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REVIEW

Brain–machine interfaces in space: Using spontaneous rather than intentionally generated brain signals

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ABSTRACT

Recent advances in non-invasive brain–machine or brain–computer interfaces (BMIs/BCIs) have demonstrated that humans can control computers or simple robotic devices using only brain signals. These successes have lead to the suggestion that BMIs could significantly improve the safety and efficiency of space operations. Electroencephalography (EEG) and near infrared spectroscopy (NIRS)-based BMIs are most relevant for potential space applications due to their portability, non-invasiveness, and relative inexpensiveness. However, BMIs using these methods are limited in their speed, content, and accuracy of information transfer. In this paper, we suggest that the performance limitations of current BMIs may reflect the incomplete information of non-invasive signals rather than merely a lack of maturity of the technology. As an alternative to using BMIs for direct control, we describe how new research on monitoring spontaneously generated brain signals may be practically applied in space operations.

Contents

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1. Introduction

Research on brain–machine interfaces (BMIs, also known as brain–computer interfaces) has advanced so quickly in the past few decades one could imagine that in a few years' time intuitive, practically effortless, and precise control of external devices will be possible through thought alone. This development could have implications for space operations, perhaps most importantly to enable direct mental teleoperation of semi-automatic manipulators in the hostile external environment from within the safety of the spacecraft [1,2].

Unfortunately, researchers are encountering significant limitations in the speed, accuracy, and usability of non-invasive BMI technology. In one view, these limitations will be overcome with more sensitive and extensive measurement equipment and more sophisticated feature extraction and machine learning algorithms [2–4]. While modest improvements in the performance of current systems are certainly achievable and will be highly valuable for certain clinical populations and some particular healthy-user applications, it is unlikely that variants of existing non-invasive techniques will reach the performance levels necessary to make BMIs an attractive option for most of the space applications proposed to date (e.g. control of external robotics, EVA suits, and other spacecraft systems [2]).

This is not to discourage BMI research for safety-critical operations in healthy users; instead, we suggest that a related yet distinct approach is much closer to implementation and offers unique benefits. 'Passive' BMIs (pBMIs) use signals which are associated with spontaneously generated brain states to provide a novel input channel to computers [5]. This process occurs without the user's attention or intention, meaning that the user's primary mode of interaction is not disturbed. Instead of providing an additional means for direct volitional control in which the user concentrates on a specific environmental stimulus or performs a mental activity that is associated with a command, pBMIs provide a secondary means of system control, enabling the improvement of human-system performance [6].

In this paper, we first provide a brief overview of BMI approaches and explore suggestions for space applications. We then describe the origin of the brain signals suggested for use in space to clarify why they may be inadequate particularly for robotic control. Finally, we describe the emerging area of pBMI research and outline its possible contributions to safe and efficient space operations.

2. Current non-invasive BMIs for space applications

2.1. Overview of BMIs

Consensus on the definition of a brain–machine interface has not been reached, with some researchers preferring to include only those interfaces which allow the user to send conscious commands to a device, while others use the more inclusive definition of any direct communication pathway between the brain and an external device. The narrower, command-oriented definition may reflect the origins of the research area, which until recently has focused exclusively on providing a means of communication and control to severely paralyzed patients. We use the broader definition for two reasons: devices often use the same equipment, technology, and techniques, thus productively forming a single research area; and in some applications it is very difficult to clearly divide conscious, intentional commands from other brain signals that could be used to control a device (e.g. in a case where a high-level command is intentionally given by the user, yet the device takes brain signals from covert neural processes, or when a device uses these identical neural processes in the absence of a high-level command).

Though the specifics differ according to the application and implementation, the common general steps in a BMI are recording a signal generated by the brain, filtering and pre-processing the acquired signal to remove known artefacts and improve the quality, and extracting aspects of the brain signal relevant for the application [7]. The results are then used as inputs for controlling a device. Communication in the reverse direction, from the device directly to the brain, is difficult and has only been achieved to some degree in invasive experiments [8]. Instead, feedback to the user is usually achieved through visual, auditory, or tactile channels.

Most methods for monitoring brain activity in medicine and research, from large scale measurement of the brain regions down to the firing of individual neurons, can be used to provide input signals for BMIs. Invasive measurement of small groups of neurons via electrodes implanted in tissue around or in the brain has produced the most impressive BMI performance, as signals of high quality and dimensionality are obtainable, and some direct feedback is possible [7,9,10,8]. Even if healthy users would voluntarily accept the risks of a craniotomy, the degree of long-term stability and safety of implants is not yet adequate for clinical use [7,10,11]. Space operations exert loads and vibrations on the body which would likely increase the risk of damage and scarring at the point of contact between the measuring probe and the brain tissue, contributing to

Table 1
Comparison of characteristics of brain signal sensor techniques used for BMI.

