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A perspective on electroencephalography sensors for brain-computer interfaces

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Abstract

This Perspective offers a concise overview of the current state-of-the-art of neural sensors for brain-machine interfaces, with particular attention towards brain-controlled robotics. We first describe current approaches, decoding models and associated choice of common paradigms, and their relation to the position and requirements of the neural sensors. While implanted intracortical sensors offer unparalleled spatial, temporal and frequency resolution, the risks related to surgery and post-surgery complications pose a significant barrier to deployment beyond severely disabled individuals. For less critical and larger scale applications, we emphasize the need to further develop dry scalp electroencephalography (EEG) sensors as non-invasive probes with high sensitivity, accuracy, comfort and robustness for prolonged and repeated use. In particular, as many of the employed paradigms require placing EEG sensors in hairy areas of the scalp, ensuring the aforementioned requirements becomes particularly challenging. Nevertheless, neural sensing technologies in this area are accelerating, also thanks to the advancement of miniaturised technologies and the engineering of novel biocompatible nanomaterials. The development of novel multifunctional nanomaterials is also expected to enable the integration of redundancy by probing the same type of information through different mechanisms for increased accuracy, as well as the integration of complementary and synergetic functions that could range from the monitoring of physiological states to incorporating optical imaging.

Keywords: neural sensors, brain-computer interfaces, brain-machine interfaces, electroencephalography, BCI paradigms

1. Introduction

The concept of brain-machine or brain-computer interfaces (BMI or BCI, respectively) had first been introduced in 1973 in a seminal work by J.J.Vidal [1]. Vidal had pointed out that the ability to identify, extract and analyse evoked responses from the brain activity to an external sensory stimulus could become the basis for a direct brain-machine interaction, free of intermediary peripherals. His seminal publication had already envisaged the potential for elevating "*the computer to a genuine prosthetic extension of the brain*", and stated that "*even on the sole basis of the present states of the art of computer science and neurophysiology, one may suggest that such a feat is potentially around the corner*" [1]. The foundations laid by

Vidal in BCI still form the basis of the paradigms and approaches currently used in this field. In fact, while today's BCIs are still unable to literally "read minds", they can detect brain responses to stimuli with high accuracy. However, if BCI technologies based on evoked potentials seemed to be already around the corner for Vidal, why is that they are not yet mainstream 50 years later? Certainly not because of lack of applications. BCIs would offer a coveted solution for seamless control of body prosthetics, for immediate communication with vehicles or robots in situations where the response time is critical, or where carrying a computer peripheral is not practical, and would make the consumers' use of personal computers no longer tied to a desk, greatly reducing the associated ergonomic risks.

While the general early BCI conceptualisation has been reinforced throughout the more recent advances in Neurosciences and Physiology, the technological challenges to make the technology viable have been overall substantially more involved than anticipated. Such challenges range from obtaining a sufficiently high accuracy and low latency of the whole BCI system to the availability of suitably biocompatible neural sensors with the necessary sensitivity, robustness and practical wearability. Advances on both the decoding approaches and algoritms side, as well as on the front-end side of the system (sensors engineering and electrode materials), and overall system miniaturisation and portability, are all key aspects for BCIs to become integral part of mainstream applications [2]. The Gartner hype cycle for emerging technologies, regularly selecting 25 innovations with high potential to yield major technological shifts, has placed two-way brain-machine interfaces on the initial rising slope of the cycle (innovation trigger phase) in their 2020 update [3]. Gartner had also suggested in the same report that the plateau of productivity for this technology could be reached within 5-10 years. In the remainder of this Perspective, we will analyse the outlook for BCIs for brain - computer interfaces from a sensor point of view. However, we will first briefly review the different components of a BCI system based on electroencephalography (EEG), which is currently the most adopted method, and the common EEG-based BCI paradigms to clarify their adoption rationales and implications for the neural sensors.

