A Survey on Unmanned Aerial Vehicle Remote Control Using Brain–Computer Interface

Amin Nourmohammadi, Mohammad Jafari, and Thorsten O. Zander

***Abstract*—Numerous methods have been developed to gain reliable real-time remote control over pilotless flying aircraft and to perform teleoperation. Recently, state-of-the-art brain–computer interface (BCI) research has provided an avant-garde approach to reach this goal. Due to its broad range of application, BCI has been the center of attention as a promising candidate for deciphering brain signals into corresponding control commands for various systems. This paper surveys the application of BCI in designing control modules for unmanned aerial vehicles (UAVs). We first describe the basic configuration of UAVs, as well as identify the principle components of their control systems. We proceeded to describe different classes of BCI with emphasis on their applicability in controlling UAVs, and highlight the potential benefits and challenges in implementing each BCI paradigm. Details will be given on how essential strategies and key techniques regarding feature extraction, and the classification of data, as well as hybrid-modality, could be applied in this field to develop robust systems demonstrating optimal fidelity and performance. Moreover, by reviewing the primary trends in previous studies, we attempt to address the missing steps in current research and shed light on the road map for future innovation.**

***Index Terms*—Brain–computer interface (BCI), brain-controlled robots, drone, electroencephalography (EEG), remote control, teleoperation, unmanned aerial vehicle (UAV).**

Nomenclature

AI	Auditory imagination.
AR	Augmented reality.
AEP	Auditory-evoked potential.
BCI	Brain–computer interface.
CAR	Common average reference.
CSAP	Common spatial analytic pattern.
DOF	Degrees of freedom.
ECoG	Electrocorticography.
EEG	Electroencephalography.
EMG	Electromyography.
EOG	Electrooculography.
ERD	Event-related desynchronization.
ERS	Event-related synchronization.
ERP	Event-related potential.
ErrP	Error-related potential.
(f)MRI	(functional)Magnetic resonance imaging.
(f)NRIS	(functional)Near-infrared spectroscopy.
GNSS	Global navigation satellite systems.
GPS	Global positioning system.
H(-M)I	Human(-machine) interface.
I/PCA	Independent/principle component analysis.
INS	Inertial navigation systems.
ITR	Information transfer rate.
LR	Logistic regression.
LDA	Linear discriminate analysis.
LFP	Local field potential.
MEG	Magnetoencephalography.
M/AI	Motor/auditory imagery.
PET	Positron emission tomography.
RMT	Response to mental tasks.
RBF	Radial basis function.
RNN	Recurrent neural network.
SCP	Slow cortical potential.
SMR	Sensory motor rhythms.
SNMT	Spatial navigation mental task.
SNR	Signal to noise ratio.
SSVEP	Steady-state visually evoked potential.
SUS	System usability scale.
TLX	Task load index.
UAV	Unmanned aerial vehicle.
UGV	Unmanned ground vehicle.
USV	Unmanned surface vehicle.
UUV	Unmanned underwater vehicle.
VEP	Visually evoked potential.

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A. Nourmohammadi is with National Center for Adaptive Neurotechnologies, Wadsworth Center, New York State Department of Health, and also with the Department of Biomedical Science, State University of New York, University at Albany, Albany, NY 12222 USA (e-mail: nourmohammadi@neurotechcenter.org).

M. Jafari is with the Department of Electrical and Biomedical Engineering, University of Nevada, Reno, NV 89557 USA (e-mail: mjafari@unr.edu).

T. O. Zander is with Zander Laboratories B.V., Amsterdam 1043 BZ, The Netherlands (e-mail: thorsten@zanderlaboratories.com).

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I. Introduction

DEVELOPING a direct communication pathway between the human brain and the outside world is a distinguished concept. Technology developed over the past two decades has allowed for the implementation of brain-computer interface (BCI), which is an outstanding innovation for recording and translating brain signals into control commands for robotic systems. Although BCI research is still in its early stages, it has been proven effective in a wide range of applications, and has thus gained significant momentum over the past few years [1]. BCI studies have primarily focused on developing rehabilitation systems to help those suffering from devastating neuromuscular disorders or chronic trauma such as amyotrophic lateral sclerosis, epilepsy, and brainstem stroke [2], [3]. Virtual keyboard and the P300 speller are among the well-established, BCI-based devices that have provided functional means of communication for patients with locked-in syndrome or other forms of aphasia [4]–[6]. Moreover, BCI has catered a revolutionary framework that allows for the engineering of real-time, brain-controlled robotic systems. This includes assistive devices that are intended for people with disabilities, such as wheelchairs and prosthetic limbs, and other robotic systems that are developed to serve healthy people on a daily basis [7]–[10]. Unmanned ariel vehicles (UAVs) is a quintessential technology in this regard, which is also experiencing a spike in interest. There has been a drastic increase of importance for the various applications of drones[1] in recent times due to their unprecedented role in performing aerial operations, where the presence of a pilot is not possible [11]. The inventive idea of developing a brain-controlled UAV gave rise to a series of ongoing investigations which were pioneered by researchers at the University of Minnesota [12]–[14]. These early efforts laid the groundwork for other research teams to develop more sophisticated prototypes of brain-controlled UAVs.

Current state-of-the-art BCI is facing fundamental technical challenges and limitations—this dictates major restrictions on the functionality of systems that incorporate BCI in their design. From a practical perspective, there are other control modalities that substantially outperform BCI in respect to the robustness and fidelity. At the same time, there are commercial UAV prototypes in the market that are claimed to operate in an autonomous mode; i.e., they do not rely on human intervention to function.[2] These facts raise a disputable question: "what is the rationale behind developing brain-controlled UAVs?" Arguably, the use of BCI, as a novel control interface, introduces unique advantages that could not be achieved otherwise. Automatic error detection is one of these utilities that in case of brain-controlled UAVs could provide a basis for switching control between smart operating agents and the pilot (see Section II). Furthermore, the progressive BCI research, which once led to the advent of primitive brain-controlled systems, holds great promises for enhancing the fidelity of the current brain-controlled UAV prototypes. In future, these integrated systems could serve more practical purposes—some conceivable applications are as follows: in hospitals where patients with severe disabilities could use them for transporting objects; in battle fields where wounded soldiers could use them to proceed with the combat; and in space where they could assist astronauts to accomplish multitask missions outside the spacecraft [15].

