Direct-Sense Brain-Computer Interfaces and Wearable Computers

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***Abstract*— Brain-computer interfaces (BCI) allow users to communicate directly with external devices via their brain signals. Recently, BCIs, and wearable computers in particular, have been receiving more attention by government and industry as an alternative means of interacting with technology. Wearable computers can combine highly-immersive virtual/augmented/mixed reality experiences for entertainment, health monitoring, utilitarian purposes, and, most importantly at present, research. With wearable computers, researchers can design, simulate, and finely control experiments to examine human brain dynamics outside the laboratory. Yet despite the power of BCIs, take-up is slow. This form of interaction is unnatural to humans and often requires external stimuli. Further, the response feedback produced by the computer part of the system is nowhere near as quick as our brains. Hence, we undertook a review of the current state-of-the-art in BCI research and distilled the current findings into a stimulus-free BCI, called direct-sense BCIs, that operates directly and seamlessly from our thinking. This is a novel paradigm that, in the short term, could substantially improve the quality of a user's experience with BCI, and, over the long term, lead to much more widespread take-up of BCI technology.**

***Index Terms*—BCI, EEG, ECoG, direct-sense BCI, machine learning**

I. Introduction

BRAIN-computer interfaces (BCIs) provide a channel for humans to interact with external artificial devices by means of their brain activity [1-4]. In most systems, a machine learning algorithm decodes electrical signals in the brain into a user's intentions and then transmits a recoded "mental command" to the device.

Since Vidal [5] demonstrated the very first BCI, the technology has been applied to a multitude of applications focusing on neurorehabilitation, i.e., restoring voluntary muscle control. However, beyond helping those who depend on artificial limbs and similar goals, the ability to directly communicate with an object outside the body has tremendous and far-reaching benefits. Consequently, in the nearly 50 years since, we have witnessed an enormous rise in BCI studies and a great expansion of the fields these studies concern. Most recently, this growth has been spurred by advances in artificial intelligence, material sensor technologies, and attention to the user-friendliness of hardware interfaces. Such is the evolution of the technology that, moreover, R&D into BCI has burst through the ivy-covered walls of academia and into the laboratories of industry [6].

Today, we find BCI in fields and applications as diverse as monitoring cognitive status [7], mental spellers [8, 9], robotics [10], and entertainment [11]. Also, a growing number of studies are combining BCIs with virtual reality (VR) [12] and augmented reality (AR) [13]. In addition to enhancing user experience, VR/AR is also being explored for its ability to construct ecologically-valid scenarios, i.e., more naturalistic experiments that better mimic real-life situations [14].

However, despite the many and wondrous benefits of BCI, only a small fraction of the population accept its use. Hence, we undertook a comprehensive review of the main components and limitations of current BCI systems. From our findings, we devised a new type of BCI that, we believe, will appeal to more users. The paper concludes with some suggestions for the research fields most likely to directly benefits from this reimagined BCI.

II. Current BCI Technologies

BCIs consist of several main components: a scenario design, modules for brain signal acquisition and feature extraction, a classifier, and a user feedback system (Fig. 1).

A. *Brain signal acquisition*

The various brain signal acquisition systems used with BCIs each rely on different types of brain activity and, accordingly, different measuring techniques. For example, functional magnetic resonance imaging (fMRI) measures change in blood oxygen level-dependent (BOLD) signals, electroencephalography (EEG) measures electric signals, and magnetoencephalography (MEG) uses magnetic induction to measure the magnetic activity in the brain. Some measurement techniques are invasive; others non-invasive BCI [2]. With invasive methods, the sensor must be placed under the scalp and, as a result, the spatiotemporal resolution of the measurements is often higher. However, for obvious reasons, invasive methods are off-putting and prolonged use raises some

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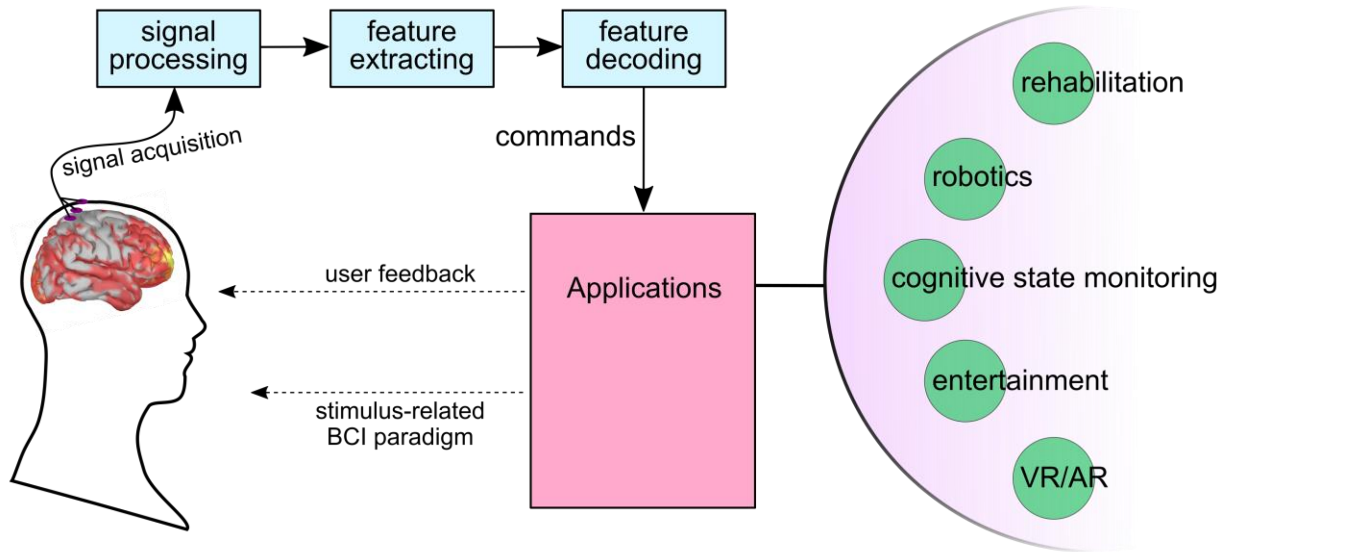

Fig. 1. A typical, basic BCI system configuration. There are five main components: a scenario design based on a BCI paradigm, modules for brain signal acquisition, process and feature extraction, a classifier, and a user feedback system.

safety concerns, both of which are likely to limit take-up. With non-invasive methods, the sensors are placed on the skin, making this category of signal acquisition far more popular. However, this comes at the cost of either spatial or temporal resolution (refer to Fig. 2). For example, fMRI readings have a high spatial resolution, but the temporal resolution is low. Conversely, MEGs and EEGs offer a high temporal resolution, but relatively poor spatial resolution. Further, non-invasive data is easily contaminated by environmental noise. Hence, these brain imaging methodologies often require participants to remain stationary during the experiment. Additionally, the signal data are normally pre-processed to remove the noise before sending them to a classifier for further processing.

