manipulator used within the FRIEND system developed by Graser *et al.* [143], [144], which is able to show the brain-controlled capabilities of robots out of a controlled laboratory situation.

Compared with other brain-controlled devices, the major difference of brain-controlled mobile robotic systems is that these mobile robots require higher safety since they are used to transport disabled people. Thus, the BCI systems that are used to develop these robots need better performance (i.e., higher accuracy and shorter classification time).

Recently, research and development of brain-controlled mobile robots have received a great deal of attention because of

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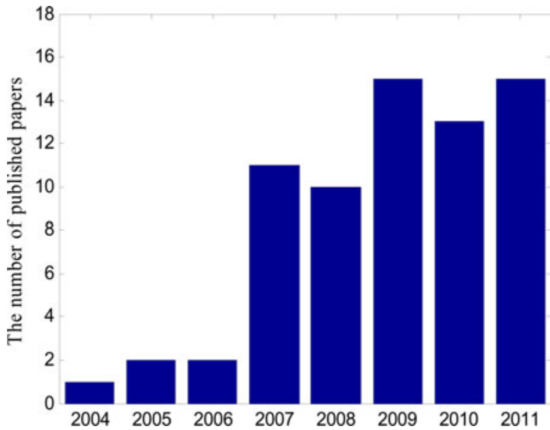

Fig. 1. Number of published papers on brain-controlled mobile robots.

their ability to bring mobility back to people with devastating neuromuscular disorders and improve the quality of life and self-independence of these users. In 2004, the first EEG-based brain-controlled mobile robot was proposed by Millán *et al.* [20]. Since then, many researchers have developed various brain-controlled mobile robots. Fig. 1 shows the number of published papers on brain-controlled mobile robots between 2004 and 2011. Although nearly a hundred papers have been published during this period, no comprehensive literature review can be found that covers brain-controlled mobile robots either in the robotics or the BCI literature, with the possible exception of two papers. Millán gave a brief introduction of the issues and challenges of brain-controlled robots [4]. Recently, Millán *et al.* reviewed the challenges that are faced by BCI-based assistive technology and its applications including communication and control, motor substitution, entertainment, and motor recovery [3].

In this paper, based on a survey of over 100 related papers, we present a comprehensive review and a critical analysis of the complete systems, key techniques, and evaluation issues of brain-controlled mobile robots along with some insights into the research and development in this area. The contribution of this review is threefold. First, we present a comprehensive review and propose a classification of various complete brain-controlled mobile robots from the perspective of their operational modes. Second, we describe and analyze the key techniques and the evaluation issues for the overall performance of brain-controlled mobile robotic systems. Third, we discuss current challenges and future research directions of brain-controlled mobile robots.

The remainder of this paper is organized as follows. In Section II, we review the complete brain-controlled mobile robot systems and related key techniques. In Section III, the evaluation issues of brain-controlled robots are described and analyzed. In Section IV, we conclude this paper with a discussion of the current challenges and future research directions.

II. Complete Systems and Key Techniques of Brain-Controlled Mobile Robots

The central tenet of a brain-controlled mobile robot is to allow the user to control the mobile robot to reach the intended destinations safely and efficiently with the user' brain signals. The core technique that is applied to implement brain-controlled robots is the BCI, which translates EEG signals into user intentions and is indispensable for any brain-controlled mobile robot. In addition to BCI, other techniques include 1) robot intelligence techniques in sensing surrounding situations, localization, path planning, and obstacle/collision avoidances and 2) shared control techniques, combining the BCI with the intelligence of robots to share the control over the robot [33], [34]. Since the intelligence of robots is a common issue which is involved in all autonomous mobile robots, we do not review it in this paper so as to make the scope of this paper manageable.

A. Brain-Controlled Mobile Robots

We divide brain-controlled mobile robots into two categories according to their operational modes. One category is called "direct control by the BCI," which means that the BCI translates EEG signals into motion commands to control robots directly. Various approaches to implement this method are shown in Table I. One typical example is the work of Tanaka *et al.* [21], who first developed a brain-controlled robotic wheelchair whose left or right turning movements are directly controlled by corresponding motion commands translated from user brain signals while imagining left or right limb movements, and tested this system in real-world situations. The robotic platform is illustrated in Fig. 2(a). Choi and coworkers [23], [28] also used a BCI based on motor imagery to build a brain-controlled mobile robot, as illustrated in Fig. 2(b), which can perform three motion commands including turning left and right and going forward, and validated this robot in a real world.

This kind of robots does not need any additional robot intelligence. Thus, their cost and computational complexity are low. In addition, users can be in charge of their movements as much as possible, as in their own motion control. However, the overall performance of these brain-controlled mobile robots mainly depends on the performance of the noninvasive BCIs, which are currently slow and uncertain. In other words, the performance of the BCI systems limits that of the robots. Further, users need to issue motor control commands rather frequently, often causing user fatigue.

To address the two questions aforementioned that the robots directly controlled by a BCI meet, so as to make the user be able to control the robot over a long period of time, the second group of brain-controlled robots has been developed from a perspective of shared control, where a user (using a BCI) and an intelligent controller (such as autonomous navigation system) share the control over the robots. Compared with the robots that are directly controlled by the BCI, the second group can depend on the intelligence of the robots. Thus, the safety of driving these robots can be better ensured, and even the accuracy of intention inference of users can be improved. In addition, users spend less time using the BCI and are less likely to develop fatigue. The disadvantage of these robots is that the cost and computational complexity are high due to the use of an array of sensors (especially laser sensors), compared with the first group. Table II shows various systems of this group. Millán *et al.* [34]