The significance of the aforementioned technologies and the lack of a well-organized report in the literature that properly addresses the technical challenges of unifying these two disciplines were the two motivating factors for the authors to provide this manuscript. This paper presents an exhaustive survey on the application of BCI in developing brain-controlled UAVs, and is intended to be used as a guideline for other researchers in the field. The authors attempted to address the missing steps in the current trend and highlighted the directions for future research, in conjunction with the corresponding discussions in each section. We believe that this inquisitive approach equips readers with tangible clues, and provides an insight into areas that could potentially be the matter of further investigations. We also included critical "remarks," where discussion about the strategies and frameworks are elucidated by referencing to previous works.

Section II is intended to educate readers on the basic UAV operational configuration. We present a customized classification scheme for UAVs, and also identify the characteristics that distinguish drones from other forms of unmanned vehicles. Special emphasis is placed on the control strategies as they are central to designing a control module for any robotic system. In light of advancements in computer vision, various gesture-based modalities have been developed to control UAVs; most of which fall into the generic category of human-machine interface [16]. For the purposes of this paper, however, we only focus on brain-controlled UAVs that engage BCI as their primary input modality. We also introduce critical concepts, such as "usability" and "workload," which are the vital considerations in designing optimum complex systems.

By focusing on the essential components of BCI architecture in Section III, we establish a framework for incorporating BCI in drones' HI. A subsection is dedicated to an in-depth discussion regarding different BCI classes, some of which have been previously used to develop control modules for ground robotic systems[9]. From this standpoint, many of these well-established strategies could potentially be applied to UAVs. However, due to their inherently unstable nature, designing BCI-based control modules for UAVs requires rigorous technical consideration. As we introduce the potential merits and shortcomings of different BCI paradigms, we review the vast collection of related research and provide critical analysis of their methodologies. As it was mentioned earlier, the performance of BCI-based devices is restricted by the limitations that BCI imposed on the system[15]. To circumvent these inefficacies, many developers attempted to reinforce their prototypes by combining BCI with other input modalities. To better introduce these systems, a subsection is devoted to describing a hybrid BCI and its configuration. We discuss how employing techniques such as electromyography (EMG) or eye tracker could remediate some of the BCI limitations and enhance systems robustness.

In Section, we conclude this review by further addressing the challenges and missing elements in the light of current discussions, with some insights into the road map that is likely to shape the field in the near future.

II. Brain-Controlled UAVs: UAV Structures and Strategies

Uninhabited, unmanned, or pilotless aerial vehicle is the name of an aircraft that flies without a human operator onboard. Among the various existing forms of automatic vehi-

[1] In this paper, the terms "drone" and "UAV" are used interchangeably.

[2] Airobotics (www.airobotics.co.il/) and Flytrex (http://www.flytrex.com) are among the companies that claim to have manufactured completely autonomous drones.

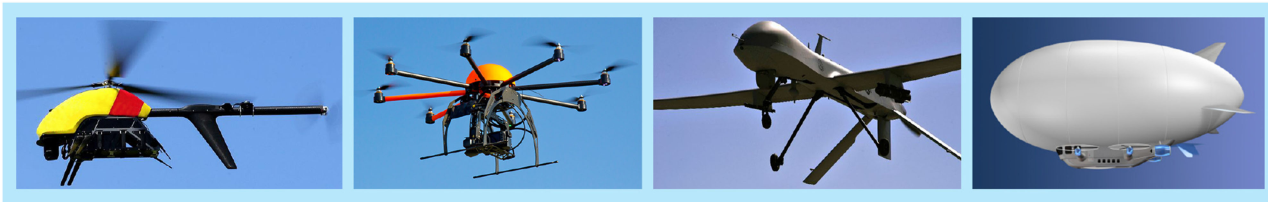

Fig. 1. Different UAV classes: (from left to right) monorotor, multirotor, fixed wing, and airship.

cles, UAVs—also known as drones—have experienced a drastic growth over the past decade, which was primarily driven by their vast functionality and their wide range of applications, but is not limited to target tracking, power and pipeline inspection, search and rescue operations, environmental monitoring, and anomaly detection [17]. Drones and other classes of unmanned vehicles[3] share common characteristics in terms of their basic architectures, communications, and also the strategies that could improve their autonomy attributes. However, certain features are associated with drones that make them distinct from their counterparts. Due to their inherently unstable nature, extra degrees of freedom in state space, and also being typically underactuated, designing control modules for UAVs requires rigorous consideration. By outlining the basics and without touching details, this section is intended to provide the essential technical knowledge about drones that is required for designing and developing brain-controlled UAVs.

A. UAV Classification

Based on operational characteristics and attributes, different classification schemes can be deemed for UAVs. Some of the common metrics for UAV classification are operating conditions, ownership, size, capabilities, or any combination of these and other characteristics [17]. In case of brain-controlled UAVs, however, the kinematic-dynamic and also the autonomy of the system were the only two classification metrics that were considered in previous studies.

1) Kinematics-Dynamics: From this standpoint, UAVs are categorized into three classes: rotary crafts, airship/dirigible balloon, and fixed-wing crafts (see Fig. 1). The structural design of each class gives rise to certain kinematic-dynamic characteristics that make it suitable for specific applications. Airships or dirigible balloons, for example, could be used for environmental monitoring missions [18], coastal surveillance [19], and also have the potential to be employed for planetary exploration [20]. Fixed-wing drones can fly with high velocity and are more suitable for fast linear flights to distant targets. They are extensively being used in the military or for applications, such as sea ice thickness mapping [21], aerial surveillance [22], agriculture, and multipurpose monitoring [23]. Rotary crafts have the most diversity in their configuration and design; they are being manufactured in different forms such as monorotor (e.g., helicopter) or multirotor (e.g., quadcopter, hexacopter, etc.). Compared to the other two classes, the rotary crafts have raised substantial attention for they demonstrate several advantages. Other than being affordable and vastly accessible, their capability of fine maneuvering in confined space makes them the ideal candidates for many applications such as indoor operations [24].

Remarks: The unique characteristics of the rotary craft put them in the center of attention for developing brain-controlled UAVs. Aside from one study that used a fixed-wing drone in its model [25], others almost exclusively used different types of rotary crafts (see Table II). Granted the diverse application area of other classes of drones, developing BCI-based control modules for other types of UAVs would merit further investigation.

