Neurosciences and Wireless Networks: The Potential of Brain-Type Communications and Their Applications

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***Abstract*—This paper presents the first comprehensive tutorial on a promising research field located at the frontier of two well-established domains, neurosciences and wireless communications, motivated by the ongoing efforts to define the Sixth Generation of Mobile Networks (6G). In particular, this tutorial first provides a novel integrative approach that bridges the gap between these two seemingly disparate fields. Then, we present the state-of-the-art and key challenges of these two topics. In particular, we propose a novel systematization that divides the contributions into two groups, one focused on what neurosciences will offer to future wireless technologies in terms of new applications and systems architecture (*Neurosciences for Wireless Networks*), and the other on how wireless communication theory and next-generation wireless systems can provide new ways to study the brain (*Wireless Networks for Neurosciences*). For the first group, we explain concretely how current scientific understanding of the brain would enable new applications within the context of a new type of service that we dub *brain-type communications* and that has more stringent requirements than human- and machine-type communication. In this regard, we expose the key requirements of brain-type communication services and discuss how future wireless networks can be equipped to deal with such services. Meanwhile, for the second group, we thoroughly explore modern communication systems paradigms, including Internet of Bio-Nano Things and wireless-integrated brain–machine interfaces, in addition to highlighting how complex systems tools can help bridging the upcoming advances of wireless technologies and applications of neurosciences. Brain-controlled vehicles are then presented as our case study to demonstrate for both groups the potential created by the convergence of neurosciences and wireless communications, probably in 6G. In summary, this tutorial is expected to provide a largely missing articulation between neurosciences and wireless communications while delineating concrete ways to move forward in such an interdisciplinary endeavor.**

***Index Terms*—Wireless communications, neurosciences, brain-type communications, brain-controlled vehicles, brain–machine interfaces, brain implants.**

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ACRONYMS

6G	Sixth Generation of Mobile Networks
AI	Artificial Intelligence
ANN	Artificial Neural Network
AoI	Age of Information
BCV	Brain-Controlled Vehicles
BMI	Brain–Machine Interface
BTC	Brain-Type Communications
D2D	Device-to-Device
eMBB	Enhanced Mobile Broadband
HTC	Human-Type Communication
IC	Integrated Circuit
IoBNT	Internet of Bio-Nano Things
IoT	Internet of Things
IRS	Intelligent Reflecting Surface
ISN	Intelligent Sensor Network
LFP	Local Field Potentials
MIMO	Multiple Input Multiple Output
mMTC	Massive Machine-Type Communication
MTC	Machine-Type Communication
QoE	Quality-of-Experience

QoPE	Quality-of-Physical-Experience
QoS	Quality-of-Service
SNR	Signal-to-Noise Ratio
URLLC	Ultra Reliable Low Latency Communication
VoI	Value of Information
XR	Extended Reality.

I. Introduction

THE LAST two decades have witnessed tremendous new developments in information and communication technologies, most remarkably in wireless communications and Artificial Intelligence (AI). At the same time, the scientific understanding of the nervous system and the brain has also grown substantially. In fact, brain research is seen as arguably the most anticipated field of research for the coming decade. This is not a historical coincidence: the evolution of both domains is strongly interlinked. For example, on the one hand, the steep growth rates of technological advances in sensors, digital processing, and computational models have always supported the research in neurosciences while, on the other hand, the knowledge of how neurons and the neurological system work have supported the development of computational methods based on the Artificial Neural Network (ANN) [1]. A comprehensive review of the topic can be found in [2].

Neurosciences and wireless communications are converging in the context of several recent wireless and AI developments, where both are going to the edge: wireless communications is quickly heading toward nano communication while AI is moving toward edge intelligence at the sensor itself based on neuromorphic computing and various edge AI techniques, such as federated learning [3]–[7]. Futuristic technological solutions like Neuralink's novel brain implant [8] or the Internet of Brains [9] are perfect illustrations of potential opportunities ahead. While the former focuses on developing high-density, invasive wireless brain implants for humans, including a neurosurgical robotic system to insert the device, the latter provides the first experimental demonstration of a network of interconnected rat brains, configured as an organic computer, that outperforms single brain in behavioral tasks. Both approaches point at a future where human brains are part of the communications grid, interacting directly and seamlessly with other man-made devices but also with other brains. In fact, the ideas behind these technologies are strongly aligned with the vision of 6G [10], which is expected within ten years from now. We are aware that 6G is far from being standardized, and thus, current works may be highly speculative; in any case, the key cases for 6G are actually being defined now as illustrated by the eleven white papers recently published by the 6Genesis Flagship [11].

In this sense, this paper argues that one of the key drivers of future wireless technologies, such as 6G, would probably be wireless brain–machine interactions based on Brain–Machine Interface (BMI), enabled by a mobile network designed to support a new type of service that we call Brain-Type Communications (BTC), which can have many contrasts and synergies with the human- and machine-type communications of previous and current network technology generations (4G and 5G, respectively).

BTC would allow for more direct interactions between users and networks as compared with current systems, which are dominantly mediated by smartphones. Furthermore, BMIs are severely limited by wired communications, given that sophisticated applications should consider groups of individuals, each with implants made of thousands of recording channels, all part of a naturalistic scenario. New services supported by wireless BMI, such as interacting with the environment with gestures, motor intentions, or emotion-driven devices, impose remarkably different performance requirements from the current 5G in terms of Quality-of-Physical-Experience (QoPE). The list of applications is extensive, to cite but a couple of examples: wireless-BMI-connected intelligent vehicles, neural-based wireless networks with sensors and actuators working as an "artificial brain", as well as the future evolution of virtual reality services [7], [12], [13].

The main contribution of this paper is a novel, holistic tutorial that focuses on this new, promising research field located at the frontier of the two established domains: Neurosciences and Wireless Communications. Our goal here is to provide a tutorial of the state-of-the-art of those fields, mapping the most relevant activities and how they have a great potential to converge with the definition of the homocentric 6G [14] through the development of BTC. To this end, we expect to contribute to the ongoing discussion about the key wireless communications applications, in particular 6G, which will then affect the standardization process. In particular, we delineate the foreseen future applications and their challenges in two threads: **Neurosciences for Wireless Networks** and **Wireless Networks for Neurosciences**.

The first one refers to how current and new scientific/technological developments arisen from neurosciences can be employed as part of wireless systems as, for instance, direct wireless brain implants. The second topic refers to how wireless communications theory and technologies (mainly 6G) can support research and technological development in neurosciences. Topics in this thread include considerations of how communications/information theory can provide the fundamental limits of neuronal communications, which have a chaotic nature. We also present a case study—Brain-Controlled Vehicles (BCV)—that we have identified as an illustrative application that would benefit from the proposed merger between wireless communications and neurosciences. Finally, we discuss the security, privacy, and ethical issues underlying both topics.

Fig. 1 presents the key ideas and topics covered by this paper, mapping the future relations between wireless communications and neurosciences. We envision an interplay between the two topics supporting the development of BTC and widespread BMIs integrated with nanotechnology, among others. Based on the current trends and the scientific development to be presented in this tutorial, we argue that the encounter between these two fields has a great potential to already take place in 6G.

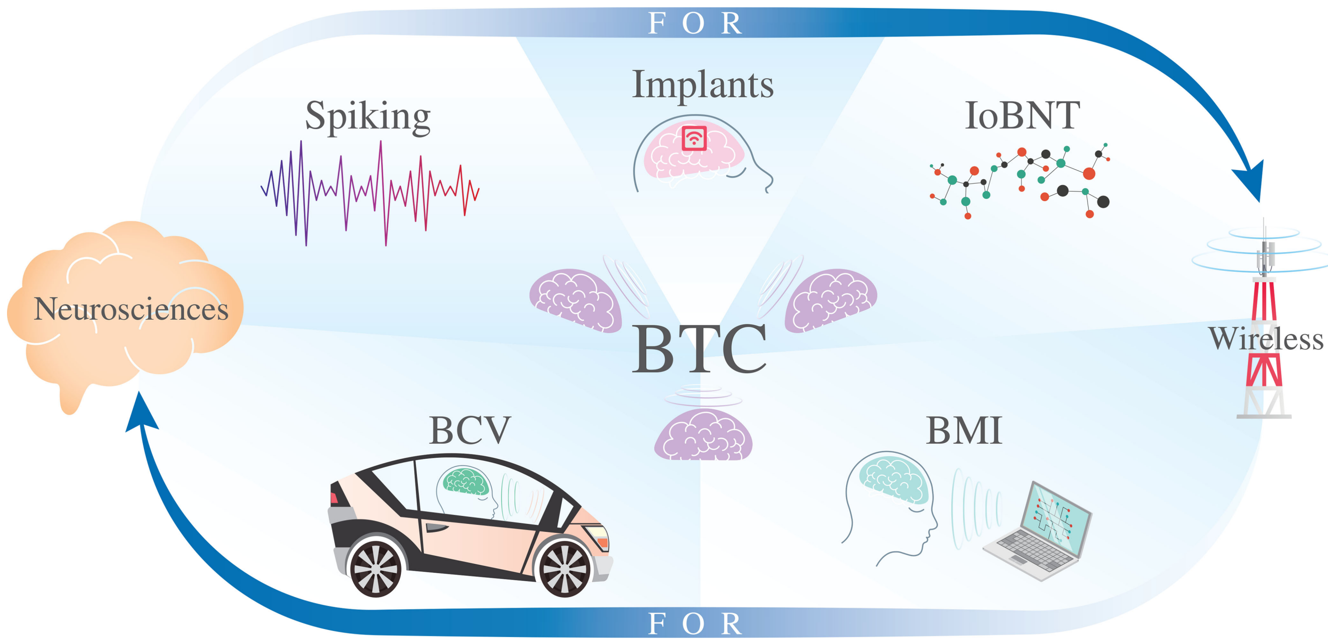

Fig. 1. Illustration of the proposed contribution along two threads: Neurosciences for Wireless Networks and Wireless Networks for Neurosciences around the concept of BTC.