Another consideration with brain imaging hardware is its portability. fMRI and MEG machines are massively heavy, hugely expensive machines that take up entire rooms. EEG systems, however, are low-cost and portable, which has made them an extremely popular choice as a signal acquisition system.

B. *BCI paradigms*

Obviously, BCIs need brain signals to work. However, it is not always appropriate to leave users to ‘think their own thoughts’ in the hopes that the BCI will work – especially in a research setting. BCI paradigms are therefore used to induce specific brain signals for the BCI to recognize. To date, the field has amassed a toolbox of scenarios that are often used to develop BCI technologies and applications [2, 15]. And new purpose-built scenarios are designed all the time. Different BCI paradigms and stimuli can induce responses in different regions of the brain. Accordingly, the scenario, the feature extractor, and the classifier usually need to be configured as a suite and tailored to the purpose at hand to at least some extent. A more detailed explanation through some common BCI paradigms follows.

P300 Event-Related Potential (P300-ERP)

Brain responses are elicited through infrequent stimuli, such as the oddball paradigm, resulting in high amplitude signals around 300-450 milliseconds after the stimulus onset. The stimulus type could be visual [8], auditory [16, 17], or tactile [18, 19]. Visual stimuli is one of the most popular modalities in P300 paradigm, especially the P300-speller scenario.

Steady-State Evoked Potential (SSEP)

Here, brain signals are elicited through repetitive stimulus at a constant frequency. Similar to the P300 paradigm, the stimuli could be visual (steady-state visually evoked potential – SSVEP) [20, 21], auditory (auditory steady-state response – ASSR) [22], or vibrotactile (steady-state somatosensory evoked potential – SSSEP) [23]. The visual modality is also the favoured stimuli type in SSEP. In addition to a contrast-change generated flicker in SSVEP, motion perception can also be used to generate a flicker as stimulus (steady-state motion visual evoked potential – SSMVEP) [24-26].

Motor Imagery (MI)

With MI paradigm, the participants think about moving their limb to either the left or the right [27] to elicit a response pattern in the corresponding sensorimotor region. These types of scenarios typically only support a few commands.

Error-related potentials (ErrP)

ErrP is an ERP in response to an error when interacting with

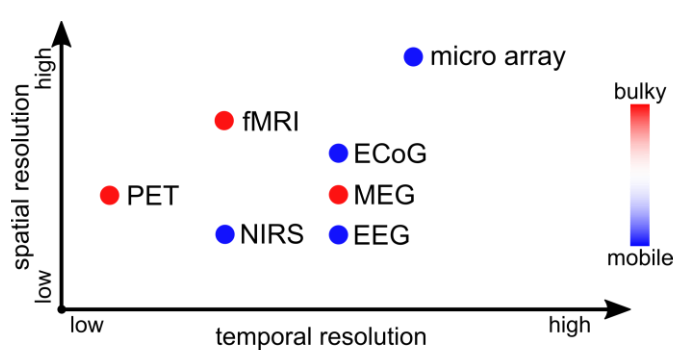

Fig. 2. The strengths and weaknesses of common brain signal acquisition systems.

the BCI. Many researchers have attempted to combine ErrP paradigms with a closed-loop system [28], MI [29], or visual P300 speller [30] to improve BCI system performance.

Continuous Cognitive State Monitoring

Cognitive state monitoring uses the BCI to model the mental state of the participant. Their brain signals and other physiological data are recorded, and the computer uses the data to predict their mental state. This technique has also been applied to other research domains, including emotion detection [31, 32] and fatigue warning [33].

The BCI paradigm can be categorized into passive, active, or reactive [34] (Fig. 3):

Passive BCI directly and involuntarily decode a user's cognitive state(s) without permission from an external stimulus. Passive BCI is normally used for monitoring mental workloads [35], drowsiness [36-38], and fatigue [33, 39], and for emotion recognition [32]. It allows users to continuously interact with the experiment or task either in a laboratory or in real-life conditions without the interruption of a stimulus. For this reason, passive BCI has been widely tested and used in nearer to real-life scenarios, such as driving [40, 41].

Active BCI translates user intentions into computer command on request, i.e., the participant signals their intention to interact with the BCI. MI is an example of active BCI [27].

Lastly, in reactive BCI, brain signals are induced by external stimulus, and the data is segmented based on the stimulus onset. This is the most popular type of monitoring for researchers. The stimulus can be visual, auditory, or tactile with visual and auditory being the most widely used.

Note that the BCI paradigm is also categorized as a hybrid BCI [42]. One type of hybrid BCIs fuses primary brain signals with: (i) other types of brain activity, such as EEG and functional near-infrared spectroscopy (fNIRS) [43, 44]; or (ii) other sensory inputs, such as eye movements [45] and heart rhythms [46]. The second type combines different BCI paradigms to enhance performance, such as combining SSVEPs with P300 [47, 48].

C. *Feature extraction*

The feature extractor's job is to draw neural features out of the data for the classifier to use in the next step. Commonly, particular measurement techniques and/or modelling scenarios correspond to particular regions of the brain. Hence, the extractor will focus on these regions. For example, with SSVEP and a visual stimulus, neural features will be extracted from the occipital region; whereas with MI, features will be mainly extracted from the sensorimotor cortex region.

D. *Classifier*

Classification is a critical step in any BCI system. The most appropriate choice is largely dependent on the dimensionality of the required solutions and the scenario. Overall, classifiers are usually supervised due to their accuracy and response times. Linear discrimination analysis (LDA) [49], is a common choice with P300- and MI-based BCIs. And canonical correlation analysis (CCA) is often used with SSVEP. Fuzzy neural networks (FNNs) [50, 51] are also a well-established strategy for decoding the mental state of user. FNNs have been shown to delivery highly accurate results with various BCI paradigms, including reactive [52, 53], active [54], and passive BCIs [55]. Nevertheless, there are so many classifiers to choose from and so many factors that come into play in that decision, that even a brief review is beyond the scope of this paper.