2) Autonomy: In principle, UAVs can operate in several modes.

a) Man-in-the-loop: The pilot in the ground station has a direct real-time control of all the aircraft systems.

b) Man-on-the-loop (also known as "semi-autonomous"): The control operation is being shared between a pilot on the ground and an onboard intelligent agent, which ensures stable and controlled flight in accordance with receiving commands. In these systems, the adjustable configuration determines the rate at which each of the two agents (i.e., human and the intelligent controller) contribute to controlling the aircraft.

c) Autonomous: The aircraft operates without direct human intervention and responds automatically to changes in its operating environment.

Remarks: Considering the limitations of BCIs, as they are discussed in the following section, and also drones' inherent instability, all the previous studies focused on using semi-autonomous aircraft to develop prototypes that operate in a shared-control mode (see Table II). The complementary role that the smart control agent plays in brain-controlled UAVs is crucial for compensating BCI inadequacies and maximizing the overall performance.

B. Control Essentials

In practice, a teleoperation is performed through controlling drone's state vector that normally consists of three position coordinates, three components of the velocity vector, and anywhere between three and nine parameters that describe the vehicle's attitude. A typical drone control system comprises two submodules: A low-level, inner-loop, onboard control system and a high-level, outer-loop, offboard control system (see Fig. 2). For major radio communications these two submodules are typically equipped with a transceiver—a multipurpose device that consists of both a transmitter and a receiver and is used for sending/receiving the commands to/from UAV. Together, the aircraft and its control system could be considered

[3]For example, UGVs, UAVs, or UUVs.

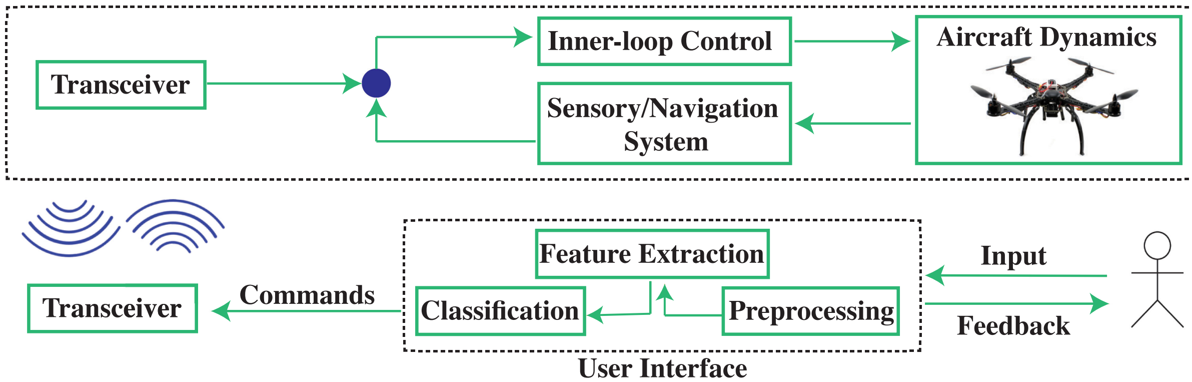

Fig. 2. Schematic of the basic configuration of brain-controlled UAVs.

as system of systems, i.e., a combination of independent and interoperable systems that are networked to achieve an overall goal [26].

1) Low-Level Control System: The onboard, inner-loop control system has two main tasks: 1) engaging the guidance system to generate the trajectory that UAV needs to follow in state space in accordance with the receiving reference commands issued by the outer-loop control; 2) operating the UAV to follow the generated trajectory and stabilizing the airframe using available sensor inputs. Global navigation satellite systems, which also include GPS and inertial navigation systems alongside with other onboard sensors, are essential components at the core of most UAV guidance-navigation systems, and are used to enhance the estimation of the vehicle state. The seminal role of the inner-loop control is even more evident, when the aircraft is required to operate in a shared-control mode with high levels of autonomy. There are myriad ways to implement the UAV inner-loop control system [27]–[29], which are not in the scope of this paper.

Remarks: As far as brain-controlled UAV developers are concerned, the significance of a low-level control system is in the complementary role it plays to sustain the set of predefined values for certain state space parameters that, in practice, cannot be adjusted by the BCI operator (see Section III).

2) High-Level Control System: The outer-loop control system, which is typically located in the ground station, gives the pilot the ability to deliver a desired mission, such as following a trajectory, to the UAV. This can be done through transmitting a simple set of navigational commands via a telemetry link. Employing a high-level control system is indispensable in aircraft that operate in the first or second autonomous mode, as these systems rely on external instructions to function. Therefore, designing a robust outer-loop control system is essential in developing brain-controlled UAVs.

C. Human Interface

Human interface (HI) is a platform that gives the operator the ability to generate the desired control commands and manipulate the aircraft in state space. Moreover, HI is responsible for representing the intelligence acquired by UAVs in an appropriate format to humans for further analysis, assessment, and action. In its most basic layout, HI could be a simple control panel such as a handheld touchscreen, a joystick, or other traditional hardware setup for interfacing. There has also been a growing momentum in utilizing more sophisticated HIs, based on eye tracking, body gesture, and BCI, which is particularly in the interest of the present paper and is thoroughly discussed in the following section.

We conclude this section by introducing two essential concepts in engineering complex systems such as brain-controlled UAVs: usability and workload. Usability is a practical notion that is primarily associated with the functionality of a system and the quality of being user-friendly, and it is generally considered to be a characteristic of HI [30]. In the context of this paper, usability indicates the extent at which pilot can navigate the aircraft with effectiveness and efficiency. System usability scale is one of the common approaches that could be used to have a fast and reliable assessment of the aircraft usability and help developers to improve ease-of-use during the design process [31], [32]. The operator's workload is the other critical factor that is of paramount importance in engineering systems that incorporate BCI in their HI. In the case of brain-controlled UAVs, while accomplishing high workload could be exhaustive for pilots and increase the likelihood of making errors, too low workload can induce boredom and consequently deteriorate their performance[33], [34]. Workload is a rather subjective concept, and different techniques are used by experimenters for its assessment. One of the most well-known approaches for quantifying workload is the NASA task load index (TLX); by definition: "The NASA TLX is a multidimensional rating procedure that provides an overall workload score based on a weighted average of ratings on six subscales: mental demands, physical demands, temporal demands, own performance, effort, and frustration" [35], [36]. As we introduce BCI in the following section, the necessity of proper distribution of workload in brain-controlled UAVs, between smart control agents and the pilot, will be clearer.