Method	Principle of operation	Signal characteristics	Portability, comfort, etc.
Functional magnetic resonance imaging (fMRI)	Hemodynamic; measures difference in magnetic properties between oxyhemoglobin and deoxy-hemoglobin. The head is placed in a strong magnetic field which causes atoms to align. Perturbations in atomic spin alignment after radio pulses of specific frequencies are used to identify changes in blood oxygenation levels.	Temporal resolution: ~ 2 s; spatial resolution: < 5 mm. Near real-time user feedback (1.3 s) has been demonstrated [13]	The scanner is large due to need for strong super-cooled magnets, and it is very loud. Subject must not move more than ~ 2 mm. Note that some more portable variants are in development but not yet in use
Magneto-encephalography (MEG)	Electromagnetic; measures weak magnetic fields at the scalp generated by neural activity via very sensitive detectors such as Superconducting QUantum Interference Devices (SQUIDs). The signal is not distorted by the biological tissues between the neurons and the sensor	Temporal resolution: ~ 1 ms; spatial resolution: ~ 1 cm	Equipment is large, a magnetically shielded room is required, and the subject must not move. Detectors do not require electrode gel and a helmet-like device can allow for the fast application of large numbers
Electro-encephalography (EEG)	Electromagnetic; measured by scalp electrodes where each channel represents the voltage difference between a given electrode and a designated reference electrode. The skull, meninges, and cerebral-spinal fluid cause some attenuation and distortion of the signal	Temporal resolution: ~ 1 ms; spatial resolution: ~ 10 cm; real-time analysis possible	Relatively small, portable, and inexpensive. Movement causes artefacts and increases signal noise, but it is possible to record useful signals during natural behaviors. Electrodes must be applied to the scalp using conductive gel or paste. Suitably sensitive 'dry' electrodes are in development
Near infrared spectroscopy (NIRS)	Hemodynamic; the difference in optical absorption and refraction properties between oxyhemoglobin and deoxy-hemoglobin in the near infrared spectral range is measured using a laser or LED light transmitted through the skull and detected several centimetres away, resulting in the examination of a shallow 'banana-shaped' volume of tissue between transmitter and receiver	Temporal resolution: ~ 2 s; spatial resolution: ~ 10 cm, limited depth of a few centimetres from the skull; real-time analysis possible. (Note: a 'fast NIRS' associated more directly with neural activity has also been reported, but its signal is weak and may not be reliably detectable [14])	Relatively small, portable, and inexpensive. Movement causes artefacts and increases noise, though it is possible to record useful signals during natural behaviors

unacceptable health risks and signal loss over time. Safe implants may eventually be developed, but are out of reach for near-term space applications.

We restrict our discussion to BMI methods which measure brain activity non-invasively; that is, without inserting sensors into the body or injecting substances to enhance biological signals. The two main aspects of brain activity that can be measured at the scalp are electromagnetic activity, which is associated with the activities of large numbers of neurons and is recordable in the order of milliseconds; and hemodynamic activity, which measures comparatively slower oxygenation changes to metabolically active brain areas over a period of seconds. In Table 1, we include a brief summary of most of the techniques used for BMIs to date [7,12,13].

Each of these methods and several combinations have been explored for BMI use (see [15] for a recent review). Electroencephalography (EEG) is the most commonly employed method for BMIs due to its portability, relative inexpensiveness, and extensive history in medicine and basic research. The use of Near infrared spectroscopy (NIRS) is increasing, yet comparatively few studies have

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been conducted. The other methods are currently unsuitable for most healthy-user applications due to size, restrictions on user movement, and expense.

BMIs can also be classified by the type of mental activity generating the BMI signals. Zander et al. suggested a rough distinction between 'active', 'passive', and 'reactive' BMIs [5]. Active BMIs (aBMIs) are those used for direct control of devices which are based on signals generated intentionally by the user, for example a wheelchair steered by signals that correspond with motor imagery tasks performed by the user. Passive BMIs (pBMIs) instead are used for supporting systems rather than directly controlling devices. They are not based on intentional thoughts, but on spontaneously generated states of the user's cognition that do not require the directed attention of the user or otherwise interfere with ongoing mental or motor activities. For example, a change in the power of EEG frequency bands can be used to predict when drivers are about to fall asleep [16]. The active vs. passive distinction is less clear in certain cases, but the categorization serves as a starting point for discussion.