1.1 BCI systems and common paradigms

A complete BCI system is composed of different parts which all need to work synergetically and synchronized, as per schematic in **Fig.1**. First, often an external stimulus is fed to the individual (leftmost part of **Fig.1**). Types of stimuli can be visual, auditory or somatosensory, although visual stimuli are by far the most common in BCI [4]. Secondly, the stimulus evokes a specific feature in the brain activity of the individual, which encodes the individual's response and thus their intention. This information is embedded in the background activity stream of the brain, which is characterised by frequencies primarily contained within ~1-150 Hz [5], and it is recorded by neural electroencephalography sensors. The neural sensors can be either external (scalp EEG) or implanted or intracranial (iEEG). Here (**Fig.1)** we exemplify the use of scalp EEG sensors, arranged in a helmet. They record signals with an amplitude of only a few μVs, which may be preamplified in-situ and transmitted to the decoder platform, where the feature can be identified, extracted, classified and translated into a command to the intended robotic platform. The robotic platform can be any type of prosthetic, rehabilitation device or external machine accepting electronic commands.

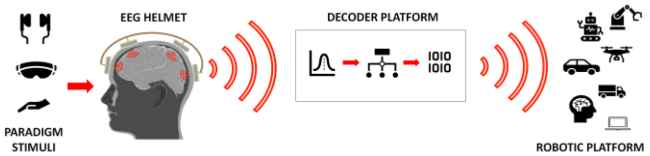

Fig.1 Schematic of a complete brain-computer interface system. When specific external stimuli are fed to an individual, they evoke unique signature responses from the brain, or biopotentials. The brain activity is continuously recorded with EEG sensors, such that those responses, which encode intentions, can be decoded – identified, classified and translated into a command to a generic electronic machine or platform.

The most common classes of EEG-based BCI paradigms are: motor imagery (MI) [6], event-related potential (ERP) [7], and steady-state visually evoked potential (SSVEP) [8]. The choice of the BCI paradigm determines the type of stimulus (if any) to be fed to the individual and hence the type of feature elicited in the brain activity, the frequency band to be monitored and the positioning of the neural sensors with respect to the functional areas of the brain cortex [9]. Also, the choice of a suitable paradigm is closely related to the targeted BCI application, the paradigm determines the level of accuracy, response time and extent of individual training required [10].

The control of mobility prosthetics often employs MI paradigms, as the act of imagining a movement of a part of the body can activate areas of the brain that are actually responsible for voluntary movement [11]. This class of paradigms typically requires a large extent of individual training but do not depend on external stimuli. EEG sensors employed for MI paradigms need to be typically positioned in correspondence to the motor cortex, over scalp locations across the top of the head, specifically C3, C4, and Cz of the international 10-20 system, as in **Fig.2 A** [12].

ERP and SSVEP both require external stimuli. One of the most common ERP paradigms is the P300 potential, which can be typically evoked via external auditory or visual stimuli [13]. One of the seminal examples is the P300 Speller [14], which aims at translating a speech letter by letter directly from the brain with the help of visual stimuli. The principle behind P300 potentials is to detect a category of events that only happens rarely (hence also known as "oddball" paradigm). This applies to the action of the speller, i.e. choosing one letter amongst the extensive choice of characters on a screen. These rare events will evoke an ERP response from the brain with a typical strong positive component appearing approximately 300ms after the stimulus, as indicated in **Fig.2 B** [13]. The advantages of P300 paradigms are a high level of accuracy with a relatively limited extent of individual training. However, downsides are the intrinsic time latency of ~300ms, creating ambiguity for events at shorter intervals, and the fact that the accuracy of the response is influenced by the cognitive state and attention of the individual, which may lead to fatigue overtime [10]. EEG scalp locations for P300 potentials are typically across the top of the head, along the nasion-inion axis [10].