III. Brain-Controlled UAVs: BCI Fundamentals and Frameworks

Among various HIs discussed in the previous section, BCI has captured remarkable attention as it gives pilots the unique ability

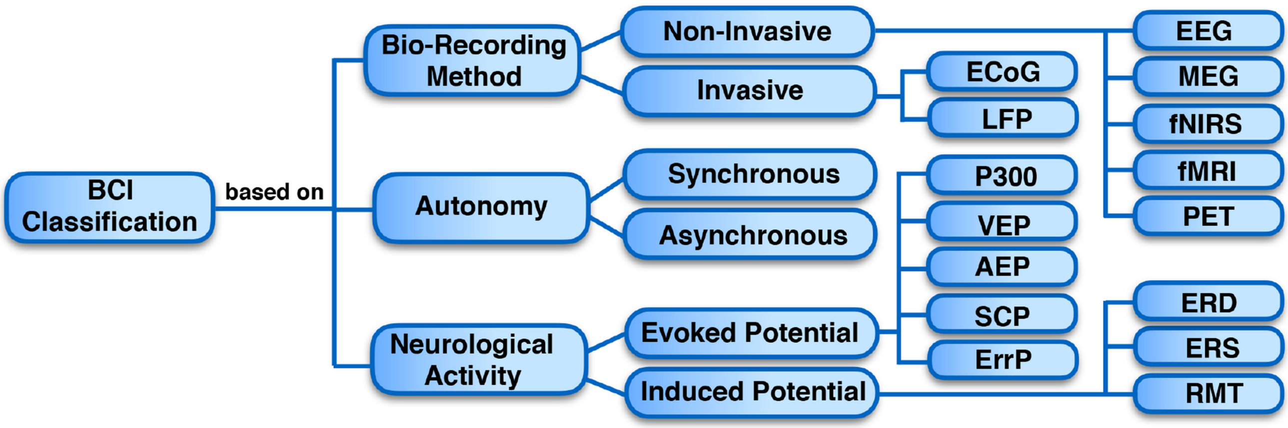

Fig. 3. BCI classification based on bio-recording method, autonomy, and neurological activity. AEP = auditory-evoked potential, ECoG = electrocorticography, EEG = electroencephalography, ERD = event-related desynchronization, ERS = event-related synchronization, ErrP = error-related potential, (f) MRI = (functional)magnetic resonance imaging, (f) NRIS = (functional)near-infrared spectroscopy, LFP = local-field potential, MEG = magnetoencephalography, PET = positron emission tomography, RMT = response to mental tasks, SCP = slow cortical potential, VEP = visually evoked potential.

to remotely control aircraft using their brain activity. BCI could be considered as a mutual communication channel that forms a closed loop between the pilot and the aircraft. On one hand, BCI decodes the pilot brain signals and translates them into control commands for the aircraft, while also being responsible for conveying system feedback to the operator (see Fig. 2). The direct consequence of this unified picture is that BCI design is not independent of the entire system's architecture, and it should be customized in accordance with the application scenario.[4] Similar to other complex interfaces, BCI entails a sequence of analytical components combined as one ensemble. Data acquisition, prepossessing, feature extraction, and classification, are the basic components of a typical BCI. Countless number of techniques and algorithms have been developed to construct a desired BCI structure, and the system robustness is the fruit of these selections, as these two are highly correlated.

A. BCI Categorization

As a multidisciplinary field, BCI could be classified based on different aspects, many of which have been outlined in literature [37], [38]. Here, we present a customized classification based on three seminal factors that are of particular interest for this paper, and play a determining role in the overall performance of the system (see Fig. 3).

1) Data Acquisition Method: Biosignals can be recorded via numerous techniques based on which BCI could be classified into: invasive and noninvasive. While in the former methods, the surgically implanted grid or microelectrodes record intracranial signals, either from cortical surface or from the inner brain tissues (LFP or single neuron recording), the latter techniques measure transcranial signals and do not require any surgical operation. Examples of this kind are fNIRS and fMRI, which measure hemodynamic responses, and EEG and magnetoencephalography, which respectively measures brain electric and magnetic fields. Certain characteristics are associated with each class, which make it suitable for specific applications [15]. According to statistics, the EEG-based BCI studies outnumber those based on other recording methods. Although EEG suffers from a low signal-to-noise ratio (SNR), its low price, portability, and wide accessibility make it a favorable recording modality. While the classic EEG systems are cumbersome and time consuming to apply and their application is mostly limited to the laboratory environment, modern designs demonstrate characteristics that make them more desirable for applications such as brain-controlled UAVs. Dry electrode and wireless EEG systems are quintessential modified EEG variations that are developed to address some of these issues [39], [40].

Remarks: A summary of the data acquisition methods in brain-controlled UAVs is presented in Table II. Aside from one study that used near-infrared spectroscopy (NIRS) in conjunction with EEG [41], all other developers almost exclusively engaged EEG to capture brain signals. In principle, hemodynamic-based recording techniques, i.e., (f)NIRS or (f)MRI, have lower temporal resolution and therefore are not suitable for the real-time control of brain-controlled UAVs. Using other biorecording techniques in this regard could be the matter of further investigation.

2) Autonomy: The autonomy of a BCI is determined by its dependency on external stimuli, which is contingent to the operational modality of its transducer.[5] Using autonomy as a metric, one can classify BCI into two categories: synchronous and asynchronous. If the presence of external stimuli is needed to evoke user's response, the transducer is in the exogenous mode, and therefore the system is synchronous; otherwise the transducer is in the endogenous mode and the system is asynchronous [42]. While in the former setup, a user relies on the external cues for issuing control commands, the asynchronous BCI enables the operator to issue control commands at their own discretion, and

[4] For instance, the BCI used in P300 speller is different with the one used in a robotic arm.

[5] Transducer is a vital component in BCI architecture and is responsible for measuring brain activities into basic control signals.