In summary, we expect that this contribution can pave the way to a fruitful collaboration between researchers active in brain research, complexity sciences, and wireless communications to support in a timely manner the necessary activities to include applications related to neurosciences in the 6G standardization discussions that are expected to take place during the upcoming years. In addition, the paper will provide a single reference that symbiotically integrates the rather disparate state-of-the-art contributions in these two fields.

The rest of this paper is organized as follows. Section II provides the required background of neurosciences and brain research, specially discussing how brain signals are expected to be part of future wireless systems. Section III describes how neurosciences are contributing to the development of the next generation of communication systems through BTC, also providing details and challenges of wireless brain implants. Section IV presents the potential advantages that wireless communications may provide to neurosciences, considering the potential new generation of BMIs based on wireless connectivity for BTC and even the Internet of Bio-Nano Things (IoBNT), as well as theoretical and practical approaches related to the chaotic nature of neuronal communications. Section V introduces BCV as an existing application that would greatly benefit from synergistic research of 6G (or other future wireless communication technology) and neurosciences as proposed here. Section VI discusses the security, privacy, and ethical issues that are fundamental to guide both wireless communications and neurosciences in the near future. Section VII summarizes the paper pointing out our perspective for future research and technological development.

II. Background

Evolution has shaped the animal brain to provide individuals with rapid, robust responses to multisensory, possibly conflicting stimuli, thus ensuring survival. We begin this section by highlighting brain design principles, with the focus on properties with direct relevance to wireless systems. Then, we describe three types of neural signals found in most of electrophysiological works, with an emphasis on spikes. We proceed by describing current implant technology for interfacing with the brain and then conclude with a review of the key concepts and current stage of BMIs.

A. Brain Design Principles

The brain is a complex organ, notably composed of nerve cells (neurons) but also of supportive cells, such as glia. Ultimately, one may attribute the diverse components, structures, and dynamics found in brains from different species [15], [16] to singular evolutionary pressures.

Brain regions that are mainly made up of electrically insulated neuron axons (myelinated) are referred to as white matter, whereas neuronal cell bodies are found in the gray matter. From a communication systems perspective, white matter may be seen as insulated wires connecting widespread neural populations in the gray matter. The probability of two cortical neurons being connected is 1 in 100 within a vertical column of 1 mm in diameter, and 1 in 1000000 for distant neurons; further, forty to sixty percent of the brain mass volume is due to wiring (for comparison, the volume fraction of wiring in a computer microchip may reach up to 90%), and only one quarter of all energy is spent by white matter [17]. The brain presents local, densely connected neural populations that are sparsely connected often with small-world properties. A direct consequence of such a connectivity pattern is a disproportionate increase in the white matter (wiring) volume as cortical gray matter increases. This poses great challenges for wireless neural recording technologies.

Evolutionary optimization of neural connectivity is certainly constrained by energy consumption. Nearly half of the brain energy consumption is due to spiking activity, arguably the essential method by which neural populations communicate [17]. Single neurons have a physiological upper limit on firing rate in the range of hundreds of Hz [18], leading to a potential bandwidth of a few Terabits/s for the whole brain. This limit, however, is never reached because of the energy limitation. Considering the human brain metabolism, the average spike rate can be no higher than 1 spike per second per neuron [19]. Thus, communication systems operating with BTC protocols should be aware of these natural brain bandwidth limits.

The locally dense, globally sparse connectivity scheme constrained by the brain energy budget may reduce the signal-to-noise ratio [20]. Considering that more reliable neurons would require a superlinear increase in energy cost (caused by neuron physiology), one alternative is to average out large numbers of (noisy) neurons. But that, in turn, would possibly lead to redundant neuronal activity, which is not energy-efficient, unless the network is able to reconfigure on the fly, suppressing connections that contribute little to good choices and reinforcing (making more efficient) those that do not. This overly simplified description is known as neural plasticity, the capacity of neural networks to modify their connectivity patterns based on correlated neural activity and behavioral feedback [21]. In summary, learning from experiencing the world to optimize behavior is a central mechanism that supports brain design principles under a limited energy budget. The immediate impact on the development of new wireless networks is that technologies underlying BTC must be adaptive to accompany brain plasticity and preserve brain learning mechanisms.

B. Neural Signals

In this section, we describe three types of neural signals that compose most of electrophysiological works [22] and that are central to BTC systems. Considering invasive recording methods, spikes relate to the rise and fall of the membrane potential of a single neuron over time [23]. Neurons are essentially formed by the soma (the cell body), dendrites, and an axon. Typically, electrical and chemical signals are received in the dendrites and soma of the neuron, whereas the neuron axon transmits an electrical signal to other neurons. Neuronal communication is mediated by synapses, in which we observe the propagation of neurotransmitters through the space between neurons (synaptic cleft). Along the neuronal axon there are voltage-gated ion channels, which regulate the ionic current flow as a response to input signals to the neuron. The rapid difference in ionic concentration inside and outside the cell originate the action potential (spike), which flows over the axon and targets other neurons. This signal has a strong nonlinear dynamics (Fig. 2) owing to neuron physiology.

Spikes are normally sampled at 40 kHz by multielectrode arrays, each electrode capturing the resultant membrane potential of the surrounding neurons. This multidimensional signal is then fed into a spike-sorting algorithm, responsible for identifying the membrane potential time series of each individual neuron [24]. Next, spike times are identified and saved either as a time stamp vector (millisecond resolution) or as a binary vector (1 if a spike has occurred, 0 otherwise). The sequence of spikes over time from a single neuron is known as a spike train, which is the data structure used as the input to the spike-based BMIs [25].

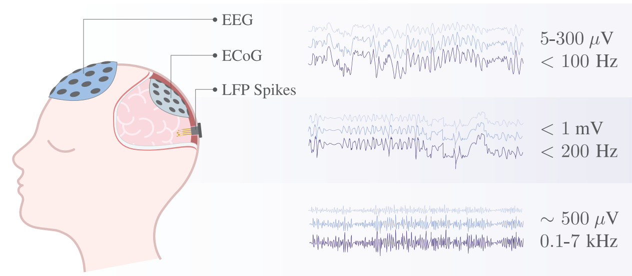

Fig. 2. Representation of the most common brain signals used in BMI: noninvasive EEG (top right panel), invasive LFP, and spike (middle and bottom panels). Electrocorticography (ECoG) signal properties are similar to those of EEG; however, because it is an invasive method, it is far less used in human studies. Figure adapted from [49].

The same time series used to construct spike trains can be used to extract another signal, the Local Field Potentials (LFP). For that, a low-pass filter ($<$300 Hz) is applied to the raw electrode signal and then downsampled, usually to 1 kHz. LFP relate to the superimposing electrical potential of thousands of neurons surrounding the recording electrode [22]. The spectral power density of this field is inversely proportional to frequency and is transmitted through brain tissue, a phenomenon known as volume conduction. The most common input in LFP-based BMIs is features extracted from the LFP frequency power spectrum [26].

The typical signal used in noninvasive approaches is the electroencephalography (EEG). EEG and LFP oscillations share similarities [22], [27], but, because the recording electrodes are further away from neuronal sources, noise, muscle contraction artifacts, and other tissue-related interference make EEG a less effective signal than invasive recordings. EEG is commonly recorded from 16 to 128 channels, studied at frequencies up to 100 Hz, and thus, the sampling rates rarely exceed 1 kHz.

C. Neural Interface Technology

For the purposes of wireless communications and BTC systems, we will focus on invasive signals. The main advantage of being invasive is the closer interface with brain cells, which leads to less noisy, more reliable readings with a more granular information content, a fundamental feature for complex applications [28], [29]. Novel signal processing algorithms have a substantially increased noninvasive (EEG) BMI performance [30], whereas standard brain implants present physical and longevity issues [31]. Nonetheless, there is a general agreement that, once technological and ethical issues have been addressed, invasive BMIs should prevail in the vast majority of applications [32], [33].

Brain implants and recording technologies have been developed for decades now. They are generally composed of six different parts: a probe, epoxy fill, an acquisition Integrated Circuit (IC), a circuit board, connectors, and an external cable [34]. The interface with the brain tissue is actually solely the probe, from which the signal travels from or to the acquisition IC that sits on the circuit board through the epoxy fill and the connector. The cable connects the whole structure, fixed on the skull, to the external supporting hardware.

One of the state-of-the-art devices regarding invasive implants are the neuropixel probes [35]. For instance, the advanced CMOS microelectronics and small, lightweight shanks allow for eight probes simultaneously implanted in a mouse brain, and more than 3000 recording sites. For each probe (384 recording channels), data acquisition is estimated at 1 GB/min at a sampling rate of 30 kHz. Considering that the mouse brain is orders of magnitude smaller than the human brain, these recording facts clearly highlight the substantial requirements in data processing and recording in the context of BMI and modern wireless communications.

The main challenges regarding invasive devices are related to their implantation procedure (sometimes through open skull surgery), biocompatibility, and longevity [36]. Implant functionality is impaired by tissue scarring as well as foreign body reactions that promote the degradation or breakage of the probes [37]. Furthermore, fully immersed implantables that rely on tethers to connect the device to an external interrogator inhibit long-term usage and reliability as this connection can be broken easily through movement or patient activity [38]. Tethers have additional challenges including the lack of scalability and a greater body reaction. The number of neuron interface channels is also limited to the number of tethers, and even though the relationship is not direct as one tether can have many probes, they are not a good choice when multiple areas of the brain are planned to be interfaced with a single system. On top of that, as the targeted area of study is deep in the brain, this will result in larger tethers that are harder to manage. Thus, the option of a wireless-based system has raised the interests of many researchers in the area (see [39] for a review).

Many technological breakthroughs will be required before functioning wireless BMIs will be widely available [34]. To begin with, wireless-based implants have to account for the many barriers imposed by the brain in order to be functional [28] (these barriers will be explained in more detail later in Section III-B). Wireless devices also need to interface with neurons whilst having the capability of converting wireless energy into circuit current (batteryless). This added complexity is nowadays feasible with energy-converting mechanisms based on microelectronics and nanotechnology [39]. Additionally, wireless implants require consideration of the human body as a communication channel. Because the brain is comprised of multiple different tissue types, and each type poses different interactions with the propagated waves, the wireless communication system between implantable and external devices, or derivations thereof, must precisely choose the frequency range and operating mode [40]. For example, while brain-stimulating devices for epilepsy require stimulation in random short-term periods, for Parkinson's disease the stimulation is constant at a particular rate at different times. The same goes for sensing applications.