Reactive BMIs (rBMIs) are somewhere in between. They are based on brain signals that are automatically generated upon perception of certain external stimuli. rBMIs can be considered more active or passive depending on the degree of intentional involvement of the user. For example, a P300 speller is closer to an aBMI. The user is presented with a matrix of letters, in which rows and columns randomly flash brightly. When the user focuses their attention on the letter they wish to select, the brain produces a unique reactive signal after the letter of interest is highlighted, which allows for its identification after several repetitions. The properties of reactively generated signals can also be used to obtain information about the user's states (more like pBMIs). For example, the latency and amplitude of reactive signals to periodically presented tones known as auditory event-related potentials is known to differ systematically with mental workload [17]. Although the user must be able to perceive the presented signals, many stimuli produce useful reactions without requiring the user's directed attention. We refer mainly to the aBMI vs. pBMI distinction for the remainder of this paper, specifying the reactive nature of the signal where necessary for clarity.

Aside from the signal recording technology and the active, passive, or reactive distinction, BMIs can be classified based on if communication from brain to machine can occur at any time or only at specific times (asynchronous vs. synchronous); if training and adaptation takes place on the part of the user or the computer; and if the signal of interest is the brain's transient response to an event or a more prolonged change such as spectral power differences between consecutive windows of time [7].

2.2. Suitable brain monitoring methods for space

Menon et al. recently outlined the preferred characteristics of BMIs for use in space flight [2]. They include non-invasiveness and user comfort; low weight and volume; high reliability, efficiency, robustness and sensitivity as compared with alternatives; and compatibility with potentially interfering devices such as those that produce electromagnetic signals. Whereas performance characteristics vary between specific BMI designs, both EEG and NIRS equipment meet the general usability requirements for space applications [18] (see Sections 2.4–2.7 for a discussion of the performance requirements of BMIs in space operations). A combined approach is currently under investigation in a number of labs that may further improve brain activity detection since EEG and NIRS operate on different principles and time scales and are susceptible to different noise sources [18].

The spaceflight environment includes factors which may affect the use and function of EEG and NIRS-based BMIs. Some of these factors, such as sensory and motor adaptation to microgravity, psychological stress, poor sleep, and vestibular disturbances, may directly alter the brain activity of the user on which a BMI is based (see [19] for a review of physiological issues in space). Despite the electrically 'noisy' environment, EEG has been used successfully to study sleep and waking brain function in space since the Gemini 7 mission in 1965. Changes in the EEG signals relating to different mental processes in space have not been systematically studied [20], although there is evidence for differences in the brain's rhythmic electroencephalographic activity in microgravity [21]. Some authors have noted the possibility of interference in EEG-based BMI function due to light flashes, which are thought to result from high-energy charged particles traversing the retina [2,3]. These are not likely to be a major problem for BMIs, since flashes are generally reported only when the cabin is dark and the astronauts' vision has adapted to the dark, likely resulting in low-intensity, transient responses in the brain during periods in which the astronaut is not working. To the best of our knowledge, NIRS has not been used in space to measure brain activity, although the prospect has been suggested [18] and several labs are developing suitable technology (e.g. [22]). The shift of fluids towards the head that occurs in microgravity will likely change the appearance of hemodynamic brain signals, and may mask or alter signals which are reliable indicators of cognitive phenomena on the ground.

While it is likely that there will be some differences in a user's BMI-related brain processes in space, particularly relating to the sensory-motor and vestibular systems, astronauts are able to function normally in space in many activities. This suggests that most brain signals usable for BMIs on the ground will also be present in space, although work is needed to determine how to adjust for differences.

2.3. Suggested space applications for BMIs

A study conducted by the Advanced Concepts Team at the European Space Agency in 2005 [1] listed control of robotic systems including robotic replacements for human extra-vehicular activities (EVAs); tele-controls of autonomous vehicles (for use in exploration, repairs, and maintenance); and hands-free direct control of cabin

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instrumentation and equipment among potential BMI applications in space. The study also mentions the potential usefulness of combining BMI with other interactive techniques, for example the control of exoskeletons using electromyography (EMG), which measures electrical signals from the muscles rather than the brain (and is therefore beyond the scope of this article). Menon and colleagues [2] emphasized the potential role of BMIs in controlling external manipulators, providing environmental or external control in EVA suits, maximizing astronaut efficiency by performing several operations using a single BMI, or by enabling multiple astronauts to command a single BMI. Broschart et al. [3] concluded that surface rovers and semiautomatic manipulators are the most relevant area of BMI application in space operations. All of these suggested applications involve intentional commands by the user, and so may be implemented with aBMIs (or in some cases rBMIs, though the necessity of presenting stimuli may be impractical). Since the idea of aBMI-controlled external robotic manipulators arises frequently, we take this as a starting point to consider the suitability of current technology for space purposes.