TABLE I
BRAIN-CONTROLLED MOBILE ROBOTS DIRECTLY OPERATED BY A BCI

Publication	Used brain signals	Classifier	Output commands
Tanaka *et al.* (2005) [21]	ERD/ERS	Nearest neighbor	Turning left and right
Choi *et al.* (2008-2011) [23][28]	ERD/ERS	SVM	Turning left and right and going forward
Pires *et al.* (2008) [24]	P300	Statistical classifier	Eight motion directions +stopping
Leeb *et al.* (2008) [25]	ERD/ERS	Linear classifier	Going forward
Craig *et al.* (2007) [26]	ERD/ERS and Alpha band	Artificial Neural Networks	Turning left and right, and stopping from alpha band
Dasgupta *et al.* (2010) [29]	SSVEP	SVM	Turing left and right, going forward, and stopping
Guger *et al.* (2009-2010) [30] [31][99]	SSVEP	LDA	Going forward and backward and turning left and right
Barbosa *et al.* (2010)[32]	ERD/ERS	Artificial Neural Networks	Turing left and right, going forward, and stopping
Hema *et al.* (2009)[96]	ERD/ERS	Artificial Neural Networks	Relax, going forward, and turning left and right
Cho *et al.* (2009)[97]	ERD/ERS	—	Turning left and right, and going forward and backward
Tsui *et al.* (2007-2009) [101] [102]	ERD/ERS	LDA	Turning left and right (in a virtual environment)
Bento *et al.* (2008)[105]	ERD/ERS	—	Turning right and left, going forward, and Stopping
Lee *et al.* （2012）[164]	SSVEP	Matched Filter Detector	Turning right and left and going forward

developed a brain-controlled robotic wheelchair, as illustrated in Fig. 2(c), with a shared-control approach, where the intelligent controller is designed to filter out the possible erroneous mental commands (including going forward and turning left and right) acquired by analyzing brain signals of motor imagery, and thus, the patient is able to continuously control the wheelchair, allowing for a more natural interaction with the wheelchair. The experimental results show the possibility of the shared control system being able to improve the overall driving performance.

Mandel *et al.* [41] proposed a shared control system to control a wheelchair, as illustrated in Fig. 2(d), with a steady-state visual evoked potential (SSVEP) BCI that issues four motor commands (turning left and right, and going forward and back) and an autonomous navigation system that safely executes the issued commands.

Another typical example of this kind of robots is the robotic wheelchair, as illustrated in Fig. 2(e), developed by Rebsamen *et al.* [38], where a desired location is selected from a list of predefined locations by using a P300 BCI, and then sent to an autonomous system, which drives the wheelchair to the desired locations in a known environment, but the user is able to stop the wheelchair by ERD/ERS BCI or a fast P300 BCI at any time.

Like Rebsamen *et al.*, Iturrate *et al.* [33] also combined a P300 BCI and an autonomous navigation system to develop a robotic wheelchair, as illustrated in Fig. 2(f). The main difference between them is that the latter allows a wheelchair to move in an unknown environment. In addition, the user is able to control the wheelchair to turn left or right at any time by focusing his/her attention on the "turn left" or "turn right" icons at the lower section of the visual display to elicit a corresponding P300.

Although many researchers have developed various brain-controlled mobile robots, to the best of our knowledge, none of the existing brain-controlled mobile robots is brought out of a controlled laboratory environment. The main reason for this is that the BCI is not stable due to the nonstationary nature of the EEG signals [146]. Thus, to make these mobile robots usable in real-world situations, stable BCI systems need to be explored. If a BCI system is not stable, other techniques should be further developed to improve the overall driving performance.