Despite the challenges, the development of wireless-based neural interface technology will support the study of freely moving animals away from highly controlled laboratories [41]–[44], which will transform research in neurosciences considering that cognitive processes emerge from brain–body–environment interactions [45]. In parallel, BTC systems may underlie the next wireless communications revolution. As we argue throughout the paper, there is an intricate but feasible technological, medical, and ethical path ahead.

D. *Brain–Machine Interfaces*

The rapid progress in neural recording technology has paved the way for the development of BMIs [25], [46]. A BMI is a closed-loop framework, in which neural signals are sampled, preprocessed, and fed into a decoding algorithm (regression or classification) that can map behavioral intents from the brain to artificial devices, whose action outcomes are perceived by the subject sensory systems, thereby closing the loop. Applications are diverse, from shedding light into basic neurosciences research [47] to contributing to motor rehabilitation in spinal-cord-injured patients [48].

From a technological perspective, BMIs rely on the continuous progress in electrode design [50], data recording [51], and signal processing [52]. However, there is a central gap in the BMI research that is shared by other fields of neuroscience: what is the essence of the neural code? In other words, what are the features of neural activity that carry information about sensory stimuli and cognitive behavior? For instance, there is solid evidence favoring rate and temporal codes [53]–[55], but it remains unclear what the anatomo-neurophysiological patterns and information processing mechanisms of such codes exactly are.

For spike-based BMIs, most decoding algorithms map the spike rate or inter-spike time interval changes into behavioral choices. The rationale is that motor and cognitive acts (or intentions) modulate single neuron responses in diverse brain regions, and thus, spikes carry sensory and task-related information. As single neuron responses vary considerably within and between task trials [56], the use of recordings from populations of neurons results in more robust interfaces [57]. The common target for brain implants is the cortex region, the outer layer of the brain, from which sensory and motor information have been successfully extracted [25]; nevertheless, deeper brain regions, such as the basal ganglia and the cerebellum, have a fundamental role in action selection and spatial localization, among other important aspects of animal behavior [23], but are harder to be reached safely.

If, instead, LFP signals are to be used, the common approach is to extract frequency power spectrum features from data blocks over time as the behavioral task unfolds [26], given that specific frequency bands have been shown to correlate with behavior [58], a fact that also holds for EEG studies.

Finally, neural plasticity is fundamental for BMIs to operate properly [47], [59], [60]. BMI design has to carefully consider processing time and sensory feedback delays, and thus, modern communication systems have plenty to contribute.

E. Wireless Communications and the Brain

As discussed above, neural signals and their application in BMI pose new challenges for wireless networks, mainly for the established communication systems that are designed to support transmissions related to humans and/or machines, not brains.

From 2G and 3G to the iPhone generation, applications have focused on *connecting people* in a variety of ways; hence Human-Type Communication (HTC). However, the past decade ushered in a whole new type of wireless communication dedicated to connecting machines within the Internet of Things (IoT) system. Indeed, the emergence of Machine-Type Communication (MTC) links has revolutionized the wireless industry and is the driving force behind the ongoing deployment of 5G wireless systems. At this juncture, it is natural to pose the following question: What types of mobile devices will disrupt the wireless industry and drive beyond 5G wireless systems in the same manner that the iPhone and the IoT have done?

Although a conclusive answer to this question is not possible at this time, it is very natural to posit that next-generation wireless devices will no longer be handheld smartphones or IoT sensors in the field, but they will rather be wearable devices along a human body, including human brain implants. This observation is not a mere speculation, but it is instead motivated by the tremendous advances that we are witnessing in the area of wearable and human-embedded devices. Neuralink's recent achievements are a prime example: a public demonstration in late August 2020 showed a successful wireless BMI in pigs using a miniature, bluetooth-based device with 1024 channels that serve both for recording and stimulating the brain. In addition, the shift toward implants is further motivated by several emerging wireless services, such as immersive Extended Reality (XR) and BMI, in which the human body and brain become an integral part of the wireless service [10]. In these services, it will soon become necessary to provide communication links among not only machines (MTC) and human users (HTC) but also among the brains of different users. Hence, we foresee that BTC will be the next frontier in wireless connectivity, as indicated in Fig. 3.

The main lesson learned in this section is related to the very specific type of signaling that constitutes brain-communication-based neuronal activity, which poses enormous challenges for communication engineers. In specific terms, BTC links must be designed in a way to seamlessly connect a human brain to a wireless network and potentially provide two-way communication among the users' brain implants and the various networks and IoT devices. A unique feature of BTC links is that they will require the network to match the operating functional complexity of the human brain with a given application of choice. In the next section, we highlight how the brain's inherent features can soon become an integral component of wireless networks that cannot be ignored when modeling, analyzing, and optimizing the wireless networks of the future.

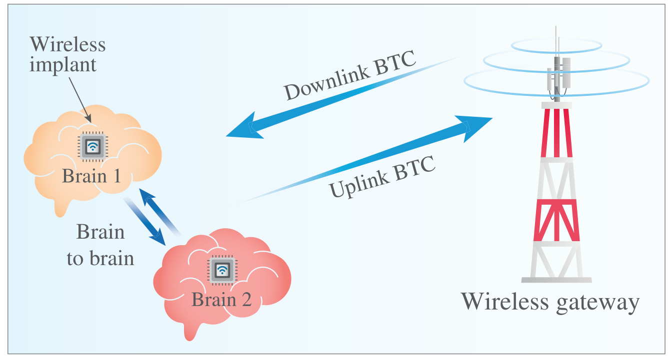

Fig. 3. Illustration of different types of BTC services in wireless networks. The figure highlights the communication between brain implants via Uplink/Downlink BTC services and a base station, or directly, via brain-to-brain BTC links between wireless implants.

III. NEUROSCIENCES FOR WIRELESS NETWORKS

In this section, we will discuss how the technological developments based on the state-of-the-art in neurosciences will open many new opportunities with related challenges in wireless communications beyond 5G systems. This will include the support of BTC and intelligent (neuromorphic) sensor networks based on spikes.

A. Direct Brain Implants That Communicate Wirelessly

Communications with brain implants will be a hallmark of next-generation wireless networks, and hence, we must have a deeper understanding of how to deliver wireless services to networks with *brain-in-the-loop*. To do so, we will first discuss some use cases that highlight different ways in which BTC will be integrated in wireless networks. Then, we delve into the various challenges associated with the identified use cases and conclude with discussions of open research problems and some preliminary results.

1) Use Cases: The first step toward understanding the unique wireless challenges of BTC links consists of delineating possible BTC use cases in an actual network. In this context, we envision three key use cases (as illustrated in Fig. 3).

- *Downlink BTC:* BTC links can be used in the downlink of a wireless network. Here, the downlink transmission links are used to transmit data from the network toward brain implants. A chief use case in this context is XR services. Indeed, next-generation XR services may tap directly into the human cognition in order to provide a truly immersive virtual world where a wireless user can navigate using brain-based signals along with various body-implanted sensors. In such use cases, the brain is the receiver of the wireless data, and thus, the downlink BTC traffic will require high data rates.
- *Uplink BTC:* BTC links can be used for uplink communications in order to transmit information extracted from

the human brain through its implants to other network devices and servers. Two key BMI examples that require uplink BTC are multi-brain-controlled cinema [61] and wireless cognition [62]. The first relates to hundreds of spectators interacting, through brain input, with an audio-visual performance that unfolds based on their emotions, reactions, and cognitive engagement. In this scenario, participants may interact among themselves and with the performance, creating a unique experience and possibly revolutionizing the entertainment industry. The latter depicts a scenario in which a drone or an autonomous vehicle is controlled by one or multiple brains (see Section V for details). The two examples highlight critical applications that require multiple, reliable recordings with several brain regions, including deep areas, such as amygdala (emotions) and cerebellum (motor control), which have to be processed to deliver real-time responses to the target application. Hence, uplink BTC is fundamental.

- *Brain-to-Brain Communications:* BTC links can be used to establish direct communications among the brain implants of different users within the same or different environments [9]. Brain-to-brain communications can be seen as the next step in Device-to-Device (D2D) communication, in which the devices are now direct brain implants. Brain-to-brain BTC links can be useful in many scenarios, such as immersive gaming, creating unique user interaction scenarios, and education, by enhancing the possibilities with which cooperative problem-solving activities can be developed with groups of students (social brain networks). In this latter scenario, there is also substantial evidence that the synchronization of brain rhythms, both individually and in a group, is related to learning. Thus, brain-to-brain links could be used to bolster student engagement as part of effective teaching methods.

2) Challenges: Having laid out the key use cases for BTC, our next step is to identify the unique challenges of these use cases, compared with traditional HTC and MTC services. First, it is well known that the bottleneck of HTC services is downlink communication, whereas the bottleneck of MTC services is uplink communication. In contrast, in BTC, we can easily see that both uplink and downlink may constitute a bottleneck for data rates. On the one hand, to provide immersive experiences, significant data must be downloaded in the downlink toward the brain implants. On the other hand, in order to provide sensory and control inputs from the human brain to the network and its services, brain data must be transmitted from the implant to the network. At first glance, one would think that the uplink input will still be short packet, small data, as is the case for MTC. However, results in [62] show that the amount of data generated by a brain for wireless cognition services can be in the order of terabytes. Hence, uplink BTC will also require ultrahigh speeds from the wireless links, which is in sharp contrast with MTC services.