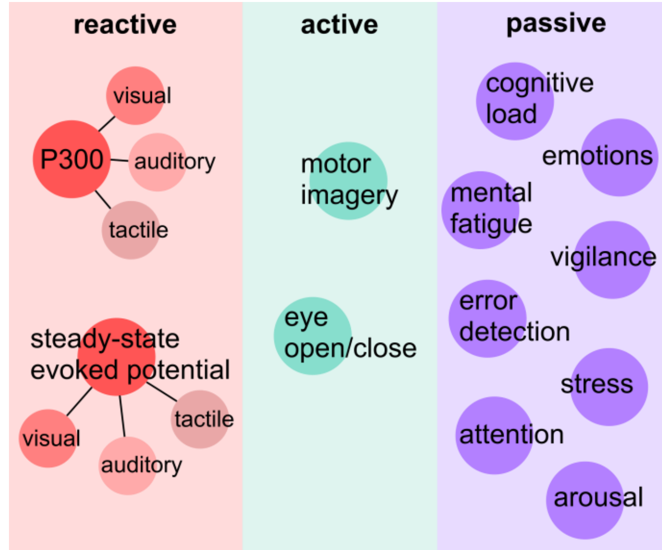

Fig. 3. The typical BCI paradigms.

E. *User-feedback*

User feedback comes in various forms but tends to be dependent on the model and application (Fig. 4). Movement is a common medium, e.g., the movement of robot [54, 56, 57], wheelchair [58-60], vehicle [61-63], or quadcopter [64] – or even a holographic image [65]. However, the most typical form is to simply provide feedback on a standard computer monitor. Not only are monitors ubiquitous and convenient, but the scenario stimulus and feedback can be provided in one place.

Recently, however, a growing number of systems are providing user feedback on a wearable computer display in the form of VR [66, 67] or AR [13, 68, 69]. Combining BCI with a wearable computer provides a richer user experience, but further, the two systems can work to mutual benefit. While the BCI provides a direct communication channel to the wearable computer, the wearable computer brings more realism to a scenario than a conventional 2D monitor.

III. Limitations of Current BCI Designs

BCI technology developed gradually, with slow and steady attention from government and, more recently, industry [6]. Yet despite the tremendous benefits BCIs might bring to our daily lives, they are still far from ubiquitous. There are still many limitations that need to be overcome before that happens. Among these many challenges are improvements to the materials sensor are made from to enhance signal acquisition, more accurate machine learning methods, solutions to low information transfer rates (ITR), and strategies or innovations to avoid stimulus-fatigue. These latter two issues are commonly felt to be today's key barriers to further development, and the two problems are somewhat interlinked. To increase ITRs,

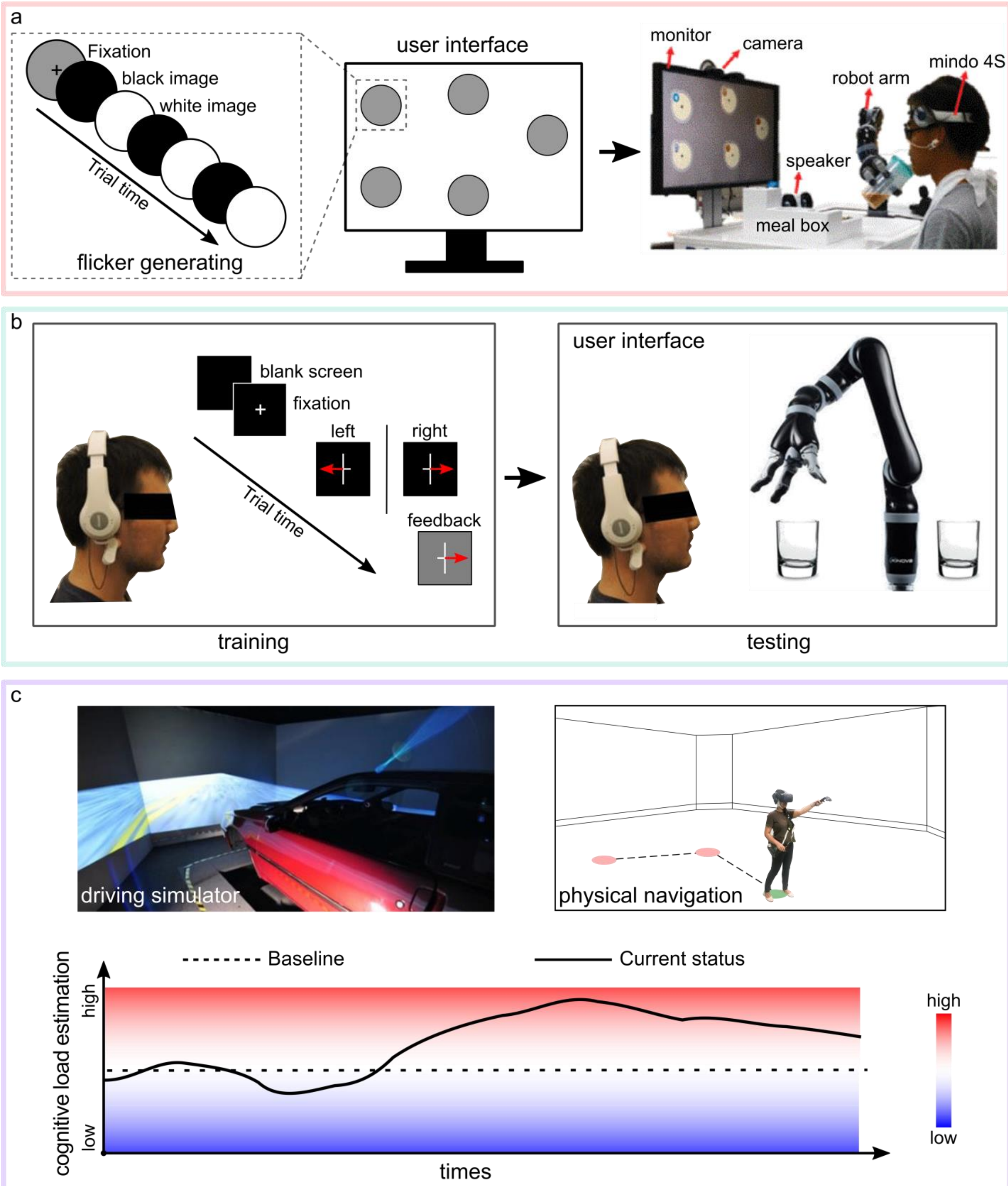

Fig. 4. Some example of the BCI applications that have been developed in Lin's laboratory – known as the Computational Intelligence and Brain-Computer Interfaces (CIBCI) lab. (a) An assistive robot system based on a SSVEP-based BCI (reactive BCI). The complete system offers five different types of assistance that can be requested through five flickers. (b) Another type of assistive robot system based on an MI-based BCI. In this system, the participant has two options to interact with the system (active BCI). (c) Mental workload estimation in more realistic situations: driving and spatial navigation. These experiments are based on passive BCIs which monitor the participants' cognitive loads as they perform the task.

BCIs often tweak visual stimuli in ways that lead to the second limitation – stimulus-fatigue [9, 20, 70-74]. One final issue is that most BCIs only work when the subject is stationary. Clearly, this precludes many real-life activities and severely limits the scope of applications BCI is useful for. These limitations are discussed in more detail in the next sections.