TABLE I
CHARACTERISTICS OF DIFFERENT BCI PARADIGMS

	Advantages	**Disadvantages**
Evoked Potentials	- Linear behavior - Do not require training - Inter-subject consistency - Higher accuracy and stable performance - Can easily be extracted by averaging over trials	- Short Peaks - Phase-locked - Stimulus dependent - Easily influenced by artifacts - Can not be used in asynchronous systems
Induced Potentials	- Larger peaks - Stimulus independent - Less influenced by artifacts - Suitable for asynchronous systems	- Non-linear behavior - Inter-subject variability - Require rigorous training - Require complex analysis techniques

also allow for autonomous adaptation of the system in concert with the assessed cognitive state of the operator [43].

3) Neurological Phenomena: It is a well-studied fact that there is a correlation between the changes in the ongoing brain electromagnetic signal, and the performing cognitive tasks (e.g., motor/auditory imagery). These changes are considered reliable biomarkers that allow for the implementation of various BCI-based systems [44]. In theory, a biomarker is considered an "evoked potential," if it is preceded by an external stimulus; otherwise it is recognized as an "induced potential" or "event-related potential (ERP)"[6] (see Fig. 3 and Table II). On this basis, the autonomy of BCI systems is contingent on the engaged neurological activities. It is also worth mentioning that in choosing between evoked and induced potentials, there is a tradeoff between the accuracy and autonomy of the system; thus, each BCI paradigm is suitable for certain applications [45], [46]. Surveying the literature reveals the fact that the P300 component is the most used ERP component in BCI systems. Also, the average consistency and performance accuracy of the BCI systems that operates based on ERP components, such as P300, steady-state visually evoked potential (SSVEP), or SCP, is higher than their counterparts [47]–[49].

Remarks: As it is outlined in Table II, the majority of brain-controlled UAVs engage different components of induced potentials in their configuration. This is mainly due to the fact that using asynchronous BCI paradigms gives the pilots the ability to control the drone at their own will and independent of any external stimulus. While in most cases the pilots controlled the drones via performing motor imagery (MI) tasks,[7] Coenen trained their subjects to perform auditory imagination and spatial navigation mental tasks to elicit response to mental task (RMT) [50]. The advantage of such approach is two-fold. First, such RMT components are generated in different cortical regions (i.e., the auditory versus visual cortex); thus, they are spatially discernible; second, it could potentially increase the number of control commands that the pilot can issue to navigate the aircraft. On the other hand, the application of ERP components in brain-controlled UAVs has been limited to two studies by Zhang *et al.* [51] and Khan *et al.* [41]. Although P300 and SSVEP are among the most common ERP components in BCIs, their application in brain-controlled UAVs will require special consideration for they require the pilot's visual focus/attention. The other notable ERP component that could be of particular interest in the context of brain-controlled UAVs is error-related potential (ErrP). Besides reducing the required training duration, which is a well-established utility associated with ErrP, this ERP component allows for monitoring pilots performance—a desired feature that is the key to developing automatic, BCI-based error-detection system and minimize pilots error rate. Furthermore, ErrP's can be used to establish implicit control through reinforcement learning [52], [53].

B. BCI Framework

Regardless of their design and application, most BCI systems share a more or less similar architecture which entails training, signal processing, feature extraction, and classification as the underlying steps [61]. Developing a BCI-based controller for an unmanned aircraft, however, is a complex task and demands rigorous considerations. Controlling a UAV in real time is a time-sensitive procedure that requires generating continuous commands with high accuracy. In designing BCI architecture, the greatest challenge for brain-controlled UAV developers is to find an optimum balance between robustness of the engaged strategies and the pace of operation, as there is a tradeoff between these two factors. The building blocks of a typical BCI are as follows.

1) Training and Feedback: Training is a sine qua non for BCI users, and in particular for brain-controlled UAV operators. The crucial importance of training could be viewed from two aspects. First, users can learn how to modulate their brain activity patterns, based on the system feedback, in order to gain a dexterous control over the aircraft. Second, the system can learn how to avoid future errors by co-adaptation via machine learning strategies. In a typical BCI, users go through an offline training phase prior to running the experiment; however, co-adaptive algorithms, offered by state-of-the-art classification, make it possible to fulfill the training online [62], [63]. Another determining factor in the training phase is BCI paradigm for systems based on induced potentials that requires a more rigorous training compared to those using evoked potentials.

[6]Additionally, there are other neurological phenomena such as synchronization of alpha rhythms that are not significant for BCI application.

[7]For example, controlling different DOF of the drone via visualizing hand, leg, or tongue movement.

TABLE II
CHRONOLOGICAL SUMMARY OF METHODOLOGIES USED IN BRAIN-CONTROLLED UAV STUDIES

Publications		**Prototype Specification**				**BCI Specification**			
Authors	Year	UAV type	DOF	Control Commands	Hybrid	Data Acquisition	Paradigm	Task	Classifier
Audrey et al. [12]	2010	virtual helicopter	2	R-L & U-D	N	EEG	ERD/ERS	MI	linear classifier
Akce et al. [25]	2010	fixed-wing	N/A	choosing trajectory	N	EEG	ERD/ERS	MI	binary classifier
Doud et al. [13]	2011	virtual helicopter	3	R-L & U-D & F-B	N	EEG	ERD/ERS	MI	linear classifier
LaFleur et al. [14]	2013	quadcopter	3	U-D & L-R & F-B	N	EEG	ERD/ERS	MI	linear classifier
Kosmyna et al. [54]–[56]	2014	quadcopter	2	U-D & F	Y	EEG & EMG	ERD/ERS	facial gesture MI	Adaptive RNN
Kim et al. [57]	2014	quadcopter	3	U-D & L-R & F-B	Y	eye tracker EEG	EOG	eye movement	Kernel-based SVM
Shi et al. [58]	2015	hexacopter	2	L-R & F	N	EEG	ERD/ERS	MI	LR
Coenen [50]	2015	drone	1	V or H	N	EEG	RMT	AI & SNMT	N/A
Ayyobe et al. [59]	2015	AR drone	N/A	N/A	N	EEG	N/A	MI	N/A
Khan et al. [41]	2015	quadcopter	2	U-D & F	Y	EEG & NIRS	ERD/ERS SSVEP	MI	LDA
Lin et al. [60]	2015	quadcopter	3	U-D & F-B & R-L	Y	EEG & EMG	N/A	facial gesture	N/A
Zhang et al. [51]	2015	quadcopter	3	U-D & F-B & R-L	Y	Google glass EEG	ERD/ERS SSVEP	head posture MI	RBF-based SVM

Acronyms: Y = yes, N = no, N/A = not available or Applicable, R = right, L = left, U = up, D = down, F = forward, B = backward, V = vertical, H = horizontal, AR = augmented reality, EEG = electroencephelography, EMG = electromyography, EOG = electrooculography, ERD = event-related desynchronization, ERS = event-related synchronization, LR = logistic regression, LDA = linear discriminant analysis, MI = motor imagery, NIRS = near-infrared spectroscopy, RMT = response to mental task, RNN = recurrent neural network, SSVEP = steady-state visually evoked potential, SVM = support vector machine.