Second, despite its immense computational abilities, the human brain has its own perceptual and cognitive limitations. These cognitive limitations can be affected by multiple human brain sources such as context, attention, fatigue, or limited cognitive abilities. From a wireless perspective, these cognitive limitations can be translated into limitations on the way in which a human brain perceives network Quality-of-Service (QoS) metrics, such as rate or delay. For example, as shown in [63], because of its architecture and neural network dynamics, the brain may exhibit intrinsic time delays that affect the way in which it perceives the world around it. Therefore, a key challenge here is to develop new techniques from neurosciences in order to provide new models for the brain that can quantify these limitations and potentially be used in a wireless network framework to map those limitations into QoS or Quality-of-Experience (QoE) metrics. Note that this challenge differs here significantly from traditional QoE metrics, such as the mean opinion, in which one can simply use interviews or basic experiments to quantify QoE. Instead, here we need to quantify the QoPE introduced in [10], in which the specifics of a human's physiological characteristics, particularly the brain, must be captured and mapped into conventional wireless QoS metrics. Note, however, that the actual requirements for BTC will be defined by the specific applications, and thus, it is unfeasible at this point to quantitatively define their minimum quality levels.

Third, 5G systems are expected to deliver three broad types of services: Enhanced Mobile Broadband (eMBB) services, in which high data rates are expected, Ultra Reliable Low Latency Communication (URLLC) services, in which reliable low latency transmissions are required for services such as IoT sensing that do not require high rates, and Massive Machine-Type Communication (mMTC) that deals with the connectivity of a massive number of IoT devices. Traditionally, these service classes are expected to be distinct from one another. For example, URLLC services are assumed to not require any data rate guarantees because they deal with short-packet transmissions of IoT sensor data. Meanwhile, eMBB services simply require a high rate and do not need much reliability or low latency guarantees. In contrast to these traditional service classes, BTC services may require, simultaneously, high reliability, low latency, and high (eMBB-level) rates. For example, wireless cognition and remotely controlling an autonomous vehicle by the brain may call for very high reliability and very low latency because of the criticality of the circulating data. Meanwhile, this remote control may also require very high rates as discussed in [62]. Hence, when dealing with some BTC services, it is potentially necessary to provide both eMBB-level rates and URLLC reliability and latency, which is yet another key challenge. Moreover, as the technology becomes more mainstream, we can anticipate massive numbers of BTC links active at a given time, and hence, in this case, mMTC features will also appear, particularly for brain-to-brain links. Clearly, the evolution toward BTC may require us to revisit the existing 5G distinction among different services. Nevertheless, a detailed comparison between BTC and the 5G-defined regimes URLLC, mMTC, and eMBB is not yet possible because it will depend on the specific definition of the BTC applications.

Fourth, although brain-to-brain BTC links share many of the aforementioned challenges, they also bring a new dimension that has to do with the interactions among human brains, which have different physiologies and cognitive capabilities. Addressing this challenge requires a better understanding of networks of brains and how they may interact with one another. Naturally, brain-to-brain communications brings in a suite of interdisciplinary challenges that require a better understanding of not only the communication features of brain-to-brain, but also the potential interactions among the brains of different users whose context, demographics, and characteristics are disparate.

A qualitative comparison between HTC, MTC, and BTC is presented in Table I. The table provides a high-level comparison between these three communication paradigms. Although the numbers for HTC and MTC have been defined by the standardization bodies, it is unfeasible for us now to numerically determine the different applications of BTC together with their particular quality requirements. Our objective is rather to indicate that BTC will open a new paradigm for diverse applications that may potentially include services that are more demanding than those defined for 5G and being under discussion for 6G.

3) Research Problems: Clearly, the aforementioned challenges bring forward interesting research problems at the intersection of neurosciences and wireless networks. In general, providing wireless networking with "brain-in-the-loop" is a rich research area with many open problems that follow directly from the identified challenges.

One of the first open problems in this area pertains to the need for new techniques that combine neurosciences with wireless network modeling in order to precisely quantify QoPE measures. On the one hand, one can take a data-driven approach to this problem and look for new machine learning techniques that can dynamically build QoPE metrics by learning from the network users and their brain behavior. Naturally, the primary limitation of this approach is that it will require significant datasets and long-term observation. However, as datasets in both the neurosciences and wireless communities are becoming more accessible, we anticipate new opportunities for designing QoPEs. On the other hand, one can forego the data-driven approach or complement it with an analytically rigorous approach to model the brain's features. In particular, one can leverage existing tools from control theory and neurosciences to view the brain as a control system with a feedback loop and, then, use this observation to quantify how different inputs (from the wireless network) are translated into meaningful information for the brain. We can potentially study the transfer function of this brain control system and understand its behavior with respect to different input excitations coming from a wireless network. By using this approach, we can potentially investigate how QoS metrics are translated into QoPE. This can benefit from some of the existing studies on how to look at the brain's control signals (e.g., see review in [65]). Last, but not least, real-world experiments with actual participants can be organized to better understand how the brain perceives QoS. These behavioral experiments can be combined with behavioral frameworks, such as prospect theory and cognitive hierarchy theory [66]–[69], that explain how humans make decisions to yield new insights into how to model the response of a brain to wireless signal inputs for different services.

Moreover, as discussed above, there is a need to calculate the processing power of the brain, using techniques of neuroscience, so as to truly quantify the amount of data needed. Here, instead of looking at brain limitations, we are more interested in the brain *capabilities* and how these can impact wireless communication. While the calculation of [62] provides a first step in this direction, there is a need for more rigorous modeling that takes into account realistic brain models or real-world brain data.

Once QoPE metrics are developed and brain capabilities are quantified, a very natural next step is to investigate how network management, multiple access, and network optimization techniques will change when dealing with BTC links and QoPE. In particular, one can design new *brain-aware* resource management techniques that can tailor the network resources and operation to match the performance required of the brain while also being cognizant of the brain capabilities as well as its inherent limitations in processing information, in general, and processing wireless QoS metrics, in particular. One fundamental question that we can pose in this area pertains to whether or not brain constraints lead to a "waste" of wireless resources because of the delivery of a QoS metric that cannot be perceived by the brain. For example, it is natural to ask whether a human brain can see a difference between two different delay values, i.e., will 10 ms be perceived as a better QoS than 20 ms?

Moreover, the coexistence of BTC, HTC, and MTC links, which is expected in early-on deployments of beyond 5G cellular systems, will bring forth a rich set of resource management questions pertaining to how one can enable a seamless coexistence of these fundamentally different service classes, as presented in Table I. Here, beyond investigating radio resource management problems, we can also investigate new ways to incorporate brain features into network slicing problems. Indeed, network slicing must now handle a new type of service, and hence, a rich set of new open problems can be observed. Furthermore, because BTC links carry characteristics of all three traditional 5G services, i.e., eMBB, URLLC, and mMTC, it is necessary to investigate how one can guarantee a high rate, low latency, and high reliability simultaneously, in the presence of a potentially large number of BTC links. Here, one can start by first identifying the achievable performance of BTC links over 5G and beyond systems (e.g., over terahertz or millimeter wave systems). In particular, there is a need to analyze the rate–reliability–latency operation regime that can come out of the deployment of BTC links over a cellular system and then translate this analysis into a feasible QoPE regime of operation that maps the rate–reliability–latency requirements into QoPE measures. Once this feasible QoPE regime is identified, one can revisit traditional problems of multiple access in order to see how all three factors—reliability, latency, and rate—can be matched to the requirement of both the user's brain and the network service that is being adopted. Indeed, here one important direction is to study how different types of services (e.g., XR, BMI) will have different brain and QoPE requirements.

TABLE I
MTC VERSUS HTC VERSUS BTC FEATURES AND REQUIREMENTS IN THE CONTEXT OF MODERN WIRELESS NETWORKS

Requirements/features	HTC over cellular	MTC over cellular	BTC over cellular
Uplink	High signaling overhead to overcome features such as mobility (handover). Relaxed/mild throughput requirements.	Reduce signaling overhead (e.g., via fast uplink grant [64]) and specialized random access procedures to support high user density. Characterized to consider short package–small data.	Brain control BTC may require reliable and low-latency transmission with varying throughput (low to high). Some special cases have high throughput requirements with high signaling overhead to support mobility.
Downlink	High throughput requirement for individual users.	Most typical applications demand low throughput for individual users, which is mostly used for software update/upgrade of the embedded systems.	High throughput requirements with high signaling overhead to support mobility.
Subscriber load	Few users that are mostly supported by small cells.	High density of devices	High user density is expected with URLLC and high data rates simultaneously.
Device Types	Broadband devices, such as smartphones, tablets, personal computers.	Devices are mostly small (IoT) devices carrying sensors with specific power constraints.	Brain implants (invasive and noninvasive).
Delay requirements	Vary between best-effort services as e-mails, and high-definition games to support human sensitivity in terms of latency.	Many delay-tolerant applications and also low-latency ones, the last mostly employed in closed-loop control systems, protection systems, and other critical applications.	Strict delay requirements for both downlink and uplink.
Energy requirements	Relatively high energy consumption because it supports many applications that run on a smart phone. In most of the cases the battery is charged once per day on average.	MTC devices usually perform specific tasks that provide flexibility to set up the data transmission duty cycle. In many cases, the battery should be recharged/replaced in long periods of time, e.g., 5 years.	High energy efficiency is needed to support a high duty cycle demand, such as the case of brain-to-brain communication.
Signaling requirements	Accurate signaling protocols are required because of uncertainties related to mobility and data usability.	Reduced requirements in UL in order to support massive numbers of users.	High level of signaling for both uplink and downlink is required to support URLLC, high data rates, and massive numbers of users simultaneously.

In this context, 5G and modern wireless technologies are essential to support mobility requirements, not only in providing high rates of data traffic but also ensuring security and privacy. It is often accepted that 5G can reliably operate up to 500 km/h, and 6G twice that velocity [70], which would facilitate coverage in high-speed trains and airplanes. Further, it is anticipated that modern wireless technologies, such as 6G, will accommodate the current conflict between high date rates and high mobility with advanced handover policies and integration of heterogeneous networks [14].