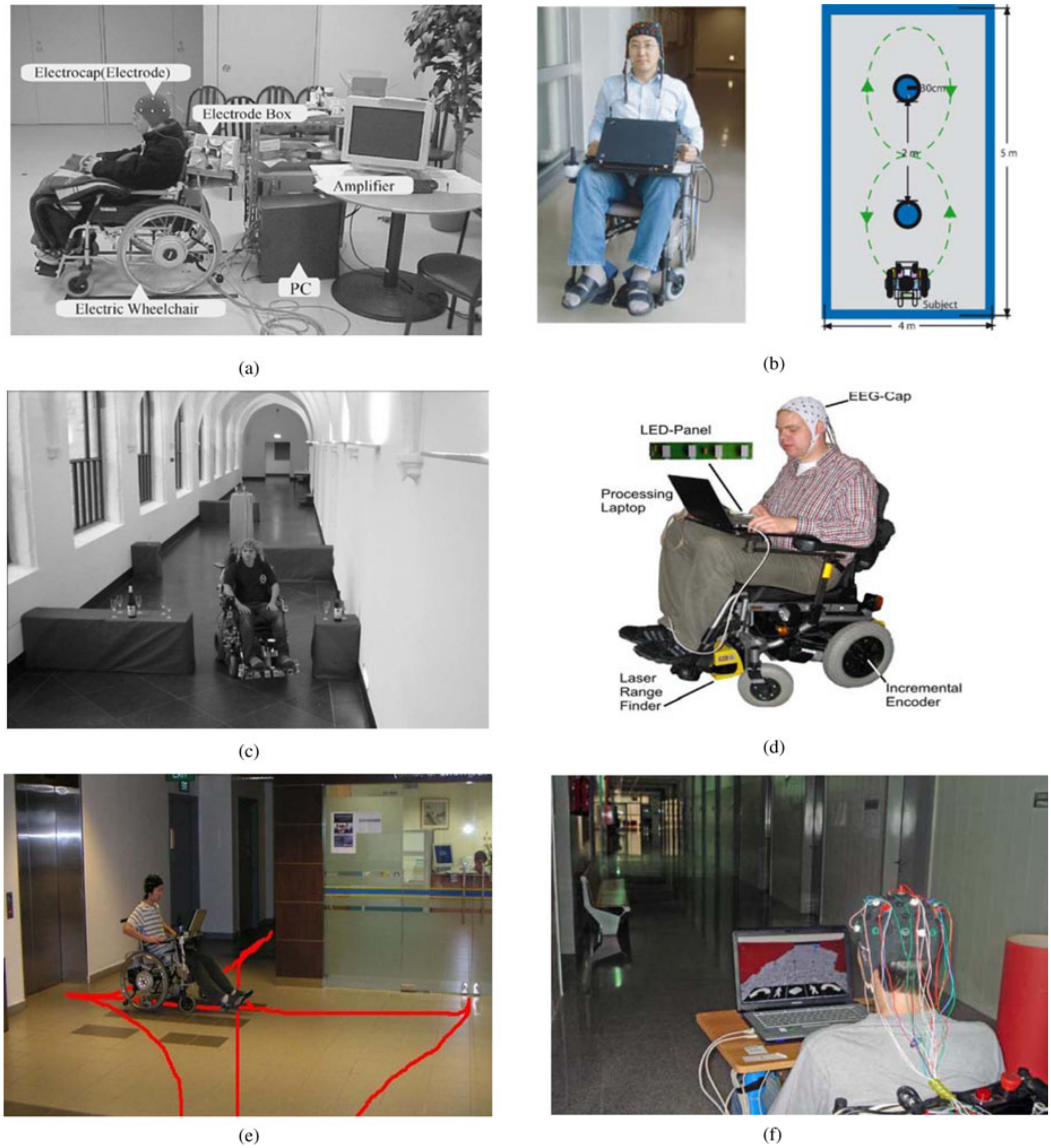

Fig. 2. Typical examples of the brain-controlled mobile robots. (a) From [21]. (b) From [23]. (c) From [56]. (d) From [41]. (e) From [38]. (f) From [33].

B. Brain-Computer Interface

The basic idea of BCI is to translate user produced patterns of brain activity into corresponding commands. A typical BCI is composed of signal acquisition and signal processing (including preprocessing, feature extraction, and classification). Although some BCI systems do not include all components and others group two or three components into one algorithm, most systems can be conceptually divided into signal acquisition, preprocessing, feature extraction, and classification. A schematic of the main BCI components is shown in Fig. 3.

1) Suitable Brain Signals: The brain signals that are widely used to develop EEG-based BCIs include 1) P300 potentials, which are a positive potential deflection on the ongoing brain activity at a latency of roughly 300 ms after the random occurrence of a desired target stimulus from nontarget stimuli (the stimuli can be in visual, auditory, or tactile modality) [7], [60], [129]; 2) SSVEP, which are visually evoked by a stimulus modulated at a fixed frequency and occur as an increase in EEG activity at the stimulus frequency [61], [62]; and 3) the event-related desynchronization (ERD) and event-related synchronization (ERS), which are induced by performing mental tasks, such as motor imagery, mental arithmetic, or mental rotation [63].

P300 BCIs and SSVEP BCIs based on external stimulation are called exogenous, stimulus-dependent BCIs, or synchronous BCIs, whereas ERD/ERS BCIs independent of external

TABLE II
BRAIN-CONTROLLED ROBOTS BASED ON SHARED CONTROL

Publication	Used brain signals	BCI		Robot intelligence		Shared control
		Classifier	Output commands	Sensors	Functions	
Rebsamen *et al.* (2006-2010) [2][36][37][38]	P300 + ERD/ERS	SVM+ Statistical model for P300; Linear classifier for ERD/ERS	Nine destinations from P300; Fast stop from ERD/ERS	A bar code scanner and a simple proximity sensor	Path planning, Collision/Obstacle avoidance	Second class of automatic switching control
Minguez *et al.* (2009-2012) [33] [40][51] [147]	P300	LDA	Destinations by reconstructed	A SICK planar laser	Map building, collision/obstacle avoidance, and path planning	Second class of automatic switching control
Graser *et al.* (2009)[41]	SSVEP	Linear classifier	Turning left and right and going forward and backward	Two laser range finders	Collision/obstacle avoidance, and path planning	Second class of automatic switching control
Blatt *et al.* (2009)[44]	P300	Logistic classifier	Four destinations	A camera and two Hokuyo laser range finders	Collision/obstacle avoidance, and path planning	Second class of automatic switching control
Millán *et al.* (2007-2011) [34][54]-[56] [158]	ERD/ERS	Statistical Classifier	Going forward and turning left and right	A laser range scanner and sonar sensors	Collision/obstacle avoidance	Third class of automatic switching control
Perrin *et al.* (2010) [1] [35]	ErrP	Statistical classifier	Yes and no	A SICK laser range finder	Map building, collision/obstacle avoidance, and path planning	Second subgroup of s automatic switching control
Millán *et al.* (2004) [20]	ERD/ERS	Statistical Classifier	Going forward and turning left /right	8 infrared sensors (in a virtual environment)	Collision/obstacle avoidance	Second subgroup of automatic switching control
Geng *et al.* (2007-2010) [57][98] [103]	ERD/ERS	LDA	Switch control, and turning left and right	— (in a virtual environment)	Collision/obstacle avoidance	Explicitly switching control
Satti *et al.* (2011) [59]	ERD/ERS	Self-organizing fuzzy neural network	Turning left and right	Infrared sensors (in a virtual environment)	Collision/obstacle avoidance, corridor following	First class of automatic switching control

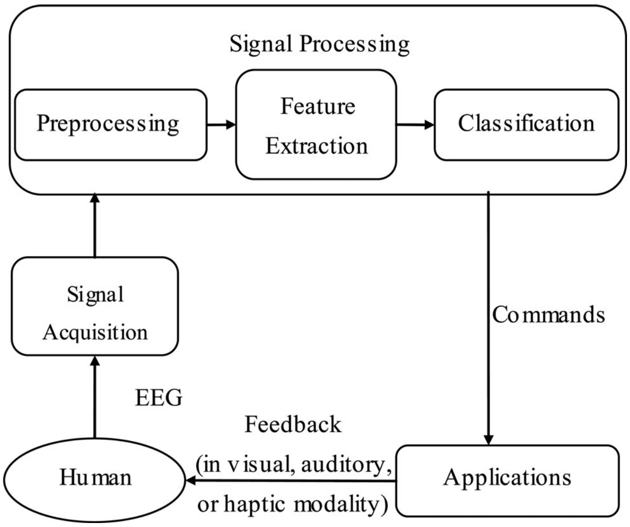

Fig. 3. Schematic of the main BCI components.

stimulation are called endogenous BCIs or asynchronous (self-paced) BCIs. Since asynchronous BCIs do not require any external stimulus, they seem to be more suitable and natural for brain-controlled mobile robots, where users need to focus their attention on driving but not on external stimuli [56].