EVAs are conducted in order to perform construction, equipment installation or removal, and repair tasks. Their reduction is desirable as safety risks to astronauts are much higher during EVA than other operations, and also because EVAs require extensive ground training and time-consuming in-flight preparation. Automated robotic solutions can take over some tasks, but are not yet sufficiently flexible and adaptable to replace many EVA activities [23]. Robotic systems that can be manually controlled from inside a spacecraft or from the ground using traditional interfaces such as joysticks and display screens are also used to reduce the need for EVAs and where EVAs are not possible. One such unit is the Special Purpose Dexterous Manipulator, a component of the International Space Station's Mobile Servicing System which is capable of handling some of the delicate assembly, replacement, and repair tasks previously performed during EVAs. However, control of teleoperated manipulators remains complex, slow, and limited in application.

Robotic systems that could be operated with high accuracy and little delay simply by thinking of movement, as one 'operates' their own limbs, would be highly desirable. At minimum to be an attractive alternative to EVAs or various existing forms of teleoperation, BMI-operated manipulators would have to enable the same level of performance in terms of speed, accuracy, safety, and flexibility that can currently be achieved.

2.4. *The information transfer gap*

Kim et al. recently published a review of aBMI developments from the perspective of robotics, in which the performance requirements for full, real time dextrous control of a robotic arm are outlined as well as some of the challenges in using invasive aBMIs for robotic control [10]. According to Kim et al., dextrous control requires a minimum of 20 commands per second, much higher than achieved by current EEG-based aBMIs with average transfer rates in the order of 0.5 bits per second (bps) for non-invasive systems to around 6.5 bps for invasive systems [9,11,24]. To illustrate the current state of BMI technology, we report recently published results for the well-known aBMI 'Berlin Brain Computer Interface', in which six subjects performed three simple cursor-control tasks using a motor imagery EEG-based aBMI [25]. After a brief period of data collection to train the classifier, five of six subjects were able to control the BMI, achieving average information transfer rates of around 0.3 bps in each of the three tasks. The information transfer rate required for dexterous control of a robotic arm (which would need to include control of direction, speed, grip strength, and perhaps complex joint structures) is therefore orders of magnitude greater than that which is currently available.

Though real-time dexterous robotic control using aBMIs is currently beyond our technological capacities, intermediate applications may be found that have more reasonable information transfer requirements. For example, aBMIs could be used to control a single dimension of interest during other operations, or for hands-free operation of environmental controls within EVA suits [2]. aBMIs could also be used to decode high-level commands which are then implemented semi-autonomously by robotics or other systems, possibly with the user monitoring activities and intervening with further high-level commands as appropriate [3,8]. This could reduce the information transfer rate required to within a range plausible for non-invasive signals, and already seems practically useful for applications such as leg neuroprostheses which are able to assist with control of balance without express commands from the brain [8].

Unfortunately, not many situations have been put forward under which aBMI activation of a complex semi-autonomous robotic activity or other low-dimensional control might be preferable to the simpler and highly reliable solution of using a button, or in the case that hands-free operation is desirable, other input modalities (e.g. voice commands, eye tracking, etc.). An additional consideration is whether the astronaut will consider a device that can be used to occasionally send a discrete command as sufficiently valuable to warrant the inconvenience of calibrating and wearing another piece of equipment.

2.5. *The accuracy gap*

Accuracy levels reached by aBMIs have depended on factors including individual differences in physiology, the type of task, the hardware and software used (including any kind of predictive mechanism or error signal correction), signal noise levels, and the particular user's ability to carry out the mental task. In classifier-based aBMIs, accuracy must be traded-off with information transfer rate and command latency, because better signals are obtained from longer windows for feature extraction algorithms in the case of aBMIs, or more stimulus presentations for rBMIs. These aspects must be considered for a meaningful comparison of BMI accuracy, but for a rough idea, the Berlin Brain Computer Interface used as an example in the preceding section achieved an average accuracy of about 90% when discriminating between two conditions, with individual accuracies ranging from 78.1% to 98.0% [25] (for an explanation of the many accuracy and performance measures used in BMI research, please refer to [26]). Accuracy can be expected to decrease with the increased dimensionality that would be needed for many tasks. Increased signal noise due to user movement or signal interference from other tasks also decreases accuracy.

Accuracy in space operations would not only be a matter of reducing user frustration and maximizing task performance. A very high level of accuracy is needed in most of the proposed applications to avoid compromising safety, damaging equipment, and impeding mission operations. The current gap in required vs. available accuracy is a major obstacle to using aBMIs for critical space control tasks.

2.6. The feedback gap

Rapid, multidimensional feedback is crucial for the accurate, smooth control of robotic arm-like devices, and to avoid causing equipment damage [9,8]. The robotic system must therefore be able to sense slip and location of forces and must be able to either act on these inputs autonomously, or communicate this information to the user in real-time such that the user can adapt their own output accordingly. Kim et al. report that the present state of tactile robotic sensors is insufficient for such fine manipulation [8]. Even it if were, the quality and content of the feedback to the user is constrained by the sensory modalities used.