Another important open problem is to quantify and measure information from brain implants. Here, information is no longer standard digital information, but instead a byproduct of a user's brain. Hence, using tools from fields such as information theory, we must study how "information" can be modeled when it is the output of a brain (e.g., using information-theoretic perspectives). Then, we can revisit the recently introduced concepts of Age of Information (AoI) [71]–[73] and Value of Information (VoI) and see how these metrics change when dealing with a brain network. For example, we can observe that the way in which information "ages" when it is transmitted among brains may no longer be linear, as is the case for traditional wireless information transmission. In this respect, aging of brain information transmitted over BTC or brain-to-brain links may require new approaches that depart from the classical linear aging process that is used in most of the AoI literature. Here, it is necessary to investigate how information propagates in a brain (e.g., using models such as those in [63]) to see how timing delays and the neural composition of the brain capture and process information. Similarly, new ways to quantify VoI when it is the output of a brain are needed. Once information is quantified and its different metrics are revisited, we can leverage this analysis for both physical layer designs as well as for routing and information flow problems, as discussed next.

At the physical layer, the deployment of BTC will require new designs. Here, we anticipate a need for merging tools from neurosciences, information theory, and communication theory. To this end, we must investigate how the brain information that is quantified using information theory techniques can be translated into digital waveforms. For example, here, by taking the control-theoretic approach for modeling the brain, we must investigate how the output of the control system model of the brain can be translated into a digital communication signal that can be transmitted over BTC links.

Finally, in terms of routing and information flow, it is necessary to develop new techniques to manage brain-to-brain and BTC links in a way to optimize AoI and VoI metrics when those metrics pertain to a brain. As already discussed, the models for these two metrics will be significantly different when dealing with human brains. As such, existing latency-optimal or rate-optimal routing and information flow algorithms will not necessarily be AoI-optimal or VoI-optimal. Hence, we envision many fundamental routing problems that can now see a wireless network as an overlay of two interrelated systems: a) a human-to-human network that receives and translates information through a brain and b) a D2D network that carries this information. Modeling the relationship between these two systems and integrating it into network routing and information flow optimization problems is clearly an important and meaningful open problem that brings together neurosciences, communication theory, and network science.

4) Sample Results: The area of wireless network design for incorporating BTCs is still in its infancy, and hence, not many works have looked at related problems. However, in [74], we have made the first step in this direction by analyzing how to use a data-driven approach that uses user brain information to create QoPE measures that map wireless delays into perceptions of the brain and, then, those perceptions are integrated into a resource allocation problem. In this early work [74], to model QoPE, we explored the observation in [63] that the brain can have multiple "modes" depending on the age, sex, demographic, time of day, and other social features, to learn how the brain perceives delay in a wireless network. The QoPE therein pertains to how one can translate a brain mode (extracted from the data) into a perception of QoS metrics, such as delay. Our work in [74] showed that, for a wireless network, the aforementioned brain mode limitations make the wireless user unable to distinguish the QoS differences between different wireless delays. In other words, the QoPE of a user maps each delay value to a different brain perception. Building on this observation, our results in [74] show that because of the cognitive limitations of the brain, delivering ultralow latency for services such as XR may not improve the user experience, because at a very low latency regime, the user's brain can no longer distinguish the difference between different delays. For instance, our results show that it is less probable that a user distinguishes between a 20 ms and a 10 ms delay compared with 30 milliseconds and 20 ms. As such, when designing BTC links, one key challenge is to properly model and capture the

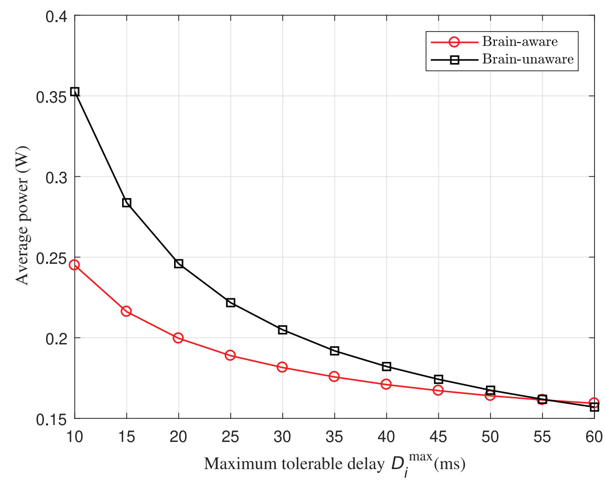

Fig. 4. Early result from [74] showing how a brain-aware resource management approach can save significant resources (in terms of power), particularly in the low latency regime, by being aware of the cognitive limitations of a brain that limit its perception of delay. Human cognition is physiologically limited in terms of sensory perception and motor control, and thus, there is a delay threshold in the sensorimotor loop below which the human brain cannot perceive any improvement in QoS. The x-axis represents here the "raw" maximum tolerable delay threshold of each user.

limitations of the brain and factor in those limitations into the wireless network design.

In addition, in [74], we then incorporated the learned brain limitations into a downlink power control problem with brain perception constraints. We did so in order to test the hypothesis that the brain-aware resource allocation approach can significantly save network resources. Here, we have particularly shown that, by explicitly accounting for the cognitive limitations of a human user's brain, i.e., the minimum delay below which users may not be able to perceive because of sensorimotor physiological limitations, the network can better distribute resources to BTC users that need it when they can actually use it. To illustrate this, let us consider an interactive and immersive gaming scenario. No human is able to perceive image flickering with frame rates above 48 Hz [75], whereas motor control is in the range of a few hundred milliseconds [76]. Thus, there are minimum visual frame rates and body tracking sampling rates above which the human brain cannot perceive any improvement in QoS. This is in stark contrast to conventional brain-agnostic network resource allocation techniques in which resources may be wasted, as they are allocated only based on application QoS without being aware of whether the human user's brain can realistically process the raw QoS target of the actual service. For instance, in Fig. 4, extracted from our work in [74], we compare the performance, in terms of power allocated to optimize the wireless system while meeting the delay threshold and reliability constraints, between a brain-aware resource allocation approach and a brain-unaware resource allocation approach. Strikingly, this figure shows that at very low latencies (below 40 ms), a brain-aware approach can save significant resources by being aware of the fact that the brain of a user (depending on the mode of the user) may not distinguish a QoS difference between different values of latency. Clearly, these promising results can be used as a building block for new research in this area that can potentially address the rich set of open problems previously identified.

B. Brain Barriers for Wireless Channels

The physical medium also poses challenges to any wireless system that would support BTC. Remarkably, the transcranial wireless channel presents many challenges to the many wireless technology options because of its structure and function. The brain is covered by the skull and surrounding head tissue that absorb or scatter high-frequency signals.

Lower-frequency signals are known to require the implantation of large devices and may increase head heat. Novel wireless solutions must cope smartly with those unwanted effects, but we must take into account that single neurons are known to have high data rate demands for sensing purposes. We now explore the listed brain barriers in [28] focusing our discussion on the wireless technologies and on the communication channel between implants and external devices.

1) Spatial-Temporal Resolution: The number of neurons and other brain cell types goes beyond the billion unit mark and is considered the major challenge in measuring the whole brain information with the existing technology and infrastructure. Naive estimates of the lower bound data rate of the whole brain recording is about 100 Gbits/s, which is already a challenge for today's wireless technologies, let alone for future BMIs. The forthcoming technologies must include compression techniques that minimize the transmission burden of single action potentials. The compression technique will have an interesting interplay with the sampling rate of signal recording and the wireless technologies and their equivalent data rates.

2) Energy Dissipation: The propagation of transcranial wireless signals that are transduced by implantable devices will result in energy dissipated through the tissue. This energy will be converted into heat, which is also dissipated. Owing to the tightly packed structure of the brain, damage can occur as a result of a minimum temperature increase of above two degrees Celsius. Wireless signals, however, can be easily modulated in order to operate below the 100% duty cycle of the system operation, which can help prevent damage caused by energy dissipation. The brain also has natural cooling mechanisms that can help restore normal brain temperature. However, the real challenge lies in the large-scale deployment of heavy and dense recording and stimulation techniques for high spatial resolution.

3) Volume Displacement: Insertion of devices into the brain can cause an increase in its volume, leading to damage to its functioning tissue. Wireless technologies can help keep these implantables small by using high-frequency transmission that enables the decrease of the dimensions of the antenna elements. If low-frequency transmission is required, the devices will become larger with larger antenna elements making them unfeasible to implant into the brain tissue. Therefore these larger devices will possibly reside above the cortex, i.e., in the sub-dural brain space. Furthermore, glial scarring (formation of glial tissue around the implant preventing its interface with neurons) may inhibit the implantable from functioning properly. Wireless interfaces can help long-term implants by packaging devices within biocompatible material that prevents foreign body reaction. Future techniques, such as Multiple Input Multiple Output (MIMO) wireless systems for implants, might help the use of low-frequency solutions for deep brain interfacing that is essential for integrating existing wireless system platforms into future wireless brain interfaces.

C. Brain Implants Assisted by Intelligent Reflecting Surfaces

Despite the increased risk of injuries and other related issues, invasive wireless brain implants exhibit numerous benefits in comparison with conventional over-the-scalp solutions. It has been shown that these prosthetic devices are capable of sensing brain activity more accurately, interacting directly with the brain and providing a higher Signal-to-Noise Ratio (SNR) [77]. These capabilities make them powerful tools for enabling BMI in future generations of wireless communications (e.g., 6G and beyond). However, before this technology becomes available to the global population, many limiting issues need first to be addressed. One important limitation of wireless brain implants is related to the strong signal attenuation caused by tissue blockage and absorption. The high quantity of water molecules in the human body can interact with the electromagnetic waves, absorb a significant part of transmitted power, and distort the radiation pattern [78]. Such a characteristic can deteriorate the communication link and impact reliability. One could, to some extent, alleviate this issue by allocating a higher transmit power; however, this parameter cannot be increased indiscriminately. Firstly, there are strong power restrictions due to human health, and because radio frequency energy heats up brain tissue, there is a safety-specific absorption rate limit of 0.4 W/kg averaged over the whole body and a maximum output power density of 10 mW/cm^2 for electromagnetic waves passing through tissue [79], [80]. For illustration purposes, the total transmission power of a wireless neural recording system reported by Schwerdt *et al.* [81] was 47 mW, whereas a device based on ultrasound communication achieved 0.12 mW [44]. Secondly, in general, the implanted devices have limited access to energy resources. Therefore, new energy-efficient strategies for improving wireless transmission performance in brain applications are required.