Because of the advantage mentioned previously, in 2004, using ERD/ERS BCIs, Millán *et al.* [20] developed the first brain-controlled mobile robot in a virtual world. They induced ERD with the following mental tasks: relax, left hand movement imagination, and right hand movement imagination or cube rotation. Since then, Millán *et al.* have continued to develop brain-controlled mobile robots using ERD/ERS BCIs [34], [54]–[56], [145], [158]. Meanwhile, some other researchers have also made attempts to apply ERD/ERS BCIs to develop brain-controlled mobile robots.

The main disadvantages of asynchronous BCIs are as follows: 1) They require extensive training that may take many weeks; and 2) their performance is quite variable between users, and their accuracy is not as high as that of synchronous BCIs. Compared with asynchronous BCIs, synchronous BCIs require minimal training and have stable performance and high accuracy. SSVEP BCIs can issue commands typically every 2–4 s, and their accuracy is typically about 80%–90%. Graser *et al.* applied an SSVEP BCI to develop a brain-controlled wheelchair, where the stimulus is an LED panel of four different diodes oscillating at 13, 14, 15, and 16 Hz, associated with turning left, turning right, going forward, and going backward, respectively [41]. Other similar examples can be seen in [29]–[31], [49], and [58]. In comparison to SSVEP BCIs, P300 BCIs take longer time to issue commands, but have higher accuracy and a more natural graphical user interface. Many researchers have developed various brain-controlled robotic wheelchairs using a P300 BCI, since Rebsamen *et al.* [38] first proposed to apply a P300 BCI to develop a brain-controlled robotic wheelchair in 2006. Table III shows a comparison of the three main types of brain signals and the corresponding examples of application in brain-controlled mobile robots.

In addition to the main brain signals that are mentioned previously, two additional types of brain signals that are used to develop brain-controlled mobile robots are 1) error-related potential (ErrP), which occurs after a user becomes aware of an error made by himself/herself or by another entity [35], [44], [64], [65] and 2) the synchronization of alpha rhythms, which significantly occurs in the visual cortex when the eyes are closed [52], [53], [104], [125], [138], [139]. Since the two kinds of BCIs can only recognize two states of subjects (error versus no error; eye closed versus open), they have been used in few brain-controlled robots. Perrin *et al.* proposed a brain-controlled wheelchair using an ErrP BCI to accept or reject the proposition made by the wheelchair navigation system [35]. Ferreira *et al.* applied the alpha-rhythm-based BCI to select the desired one from a list of predefined commands in a screen, which are activated in turn [52].

Recently, to improve BCI performance, some researchers have started to develop a hybrid BCI, which consists of one BCI and another system (which can be another BCI) [66], [67], [140], which is likely a promising research direction.

2) Electroencephalogram Signal Acquisition and Processing: After the suitable brain signal used to develop the EEG-based BCI is determined, EEG signal acquisition and processing need to be performed so as to build the BCI system.

a) Signal Acquisition: EEG signals can be collected with electrodes that are placed on the surface of the scalp. The most widely used electrodes are silver/silver chloride (Ag/AgCl) because they have low cost, low contact impedance, and relatively good stability. Furthermore, there are rather mature commercialized acquisition systems including the amplifier and EEG cap with integrated Ag/AgCl electrodes, which have been successfully applied in scientific research and clinical diagnosis. However, using Ag/AgCl electrodes requires removing outer skin layer and filling gel between electrodes and scalp (and thus, this kind of electrodes is also called "wet" electrodes). These operations take long time and are uncomfortable to users.

To address these limitations of "wet" electrodes, some researchers have been exploring "dry" electrodes, which do not need to use gel and skin cleaning [68]–[71]. The main disadvantage of existing dry electrodes is that the acquired EEG signals are worse than those acquired with conventional electrodes due to the increase of contact impedance [72]. Some companies (such as Quasar Inc., Emotiv Systems Inc., and Neuro Sky Inc.) have been commercializing acquisition systems based on dry electrodes [73], [74]. However, they are not yet mature, and some researchers have doubts about what physiological signals these systems actually acquire [3]. Therefore, until now, all brain-controlled wheelchairs adopt "wet" electrodes to collect brain signals.