Remarks: Training brain-controlled UAV operators can be done either in a virtual or real environment or both. Since the underlying idea behind most MI-based BCI controllers is similar, controlling a cursor is a putative means for training pilots prior to performing teleoperation in the real world. Fig. is a demonstration of such a training sequence [14], [63]. Providing feedback for a brain-controlled UAV operator is different from other BCI-based devices, since during teleoperation having a direct visual contact with the aircraft is not feasible. Therefore, a visual interface is needed to present the recorded footage by the onboard camera and provide feedback for the pilot. In an attempt to minimize pilots' training time, Kosmyna *et al.* proposed a co-learning based BCI; using an ad hoc bi-directional feedback channel, the operators could validate the BCI output by providing an affirmative feedback to the system [54].

2) Control Strategies: Depending on the BCI design, the brain-controlled UAV operator can either control the aircraft directly or indirectly. In the former approach, the pilot uses BCI to directly actuate the aircraft in the state space (i.e., navigating the aircraft to right/left, up/down, forward/backward, etc.) [see Fig. (a)]. Contrarily, in the indirect approach, the operator controls the aircraft through specifying its future trajectory and/or destination. The inner-loop onboard control system is responsible for the continuous adjustment of the aircraft states to ensure it is following the assigned trajectory. This approach was adopted in a study by Akce *et al.*, where they used an interface comprising an ordered symbolic language of smooth planar curves to specify the desired paths for the aircraft [25] [see Fig. (b)]. Implicit control is yet another form of an indirect approach that is based on using natural responses of the operator's brain and interprets them in the given context. A BCI properly trained to detect such responses could directly and unobtrusively be used for implicitly controlling a drone, as outlined by Thorsten *et al.* [64].

3) Preprocessing: Special treatment is needed to transform the noisy raw data into clean signals that can be translated into control commands. Depending on the applied data acquisition method and the BCI application, preprocessing might vary case by case. The simplest and most widely used method to remove artifacts and extract the desired frequency band is filtering. The most common filters include high-pass, low-pass, band-pass, and notch filter, which can be combined with other computational techniques such as independent component analysis (ICA) or common average reference to remove artifacts and improve SNR [65].

4) Feature Extraction: Numerous features have been used in different BCI systems, namely signal amplitude, band power, power spectral density values, adaptive autoregression param-

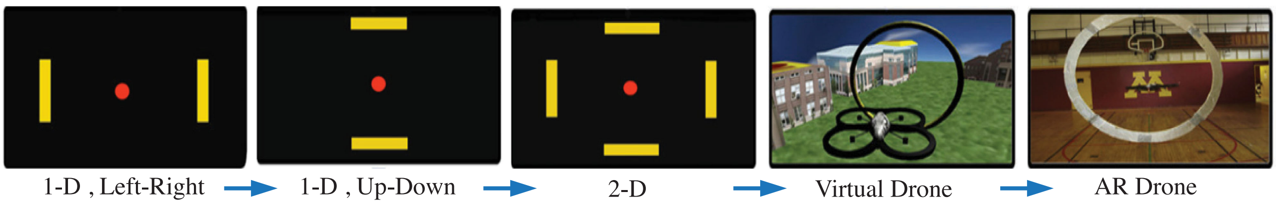

Fig. 4. Training platform in virtual and real environment [14].