For precise normal-speed movements in complex dynamic systems, the commonly used visual modality may introduce problematically long latencies [9], although real-time visual feedback has been successfully used for basic robotic control in invasive animal studies [8]. Incorporating other modalities, for example through tactile cues provided by pneumatic pressure cuffs and vibrating transmitters, can increase the amount of information transferred and perhaps reduce feedback latencies; however, preliminary studies on tactile feedback suggest that it will be very difficult to communicate the level of detail and dimensionality to the user required for fine and flexible manipulation [8]. Recent interest in distance surgery applications are fueling rapid development in this area (for example see [27]), but for now, feedback requirements are another obstacle for proposed BMI implementations in space.

2.7. The intuitive use gap

One goal of aBMI researchers is to achieve intuitive interactions, whereby a robotic system may be 'managed by the astronaut as a sort of appendix of his body' [3]. There appears to be an assumption in the literature that aBMIs are inherently more intuitive to use than physical means of controlling machines. As most people would likely agree who have tried to make a ball that is sliding across a screen move upward by imagining moving their right hand (while inhibiting any actual motion), this is not necessarily the case.

The assumption that aBMIs are intuitive may arise from a lack of clarity about what is meant by 'intuitiveness' in common speech. As a working definition, we suggest that the intuitive usability goal of aBMIs should be specified to mean either: (1) that the user can learn to operate the system easily because its operation is based on either high-level intentions or skills similar to existing, well-learned skills; or (2) that the normal operation of the system can become automatic (i.e. in the same way that skills such as riding a bicycle become routine with practice), thus minimizing the cognitive demands and required effort during normal use. The 'learnability' factor may be less important for astronauts than the general public, although it could reduce time required for training. The degree to which aBMI use can become automatic for the user is critical, as it will determine if the aBMI can augment astronaut abilities, or can only be used in lieu of other output modalities.

According to these definitions, the use of existing aBMIs is less intuitive than many conventional and novel means of human-computer interaction. A BMI user's experience may include focusing on one of a set of options repeatedly presented on a screen or through speakers (rBMIs), imagining a left or right hand movement arbitrarily associated with an outcome, or voluntary regulation of signals known as slow cortical potentials after biofeedback training (aBMIs). Even if these activities prove to be somewhat 'automatable' with extensive practice, intentionally controlled BMIs engage perceptual pathways and attention, thus reducing their availability for other activities. The degree to which intentionally generated signals are changed or obscured by signals generated spontaneously by users engaged in other tasks is unknown.

Far from improving astronaut performance by augmenting their capabilities, foreseeable aBMIs might actually reduce their capacity to carry out normal tasks while offering only a slow and limited alternative communication channel. In contrast, new ways of guiding robotics are currently in development which are improving upon the intuitiveness of existing controls. For example, a 'data glove' which instructs a robotic arm to mimic the user's arm position (see [28]) might be both intuitive to learn and to use, as it relies on well-developed skills of arm control.

2.8. Expected improvements

The information transfer rate and classification accuracy of aBMIs is being gradually improved by the development of data cleaning techniques and machine learning algorithms which allow for real-time single trial analysis, and reduce the need for subject training or data collection for algorithm adaptation (for example, see [25]). It is likely that future refinements in aBMI technology will be able to better compensate for

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inter-individual differences which currently lead to a wide range of performance in BMI control, for example by selecting optimal sensor placements and using advanced feature extraction algorithms. Using predictive technology based on task requirements or user patterns (e.g. T9 word completion software by Nuance Communications) and incorporating feedback from the brain's intrinsic reactions to error should further improve performance [29], as well as combining EEG and NIRS technology in a single device to take advantage of the strengths of each (for example, see [30–32]). Some researchers are experimenting with using cheaper, simpler equipment such as one and two-channel EEG to identify robust signals for specific applications [33]. Interest of the entertainment and gaming industry is contributing to the speed of development of this technology. Together, these trends are likely to increase the usefulness of aBMIs in clinical settings and some healthy-user applications.

In the following section, we describe why we do not feel that non-invasive aBMIs will be able to reach performance levels suitable for proposed space applications like controlling robotic manipulators. It remains possible that aBMIs may be usefully applied to some low-dimensionality non-critical tasks in space operations. The value of aBMI-based solutions to space human-machine interaction challenges will have to be considered on a case-by-case basis, taking into account the operational environment and all available solutions.

3. Inherent limitations of non-invasive brain signals

If the signal recorded from the brain is fundamentally lacking in the depth and dimensionality of information necessary to control such a device, no amount of clever signal processing will enable its recovery. The non-invasive techniques discussed in this paper do not provide unlimited access to cognitive processes. We provide a brief explanation of the relationship between neural activity and its non-invasive measurement. The interested reader is referred to [34] for a comprehensive review of the cognitive basis of motor control, which will provide a deeper insight into the limitations of these non-invasive techniques to capture relevant information for fine movements. In-depth information on the brain's electrophysiological and hemodynamic activity and responses can be found in [35,36].