Another important issue of EEG acquisition is the locations on the scalp where electrodes are placed. Generally, the electrodes are placed according to the standard of 10–20 international system, which means that electrodes are located on the scalp at 10% and 20% of a measured distance from reference sites including nasion, inion, left, and right preauricular [75], as shown in Fig. 4. Generally, for P300 BCIs, the EEG signals are recorded at locations of the inferior frontal, central, and parietal

TABLE III
COMPARISON OF THREE MAIN TYPES OF BRAIN SIGNALS WIDELY USED TO DEVELOP BCIs AND APPLICATIONS IN ROBOTS

Suitable brain signals	Training time	Stimulation	Accuracy	Issuing command interval	Robot examples
P300	Almost no	Visual, auditory, or tactile stimuli presenting randomly	High (Typically 90%)	Long (Typically 10-20s)	[2][7][22][24][33][36][37] [38][40][42][43][44][50][51] [60] [115][118][119][122][126] [127][128][131][132][133] [134]
SSVEP	Almost no	Visually evoked by stimuli modulated at fixed frequencies	High (Typically 80%-90%)	Short (Typically 2-4 s)	[29][30][31][41][42][45][49] [58][61][62] [95][99] [100] [130][136]
ERD/ERS	Many weeks or longer	No	Low (Typically 60%-70%)	Short (Typically 0.5-4 s)	[2][20][21][23][25][26][27] [28][32][34][46][47][48] [54][55][56][59][96][97][98] [101][102][103][105][116] [117][120][121][123] [124][135][141] [142]

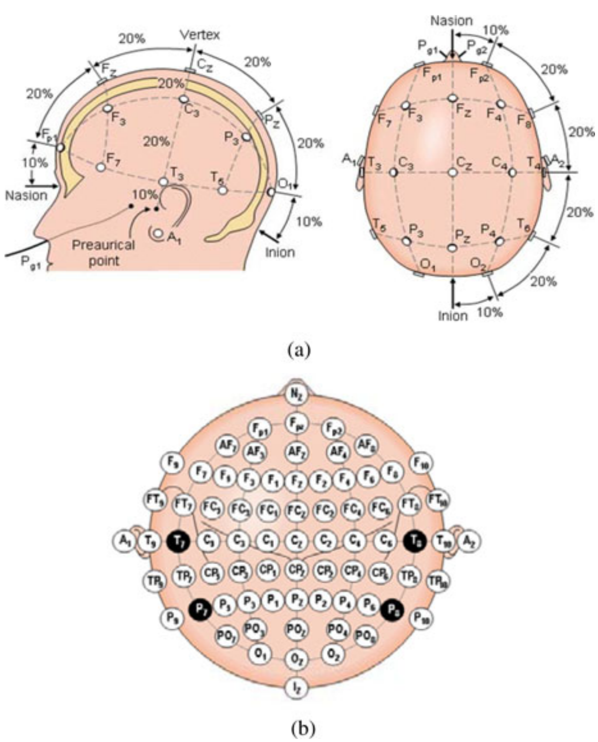

Fig. 4. (a) International 10–20 system seen from left and above the head. A = ear lobe, C = central, Pg = nasopharyngeal, P = parietal, F = frontal, Fp = frontal polar, O = occipital. (b) Extension of the international 10–20 system (from [75]).

regions (e.g., F3, F4, C3, C4, P3, P4, P7, P8, F7, and F8); for ERD BCIs, some electrode locations at frontal, central, and parietal regions are selected to acquire EEG signals (e.g., F3, F4, C3, Cz, C4, P3, Pz, and P4), whereas, for SSVEP BCIs, electrodes are placed at the occipital region (e.g., O1, O2, and OZ).

b) Signal Processing: The acquired signals are first preprocessed in order to remove artifacts such as power line noise, electromyogram (EMG), electrocardiogram (ECG), electrooculogram (EOG), and body movement. Features, such as the inputs to the classifier, are then extracted from the preprocessed signals. Finally, the classifier translates these extracted features into commands that subjects desire to output.

Preprocessing: The simplest and most widely used method to remove artifacts is filtering including low-pass, high-pass, band-pass, and notch filtering, which is appropriate to remove line noise and other frequency-specific noise such as body movement. However, this method filters useful components of EEG signals with the same frequency band as artifacts. Independent component analysis (ICA), which is a computational method to divide a mixed signal into its statistically independent components, is another approach frequently used to eliminate artifacts of EEG signals, and many studies have demonstrated its efficacy in removing these artifacts [76]–[83]. In the brain-controlled mobile robot of [23], ICA was used to remove artifacts. However, ICA is difficult to use, and algorithmic complexity is high, compared with filtering. That is why almost all of the existing brain-controlled wheelchairs used filters to eliminate artifacts. Additional methods to remove artifacts such as wavelet transform can be seen in [84] and [85].

Feature extraction: To make classifiers of BCI systems have good performance, features that can significantly distinguish different classes are extracted. Features that are applied to BCI systems of brain-controlled mobile robots can be divided

TABLE IV
TYPICAL CLASSIFIERS APPLIED IN BRAIN-CONTROLLED MOBILE ROBOTS

Classifier	Mechanism	Properties	Robot examples		
			P300-based	ERD/ERS-based	SSVEP-based
Linear discriminant analysis (LDA)	Finds a decision plane by maximizing the distance between the averages of the two classes and minimizing the variances of the data inside each class.	-Simple to use -Low computational cost -Poor results on complex nonlinear data	[33][40][51] [126]	[2][25][27][36][37] [38][46][47][57] [98][101][102][121]	[30][31] [41][99]
Support vector machines (SVM)	Finds a decision hyper plane by maximizing the margin between the different classes	-Good generalization characteristics -Linear and nonlinear classifiers -High computational cost for nonlinear classifier	[2][36][37] [38][43][50]	[23][28][48][142]	[29]
Statistical classifiers	Estimates the probability of each class and assigns new instances into the class with the highest probability	-Efficient to represent uncertain samples -Nonlinear classifier -Informative	[24][119][132]	[20][34][54][55] [56]	—
Artificial Neural Networks (ANNs)	Finds a nonlinear decision plane by minimizing the error in classifying training data	-Needs to be subjectively set many parameters - Nonlinear classifier -Sensitive to overtraining -High computational cost	—	[26][32][59][96] [117][135][141]	

into two main categories: features in time domain, which are typically amplitudes of event-evoked potentials, and features in frequency domain, which are typically frequency power spectra of EEG signals that can be estimated with Welch's periodogram algorithm or other estimation algorithms. Generally, P300 BCIs use temporal features, whereas ERD and SSVEP BCIs employ frequency features. In addition to the two types of features, other features such as time-frequency features [86], [87] and autoregressive parameters [88], and adaptive autoregressive parameters [89] were used to design BCI systems.