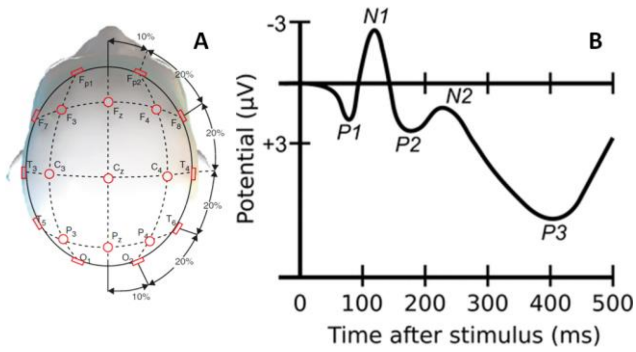

Fig.2 (A) shows a representation of the international 10-20 international system [12]. The necessary electrode locations for BCIs are related to the chosen paradigm. C3, C4, and Cz are used for motor imagery paradigms, while visual paradigms need recording of occipital areas, in correspondence to the visual cortex. The schematic in (B) represents the typical components of an ERP response. The P3 component, which is strongly negative and appears roughly after ~300ms, is the one elicited via the "oddball" paradigm or P300 [15]. (A) Adapted by permission from Springer Nature Customer Service Centre GmbH: [12] © 2020, (B) From [15]. CC BY-NC 3.0. To view a copy of this license, visit https://creativecommons.org/licenses/by-nc/3.0/.

Lastly, the SSVEP focuses on visual stimuli only (although equivalent paradigms, using for example somatosensory stimuli, also exist). The stimuli presentation is given through images (representing possible choices) flickering at specific frequencies. The steady-state evoked potential at the visual cortex will exhibit neuronal firing rates at the same frequency as that of the chosen option, plus its subharmonics [16]. SSVEP is considered a zero-training paradigm, as the evoked potential is comparatively robust with respect to the individual cognitive state [17], although minor modulations are still present [18]. This characteristics makes SSVEP an appealing paradigm. Drawbacks could be fatigue related to the long-term use of the flickering stimuli, and the fact that the visual stimulus is not well-suited to individuals with visual impairments [10]. SSVEP potentials are read out in correspondence to the visual cortex, hence mainly from the occipital lobes of the brain.

Overall, many more paradigms are available and are being continuosly improved in terms of accuracy, latency, and information-transfer-rate (ITR). Most recently, with the aid of deep neural learning, a stimulus-free BCI, called direct-sense BCI, is proposed to operate directly and seamlessly from our thinking. The technology can enhance the ITR and seamless communication through BCI [18]. As an example, the direct-sight BCI can 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.

2. Intracranial versus scalp EEG

While the different BCI paradigms reviewed above are primarily based on scalp EEG sensing, similar BCI principles can be employed for intracranial EEG (iEEG), the invasive version of EEG based on a variety of electrode types that can be implanted underneath the skull, which encompasses ECoG, with flat electrodes placed the surface of the cortex, and stereotaxic-EEG, using thin probes and probe arrays accessing deeper regions in the brain [19]. An overview of the type of intracranial sensors is graphically given in **Fig.3** [20].

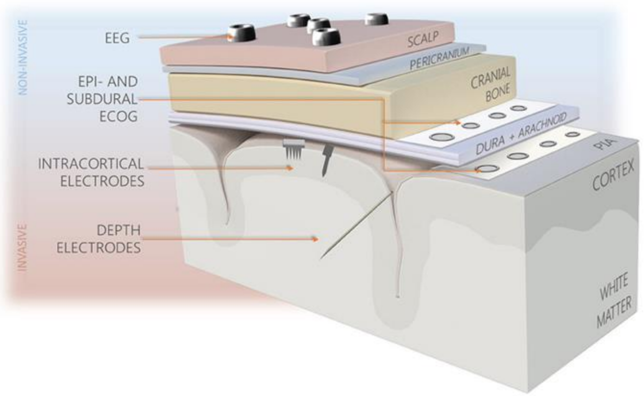

Fig.3 Schematic showing scalp EEG electrodes against the different types of intracranial sensors: ECoG electrodes wich can be placed on the dura or on the surface of the cortex, as well as high aspect ratio electrodes, able to reach deeper in the brain and sense from local-field potentials down to action potentials from a single neuron. Reproduced from [20]. CC