3.1. Electroencephalography

EEG is recorded as a set of weak time-varying differences in voltage (100 ms, with a frequency spectrum of ~ 0.1 to ~ 60 Hz) between electrodes in contact with the scalp and a reference electrode attached somewhere on the head or body. These small voltage differences are produced by the activity of neurons, which create local currents when charged ions flow in and out of the cell [37].

Particular types of currents are measurable as EEG signal at the scalp under a very specific set of conditions. The signal origin must be close to the skull, meaning EEG originates mainly in the outer layer of the brain known as the cerebral cortex, a 4–5 mm thick highly folded brain region responsible for activities such as movement initiation, conscious awareness of sensation, language, and higher-order cognitive functions [37]. Only large groups of neurons which are precisely aligned and firing in concert can contribute to EEG signals; otherwise the current is not strong enough to be detected, or opposite charges may cancel out. The laminar structure of the cortex facilitates the summation of an aspect of neural activity known as postsynaptic potentials, which represent the reception of both inhibitory and excitatory signals rather than neural firing itself [38]. Much of the brain's activity is invisible to EEG electrodes, therefore the EEG represents a small sampling of neural activity from only one of many brain structures involved in activities of interest for aBMIs such as motor control [35]. Furthermore, this signal is attenuated and spatially smeared as it is conducted through the cerebral spinal fluid, meninges, and highly resistive skull. This results in poor spatial resolution even with high numbers of electrodes because reconstructing the location of the signal origins is an inverse problem with no unique mathematical solution [38]. The signal is also easily obscured by higher-amplitude artifacts, which may be generated by muscle activity, eye blinks or eye movements, cardiac rhythm, and ambient electrical noise. This is normally handled by discarding contaminated data segments, filtering, averaging, or in the case of eye blinks, applying corrections.

For these reasons, useful details about the intended movement possibly present in cerebral motor areas such as the direction, speed, and limb configuration are very difficult or impossible to discern from EEG signals [9]. Kim et al. concluded that scalp EEG recordings lack the resolution required for dexterous control of robotic devices in real time [8].

3.2. Near infrared spectroscopy

Near infrared light is weakly absorbed by water and hemoglobin and is able to penetrate up to several centimetres into brain tissue, including the layers of the cerebral cortex and possibly some underlying white matter [39]. Basic NIRS equipment known as 'continuous wave' NIRS can measure the relative changes in concentration of oxygenated and deoxygenated blood over time (more complex NIRS equipment also exists which can measure absolute concentrations).

NIRS signals correlate highly with blood oxygen-level dependent (BOLD) fMRI, which has been extensively studied in the last decades [39]. The strong correlation between the two means that many fMRI findings of regional activity specificity in the cerebral cortex can be used to guide NIRS research and applications, and to better understand experimental results.

When a brain area is activated, metabolic activity increases, leading to a brief decrease in oxyhemoglobin and increase in deoxyhemoglobin after about 2 s in the immediate vicinity of the activated neurons. This stimulates the increase of blood flow to a wider area, which

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causes oxyhemoglobin levels to begin to increase to a peak at about 5 s following neural firing, and then slowly declining over about 5–10 s after neural activity returns to normal [36]. NIRS signals therefore measure an indirect, delayed, non-specific, and not completely understood chain of events relating to the energy use of large areas of cortical neurons.

4. Passive BMIs

aBMIs use significant effort and mental resources to send commands that are generally more effectively communicated through other means. Instead, pBMIs offer valuable information at no performance cost that is not available using other modalities. The signals of interest for pBMIs occur spontaneously in association with changes in the cognitive activity of the user. It has long been known that EEG is sensitive to many of aspects of mental states, for example by showing changes in the power of certain frequency bands [37]. Similarly, NIRS can detect cognitive state-related brain activations. Signals have been obtained that reliably relate to attention level, workload, task engagement, awareness of aspects of the environment, alertness or fatigue, and awareness of erroneous responses, among others [6,29,40,41], with progress made towards real-time classification [25,33,42].

Since pBMIs use similar equipment and techniques as other BMIs, they are subject to similar speed and accuracy limitations. However, pBMI applications do not require such high communication performance as direct control devices operated by aBMIs. For example, an aBMI that requires 5 s of data to generate a command would be of limited use for most applications, but a pBMI that can cause a change in automation level of a human-machine interface within 5 s of an increased workload would likely be adequate to improve user performance.

There are three areas in which pBMIs may be useful for space applications. Only the first can be properly called a BMI, in which real-time signals are used to modify the interaction between human and machine in operational roles. The second type of application is in the research and design phase of astronaut (or flight controller) equipment and tasks, in which pBMI techniques can be used to objectively measure and compare the usability of different designs. The third application may be thought of as an additional benefit of using the first; signals collected for practical use may be recorded and stored for later analysis, providing scientists with a wealth of information for basic research during real tasks. These data are scarce, as recording equipment is usually used during discrete, independent experiments.