Classification: A variety of classifiers have been used to translate these extracted features from EEG signals into an output command, from simple classifiers such as nearest neighbor, linear discriminant analysis (LDA), to nonlinear neural networks (NN), support vector machines (SVM), and statistical classifiers. Table IV summarizes the typical classifiers that are applied in brain-controlled mobile robots.

LDA is a widely used linear classifier. Compared with the other methods, the main advantages of LDA include the following: 1) It is simple to use and 2) it has low computational complexity. Thus, numerous brain-controlled mobile robots used LDA to develop the classifiers of BCI systems. Artificial neural network (ANN) is a widely used nonlinear modeling method for regression analysis and classification, which is based on biological neural networks. The main advantage of ANN as a classification method is its ability to approximate arbitrary nonlinear decision functions by minimizing the error in classifying training data. Unlike ANN, SVM does not need to set up many configurations and parameters. Another advantage of SVM is that it has good generalization characteristics and is especially suitable for the cases, where a small amount of training data is gained. In addition, the two kinds of classifiers were widely applied into brain-controlled mobile robots. Statistical classifiers classify one new instance into a particular class by selecting the highest one from the estimated posterior probabilities of all classes based on observed features of the new instance and prior knowledge. The main advantage of statistical classifiers is that it can represent the uncertainty of EEG signals. It has been applied into brain-controlled mobile robots [24], [34].

However, the robustness of all existing BCI systems is not satisfactory due to the nonstationary nature of noninvasive EEG signals. Considering that the natural change of brain signals over time and the change of brain activity patterns since the users develop new capabilities as subjects gain experience, Millán *et al.* proposed that a possible research direction to improve the robustness is the online adaptation of the classifier during its use to drifts in the brain signals, and preliminary results have shown the feasibility and advantage of this method [159].

In addition, there are a few software tools that are widely used to process the EEG data such as EEGLAB [160] and BCI 2000 [161], which can help researchers develop brain-controlled mobile robots. More details of classifiers, applications, and issues regarding BCI systems can be seen in several reviews of BCI [3], [4], [66], [90]–[94], [137].

C. Shared Control

Shared control is intended to overcome problems such as dangerous situations and accidents, accuracy of human control, as well as fatigue during a continuous control over a device, due to the lack of human control capacities [149], [156], which means that a human and one or more intelligent controller(s) have influence on a device controlled. It has been widely applied into robotics. The shared control approaches can be classified into two groups according to the switching mode between a human and an intelligent controller. One group of approaches requires the user to explicitly switch the control [150], [151]. In brain-controlled robots, Geng *et al.* [57], [98], [103] proposed a shared control system to develop brain-controlled mobile robots, where the user controls the turning left and right by imagining moving his/her left and right hands, and the navigation system controls going forward at different timing switched by the user via imagining moving his/her feet.

Another group provides automatic (implicit) switching control between a person and an intelligent controller [149], [152]–[155], [157]. Because this switching control method is more natural and efficient for disabled people [34], it has received more research attention in the assistive technology community. Roughly speaking, the automatic switching approaches can be categorized into the following several classes.

The first class of automatic switching approaches needs the human to control a robot most of time, and the intelligent controller only works when predefined situations are detected such as obstacle avoidance [152]. In brain-controlled mobile robots, Satti *et al.* [59] used such kind of approach to develop a robotic system, where the user controls the robot by the BCI based on motor imagery, whereas the intelligent controller is only triggered in the situations of obstacle avoidance and corridor following in an automatic way. In addition, using this shared control approach, Millán *et al.* [145] developed a brain-controlled telepresence robot based on an ERD/ERS BCI, where the intelligent controller is in charge of obstacle avoidance.

The second class of automatic switching approaches requires the user to provide a target (such as an intended location or intended motion command), and the intelligent controller is responsible for reaching the target [153], [154]. However, the user can override the automatic control and take over at any time. In brain-controlled mobile robots, a typical example of this kind of robots is the robotic wheelchair which was developed by Rebsamen *et al.* [2], where a desired location is selected from a list of predefined locations by using a P300 BCI, and then sent to an autonomous system, which drives the wheelchair to the desired locations in a known environment, but the user is able to stop the wheelchair by ERD/ERS BCI or a fast P300 BCI at any time. Like Rebsamen *et al.*, Iturrate *et al.* [33] also combined a P300 BCI and an autonomous navigation system to develop a robotic wheelchair with such kind of approach. The main difference between them is that the latter allows a wheelchair to move in an unknown environment. A virtual 3-D map of the surrounding environment that is reconstructed from sensory data by a laser scanner is displayed on a computer screen, and a set of points in the free space is presented, from which users select the desired one via this P300 BCI. In addition, the user is able to control the wheelchair to turn left or right at any time by focusing his/her attention on the "turn left" or "turn right" icons at the lower section of the visual display to elicit a corresponding P300. Perrin *et al.* used Bayesian networks to combine the BCI and a navigation system to develop a brain-controlled robot. First, a navigation system proposes the most probable action according to sensory data, and then users make a decision whether to accept it by using a BCI system based on error-related EEG signals [35]. Finally, the action command is determined by using Bayesian networks to fuse the result of the BCI and the proposition of the navigation system, and is implemented by the autonomous navigation system. Mandel *et al.* [41] proposed a shared control system to control a wheelchair with an SSVEP BCI that issues four motor commands (turning left and right, and going forward and back) and an autonomous navigation system that safely executes the issued commands.