While scalp EEG records the post-synaptic summation of synchronous activity (oscillations) of thousands to millions of neurons, iEEG readings include local field potentials (LFPs) down to multi-unit and single-unit biopotentials [12]. LFPs are relatively slow electrical changes in the brain activity typically found at low frequencies, akin to the oscillations recorded by scalp EEG, but corresponding to a much smaller neuronal population [21]. Single- and multi-unit biopotentials are representative of the spiking activity of a single or of multiple neurons in the vicinity the iEEG probe, occurring at higher frequencies than LFPs, typically above 300 Hz [22].

ECoG is being broadly investigated for BCI applications. The capability of ECoG to access directly the brain cortex enables a far superior spatio-temporal resolution of the neural activity [23]. In addition, ECoG benefits from an intrinsically superior signal-to-noise ratio, as it is not affected by signal attenuation by the skull and scalp barriers like in the case of scalp EEG [24]. Implantable system are also more effective than scalp EEG when sensing needs to be combined to deep brain stimulation [25]. These characteristics allow for BCI technologies based on iEEG to go far beyond the level of control and granularity achievable with scalp EEG. iEEG - based BCIs are thus of particular interest for movement of prosthetic limbs [26] and for speller prosthetics aimed at improving quality of life of severely disabled individuals [27].

Implanted iEEG systems typically comprise 1) the neural electrodes, which can be in the form of an array of microwires or microstrips, or in the form of micromeshes for ECoG, or deep probes for s-EEG, plus 2) pre-processing electronics and antennas and 3) associated power sources. The conductive electrodes are usually encapsulated in insulators except for their contact area, to improve the biocompatibility and longer-term stability of the sensor [22].

There is a variety of approaches being investigated for iEEG. Some of the iEEG technologies at various stages of clinical trials and commercialisation include the one from Neuralink, organised in arrays of flexible threads containing each 32 microelectrodes for ECoG reading [28], and the *stentrode* BCI from Synchron, an endovascular approach containining “a self-expanding monolithic thin-film stent-electrode array” as a motor neuroprosthesis [29]. An advantage of the latter approach is that it does not need brain surgery, although it still requires a delicate application procedure through the jugular vein reaching up to the brain cortex.

The considerable risks related to the surgery for implant application, added to the post-surgery risks, including potential implant rejection, biofouling and implant migration [30] have so far strongly limited deployment of iEEE BCIs to neuroscience research and potentially to severely impaired individuals. Alongside ITR limitations [31], the long-term performance and biocompatibility of implanted devices remains one of the most critical challenges for iEEG-based BCIs, where biocompatibility needs to guarantee the absense of any type harmful interactions between the body tissue/fluid with the sensor and viceversa [22]. Nevertheless, this does not preclude that in the future, a friendlier version of such implants may be available and pave the way to a larger scale deployment. After all, we are already familiar with an extremely successful example of commercial neural prosthetics with the Cochlear implants [32, 33], which, according to the NIH, by 2019 had already restored some level of auditory capabilities to over 700,000 deaf or hard-of-hearing people worldwide [34].

Sensor technologies for implantable devices have recently made remarkable improvements, also thanks to substantial progress in electronics, nanotechnology and nanomaterials. This process has enabled additional miniaturisation of all components, an improved overall biocompatibility, and implants of power sources can now potentially be avoided altogether thanks to the availability of ambient energy harvesting [35] and wireless power transfer technologies [36].

For example, the start-up INBRAIN has developed graphene-based flexible deep probes [37]. In this case, a linear array of graphene transistors record activity deep in the brain, as demonstrated by accessing the hippocampus of a mouse. Note that graphene, a one-atom thick nanomaterial made exclusively of sp2-hybridized carbon sheets [38], is generally heralded as an ideal material for neural interfaces, thanks to its superior biocompatibility, resistance to corrosion, electrical and thermal conductivity as compared to most metals [38], its mechanical flexibility [39] and its exceptional electronic and optical functionalities [40]. Note that in addition to its chemical inertness, the ultra-thin and flexible nature of graphene could also alleviate the mechanical stress and related inflammatory issues arising from the modulus mismatch between the soft brain tissue and that of implanted probes [41]. Therefore, on the one hand, graphene could hence help reduce overall compatibility issues and improve the long-term durability, and on the other hand, it could also open the possibility for recording additional/complementary information through optical means [42].