4.1. Operational roles for pBMIs

Extensive literature indicates that task conditions that impose high cognitive workload lead to performance errors even in alert individuals working under routine conditions, and that modest amounts of sleep loss or circadian desynchronization can further degrade performance [12,38]. Increasingly, high-technology operational jobs (such as in aviation, industry, and the military) include automated systems which reduce the need for human involvement in routine tasks and computations. While automation does decrease certain types of errors, it also changes the nature of the user workload from active involvement to passive monitoring. This can give rise to critical errors or omissions when the human-machine team fails to communicate relevant aspects of their tasks, and the user loses full awareness of the situation [40].

Augmented cognition is an area of study which aims to enhance human task performance and cognitive capabilities by reducing stress, fatigue, and information overload or underload. This is accomplished by regulating displays and controls for complex systems, or by optimally redistributing shared tasks between human and machine, based on real-time measures of the user's state [43]. Changes in displays or automation level could simply be initiated by the user (e.g. the use of autopilot in aviation); however, several studies have found that the need to monitor one's own workload actually further increases workload and leads to reduced performance [44,45]. Also, operators may not always be the best judges of when levels of automation need to change. Adaptive automation based on mental state measures has been shown to increase situational awareness in military monitoring-type experiments as well as simple laboratory tasks, and to reduce potential costs due to complacency, fatigue, and skill degradation [46,44,6,40]. Significant performance improvements are found even though current real-time brain state classifiers typically produce accuracy rates of only 70–85% [6].

One such study by Kohlmorgen et al. [47] demonstrated an EEG-based system able to detect high mental workload periods in a real driving situation where subjects were asked to simultaneously perform secondary and tertiary tasks. The secondary task was designed to assess the driving-relevant performance measure of reaction time without imposing much additional workload, and required the participant to react to recorded instructions ('left' or 'right') with a button press throughout both high and low workload periods. The tertiary task was either an auditory workload scheme or a mental calculation task meant to represent common driving activities such as interacting with other vehicle occupants or with electronic equipment. An EEG classifier was trained using data collected in an initial session, and was then used in real-time to distinguish between high and low workload periods using a sliding window of 10–30 s (adapted for the user). The input to the workload classifier was the power of each bandpass-filtered EEG channel. If high workload was detected, the driver's workload was relieved by temporarily suspending the secondary task. Average reaction time performance was compared with that in the training session, in which the secondary task was not altered by user workload measurements. Despite significant variability in classification accuracy between subjects (from around 50% (chance level) to over 90%), Kohlmorgen et al. found that the adaptive strategy leads to better reaction times on average as compared with the unmitigated session. The differences were both statistically significant and significant in task-relevant terms (i.e. reaction time

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improvements were of magnitudes shown previously to affect accident rates).

Space applications could build on early work such as this, but would require a thorough environment and task analysis to determine which measures, paradigms, and combinations are relevant for a particular job. Numerous applications are possible. For example, pBMIs could be used in training to provide feedback on behaviors that increase alertness and concentration. pBMIs could be used to offload routine tasks during flight operations such as docking procedures to automated systems when there is a risk of cognitive overload. pBMIs could also be used to provide the astronaut with activity planning and time management suggestions, such as when might be the best time to take a break, exercise, or perform simple routine tasks based on their own alertness and fatigue profiles and upcoming unmovable mission tasks. pBMIs could provide information to astronauts on their own readiness to perform a complex task. If operational pressures have resulted in inadequate rest or a disturbed circadian rhythm, an astronaut could compare his/her measurements during a diagnostic task with personal stored profiles to help gage if a change in schedule or reassignment of a safety-critical task is in order. A pBMI could be worn during lengthy activities to warn of reduced vigilance or impending 'microsleeps', which are associated with declines in performance [12]. Well-known evoked brain signals such as the error negativity or P300 could be used to detect and mitigate user errors before they cause operational problems, or even to create a tool which help astronauts to quickly recognize needed items amid clutter (i.e. in combination with an eye-tracker).

4.2. Neuroergonomics roles for pBMIs

Factors that influence human performance are normally examined using subjective reports, performance measures such as reaction time, and some non-brain physiological signals (e.g. cardiovascular measures, respiration, galvanic skin response, ocular motor activity, and speech) [41]. Since these measures are somewhat indirectly related to the thought processes responsible for task performance, researchers are now adding brain imaging techniques to their toolboxes [33,25]. The new field of neuroergonomics explores how current research and developments in cognitive science and neuroscience can be used to further improve performance in real-world environments [40].