A. Fatigue-related stimuli

Visual stimulus is the most commonly used with high-ITR systems [20, 70-73], but it often results in eye fatigue for the participant, which means scenarios must be short. For this reason, there have been many attempts to make visual stimuli more comfortable for the participant. For example, with SSVEP, researchers have explored ways to develop a high-frequency flicker, which is believed to help reduce visual fatigue. Typically, the target flicker frequency is between 50-60 Hz – a level referred to as critical flicker frequency (CFF) – which is where the flicker becomes undiscernible to the naked eye. With even higher frequencies, some researchers have reported smaller SSVEP amplitudes. However, in an experiment with LED lights, Sakurada, et al. [75] were able to detect higher-amplitude SSVEP signals at flicker frequencies greater than CFF. Thus, efforts to evaluate the optimal stimulus/feedback device among monitors, head-mounted displays, and other alternatives is ongoing.

Another attempt to ease the fatigue caused by visual stimuli was to introduce motion [24, 25]. In contrast to switching between black and white colour or twinkling, as is common with SSVEP, SSMVEP generates a stimulus that drifts in a non-specific direction. This elicits brain signals in the occipital region. Unfortunately, SSMVEP models are still limited to a few commands.

B. Low information transfer rates (ITRs)

The communication speed of BCIs is measured in terms of information transfer rates (ITR) [76], calculated by the formula

$$B = log_2 N + P\, log_2 P + (1-P) log_2 \frac{1-P}{N-1} \quad (1)$$

where N is the number of targets, and P is the probability of hitting a target.

Other metrics for measuring BCI performance have been proposed, but ITR is by far the most widely used. These alternatives include word symbol rate (WSR) [16], practical bit rate (PBR) [77], characters per minute (CPM) [78], output characters per minute (OCM) [79], mutual information [80].

The two main methods of increasing an ITR are either to increase the number of commands or to increase the accuracy of classifications for the brain signals. However, even with speed improvements, the current rates do not meet the standards required for a BCI to become a part of one’s daily life. The BCI with highest reported ITR can reach up to 325.33 ± 38.17 bits per minute [70]. However, their scenario decoded single character per time, which is not like our daily communication – by full sentences. Furthermore, extending these results to larger scales has not been successful so far.

C. Stationary BCI

Conventionally, BCI studies are performed in a laboratory with subjects who participate in a scenario while maintaining a stationary position. Introducing BCI into real-life activities presents huge challenges. First, real-life situations are more complex than the relatively controlled environment of a lab, and, second, as previously mentioned, most non-invasive systems are highly sensitive to noise and not clever enough to distinguish between their human host and, say, a radio. To overcome these limitations, Gramann et al. [81] developed a mobile brain/body imaging (MoBI) system. This advancement sparked a host of studies in cognitive neuroscience on human brain dynamics in ambulatory conditions [see, e.g., [81]. Yet, the majority of MoBI studies are still heavily focused on offline analysis. Most of the benefits MoBI promises in bringing BCI closer to real-life conditions are yet to be realized.

IV. Direct-Sense BCIs

BCIs, which allow the brain to collaborate with a device and interact directly with the environment, are widely considered to be a "disruptive technology". This is certainly so for the next-generation of wearable human-computer interfaces (HCI), such as AR glasses. However, the existing BCI technology still relies on stimuli that is unnatural to humans. We do not stare at (flickering) lights or look at flashing photos to silently interact with people or things. We do not train our thoughts to move our left hand or blink our eyes twice to catch somebody’s attention. What is natural to us is to see, hear, and speak to the world. In the vein, electrocorticography (ECoG) signals, sensed by invasive intracranial measurement, can decode speech [82, 83] and also determine the object of one’s attention in thought [84]. Despite the rich, informative resolution invasive sensors provide, today’s investigation are largely limited to animals, such as pigs [85], rodents [86], and monkeys [84]. And, even though a 2-month test with pigs show the latest technology in invasive sensors from Neuralink might be safe for longer-term use, FDA-approved permanent human implants are likely decades away. Moreover, invasive BCI is thought by most to be the stuff of dystopian science fiction, not a trendy-and-oh-so-useful fashion accessory, and overcoming these preconceptions will not be easy or quick. For the foreseeable future, non-invasive sensors provide the only practical opportunity for investigating cognitive processes in the brain.

That said, non-invasive sensors can only detect cortical activity from large populations of nearby synchronized neurons. Therefore, despite gradual advancements in non-invasive sensors over the last decade, most BCI applications still rely heavily on external stimulus to induce neural activity. The choice of stimulus type depends on the scenario, but whether visual or auditory, stimulus-related fatigue or a low ITR is all but unavoidable. In addition, trials generally need to be repeated many times to ensure a high signal-to-noise ratio (SNR). These drawbacks mean BCI applications are still a long way from finding their way into our daily lives.

The development of technology that allows users to communicate without audible speech has been an active area investigation, with several modalities along the lines of movement emerging from this research – for example, spellers[87], SSVEPs [88], and MI-based BCIs [89]. These interfaces have taken numerous forms to provide a more naturalistic, language-based mode of communication, including word recognition via magnetic implants and sensors [90]. However, approaches such as these require active motor skills; they are not movement-independent. Moreover, they are not a particularly natural way of communicating. A more natural approach is to capture and decode the neural signals that directly correspond to speech production [91-95], i.e., to use ‘the voice in our head’. Such systems not only have great potential to transform the lives of patients with severe motor dysfunction, they also provide great opportunities to unveil how the brain expresses human intention.

A new system being developed in the laboratory of Chang [83] indicates that it is possible to create a synthesized version of a person's voice that can be controlled by activity in the speech centre of the brain. Their demonstration showcased the BCI's ability to generate entire spoken sentences based on an individual's brain activity. Unfortunately, the system currently only operates off multi-channel intracranial EEG recordings and is limited to preparing patients for epilepsy diagnosis. Nevertheless, the knowledge and results gleaned from their research are still incredibly valuable in the pursuit of EEG-based direct-speech BCIs.

In this article, we foresee a next-generation solution in the field of BCI technology called direct-sense BCI (DS-BCI) that can seamlessly decode the brain signals linked to our natural senses without additional stimulus – speech and vision to begin with – in two separate systems called direct-speech BCI and direct-sight BCI, respectively. In the sections that follow, we first review the current literature on direct speech/direct sight, and then discuss our proposals for further development.

V. Direct-speech BCIs

The ultimate goal of the direct-speech BCI is to translate silent speech from neural signals into system commands. This approach not only provides an alternative channel of interaction with BCIs for healthy users, it could also be an important assistive tool for people who are not able to speak.