3. Sensors for scalp EEG: requirements and evolution

As mentioned in the previous section, scalp EEG sensors have the challenging task of detecting brain potentials at a distance from the cortex, with interposed thick barriers such as the skull and the scalp attenuating signals substantially [43]. Since the biosignal amplitude at the scalp is just in the order of a few μV, any system or environment noise can potentially affect the recording. EEG sensors and EEG helmet systems are thus required to have a low intrinsic signal-to-noise ratio (SNR) [44]. The brain itself can be another source of artifacts, which often can be eliminated by band-pass filtering [12]. Environmental noise can be mitigated by using active sensors, ie sensors with an integrated a pre-amplifier [12]. Overall, the choice of the reference electrode, against which all potentials are going to be measured, and its location for EEG is quite critical. Reference electrodes are usually placed on the ear or on the mastoid, as they require minimal interference from the brain activity.

Another key aspect for scalp EEG is the long-term quality of the contact of the sensor electrode with the scalp skin, as a stable and low contact impedance is critical and needs to be maintained for prolonged times in many BCI applications [45]. Wet sensors -where an amount of conductive gel electrolyte is delivered at the sensor/skin contact- represent the original approach and still are considered the gold standard for scalp EEG [12]. The contact quality for wet sensor can be simply described by a contact resistance R_{es}, determined by the sensor area and resistivity of the electrolyte, as seen in the equivalent circuit model in **Fig.4** [46]. In the absence of an external electrolyte, the electrical contact for dry sensors is represented by a contact capacitance and contact resistance in parallel (hence, its contact quality is represented by a complex impedance) and often dominated by the scalp-electrode capacitance, C_{es} [46]. The presence of sweat and moisture on the scalp can help lowering R_{es} by lowering the resistance component of the contact in **Fig.4**, however this effect is limited by the fact that the scalp surface is typically contaminated by oils, flakes and is often covered by hair of different densities and thickness.

Wet electrodes can routinely achieve a low skin-electrode contact impedance between 5-10 kΩ/cm^2, however, their use strongly limit the deployment of EEG outside of clinical settings, as the gel needs to be periodically replenished to avoid signal degradation overtime [12], which is a major limitation for BCI deployment. A plethora of designs for dry electrodes has been thus developed over the years in order to overcome this limitation. Some examples are shown in **Fig.5** [47]. Those vary from metal to conductive meshes or foams to silicone/silver nanoparticles composites [48], and many can be bought commercially.

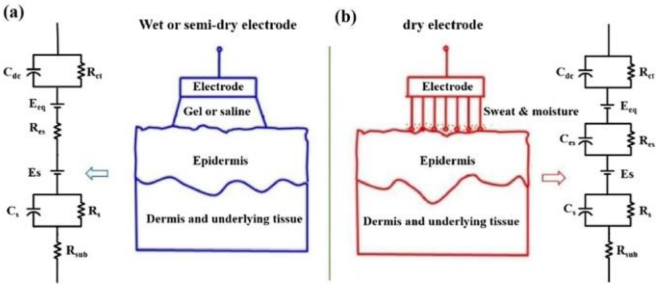

Fig.4 Equivalent circuits for (a) wet or semi-dry and (b) for dry EEG scalp electrodes. Dry electrodes do not use any additional electrolytes to achieve contact with the skin, therefore their contact is described by an additional capacitive contribution, but they may benefit from the presence of surface moisture and sweat. Reprinted from [46], © 2018, with permission from Elsevier.