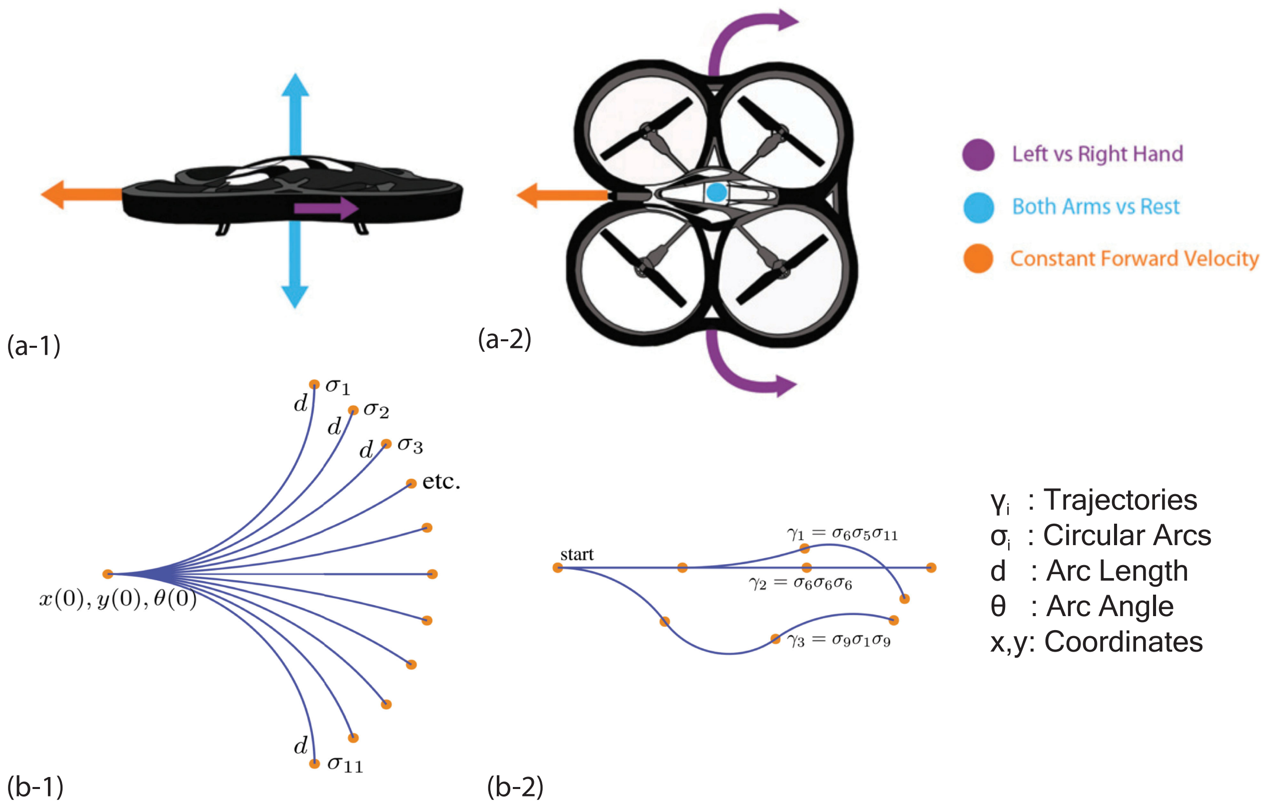

Fig. 5. (a) Direct control: Actuating drone by performing complex MI tasks [66]. (b) Indirect control: Navigating drone by specifying its future trajectories [25].

eters, phase coherency, common spatial pattern, etc. [67]. Features are typically determined in accordance with the system architecture; for instance, temporal and spectral features are respectively associated with evoked and induced potentials. Also, considering the fact that the spectral and spatiotemporal features in brain activities (e.g., EEG signals) are known to be highly subject-specific, prime attention has been directed toward trainable feature extraction algorithms that allow for dynamic customization of the optimum set of features [68], [69]. Using a proper set of features is the key to minimizing the number of dimensions in feature space and reducing the computational load on classifiers.

Remarks: In brain-controlled UAVs, MI is the most common task performed by operators (see Table II), and it induces a change in SMRs in specific frequency bands[8]; thus, spectral-temporal features are favorable candidates for these types of systems. Also, different source space analyses could be used to identify the spacial features, that is, electrodes[9] embedding features that have the highest correlation with the ongoing mental task [70], [71]. Finally, given the fact that navigating a drone in real time is a time-sensitive task, some prototypes also incorporate nonmental features (e.g., eye/muscle movement) to minimize the operation delay (see Section III-C).

5) Classification: In order to translate the extracted features into control commands in BCI systems, a variety of classification algorithms have been used. The five general classes of classifiers are as follows: linear classifiers, nonlinear Bayesian classifiers, neural networks, nearest neighbor classifiers, and any combination of these classifiers [67]. Using time responsiveness as a metric, classifiers can also be categorized as stable and dynamic; while dynamic classifiers outperform the former class in

[8]Typically in alpha (8–12 Hz) and lower beta (12–15 Hz).

[9]That is, localizing the neural source of activity within the brain at a given time.

synchronous BCIs, they lose their superiority in asynchronous systems[10] [72]. Also, due to the nonstationary nature of EEG signals, a vast body of related research focused on adaptive classifiers based on robust supervised machine learning algorithms [73]–[75].

Remarks: Considering the fact that in choosing the best classification algorithm, there is a tradeoff between robustness and computational cost on the one hand, and the analysis speed on the other. Linear classifiers are generally the preferred class for developing brain-controlled UAVs. Linear discriminate analysis and support vector machine (SVM) are the main two types that have been widely used in previous prototypes (see Table II). To the best of our knowledge, the only exception in this trend is the study by Kosmyna *et al.*, where they reported developing an ad hoc, co-learning-based BCI using recurrent neural network (i.e., a nonlinear classifier) [54]. In prototypes that use basic MI-based BCI, the pilot imagines right/left hand movement to actuate the aircraft to right/left, and therefore the system needs a binary classifier to distinguish between the two classes. However, in pursuit of increasing degrees of freedom, the majority of developers used multiclass classifiers to map complex MI tasks[11] into several output control commands for the aircraft [65], [67].

C. Hybrid Modality

State-of-the-art BCI suffers from a number of serious deficiencies that indeed limit the overall performance of the system, namely a lack of high accuracy and reliability, low information transfer rate, and user acceptability [76]. Brain activities, and in particular EEG signals, are nonstationary and demonstrate significant intersubject variance. Also, performing a continuous mental task to control an aircraft in real time could be an exhausting procedure—when added to environmental distractions, it can lead to a loss of control over the aircraft. The limited number of output channels is another serious drawback in conventional BCIs that poses a serious challenge on developing BCI-based controller for complex robotic systems such as UAVs.

In the interest of eliminating these limitations and enhancing the fidelity and performance of BCI systems, developers engineer hybrid BCI. In a broad sense, the term "hybrid BCI" refers to a multimodal control approach that at least includes one control stream based on BCI technology. From this, two classes of systems are derived. The first class is based on combining different BCI paradigms, whereas in the second class, feeding the system is fulfilled through integrating BCI with non-BCI input modalities (i.e., not based on brain signals), such as EMG, eye/gaze tracker, electrooculography, and standard input devices (e.g., flight stick, mouse, and keyboard). Modern BCIs may also combine invasive and noninvasive biorecording techniques to incorporate a set of electromagnetic and/or hemodynamic biomarkers as the input source for the system [77].

Regardless of their underlying configuration, the basic principle that governs different hybrid BCIs remains the same; one of the engaged modalities is counterbalancing limitations of the other and vice versa. In these systems, the grand hierarchy determines whether different components are engaged concurrently or sequentially. In the first case, recorded signals from different sources are processed in parallel and subsequently mapped to control commands. The simultaneous use of different input modalities could significantly improve the BCI bit-rate and the information throughput [78]. On the other hand, in sequential hybrid BCIs, the output of one modality serves as the input for others. The practical merit of sequential hybrid BCIs is twofold. First, they could be designed in a way that enables the operator to selectively initiate/terminate other control processes, e.g., a sequential ERS-based brain switch could be used to turn ON/OFF an SSVEP BCI [79]. Second, by the same token, a sequential hybrid BCI could enable the operator to rectify, reinforce, or cancel the issued control commands and, therefore, reduce the overall false positive rate of the system [80]. Numerous studies were dedicated to review the design and application of the hybrid BCI [66], [81], [82].