The two classes that are mentioned previously only control a robot by either the human or the intelligent controller at a particular time, whereas the last class of approaches requires that the control is distributed between the human and the intelligent controller at all times [148]. Millán *et al.* [34] employed this kind of approach to develop a brain-controlled robot. In their shared control system, the user's control commands representing the probabilities that the user wants to go forward, right, or left are first acquired by translating brain signals of motor imagery. The share control system then combines these control commands and the corresponding commands in a probability form attained by the intelligence of the robot according to data from laser sensors with a simple weighting method. Finally, the command with the maximum probability is selected as the motor command to control the robot.

Although the current shared control techniques have significantly improved the overall driving performance of brain-controlled mobile robots, they cannot yet make these robots be used in a real world. Thus, other methods of shared control or other techniques should be developed to guarantee the overall performance of brain-controlled mobile robots under the constraints of BCI system.

III. Performance Evaluation of Brain-Controlled Mobile Robots

Evaluating and comparing performance of a variety of brain-controlled mobile robots plays a critical role in facilitating the research and development of brain-controlled mobile robots. However, standardized performance evaluation method has not yet been established. The related issues of performance evaluation can be summarized and discussed as the following aspects.

A. Subjects

Since brain-controlled mobile robots need to use the EEG of users to control robots, the performance of such robots should be affected by the conditions of the users (i.e., healthy or disabled ones, and different levels of disability). Almost all of the existing brain-controlled mobile robots used healthy participants to evaluate their systems with several exceptions: 1) Leeb *et al.* used a tetraplegic subject, who has a complete motor and sensory lesion below C5 and an incomplete lesion below C4, to evaluate their proposed brain-controlled mobile robot system, which can only go forward and stop [25]; 2) a subject suffering from ALS was applied to evaluate the proposed BCI telepresence robotic system [51]; and 3) Millán *et al.* presented the results of two disabled subjects in a brain-controlled telepresence robot [158].

However, some studies have shown that good performance of a BCI system for healthy participants does not necessarily mean good performance for the disabled population [106]–[108], [163]. Li *et al.* have found that the performance of a P300 BCI for participants with motor disabilities is quite inferior compared with that of the BCI for nondisabled participants [109]. Further, Ortner *et al.* [162] have found a result consistent with that of Li *et al.* However, there is one study that suggested that disabled subjects performed similarly to the healthy subjects in using an ERD/ERS BCI system to perform a telepresence robot, although the conclusion was drawn from the experimental results of only two disabled subjects [158].

B. Tasks and Environments

In addition to the issue of participants, evaluating brain-controlled robots requires the specification of the test environments and tasks. The commonly adopted test tasks are to require subjects to control robots to reach destinations (which are predefined in some studies such as [2], [41]), from one certain starting point under specified environments (which are known environments in some studies such as [2] and [41]).

The test environments can be classified into two categories: 1) simulated conditions (like [20], [57], and [59]), where both robots and environments are simulated and 2) realistic conditions (like [1], [35]–[38], and [41]), where both robots and environments are realistic.

The simulated robots and environments have at least the following two advantages. First, they help save money and time. Second, they allow extensively testing of different robots system configurations and experimental conditions. The weakness is that they cannot fully replicate realistic robots and environments. Thus, to evaluate and compare the performance of different brain-controlled mobile robots, both simulated and realistic environments should be used. Further, it is difficult to compare and evaluate research results between studies that use simulated versus realistic environments and studies that used known versus unknown environments. Standardized tasks and environments should be established and used to compare the performance of these robots.

C. Evaluation Metrics

The metrics used to evaluate brain-controlled mobile robot systems can be classified into two major categories. One is called task metrics, which focus on how well specified tasks can be performed with the brain-controlled robots. The widely used and easiest task metric is task success, describing the degree of accomplishment of the task. Other used metrics are task completion time or mission time (used in [2], [33], and [55]), path length traveled (used in [33], [35], and [55]), number of collisions (used in [33] and [34]), and BCI accuracy (used in [33], [34], and [55]).

The second category of evaluation metrics is ergonomic metrics, representing the state of the user rather than his/her performance. Workload is a commonly used ergonomic metric, measuring user mental effort when using brain-controlled robot systems. In [2] and [59], concentration time defined as the time spent controlling the BCI was used to evaluate the workload, whereas Iturrate *et al.* [33] applied a subjective questionnaire to measure workload. Two other ergonomic metrics include learnability, representing the ease of learning to use the robot, and level of confidence experienced by the participants (and both metrics were only used in [33]).

The cost factor should also be considered in evaluating the robot systems. This is particularly important when they are put into practice. However, few existing studies on brain-controlled robots have considered this factor except that Rebsamen *et al.* [2] pointed out this factor in their paper. Thus, to measure the performance of brain-controlled robot systems comprehensively, at least the task metrics, ergonomic metrics, and the cost metric should be used.

D. Comparison Among Several Typical Brain-Controlled Mobile Robots

Few existing studies have quantitatively compared the performance of various types of robots developed with different techniques since standard performance evaluation method has not yet been established. Rebsamen *et al.* [2] proposed a cost function as a measure of control efficiency to evaluate the overall performance of brain-controlled mobile robots and gave the comparison results of several typical robots (including robots based on P300 BCI or ERD/ERS BCI) according to the experimental results published in the literature. The cost is computed as an addition of concentration time ratio (CTR), which is the ratio of the concentration time to the nominal time, meaning the minimal time required to complete the task, and the mission time ratio (MTR), which is the mission time over the nominal time.