As mentioned, there are currently ECoG-based invasive direct-speech tools [82, 96-99] and non-invasive EEG sensors that can decode inner speech.

A. Studies on invasive direct-speech BCIs

Direct speech tools can be divided into those where the participants imagine speaking and where they actively speak without sound [82, 83, 96-100], known as imagined articulations [97, 99] or imagined words [98], and silent speech [101], respectively.

The superior temporal gyrus (STG) in the human auditory region plays a vital role in understanding spoken language [82, 102, 103]. Thus, it is in this region that we find stable data features for direct-speech BCIs. For example, Pasley, et al. [103] demonstrate STG neural activity recorded by invasive sensor ECoG can be directly decoded into acoustics. Further, its high gamma power makes it one of the more stable neural features for speech recognition. Moses, et al. [104] used high gamma powers to decode English phonemes, while Mugler, et al. [105] reached 63% accuracy when classifying a single phoneme. Recognition accuracy can get higher still when gamma power is combined with lower frequency power [106].

The sensorimotor has also been reported as providing good signals for decoding intended speech. Studies have reported high classification accuracy with anywhere from 2 up to 39 classes. Exact statistics include 70% for 2 classes [107], 73% for 3 classes [108], 41-45% for 4 classes [98, 105], 20% for 38 classes [109], and 37% for 39 classes [110].

All these studies, however, are limited to speech classification, and the results are highly dependent on the segment length of the neural data. Therefore, these solutions only work with small vocabularies, and the potential to extend their capabilities to a larger vocabulary size might be limited.

It is also unclear as to whether these techniques will ever be able to reach normal communication speeds. To date, only Anumanchipalli et al.'s [61] strategy of combining neural data from both the STG and the sensorimotor region has achieved high communication speeds. This approach fuses neural signals from vocal track movements during acoustic production to decode full spoken sentences. Although variations in sensor locations, patient status, and other factors make it is difficult to directly compare the different invasive systems, the ability to decode an entire sentence from neural activity in [83] brings hope to developing a non-invasive counterpart for use by the wider population.

B. Studies on non-invasive direct-speech BCIs

As a non-invasive measurement technique, EEG-based BCI technology is easily deployable and can be used without the need for neurosurgery – a big plus. However, there is limited literature on classifying imagined articulations and words from EEG signals. Most studies to date are only at the stage of deciphering vowels, comparing two different phonemes [111], or distinguishing between several specific single words [112, 113]. Zhao and Rudzicz [114] used a classification approach to identify phonological categories from EEG-based silent speech. In this same line, González-Castañeda et al. [115] were able to classify five different imagined words: up, down, left, right, and select. Krishna et al. [116] devised an automatic speech recognition system based on deep learning that could decipher continuous EEG signals into a limited English vocabulary of four words and five vowels. These results have inspired the team to explore an online direct-speech BCI with portability.

As this review shows, EEG-based speech recognition is only at the stage of handling extremely limited vocabularies. Even a full sentence is still beyond the grasp of this technology, and recognition rates still have much room for improvement. Bottom line, non-invasive direct-speech BCIs are far away from being able to interpret naturistic silent speech.

C. Further development for direct-speech BCIs

The relationship between overt and covert speech has been debated extensively [117-119]. Although at present there is no definitive position on the precise nature of this relationship, it has been posited that covert speech is a truncated form of overt speech in that the stages of production are the same for both up until the point of vocalization [118]. Phonemic similarity has been observed with similar magnitudes for both overt and covert speech production [117]. According to Levelt [120], covert speech is part of an overall speech production system that is used for predictive simulation. These "forward models" of linguistic representations suggest that cover speech is produced in much the same way as overt speech, minus vocal articulation [120]. Nevertheless, there are still some significant differences in brain activity between the two processes. For example, fMRI data reveals that covert speech elicits greater activation in several areas of the brain [121]. These findings require further evaluations with non-invasive EEG systems and overt/covert speech.

Limited success aside, given the immaturity of this technology, arguably, the two greatest limitations at present are low accuracy and participant population too heavily drawn from patients, not normal, healthy people. Thus, future research into direct-speech BCIs may look to improving classifiers, and doing so with data recorded from healthy users. One approach might be to combine fruitful neural features from studies with invasive techniques, such as combining low and high-frequency powers from the auditory and sensorimotor regions [106].

VI. DIRECT-SIGHT BCIS

The aim of direct-sight BCI is to momentarily detect *what* and *which* object in the scene is the target object in a person's mind based on their EEG signals as they naturally look around an environment. This is an innovative approach to target detection as current BCI methods still rely on stimulus onset to induce event-related potential (ERP), such as P300. For example, a scenario might repeatedly display a series of candidate object images, which is an unnatural and nonintuitive way of communicating.

The ability to rapidly recognize an object visually is an essential skill in our daily life, which is one of the reasons why object recognition is an active research field in both computer vision and visual neuroscience studies [122, 123]. In this regard, these two fields have a strong bilateral relationship. The following review does not cover all findings in both fields, rather, just some key results object recognition that might prove useful to the future development of direct-sight BCIs.

A. Studies on invasive direct-sight BCIs

The ventral stream of the brain is closely related to object recognition [124]. While the parts of the brain at the beginning of the visual system, like V1, process the basic features of an object, such as its edges, the higher-level regions, such as inferior temporal cortex (IT), perform a kind of object recognition that associates the things we see with categories. The V2 and V3 regions are believed to process intermediate data in a transition from a shape at the low-level to follow object recognition at the high-level. The IT plays an important role in object recognition [123, 125] because it is believed that this is where the brain stores object representations.

Hung, et al. [125] presented a classifier that could reach up to 70% accuracy in object categorization (out of 8 categories of objects) and around 23% for object identification (out of 77 grey-scale objects). Kar, et al. [84] demonstrated the critical of recurrent neural circuitry of a brain’s ventral stream network in an object identification. Two adult male rhesus monkeys participated in the task. One had three microelectrode arrays implanted in the IT cortex of his left hemisphere and two in the right as well as one array in the V4 cortex of the right hemisphere. The other monkey had the same implants, just in reverse. The scenario was designed such that the subjects recognized an object one in ten times from a stimulus of 1,320 images (132 images per object). The nine non-recognizable images showed the object with various odd treatments, including scale, eccentricity, contrast, blur, clutter, and occlusion. Their results show that recurrent circuits in the ventral stream (V1, V2, V4, and IT) are an essential part of identifying objects. Hence, features from the IT [125] or recurrent circuitry [84] of the ventral stream that are currently proving useful to object recognition could, with adaption, prove valuable to direct-sight BCI.

B. Studies on non-invasive direct-sight BCIs

Most humans can recognize an object within tens of milliseconds [126]. Thus, a fast-paced time series style of brain imaging like MEG or EEG might be a more suitable choice for direct-sight (and generic) BCIs than fMRI or fNIR.