Unfortunately, although dry sensors may show more stable impedance values, their contact impedance with the skin is invariably substantially higher than that of wet electrodes [46]. In some cases, skin abrasion has been explored in order to sensibly lower the skin contact impedance with dry sensors, and particularly, through the use of electrodes with microsized spikes that can penetrate the upmost layer of the stratum corneum [43].

In recent years, semi-dry electrodes have also been developed to overcome the gap in the impedance obtainable with wet versus dry electrodes [49]. Semi-dry electrodes typically use a reduced amount of electrolyte (1-2 ml) to establish a stable contact between skin and sensor, and rely on a controlled release of small gel quantities at the contact with the skin based on capillary or other forms of continued fluid release [49].

Scalp EEG sensors have been developed also with macroscopic pins or acicular design (**Fig.5**) in order to reach the scalp through the hairy sites of the scalp. The pins of such acicular designs are typically made out of the same electrode material as the flat sensors, ofter gold or other types of conductive and biocompatible material, and can be several mm long and hundreds of microns thick, as shown in **Fig.5** [43, 47]. Acicular electrodes obviously need to trade off the achievement of a reasonable contact with the scalp through the human hair via the tips of the pins, with the limited total contact area [48]. Some designs have also been developed with spring-loaded pins to ensure a better contact with the scalp. While pressure on the sensors tip improves the contact quality, from our own experience, the drawback of this approach is the poor user comfort, particularly over prolonged use, due to the pressure applied by the macroscopic pins on the skin.

Fig.5 Recent evolution of dry EEG sensors. Acicular designs and advanced conductive materials and fabrication options have been investigated in recent years. Notably, graphene has more recently joined the class of investigated materials, holding promise of superior biocompatibility and electrical conductivity.

Finally, the requirements on biocompatibility, although still important for scalp EEG, they are obviously much less restrictive than in the case of intracranial EEG. Nevertheless, strong requirements of inertness and non-biofouling still need to be placed on scalp electrodes, to ensure long-term usage with no degradation of performance, particularly in terms of contact quality [50].

As for the iEEG sensors, the advancement of scalp EEG sensors have recently greatly benefitted from the availability and engineering of nanomaterials such as 2D materials [51]. Graphene is a preferred choice for electrode materials because of its superior biocompatibility, capability for tailored surface functionalisation and micro/nanopatterning, its flexibility and high electrical conductivity [40]. The capabilities of graphene have been mainly been explored to obtain highly flexible [52], disposable [53] or even tattoo-like approaches [54].

4. Sensors for scalp EEG: current challenges

The previous section has provided a helicopter view of the state-of-the-art for non-invasive EEG sensors, emphasizing the need to move away from wet sensors for BCIs to be employed outside of clinical settings. Here we briefly review the current challenges from a sensor point of view towards robust and accurate BCIs based on scalp EEG.

First of all, semi-dry sensors can achieve comparable levels of skin contact impedance to wet sensors, but open the possibility to deployment outside of labs and hospitals. The second-generation controlled release sensors still need replenishment, although not as frequently as wet sensors. Next generation semi-dry sensors may allow for the automatic charge and discharge of the electrolyte [49]. While such technologies are still under development, one drawback of this approach is that the form factor of such solution tends to be bulky.

4.1 Dry sensors

Here following we review, without being exhaustive, some of the key challenges currently faced by dry sensors technologies.

1.1.1 Contact impedance. It was indicated that skin contact impedances as high as 40 kΩ can still yield excellent quality signals when coupled to appropriate high-impedance amplifiers [55]. While this is a threshold rarely achieved with dry sensors, with more typical values above 100 kΩ/cm^2, this target appears more consistently achievable with future developments [56]. Approaches to quickly reach a stable thin-boundary layer hydration using the skin moisture like recently demostrated with multilayer graphene electrodes [57], could hold the key to realise dry sensors with low impedance thanks to a mostly resistive contact like for gel-based sensors [46].