In particular, Intelligent Reflecting Surfaces (IRSs) have recently arisen as appealing devices for smart control of the electromagnetic propagation environment. An IRS consists of a two-dimensional structure that comprises a large number of nearly passive subwavelength metamaterial elements with tunable electromagnetic properties. These elements can be dynamically configured to collectively change the behavior of impinging wavefronts so that capabilities like steering, polarization, filtering, and collimation can be achieved [82]. Such features make the IRS technology attractive for improving the performance of wireless communication in brain implants.

Conceptually, if the prosthetic implanted device is assisted by an IRS, it could send and receive information more reliably without increasing its power consumption. This improved brain communication system could be implemented, for example, by implanting IRSs between the skull bone and the scalp for assisting sensors and actuators implanted deeper in the brain. In this architecture, the deeper implants would exchange information directly with the brain, while the IRSs would assist the wireless communication established with external devices. An IRS-assisted BMI can become able to provide the following capabilities.

- *Improved Reliability in wireless data transfer:* by proper tuning of the IRS elements, the signal transmitted from the brain implants can be boosted so that a higher SNR can be achieved at an external receiver, thereby improving the communication reliability.
- *Reduced power consumption in the brain implants:* because the SNR can be improved with the help of IRSs, one can decrease the transmit power at the brain implant and still achieve a satisfactory communication performance. This would reduce energy supply requirements and prolong the battery life of the implanted devices.
- *Improved communication security:* because implants can sense and stimulate the brain, security issues become a critical concern in BMI. An IRS can also be beneficial in this context: it can null out information leakage at a potential eavesdropper, or it can operate in the shield mode to avoid brain hacking; that is, by properly optimizing the IRS elements so that transmissions to the brain implants from a hacker can be completely absorbed/blocked.

All in all, the development of IRS technologies in the years to come combined with brain implants would support the development of BTC applications in the next generations of wireless systems.

D. Lessons Learned

Throughout this section, we have provided what we foresee as a new paradigm for a future wireless communications system: the brain-type communication (or simply BTC). The main differences from existing human- and machine-type communications are schematically presented in Table I. We have also put forth an argument that BTC has the potential to emerge as one of the main application domains of the forthcoming 6G. We have also described the challenges that the "brain environment" poses to the deployment of wireless channels. Overall, in developing BTC systems, we should be aware of the fact that there are strict delay and high data rate requirements for both downlink and uplink connections, with a high duty cycle, which calls for high energy efficiency. These are essential to ensure QoPE in wireless networks with "brain-in-the-loop". Moreover, brain implants must address biocompatibility issues, high channel density and data transfer, and communication security. In this context, we describe intelligent reflecting surfaces as a promising approach. In the next section, we will move toward our second path by describing the contributions that wireless communications can bring to neurosciences.

IV. Wireless Networks for Neurosciences

Up to now, we have discussed different ways in which neurosciences would become part of the future wireless communication systems through BTC, possibly already with the upcoming 6G. In this section, we will describe how wireless communication theory and specific communication systems (in particular, beyond 5G systems) can support future research and technological development in neurosciences considering the development of BTC as described in the previous section.

A. BTC Performance for Neurosciences

While the plurality of applications are waiting for the real development of wireless BMIs, we must conduct an initial assessment of the existing metrics, or new metrics, that allow understanding of what is required in the definition of wireless communication systems for Brains-to-Wireless infrastructure connections. This initial analysis is made based on the recent breakthroughs in the 5G and Beyond 5G research, which is the cornerstone of 6G (supporting our argument that BTC applications could be included in its standardization process), as well as recent engineering advancements in neural interfaces, which are the central elements of BMIs. In this section, we will indicate the requirements that 6G, or any future wireless system to support BTC, needs to meet to allow for new neurosciences-based applications. The key vision is to achieve fine granularity of brain functions from both sensing and actuation capabilities by integration with a specific wireless communication technology. Then, the performance expected of 6G or any other technology is drawn upon the ability of delivering enough performance that maintains the functioning of future BMIs for a long time with security and safety for users.

1) Data Rate: A naive estimation of the total brain recording demand is about 100 Gbits/s, which is not supported by existing and near-deployment 5G infrastructures. However, in the context of individual connections, this is a considerable demand for future technologies, which are currently not being considered because of the lack of popularity of BMIs. This estimation was also naively performed because it does not consider the current and future technology for BMI, which surely can increase this number as more and more techniques are capable of obtaining not only electrophysiological neuron signals but also signals from other cell types in the brain, and lastly, other types of information, such as biomarkers. On top of that, this naive estimation is also based on the standard sampling rate of neural signal acquisition (1 kHz), which varies between technologies and recording strategies. The needs for an increased data rate must deal with all the aforementioned information, even though it requires more investigation into the real data rate requirements of BMI. By looking at increased requirements for spectrum resources, one must keep in mind that BMI is one of the multiple applications that future wireless systems will likely accommodate. Together with multimedia, gaming, e-health applications, and more, BMI can increase the burden on future network generations for more data rate requirements than previously expected.

2) Reliability: BMIs as a technology can open a wide variety of applications sensitive to network disruption. For example, remote treatment of epileptic patients will require a constant usage of the BMI for detecting random seizure events as well as treating the disease by using current stimulation techniques also driven by the BMI solution. In this case, the implications of network disruption are above from conventional application delays or stream interruptions that are commonly found in conventional networks. In this context, the disease control mechanisms that are based on a BMI solution could be disrupted in a way that either can start unpleasant symptoms in patients or not support advance signal processing techniques for temporal variant data that support diagnosis systems. Based on the assumption of BMIs actively being used in small cells, this means not only that high frequencies must be managed to provide reliable connections that are not interfered by obstacles and environmental molecular effects, such as water vapor. These phenomena are known as the major challenges in small cells for present beyond-5G technologies, where intelligent reflecting surfaces are being currently the best choice to provide highly reliable connections. However, this technology is far away from being mature to guarantee high levels of network reliability based on the primary focus on physical mechanisms of beam-steering of high frequencies as opposed to the study of network resilience, which must be the next step of the research in this topic. The importance of network reliability brings the focus again to solutions that maintain a constant data rate in certain applications, where conventional network solutions must be upgraded in future technologies, likely already in 6G.

3) Energy Management: Wireless BMIs based on brain implants will most likely operate on different wireless media than the wireless infrastructure. For example, while RF is an option for wireless BMIs, high frequencies are unlikely to be used because of signal absorption and scattering resulting from the high water molecule profile of the tissue and skull. However, the two better fitting options are magnetic induction and the ultrasound system. Their differences are highlighted by their performance profile; magnetic induction is better for the implant data rate, whereas the ultrasound system enables deepness of implantation. The major challenge is that future technologies including 6G will most likely operate around the sub-Terahertz bands, which means that constant frequency conversion is required in order to provide integration of wireless BMIs into the wireless infrastructure. Because frequency homogenization is not an option, it can be easily foreseen that BMIs must have short-term memory strategies that support the frequency translations without loss of data. The issue here is then that both the frequency conversion techniques and memory are energy expensive, which adds the concerns for the constant usage of BMIs for chronic patients, or other applications, such as streaming or gaming. Energy management solutions must emerge not only at the device level, but also at the network level, which can work together by using advanced protocols or virtual infrastructures that enable efficient and data lossless connections with BMIs.

4) Latency: Today's communication infrastructure is guided by techniques that provide massive ultrareliable and low-latency communication. This shall not change for communication with BMIs. The importance of these strategies is directly linked with the future of BMIs and their success, because the main goal is to allow constant daily usage for patients and other users. The radical societal change based on BMI will only happen when we are capable of using this technology integrated into our daily activities, either to support or enhance them. 6G and future technologies involve the idea of massive sensing, which fits into the future BMI technology that envisions hundreds or thousands of nano-scale devices that interface with neuronal cells. The information on that scale, i.e., the LFP, enables rich cellular information that is now used to make precise predictions of disease states and trigger events. In addition to that, the idea of massive stimulation can also be implemented, where these several devices will act on the neural tissue to stimulate whole cell populations or parts of them. Here, latency is crucial in order to operate these functions remotely while maintaining the safety and security of each user. At the same time, BMI has to be perfectly modeled and tackled in a way that allows scalability. Scalable BMIs are practically nonexistent, and 6G might as well be the technology needed to open these doors.

B. *Wireless-Based Brain–Machine Interfaces*

A more direct application of the future generation of wireless technology that neurosciences would benefit from would be a new generation of BMIs. BMIs have been used to alleviate motor deficits but also as a tool to characterize neural correlates of behavior [46]. Here, tethered neural recording systems are a major limitation because they hinder natural and social behavioral interactions. Most notably, in the late 2000s, novel wireless recording technologies have become available, which can simultaneously sample several hundreds of neurons from different brain regions (see [50] for a review of recording technologies).

Schwarz *et al.* [83] developed a bidirectional wireless system capable of implementing part of the signal processing pipeline at the headstage and transceivers attached to an animal's head. Four transceivers were used; each transceiver was connected to 128 recording channels sampled at 31.25 kHz per channel, consuming 2 mW per channel, with a total of 48 Mbps aggregate rate of data acquisition, and an optimal operating range of 3 m. The device was reported to be able to continuously operate for over 30 h. With the device implanted in a monkey, authors were able to record 494 neurons from four different brain regions. The animal successfully performed established BMI tasks wirelessly [84], which confirmed the suitability for studying natural, social interactions and complex movement behaviors.

More recently, the first wireless invasive BMI has been demonstrated in humans [85]. The interface had 192 electrodes, with 20 kSamples/s per electrode (12 bits per sample). Prior to wireless transmission, Manchester encoding was used to reduce error and improve reliability. Each data frame contained one 50 μs 12-bit sample from all electrodes and was transmitted at 3.3 GHz or 3.5 GHz. Recordings were carried out uninterruptedly for a 24 h period, and subjects successfully performed a computer cursor BMI task.

One major problem is common to invasive recording systems: implants inevitably cause lesions in the brain tissue, resulting in inflammation and limiting the sampling of deeper brain regions. To alleviate this problem, wireless sub-millimeter scale devices are being developed that can both record and stimulate neural activity. Ghanbari *et al.* [86] describe an ultrasonically powered neural recording implant, with simultaneous power-up and communication, that can achieve an over 35 kbps/mote equivalent uplink data rate. Thus, in principle, this device could operate as part of a wireless BMI.