TABLE V
EVALUATION OF SEVERAL TYPICAL BRAIN-CONTROLLED MOBILE ROBOTS

	BCW [2]		MAIA [55]	Toyota [23]	Iturrate *et al* .[33]		Mandel *et al.* [41]
	No false stop	Some false stops			Complex envt.	Open space	
Number of false stops	0	1.21	NA	NA	NA	NA	NA
nominal time (s)	100	100	100	17	24	64	210.75
Mission time (s)	112	128	200	22.88	571	659	245
Mission time ratio	1.13	1.28	2	1.35	25	10.3	1.16
Concentration time (s)	12.6	28.3	200	22.88	447	439	34.25
Concentration time ratio	0.13	0.28	2	1.35	18.6	6.8	0.16
Total cost	1.26	1.56	4	2.7	43.6	17.1	1.32

Implementing and evaluating all the existing robotic systems is certainly beyond the scope of this review paper. Instead, as an illustration, we extended the comparison results of [2], by adding a typical brain-controlled mobile robot based on SSVEP, as shown in Table V. It seems that robots in [2] and [41] perform best and the one in [33] does worst. However, there are several weaknesses about the comparison method. First, to make these robots comparable, the nominal times of all examples were computed according to the velocity of 0.5 m/s. However, in fact, some robots did not travel at this velocity during experiments. For example, in [33], the robot ran actually at 0.18 m/s under open space and at 0.13 m/s under complex environment; thus, the computed nominal times of [2] were less than the actual values, causing the higher estimation than the actual value of the cost in [33]. Second, the concentration times for some brain-controlled robots depend on the specific path. For example, if the robots in [23], [33], and [55] traveled in a path with less curved parts, the user would need less BCI operations, causing less concentration time and thus leading smaller cost. Third, some robots were evaluated in simulated environments like [55] (even only by using numerical simulation results but without conducting any experiments in [2]), whereas others (i.e., [23], [33], [41]) in realistic ones; some (i.e., [2] and [41]) were evaluated in known environments, whereas others in unknown ones. Fourth, the performances were compared on obstacle free paths. Thus, the comparison cannot reflect obstacle avoidance performance.

Furthermore, it is not truly fair to use this single metric to compare these greatly different systems in vastly different situations because the single metric cannot reflect all characteristics of various brain-controlled robots.

In summary, evaluating and comparing performance of various brain-controlled mobile robots are hard and complex. To make the evaluation and comparison more reasonable, standardized performance evaluation should be established, and the related issues including subjects, tasks and environments, and evaluation metrics should be comprehensive and specified.

IV. DISCUSSION AND CONCLUSION

The research and development of brain-controlled mobile robots have received a great deal of attention because they can help bring mobility back to people with devastating neuromuscular disorders and thus improve their quality of life. In this paper, we presented a comprehensive up-to-date review of the complete systems, key techniques, and evaluation issues of brain-controlled mobile robots.

The major difference between brain-controlled mobile robots and other brain-controlled devices is that these mobile robots require higher safety because they are used to transport disabled people. Many researchers have developed various brain-controlled mobile robots using different BCI techniques as well as other techniques such as intelligence techniques (in sensing situations, localization, and path planning) and shared control techniques so as to make these robots safer. However, much work remains to be done before brain-controlled mobile robots can be applied in practice, including finding ways to improve the performance (especially robustness) of BCI systems, to improve the overall driving performance given the constraints of the BCI system, and to establish standard evaluation method to facilitate the research and development of brain-controlled mobile robots.

First, improving the BCI system performance (especially robustness) is critical to make brain-controlled mobile robots usable in real-world situations. One possible research direction is the online adaptation of the BCI classifier to drifts in the brain signals, considering the natural change of brain signals over time and the change of brain activity patterns as the users develop new capabilities with experience; preliminary results have shown the feasibility and advantage of this method [159]. Another direction is developing hybrid BCI systems and applying them in brain-controlled mobile robots. The BCI systems that are used in all existing brain-controlled systems rely on only one type of suitable brain signals (such as P300, ERD, or SSVEP) to translate user intentions into commands. However, the BCI systems that are based on a single signal do not work for all users [90], [111]–[113]. Some users cannot produce the necessary brain activity patterns for a particular kind of BCI systems. Recent studies have shown that some subjects could not yield corresponding brain activity patterns for an ERD BCI, but they could produce the needed activity patterns for an SSVEP BCI and vice versa [39], [114]. Moreover, all the subjects who could not generate the ERD or SSVEP patterns could likely use a "hybrid" BCI that combines the two approaches to improve accuracy [39], [114]. Thus, to broaden the user coverage of brain-controlled mobile robot systems and improve accuracy of their BCI systems, various hybrid BCI systems should be further investigated and adopted. Furthermore, discovering some new modes of brain signals that are more stationary and distinguishable, and developing corresponding BCI systems represents another open and challenging research direction to improve the BCI system performance. These lessons are also useful for wider BCI applications.

Second, under the constraints of the limited and unstable performance of all existing BCI systems, finding ways to enhance and ensure the overall driving performance of the robotic systems is very important. From the perspective of shared control, some methods have been proposed to combine the BCI and robot intelligence to improve the overall performance of brain-controlled mobile robots, as mentioned in Section II. However, current research only represents the first step toward this direction. We think that future potential directions are 1) developing new methods to combine the information from the BCI and robot intelligence, such as using BCI in conjunction with machine learning not only to control but also to teach the robot the motion task [165], [166], and 2) fusing additional useful information from other sources, such as predicted driver intentions.

Third, to evaluate and compare the performance of different methods and systems, standardized performance evaluation method (involving subjects, tasks and environments, and performance metrics) should be established. For example, most of the existing studies used healthy subjects to test and validate their proposed systems. However, it remains an open research question whether good performance of a BCI system for healthy participants necessarily means good performance for the disable population and whether such relationships depend on the specific disabilities as well as specific BCI systems and applications. Thus, to ensure the proposed brain-controlled mobile robots to be usable by the targeted disabled population, they need to be designed for and tested by the targeted population.

Research on brain-controlled robot systems has achieved many significant accomplishments. Further work and success of this research would lead to the development of robotic systems that can be used by disabled users, and thus improve their mobility, independence, and quality of life.

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