1.1.2 *Durability and resistance to corrosion.* While the accumulation of moisture and sweat on the skin at the interface with EEG electrodes can improve the contact impedance, over prolonged times the accumulation of ions from sweat can also lead to electrode corrosion for most metals [58]. Graphene is one electrode material with extraordinary resistance to corrosion, however, delamination is often an issue for large-grain graphene [59], due to its very low surface energy. This issue could be resolved with the use of binders or of a graphene with high adhesion to its substrate [57]. Preventing electrode corrosion and delamination is also critical to enabling the re-use of EEG sensors.

1.1.3 Sensing through hairy scalp. As discussed, the most common BCI paradigms are visual, and require accessing areas of the scalp that are usually covered with variable density of hair. Without the assistance of a wet electrolyte to bridge the electrode-scalp contact in the presence of interposed hair, this aspect becomes a particularly challenging area for dry EEG. Also, given a typical human hair thickness of a few tens to hundreds microns and their high density on the scalp, acicular sensor designs require macroscopic pins that are usually beyond the capabilities of thin-film microfabrication. Consequently, it becomes more complex to take advantage of nanomaterials, particularly 2D materials, for fabricating acicular EEG electrodes unless the composite materials route is chosen.

1.1.4 Other challenges. Remaining open challenges for dry EEG sensors include the prevention of motion artefacts during movement of the individual, which can be obtained by skin abrasion and the application of pressure at the skin-electrode contact. These approaches need to be traded off though with the comfort for long-term and repeated usage. The bulkiness of the sensors can also be a barrier to comfort, including in terms of discretion.

5. Considerations on the choice of BCI sensors

Overall, as **Fig.1** exemplifies, it appears clear that EEG sensors are only one part of a complete BCI system. As for all systems, the final performance relies on the performance of the single parts, as well as on their synergy. One of the key performance parameters for BCIs is the accuracy that can be guaranteed by the system within a reasonable latency window [60, 61]. The accuracy obtained depends on the chosen paradigm, on the integrated sensor performance in a band or helmet, and on the performance of the decoder system, ie on the speed and accuracy of the employed algorithms for classification. Each of those parts needs to be selected and co-optimised according to the intended application. The achievable BCI system performance will be limited by the lowest performing part in the chain.
In terms of sensors, there is availability of diverse commercial designs, and there is an extraordinary amount of sensor designs at various R&D stages, aiming to address some of the challenges discussed in the previous sections. Covering all of the different specific sensor types and approaches is beyond the scope of this perspective. However, based on the discussions in the previous sections, we provide in **Table 1** and **2** a qualitative guidance to the main sensor strategies and related key parameters and considerations.

	iEEG	**Scalp EEG**		
	ECoG and other probes	Wet	Semi-dry	Dry
Ease of application	Implanted, surgery required	Non-invasive, high amounts of electrolytic gel	Wearable	Wearable
Spatial resolution	High -LFPs and single/multi unit biopotentials	Poor – 10^4 – 10^6 neurons	Poor – 10^4 – 10^6 neurons	Poor – 10^4 – 10^6 neurons
Biocompatibility requiremens	Most stringent	Less critical – only skin contact	Less critical – only skin contact	Less critical – only skin contact
Use outside of lab/clinic	Possible	Limited	Possible	Possible

Table 1 Qualitative comparison of the different sensors strategies for BCI systems. Note that the need for surgery and stringent biocompatibility requirements is currently limiting the choice of implants to with assist severe disabilities.

	Scalp EEG		
	Wet	Semi-dry	Dry
Contact impedance with skin	Gold standard, <5kΩ	Can reach wet sensor values	Higher, typically >100kΩ
Long -term performance stability	Poor	Can be high	Strongly dependent on design
Contact through hair	Possible	Possible with acicular design	Possible with acicular design
Size reduction	Not pursued	Difficult, bulky design	Possible

Table 2 Qualitative comparison of the different sensors strategies for BCI systems based on scalp EEG. Note that wet sensors, although gold standard in the lab, score poorly on long -term stability.

6. Future developments

Further miniaturisation capabilities of all sensor system components will underpin future EEG capabilities and hence EEG-based BCIs.