In terms of noninvasive wireless BMIs, EEG is arguably the most common recording strategy. By avoiding surgical procedures, EEG has been widely used in human BMIs. However, EEG signals reflect the activity of millions of neurons from the surface of the brain, thus hindering decoding performance, which leads to a limited set of motor commands that can be extracted in noninvasive BMIs. Common commercial wireless devices range from 8 to 64 channels, with sampling frequencies of up to 1 kHz and a few dozen meters of transmission [87]. Nevertheless, modern hardware and computational intelligence methods, such as flexible electronics and deep learning, have been shown to boost wireless EEG-based BMI performance, reaching up to 122 bits per minute of information transfer rate [88].

C. Internet of Bio-Nano Things

Another key promising application is the IoBNT [89]. The IoBNT can aid the diversity of BMIs and their types by interacting with the brain using molecules, peptides, and molecular structures in general [90]. As it stands, no molecules are used to convey synthetic information of any type, which means that a whole biodiversity of information is being underutilized as opposed to enhanced means of communication between implantable devices and brain tissue. The research area of molecular communications promotes the usage of molecules as carriers for interactions between implantable–implantable and between implantable–biological systems [91]. Increased biocompatibility is thus reached when understanding and using molecules that are currently being used in biological systems, now with the purpose of controllable biological communication [92]. This infrastructure is envisioned to bridge to the Internet by means of synthetic biology and advanced nanotechnology, where electromagnetic-molecular signal translation is performed toward remote digital control of the internal cellular process of either Eukaryotic and prokaryotic cells.

The diversity of molecules inside a human body is assumed to be huge, and therefore, a means of translating molecular information between tissues is considered to be of great importance even with the limited investigation by the scientific community so far. The idea for the future technology is that there are internal synthetic cells capable of converging molecular information from different types of tissues and vice versa in order to support the idea of biomolecular intrabody networks [93]. Therefore, implantables or even bionanomachines located in different tissues can communicate with each other without the need of predetermined molecular coherence, which can empower flexibility and performance of these systems. At the edge of these networks, the molecular information is translated into electromagnetic information by biocyber interfaces that are also capable of translating the opposite case [94].

Inside the brain, implantables of bionanomachine devices have the main purpose of influencing the brain activity by manipulating the ionic channels that are understood to be a major part of the information propagation in the brain. There are a variety of molecules on the micro scales of the brain, including calcium, potassium, and sodium. Neurotransmitters and gliotransmitters are ions that regulate the information propagation inside the synaptic channel between neurons. These molecules have been studied and analyzed for many decades and are controlled to treat many neurodegenerative diseases. Brain–machine interfaces for molecular interactions have a huge impact in the future of the neurodegenerative diseases. The levels of control that can be reached by digital systems can be tremendously beneficial to chaotic systems, such as biological systems in the brain [95]. The main challenge is that the major biological properties of the brain have been well understood before considering them as control variables; the understanding of these properties is a time-consuming effort that has to focus on neuroscientific efforts undertaken through many decades.

However, there are works that demonstrate the idea of IoBNT prevailing through existing disease challenges together with biotechnology as well as future oncology efforts. The EU-H2020-FET Gladiator project deploys a hybrid neural interface that is implanted into the brains of patients with glioblastoma, with the main goals of utilizing the modulation of drug propagation in the brain that maximizes drug efficacy while minimizing its side effects [96]. For that, wireless external signals control these hybrid neural interfaces to produce molecules that contain multiple drug molecules inside them, called exosomes. These exosomes are drug carriers that ultimately dictate how and when the tumors in the brain are being treated by this novel cancel therapy. The novel paradigm of molecular communication is used to characterize the data rate and capacity of exososome-based communication systems between the hybrid interface and the brain cancer. Here, the channel is understood to be the extracellular brain space in which the exosomes can propagate through a biased random motion. The many brain cells create tight spaces in which the exosomes propagate and where there is enough brain fluid to drive movement, called brain parechyma. The research is now focusing on the development of both theoretical and in-vitro models that demonstrate the above-mentioned system, which can radically change the existing state-of-the-art of cancer treatment methods.

D. Complex and Chaotic Communications to Quantify Neural Activity

Tools of communications and information theory can also provide interesting analytical approaches to assess the behavior and fundamental limits of neural communications, which, by nature, exhibit chaotic properties. Neurons, themselves, have a complex morphology that allows the connection to many other neurons. They have several morphological types, but also varied electrical activity profiles. A single neuron can be connected to thousands of other neurons and non-neuron cells through millions of synapses. Once these neurons comprise a large complex network of cells, its nonlinear effects result in complex or chaotic dynamics. The individual elements of the network contribute cumulatively to these high-order dynamics with their simple, yet diverse actions, which can be deterministic or stochastic themselves. Analyzing neural networks with modeling approaches based on complexity and/or chaos can provide rich dynamics that are governed by deterministic processes (i.e., action potentials) in order to obtain nontrivial patterns and behavior. This is essential to not only understand and characterize neural networks but at the same time provide communication systems that can interact with them.

The analysis of neural signals using chaos-based principles started with EEG signals [97]. It is now accepted, from measures of entropy, that the brain indeed presents itself, at least in certain modes of operation, as a chaotic-behaving system. For example, studies of diseases have been further analyzed using chaos-based principles, like schizophrenia, which is suggested to be a decay of complexity, either on the side of randomness (infinite entropy) or order (zero entropy) [98]. Another example is the effect of drugs, like LSD, that are connected to periodic neural oscillations, thus losing chaoticity and decreasing complexity [99].

Even though the effort to discover organization in nature had its origins in randomness, it was realized that measures of randomness do not capture the property of organization [100]. This is a very important issue in neurosciences, as the knowledge of organization and activity needs to be bridged in order to provide reliable communications with the brain [101], [102]. In signal processing, one can find measures that capture a system's complexity—organization, structure, memory, symmetry, and pattern. Complexity measures would allow us to quantify the hidden micro-level relationships between system parts that result in the system properties obtainable at the macro level, which would, for example, quantify the relationship between cellular to network levels [103]. The authors of [104], [105] argue that a complex system lives in between a random and a completely regular system, leading to the conclusion that a lot of the complexity metrics (e.g., Kolmogorov complexity in algorithmic information theory, dimensional complexity in neurobiology) do not measure "true complexity" because they do not attain small values for both random and regular systems. Random systems have no structure at any level, which results in high entropy and low complexity. On the other hand, regular systems exhibit low entropy and low complexity because of the repetition of structures at multiple levels. Therefore, it is obvious that complexity and entropy are two distinct quantities. As highlighted in [106], entropy captures the disorder and inhomogeneity rather than the correlation and structure of a system. Therefore, the measure of randomness, which has previously been applied to neurosciences to quantify neural activity, might be re-evaluated in terms of capturing the true complexity of neuron activity inside the brain. It may also be used on multiple scales—for example, by linking spiking activity in subcortical regions to the whole brain. Even though we believe that we can recognize complexity when we see it, complexity is an attribute that is often without any conceptual clarity or quantification per se; however, because of the many unknowns in neurosciences, it should be further explored. For this purpose, the brain can also be studied as a complex communication network associated with structure and function, and evaluated with information-theory-inspired metrics and distributed communication system performance indicators. This knowledge translation from complex networks to a brain network can shed light on organization and structures of the brain that are currently unknown.

E. Lessons Learned

In this section, we indicated how the future generation of wireless systems, potentially 6G, would benefit the neurosciences community. We have shown the main requirements that, from our view, future technology would need to meet to incorporate BTC-based applications, BMI in particular. We highlight that high data rates, reliability, latency, and energy management should be the focus of research in wireless-based BMIs. In this context, considering the particularities of neuronal activity, we brought the discussion to a highly promising research path: IoBNT, which incorporates molecular-level communications into the more widely discussed electrical communications. Finally, we have explored complexity sciences and chaos theory as theoretical tools that could be helpful to measure and analyze brain activity, and help the design of more effective dedicated communication systems.

V. Case Study: Brain-Controlled Vehicles

In this section, we present the state-of-the-art of one particular application called brain-controlled vehicles (BCVs) and how we foresee its development based on 6G (or other future wireless technology). BCVs are an interesting, nonmedical application that involves both neurosciences for wireless networks and wireless networks for neurosciences. The automotive industry is one of the world's largest industries, highly competitive and exposed to novel technologies, and therefore, BCVs could be a disruptive factor in promoting the development of BTC technology. Clearly, advanced BCVs cannot rely on noninvasive technology, but rather on the novel neuroscientific and wireless technologies that we have discussed thus far. Therefore, the goal of the case study is to show one promising application in a highly relevant industry and emphasize how modern BMIs (based on invasive signals) and modern wireless communications could expand it.