Kietzmann, et al. [127], for example, measured the brain signals of 16 right-handed participants while they identified objects using a high-density MEG system [127]. In the scenario design, there were 92 different objects across a number of categories, including human body parts, human faces, animal bodies, animal heads, natural objects, and artificial/manmade objects. They found that a substantial recurrent process happens within first 300 milliseconds after stimuli onset that involves both cascading forward and reversing information exchanged across regions in the ventral stream. Moreover, they demonstrated that a deep recurrent neural network performs better than a feed-forward deep neural network with object recognition. Such brain-inspired recurrent network models have already proven to be significantly useful to the field of machine vision [127, 128] and could do the same for non-invasive direct-sight BCIs.

Classifying image-related EEG signals is another relevant aspect of direct-sight BCIs. In this stream, El-Lone et al. [129] used a traditional classifier to distinguish between biological and non-biological objects from EEG signals with 82.7% accuracy. Parekh et al. [130] used advanced deep learning algorithms to enhance the performance of object recognition. The architecture comprised a CNN with outlier removal to classify 2-class EEG signals, which achieved 88.0% accuracy. Additionally, a set of RNN-based visual discriminative models were used to learn from EEG manifold data. This configuration reached a maximum accuracy of 82.9% on 40 classes. Parekh et al.’s [112] study marks the beginning of research into visual recognition with multiple-classes of objects from EEG signals. Another approach taken by two different teams of researchers, [131, 132], is to combine deep and ensemble learning with an ICA region-level bi-directional neural network. With the same 40-class dataset, this strategy yielded a maximum accuracy of 97.1%, showing that EEG-based object recognition is feasible. Clearly, much more development is required as the current systems are limited to working with only a few object categories at a time, and the tasks are both simple and designed to be performed under laboratory conditions. Also, recognizing and classifying high-resolution objects is not a quick process. Transplanted into the real-world, with clutter, background scenery, and motion, the knowledge and results gleaned so far might not hold.

C. Further development of direct-sight BCIs

To date, most neuroscience studies on object recognition are based on MEG or MRI signals and only involve invariant images (i.e., objects of the same size on a blank or simple background) [127, 133]. Thus, the related findings might not be

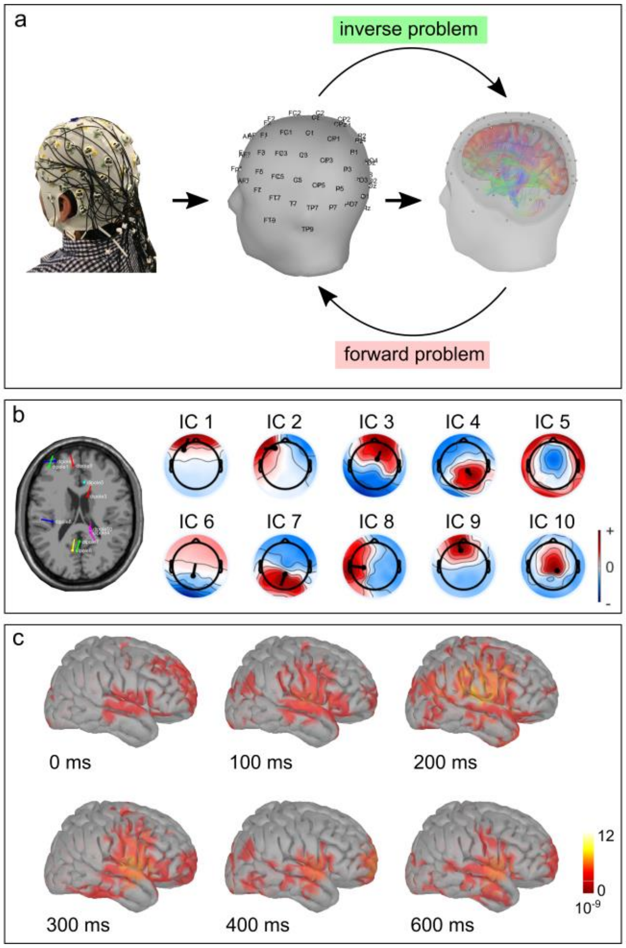

Fig. 5. The inverse solution for brain source localization from M/EEG data. (a) The schematic of the forward/inverse problem in M/EEG. (b) The dipole fitting solution. (c) The distributed source solution.

generated features, which can be applied for complex daily activity [134]. Moreover, most studies have focused on features drawn from signals in the ventral stream, known to be mental object representations from the inferior temporal (IT) region. However, the human brain is a comprehensive biological system that can provide fast, efficient, and robust solutions to object recognition. Therefore, examining the whole-brain connectivity may uncover a much more extensive underlying mechanism of object recognition.

More importantly, in conventional EEG-based studies, the P300 paradigm has been used extensively, usually in conjunction with the occipital (O1, O2, Oz channels) and/or parietal regions (Pz channels). However, direct-sight BCIs may benefit substantially more if conventional features from the posterior region were combined with the neuroscientific findings from the ventral stream.

VII. The Feasibility of Non-Invasive Direct-Sense BCIs

Developing DS-BCIs will present challenges that require tremendous effort to overcome. The first and greatest barrier to general use is the issue of invasive vs. non-invasive sensors. No matter which technique proves to be the ultimate medium, the sensors will need to be safe, easy to use, reusable and affordable if BCIs are to develop broad appeal. It is hard to envisage invasive techniques winning this battle.

Among the non-invasive brain imaging methodologies, M/EEG seems more suitable for real-time BCI application due to its high temporal resolution. However, the great concern is its poor spatial resolution, which might be a barrier for accurately detecting the source location of brain activity. Solutions to this problem include estimating cortical activity by solving the inverse problem from high-density M/EEG channels [127] (Fig. 5). There are many toolboxes that offer support for solving the inverse problem of M/EEG [135], such as EEGLAB [136], brainstorm [137] and MNE [138]. However, optimizing these algorithms for fast computation online takes time and effort.

Noise is another concern. Non-invasive EEG data is quite sensitive and easily affected by the noise created when participants move or physically interact with the environment. Even eye-blinking can introduce noise. Therefore, almost all results involving non-invasive BCIs are based on stationary subjects. The advent of MoBI systems is helping to solve this problem with greater tolerance to body movements and better noise-cleaning techniques [139-143]. Moreover, the MoBI approach is demonstrating that useful neural features can be extracted from the occipital region of participants as they walk via a visual epoch potential paradigm [144]. Even in extreme situations where the participant is running, the MoBI approach still performs quite well [145].