Regarding iEEG, while further miniaturisation of the electrodes is no longer by itself a limiting factor, as the size of a single neuron of the order of several hundred microns can be easily matched by modern microfabrication capabilities to record single action potentials [62, 63], the miniaturisation of all components to be implanted is key to limit invasiveness and reduce the occurrence of adverse reactions during and after surgery. This includes the continued development of low-power consumption sensors, efficient microbatteries [64] and/or energy harvesting [65] or transfer systems to power the implanted systems [66]. One notable example of such development is the "neural dust", an active two-ways implanted microsensor able to be powered through ultrasonic sound waves instead of the less efficient induction-based energy transfer [67]. Further advances in (nano)materials as active and/or protective coating will also propel this approach further.

Further miniaturisation, additional nanomaterials engineering and the advancement of alternate fabrication capabilities like 3D printing of nanomaterials [68] will greatly benefit also advances in scalp EEG sensors [51]. The portability of unthethered sensors and sensor components, including power sources, will lower significantly the barrier to large-scale deployment, together with additional considerations around validity, necessity and costs [2].

As discussed, the final accuracy and total latency of a BCI system is determined by the whole system, of which an important part is the decoder platform. While refined paradigms, data quality and spatial resolution, algorithms and classification, coupled to more powerful microprocessors, will continue improving obtainable accuracies, added sensing redundancy is another way to ensure higher overall accuracies [69]. This can be obtained by adding more EEG sensors in the BCI system, but also by integrating complementary types of sensors. For example, the integration of optical imaging sensors, functional magnetic resonance (fMRI) and molecular probes with electrical methods could add substantial value as each mechanism has different limiting factors (**Fig.6**) [70]. Nanotechnology offer nowadays a vast array of nanoprobes as nanosensors and nanoactuators that could greatly benefit Neuroscience and future BCI systems [71]).

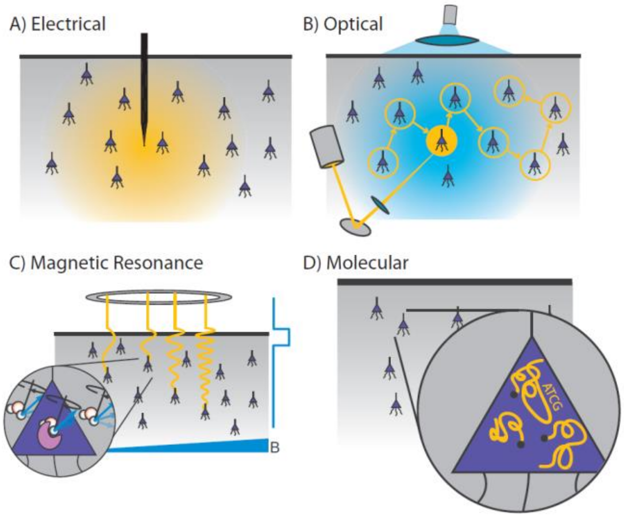

Fig.6 Alternative mechanisms for reading brain activity which could be used to complement electrical-based read-out (A) for enhanced accuracy. Optical methods like the scanning microscopy depicted in (B) can record the evolution of brain activity using tailored fluorescent protein tagging. fMRI in (C) uses tailored contrast agents based on the nuclear resonance of protons in an applied magnetic field to record how responses are affected by the local brain activity. Finally, in (D) it is anticipated that biomolecules such as DNA could be used as “molecular recorder”, locally encoding brain activity. Reproduced from [70]. CC BY 3.0. To view a copy of this license, visit http://creativecommons.org/licenses/by/3.0/.

In summary, sensors for BCIs have advanced substantially in recent years, and the future could bring the convergence of increasingly more powerful technologies all synergetically working towards vastly improved brain-interface systems. While BCIs based on iEEG are expected to have unprecendented impact on the rehabilitation and prosthetic control of severly disabled individuals, the large-scale deployment of neural interfaces for BCIs hold the promise of sparking a similar type of paradigm shift as the introduction of personal computers in the 1970s [2].

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