The same brain state information proposed for use in real-time operation can be used for the evaluation and development of human tasks and interfaces. Data could be collected during dedicated experiments, during personnel training, or even during real operations, which would provide varying degrees of experimental control and real-world validity. In transportation safety research, EEG has been used to analyze cognitively demanding situations encountered during simulated driving or piloting tasks [47]. Points where errors frequently occur can be identified and countered with displays that most clearly provide critical information and repress irrelevant tasks, fail-safes to prevent common errors, and operating procedures that facilitate perception of critical information (e.g. the visual scan patterns used by pilots to examine subsets of their instruments during piloting activities). The inclusion of EEG and NIRS among other measurements provides further insight into cognitive resource use, based on temporal and spatial patterns of brain activation [48].

In principle, EEG and/or NIRS equipment could already be used to examine any astronaut or flight controller task for some of the aspects that have already been reasonably well studied, such as workload and vigilance [6]. Good places to start include areas in which tasks and designs are performed frequently, are safety-critical, and are similar to tasks in other, larger industries in which progress has already been made, for example in flight, air traffic control, and road and rail transportation.

4.3. Basic research using pBMIs

While neuroscience findings can aid in the development of pBMI applications, the reverse is also true; pBMIs have the potential to significantly contribute to our understanding of human cognition [6,25]. This would likewise be true of any aBMIs developed for space use (although aBMIs tend to be specialized for the collection of sensory-motor signals, which are less relevant for higher-level cognitive tasks). There is often a big difference in human behavior and cognition between laboratory tasks and the real environment they are meant to represent [49]. pBMIs can increase scientists' access to human cognition in complex, real-world environments.

There are limited opportunities in space for dedicated neuroscience experiments as they compete for time with many operational and scientific objectives. Portable pBMIs could enable researchers to gather large amounts of data about cognition during real operations, which could yield valuable information. It will be necessary to determine what activities and periods the astronaut would accept to wear the device, and what extra information would be necessary for scientists to answer a given research question (e.g. a record of environmental parameters within an EVA suit, a detailed daily schedule, body temperature, and heart rate). Sample topics of particular interest for space researchers might include: perceptuomotor adaptation to body movements in three dimensions, space motion sickness during free movement, circadian rhythm adaptation to schedule changes in the absence of natural zeitgebers, stress and workload imposes by the daily timeline, sleep disturbances and differences in sleep architecture, and the cognitive and performance correlates of various interactions with other crew and with equipment.

4.4. Next steps for pBMIs in space

Although pBMIs are much closer to implementation than aBMIs, work is still required, particularly for in-space operational deployment. Ideally, equipment should be developed to include a comfortable head attachment with

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a minimum of sensors and amplifiers that communicate wirelessly to a small processing unit or existing computer, all of which is compatible with existing space systems and regulations. Equipment should be light and robust, and should require minimal set-up time prior to use. The differences in cognitive processes in the microgravity environment and in their appearance in physiological recordings must be investigated. Suitable applications for augmented cognition techniques must be identified, which would include task analysis to determine what real-time adjustments in automation or interaction can be safely and usefully made [6]. Brain signals which indicate cognitive states of interest need to be identified and verified to ensure their suitability, first in simulated task environments on ground, followed by environments that approximate space flight conditions (e.g. parabolic flights or bed-rest studies), followed by in-flight validation. Classification algorithms that adapt optimally to the user's brain signal and to aspects of the space environment that could affect system operations must be developed. Appropriate directions for basic research use of a BMI system have to be developed, taking into consideration existing research programs, the unique opportunities and operational constraints of space flight, and the astronauts' privacy.

5. Conclusions

In our opinion, non-invasive brain machine interfaces capable of interpreting brain signals to precisely control external artificial systems such as robotic manipulators and unmanned vehicles in the relatively near future is highly unlikely, due to inherent limitations in the information content and quality of non-invasively obtained signals like EEG and NIRS. Important goals such as reducing the need for astronauts to physically perform labor outside of their spacecraft may be more effectively and quickly tackled through other means, including development of intelligent autonomous robotics and where human involvement is required, more intuitive variations on traditional physical control and feedback methods. Uses for intentionally controlled BMIs may have some limited relevance to assist in hands-free operation of non-critical equipment, but will not be suitable for replacement of many existing equipment and system control solutions.

Recent advances in EEG and NIRS BMI technology and basic research in neuroergonomics have enabled the relatively straightforward development of systems that could use spontaneously generated signals to contribute to the safety and effectiveness of space operations. This is possible through real-time adaptive automation, and for offline analysis and development of better human interfaces. Technology used in either of these applications could also be employed to simultaneously record data for basic and space-related neuroscience research. The main benefits of this direction are that valuable additional information is made available without compromising existing astronaut capability, since pBMIs obtain information from naturally occurring brain signals without making demands on the user's physical and mental resources.

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