The next challenge turns us to the realm of machine learning and the methods BCIs rely on. Studies on invasive DS-BCIs have yielded high decoding accuracies with recurrent neural networks in offline conditions. Considering the advancements in deep learning in recent years, neural networks, computer vision, and DS-BCIs may benefit substantially from new feature extraction, and classification methodologies. Developments in models may also assist with the shift from offline to online settings.

Last but not least, the portability of brain imaging hardware will need to be tackled. EEG systems are already portable, and there are many models in the market, but the types with gel-based sensors are unwieldy and can be time-consuming to put on. However, experiments show that some of the models with dry sensors can provide reliable output in a range of evaluation scenarios from auditory oddball [146] and MI [147], to driver vigilance [148] or security [149]. Thus, the high-quality dry sensors that are emerging may help overcome this problem [150-154]. In addition, there has been intensive progress in the development of portable brain scanners – mobile MEG [155]. Therefore, there is a new horizon in mobile brain imaging hardware to explore that will help us investigate cognitive performance in a much more natural setting.

VIII. BCIs Meet Wearable Computers

For our purposes, the term “wearable computers” refers to wearable VR and AR headsets. These devices are characterized

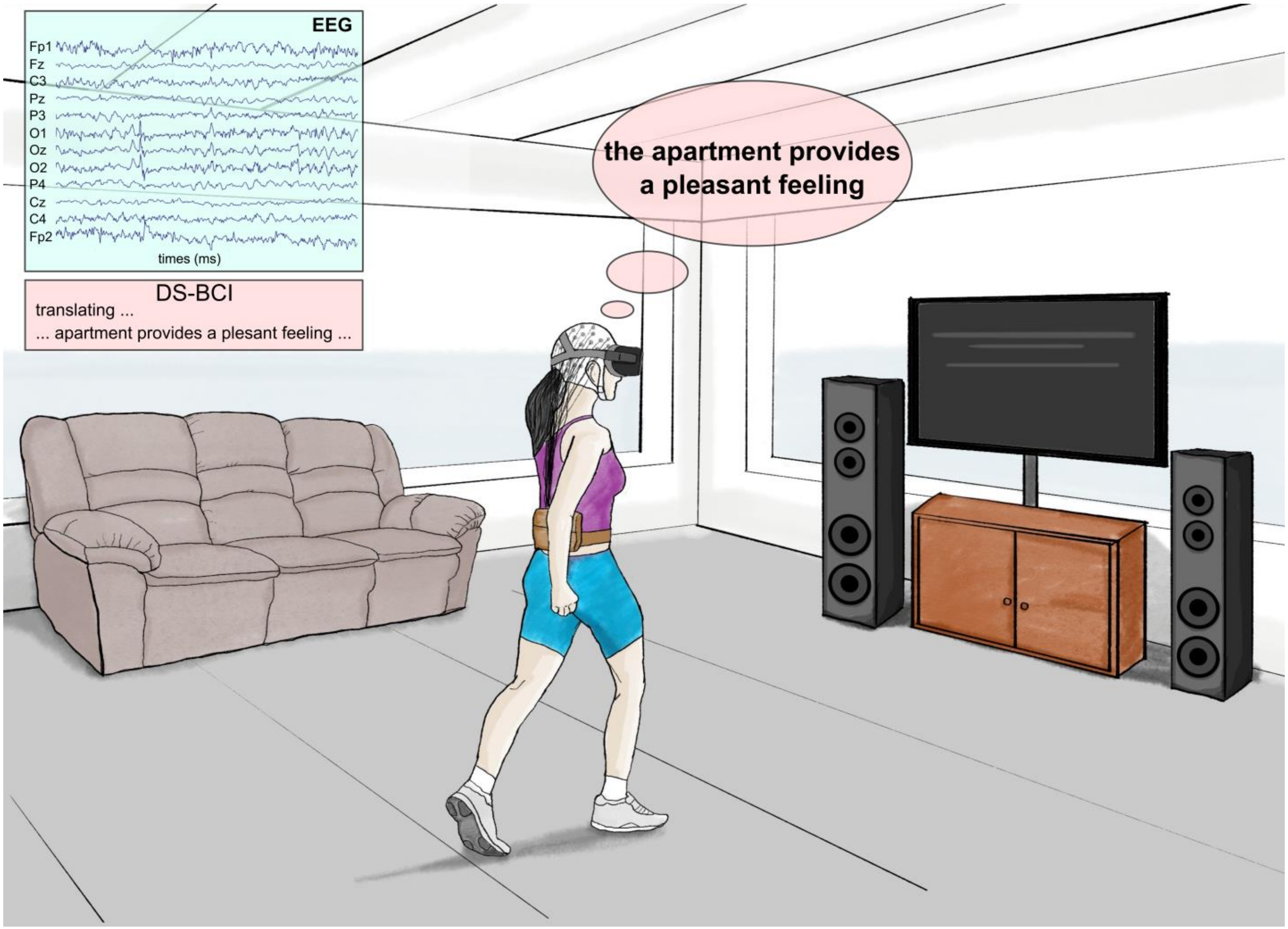

Fig. 6. The direct-sense BCI system in real-life situation.

by their fast computation speeds, ability to generate digital content and capacity to offer deeply immersive user experiences. Conventionally, users interact with a BCI through static and simple stimuli, which lacks the natural dynamism of real-life [14]. VR/AR could give researchers more freedom to simulate scenarios that are much closer to real-life tasks as stimuli to collect neural data [14, 156-158].

In addition, beyond the ability to directly decode a subject's sensory information, DS-BCI frameworks might also provide new infrastructures for investigating the neural mechanisms of other cognitive processes and in more natural situations including those involving physical interaction and motor execution. As such, the combination of DS-BCIs and wearable computers shows great potential for leveraging user experiences (Fig. 6). For instance, Fig. 7 illustrates a combined mobile wet-sensor EEG system (the MOVE system by Brain Product, Munich, Germany) and the Microsoft Hololens 2, with an MI-based BCI experiment. This completely mobile AR-BCI system can examine cognitive processes in humans in various scenarios outside of the laboratory without conventional restrictions. Furthermore, configuration and setup of this system could be made substantially easier by using a high-quality dry-sensor EEG (Fig. 8).

In the following sections, we explore three potential applications for DS-BCIs, reviewing progress to date and showcasing the future promise of this technology. These applications are spatial navigation, inattentional blindness, and motion sickness.

A. *Ambulatory Spatial Navigation*

Navigation is an essential skill that humans use every day. It is not a perspective we really think about, but "not getting lost" substantially reduces stress, conserves effort and energy, and frees up an enormous amount of mental resources that can be allocated to other tasks.