Remarks: Enhanced information transfer rate (ITR) and the possibility of rectifying control commands are the two unique advantages of hybrid BCIs, which are central to the functioning of brain-controlled UAVs. A summary of the prototypes that uses hybrid BCI in their configuration is presented in Table II. For instance, Zhang *et al.* combined Emotive EEG headset with a Google Glass[12] to record brain signal and capture head postures. Therefore, the pilot was able to engage head movements in concert with the MI task to gain a dexterous control over the aircraft[13] [51]. Other studies used facial gesture and/or eye movement as supplementary sources of input for the system [55], [57], [60]. The application of other biorecording techniques, however, is limited to a study by Khan *et al.*, where they used NIRS to reinforce the commands issued via MI task and SSVEP [41]. The application of different hybrid BCI in brain-controlled UAVs could be the matter of further investigation.

D. Performance Evaluation and Comparison

Despite the significant progress that has been made in the field of BCI, the lack of a widely accepted platform for evaluating and comparing the performance of different BCI systems is being felt. Several key factors can be enumerated, whose variability is considered as the main impediment on the way of reaching a common ground for assessment within the BCI community; subjects, data acquisition methods, experiment protocols and tasks, and evaluation metrics are among these factors [82]. Nevertheless, performance evaluation and comparison are feasible on the basis of a particular parameter such as speed and accuracy, ITR, or receiver operating characteristic (ROC) curve[14] [17].

Remarks: Several ad hoc strategies have been used in previous studies to evaluate the performance of developed brain-control

[10] This is mainly due to their association with the evoked and induced potentials, respectively.

[11] For example, hands versus feet versus tongue movements.

[12] Google Glass is a commercially available device made by Google, which is equipped with an accelerometer, a gyroscope, and a magnetometer on the optics pod and is able to detect head posture.

[13] Authors also reported an unsuccessful attempt to integrate SSVEP into their design.

[14] An ROC curve is a graphical plot of sensitivity versus (1-specificity).

UAVs. LaFleur *et al.* used ITR metric based on Shanon's work, customized for asynchronous BCI [14]. In many of these studies, performance assessment is task specific and is measured intrinsically for each subject [13], [56]. A universal framework for assessing the performance of brain-controlled UAVs is yet to be established.

IV. Discussion and Conclusion

The intriguing idea of deciphering brain signals into direct, indirect, and implicit control commands for different devices has been the greatest motivation for numerous scientists around the globe to orient their research on developing BCI-based systems. These early efforts set the stage for others to engage BCI for controlling various robotic systems, and in particular flying robots. In this paper, we presented a comprehensive review of how state-of-the-art BCI could be employed to develop a control module for UAVs. A successful design and implementation of a brain-controlled UAV require a great deal of knowledge and expertise in both involved technologies (i.e., BCI and UAV). The key point in engineering integrated systems, such as brain-controlled UAVs, is to consider the involved components as parts of the entire ensemble and not as an independent, secluded entities. Choosing proper techniques for implementation of different elements is highly influenced by the entire system's configuration. From this standpoint, the architecture of the employed BCI in a brain-controlled UAV is different from other robotic systems, for they demonstrate an inherently unstable nature. In addition, controlling an aircraft in real-time is a continuous task that requires a high ITR; this poses a technical challenge on developing BCI-based control systems for drones. Using efficient control strategies is another essential consideration in these systems. Controlling a drone by executing the MI task is an exhausting procedure that can restrict pilots' capability to maneuver the aircraft. Path planning or target selection, on the other hand, are indirect control approaches that provides more degrees of freedom for the BCI operator.

So far, the main focus of developers has been on using induced potential components and particularly ERD/ERS; therefore, a lack of comprehensive research on the role of evoked potentials in developing the brain-controlled UAVs is evident. The other important aspect that demands special attention is choosing the proper feature extraction and classification analysis, as they are pivotal in designing robust BCI-based controllers. Especially, in the case of brain-controlled UAVs, the algorithm of these important analysis must be customized in accordance with the type and properties of drones. In particular, the role of co-adaptive learning through engaging proper adaptive classifiers and machine learning techniques merits further investigation. Advancements in different technologies have introduced new interfaces that could be used in conjunction with BCI, in order to develop hybrid modalities. The application of hybrid BCI in brain-controlled UAVs has hitherto been limited to a few studies that used eye trackers and facial/head gesture detectors as complementary input modalities for the system. Thus, employing various other forms of hybrid BCI in brain-controlled UAVs demands further investigation. The potential of the hybrid BCI approach to overcome the limitations of psychophysiology measures in combination with smart control strategies, including implicit control, shows a clear path to significantly improve human–machine interaction in UAV scenarios.

Previous research on brain-controlled UAVs has paved the way for successful implementation of these systems. From the very first developed prototype, brain-controlled UAVs have experienced considerable improvement. However, significant progress is still needed to enhance their fidelity and robustness in order to see the application of these systems transcends just laboratories, and finds its way into our daily life.

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Amin Nourmohammadi received three M.S. degrees in nanotechnology, physics, and biomedical engineering. He is currently working toward the Ph.D. degree at the Biomedical Science Department, State University of New York (SUNY) University at Albany, Albany, NY, USA.

He is actively investigating system neuroscience as well as neural engineering. His research interests include brain–computer interface, neuromodulation, and neuroadaptive technology.

Mohammad Jafari was born in Tehran, Iran. He received the B.S. degree in computer hardware engineering and the first M.S. degree in mechatronics engineering both from Iran, in 2007 and 2012, respectively. He received the second M.S. degree in computer science and engineering from the University of Nevada, Reno, NV, USA, in 2015. He is currently working toward the Ph.D. degree at the Department of Electrical & Biomedical Engineering, the University of Nevada.

His research interests include control systems and robotics.

Thorsten O. Zander leads Zander Laboratories, Amsterdam, The Netherlands, and the research group Team PhyPA, Berlin, Germany. His research interests include using neurophysiological signals to decode the cognitive or affective state of a user. By developing novel BCIs, his groups aim to automatically assess information about the users state to augment and automatically adapt human-computer interaction. He is considered as a pioneer in the field of passive BCIs, recently published his vision about neuroadaptive technology in the *Proceedings of the National Academy of Science of the United States of America*. Furthermore, he is affiliated with the Leibnitz Institute Knowledge Research Center and the Excellence Cluster LEAD Graduate School in Tübingen as well as the Swartz Center for Computational Neuroscience, University of California, San Diego.