Yet most investigations of navigation in neural dynamics have been conducted with the participants sitting still. It is, therefore, reasonable to consider that the neural features we find in stationary examinations might not fully reflect the same cognitive processes we use when actually physically navigating in real life. Most of what we know in this regard has been determined from studies with animals and extrapolated to humans or painstakingly replicated in carefully designed experiments. For example, findings from a grid-cell scenario with rodent neural networks [159] have been replicated in humans through fMRI [160]. Theta modulations during ambulation have also been found to be consistent between the rodent [86] and human brain networks [161]. However, the

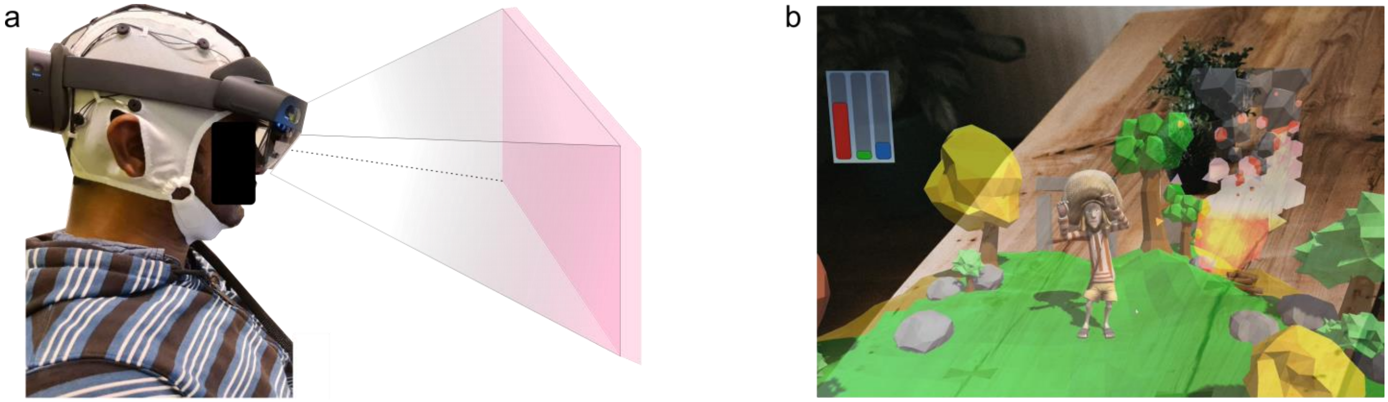

Fig. 7. A portable AR-BCI system. (a) A participant interacts with AR content via a Microsoft Hololens 2 device and an MI-based BCI. The brain signals are recorded with Brain Product's MOVE system. (b) The AR content is seen projected into the participant's view as an overlay on top of a real table. There are three actions the participant can control the cartoon character to perform: waving one hand (by thinking about moving one's left hand), clapping both hands (by thinking about moving one's right hand), and dance (by thinking about moving two's foot). The classifier output is presented as a bar plot (top right corner) of the three corresponding actions.

participants in these studies were patients suffering from epilepsy, and it is possible that their disease has an impact on the neural features extracted from their brain activity. Progress in DS-BCIs could help researchers inspect more specific neural during more natural forms of navigation, including with healthy participants. Recently, Kim and Maguire [162] published evidence of disorientation in neural activity from a stationary fMRI investigation. Greater understanding of this finding and adapting the insights to DS-BCIs could lead to an application that stops people from becoming lost. We imagine an AR headset that recognizes when a person is becoming disoriented and displays information to help them correct their route.

B. Inattentional Blindness

Inattentional blindness (IB) is the word for when you're staring right at something and can't even see it [163, 164]. The general thinking is that it occurs when one's attention is preoccupied. However, at present, our knowledge of the EEG-based biomarkers for detecting IB in real-time and the efficacy of these markers in mixed-reality scenarios is not well understood. DS-BCIs could address this gap with modelling that recognizes "see but not perceive" phenomena in AR scenarios.

Fig. 8. The fully portable system that combines a dry-sensor EEG system and AR glasses. The participant wears a dry-sensor MINDO 8 device and Microsoft HoloLens 2 at the side and front views. Brain data on the participant's cognitive state is collected for decoding via the portable MINDO 8 device while they interact with the AR content via Microsoft HoloLens 2.

Although some studies have explored the potential neurophysiological correlations between IB and brain activity, such as visual awareness negativity and post-stimulus alpha suppression [165-167], no systematic research has been undertaken on reliable EEG-based biomarkers for building a model that can detect IB in real-time in natural scenarios. In a recent VR project, Schöne et al. [168] implemented the famous gorilla paradigm proposed in [163] as a real-life 3D scenario. They found participants were significantly more likely to notice the gorilla in this format. However, as yet, no study on IB biomarkers has adopted an immersive mixed-reality scenario (i.e., AR) where virtual objects will pop up in a real visual scene. In future, DS-BCIs could provide a framework that would not only make this possible but also easy.

Further, there is limited information on how the adaptive presentation of virtual objects might mitigate IB or enhance situational awareness in AR scenarios. Morse et al. [169] modelled the role of transient dynamics in IB by manipulating relevant stimulus input features in an offline experiment design. Some studies on predicting the incidence of IB have investigated different factors that might affect and, more particularly, reduce its occurrence [163, 170]. However, no study explains how to handle unexpected objects to reduce IB and enhance situational awareness in real-time. A closed-loop DS-BCI scheme may help researchers address any subject-dependent factors that could affect IB, as evidenced in [171]. Our vision is for a wearable device that can increase the user's situational awareness by triggering a visual/auditory/tactile warning when it detects an inattentional visual object in the user's field of view.

C. Predicting motion sickness to enhance the user experience

As the popularity of wearable computers grows, so do reports of motion sickness while using a head-mounted display [172-175]. There are various reasons for why AR and VR lead to motion sickness, attributed to both software and hardware [176], but one of the major factors is content. Among the many efforts to prevent motion sickness in general, and with VR specifically, Chen, et al. [177] finds evidence for strong links to alpha power at the occipital midline from a simulated VR driving scenario (see also [178, 179]). Thus, brain dynamics can predict motion sickness.

Again, however, most of the studies in this area involve stationary participants. DS-BCIs would allow researchers to explore the neural features associated with motion sickness in much greater detail, in more scenarios, and in more realistic scenarios. From this level of research, we could unpack stable and reliable motion sickness biomarkers. Ultimately, a wearable DS-BCI would not only benefit the end user's experience of the content by preventing motion sickness, but also enhance the development of both technologies.

IX. Conclusion

Recent advancements in the field of BCIs have been striking. This article surveys these most recent contributions. What we find is that building a closed-loop system to translate user intentions into BCI instructions has moved from a distant goal to a feasible possibility. From a comprehensive review of the current state-of-play in stimulus-free, DS-BCI systems, we foresee a novel, wearable system that can directly decode a user's sensory data. We believe the high transfer rate and natural interaction modes of these next-generation BCIs will bring this technology closer to real-life application.

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