A. State-of-the-Art

The field of BCVs with EEG-based BMI has experienced a steady growth since 2010, usually focusing on applications to support disabled patients. In addition to the already discussed challenges of BMI in relation to developing effective algorithms for feature extraction and classification, current

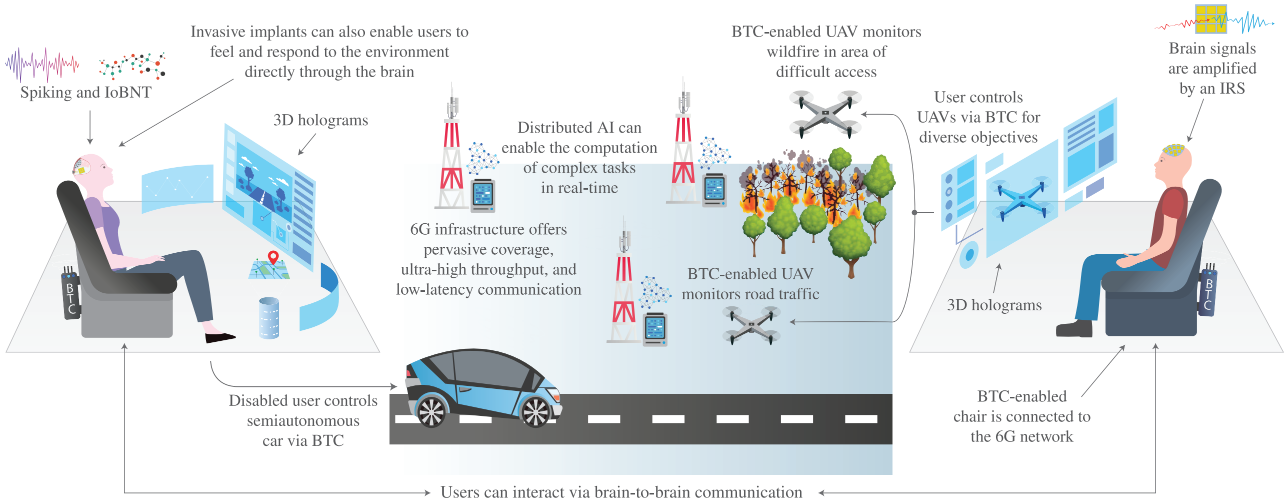

Fig. 5. Future direction of a BCV application, depicting a rescue mission. Users are seated in BTC-enabled chairs with sensors, wearables, and XR devices connected to the 6G network, and have seamless access to all relevant information for the mission. Neural spikes and molecular signals are registered and integrated into the IoBNT, supported by the wireless network infrastructure. Simultaneously, users also receive sensory feedback directly by the same invasive implants. Distributed AI algorithms ensure low-latency communication between users and vehicles as well as between brains. Ambient information, together with users' action intentions and emotional state, creates a broad structure of awareness which, altogether, contributes to a successful operation.

BMI hardware has well-known limitations concerning the communication range and speed.

Despite these challenges, several studies have demonstrated the feasibility of BCVs. We can mention, for instance, control of a vehicle in four main directions [107], [108], methods for obstacle avoidance [109], [110], and hand brake assistance in emergency situations [111], [112], using diverse platforms such as vehicle simulators, virtual reality vehicles, vehicles in video games, quadcopters, drones, helicopters, and fixed-wings aircrafts. A general simulator-based procedure for training a participant is shown in Fig. 5.

In a seminal work, Haufe *et al.* [113] implemented an assistant brake system in emergency cases for BCV applications based on EEG and electromyography (EMG) signals, which was tested on a simulated vehicle. The algorithm identifies brain activity patterns related to emergency braking intentions in a simulated graphical racing car task. In a similar vein, Kim *et al.* [114] attempted to detect the driver's emergency braking intention in different situations for a simulated vehicle based on EEG and EMG signals. This method was further improved in [115], including a real-world experimental task. In Göhring *et al.* [116], a semi-autonomous vehicle was implemented with different external sensors and a camera, and then controlled using EEG-based brain activity patterns. To control the vehicle, two different scenarios, obstacle avoidance and braking and steering, were used.

In a series of studies by Bi *et al.* [111], [117]–[121], different approaches to identify and predict the driver's intention for moving forward, turning left and right, as well as emergency braking, were studied. The development of AI-based learning methods is leading to improvements in those tasks, as reported in [108], [122]–[128]. Similar research has also been carried out to study BCVs for aerial vehicles, as in [129]–[131]. A major challenge lies in separating those features of brain signals that relate to vehicle control from those that are not. The second task to enhance the results is to develop or modify the existing classifiers into a highly accurate multiclassifier, such as a deep belief learning algorithm. The third limitation is the limited number of participants for training and testing of the algorithms.

Arguably, the major limitation on BCVs is the availability of more informative neural signals than those that EEG or EMG can provide. The use of noninvasive brain signals has led to significant contributions, in particular, better braking systems, but a comprehensive control of a vehicle requires fine-tuned actions. State-of-the-art EEG-based BMIs boosted by deep-learning methods have proven to be feasible for multidirectional 3D robotic arm control, with success rates of about 60% [132]. Even the more invasive methods, such as ECoG, hardly surpass the 80% success rate in 2D cursor control tasks [133]. Although these are impressive results with a wide range of practical applications, BCVs require stable, high success rates. Furthermore, noninvasive methods have access to cortical information, the outermost layer of the brain, whereas other deeper brain regions, like the cerebellum or basal ganglia, may convey information that is fundamental for a successful vehicle operation.

For a comparison, Gopal *et al.* [134] report a tethered 96-electrode BMI with a performance of 6.5 bps, which would correspond to typing 15 words/min with a basic alphanumeric keyboard, whereas a standard EEG-based BMI has a performance of $\sim$1.0 bps, or 3 words/min [135]. Considering the BMI performance scales with the number of neurons recorded, modern prototype interfaces with thousands of electrodes, such as the one developed by Neuralink [8], indicate a promising future for BCV.

As we discussed in Section III, the progress in direct brain implants that communicate wirelessly, supported by 6G or other technologies, will enhance the repertoire of brain commands to the vehicle and also facilitate bidirectional communication, in which signals from the vehicle and its surroundings may be delivered directly to the driver's brain. In addition, future wireless networks would need to accommodate BTC protocols and AI algorithms that can integrate all of the required processing stages for a robust, pleasant, and secure driving experience.

B. Future Direction: Neurosciences–Wireless Networks Converged Applications

Although successfully tested under different conditions, BCVs as designed today are not a scalable solution as they would require a wireless connection to support BTC with high coverage, availability, speed, and low latency to provide reliability and safety for the end-users. As discussed above, despite the great development of wireless communications (remarkably 5G), the existing solutions would not work today because of the stringent requirements of BTC (see Section III). However, if the path indicated in this paper was realized, a scalable BCVs would become feasible by using a new generation of wireless-connected BMI with 6G-connected high-density implants supported by IRSs to enable BTC. This would also be associated with the possibility of acquiring and processing more biosignals via IoTBNT, linked with Intelligent Sensor Networks (ISNs) that could sample the environment in which the BCV is moving. Furthermore, AI-enabled distributed cloud algorithms could support sophisticated signal processing in the fraction of the second scale required by a safe driving experience. The performance limits of such communicative brain devices could be derived from information- and communication-theoretical tools applied for chaotic and spiking systems, while new chaos-based waveforms for communication might also be developed.

As a rough example, we could imagine the following future scenario in 10–15 years from now. A major fire outbreak triggers an emergency response central, and multiple BCV, both aerial and terrestrial, are sent to the dangerous site. Modern wireless networks, with distributed AI algorithms, support pervasive coverage, ultrahigh throughput, and low-latency communication. Remote operators are seated in BTC-enabled chairs with sensors, wearables, and XR devices connected to the 6G network, and have seamless access to all relevant information for the mission. The users can communicate directly via brain-to-brain communication. Invasive implants, together with the IRS and IoBNT infrastructure, establish a bidirectional link with the users' brains to operate the semiautonomous vehicles. Ambient information, users' action intentions, and emotional state create a broad structure of awareness, which, altogether, contributes to a successful operation.

Clearly, this scenario could be extended and rethought, but it illustrates a potential future that we believe is technologically feasible given the state-of-the-art in wireless communications and neurosciences, as well as in biosignal processing and computer sciences. The main lesson to be learned is that the convergence of those fields is more likely to happen if stimulated by the definition of the future generation of wireless systems. In particular, having BTC as part of 6G research agenda would provide clear guidance of how those kinds of potential futures could become a reality for many applications related to future 6G-connected BMIs, as the BCV example indicated.

VI. Security, Privacy, and Ethical Aspects

Current BMIs are applied mostly in the medical and therapeutic context, in which rigid protocols regarding experimental design and the usage of data are enforced. A substantial body of literature has proven that it is possible to decode and manipulate brain activity, thus granting access to one's feelings, emotions, and intentions in an unprecedented way. Clearly, one of the main challenges for the development of BTC systems relate to security, privacy, and ethical aspects in BMIs [136]–[138].

First and foremost, despite the astonishing progress in recording technology, it is still unclear if a long-term neural implant can be placed without damaging neural tissue (see Section II-C). This is definitely one of the crucial steps toward BTCs, because invasive recordings offer access to biosignals unavailable to noninvasive methods. Thus, the futures of BTC and neural recording technology are intertwined. Novel works offer promising initiatives, from nanorobotics to molecular communication [93].

Then, the capacity to read from and write to an individual's brain opens access points to memories and may even be used to change one's behavior. Even if implants and communication networks are safe, BTCs mean that artificial devices will constantly interact with individuals, possibly shaping their agency and affecting social behavior. Moreover, human reason becomes distributed and the sense of responsibility is dramatically impaired: if a harmful action results from the operation of a BMI, who should be accounted for the damage? The ethical controversy underlying self-driving vehicles gives a indication that ethics may play as important a role for technological development as technical challenges [137].

To ensure that novel technologies that exploit BMIs abide by international standards and human rights, some of the most representative researchers in the field have claimed for guidelines to be established [139]–[141]. Overall, four main concerns are highlighted: privacy and consent; agency and identity; augmentation; and bias. In this context, neural information and neural applications should be strictly regulated, decentralized, and subject to transparent social scrutiny and user consent, especially if military purposes are considered.

From a different but related perspective, established communication networks approaches have addressed security, privacy, and ethical aspects of their usage, regardless of the underlying technologies. The advent of BTCs and novel BMIs complicate this nontrivial debate, considering that novel applications emerge in parallel with the standardization protocols. More recently, even though 5G networks are yet to be fully deployed, there has been an intense security and privacy concern [142], [143]. In comparison with 5G, 6G, or other potential future wireless networks will boost real-time responsive systems, capable of AI-based autonomous decisions, interfacing brains and machines. This draws attention to specific vulnerabilities related to authentication, access control, malicious behavior, encryption, and data transmission, which are closely linked to the novel technologies that support future technologies [144].

In addition, the advent of two-way BTC systems is accompanied by novel vulnerabilities, such as neuronal cyberattacks to brains [145], which are still largely ignored in the BMI literature. Until now, the possibility of influence on human behavior by directly modulating the brain has always been limited to clinical environments, but here we envision that future BMIs and BTC systems must take into account the hypothesis of undesired signals, not necessarily malicious, that affect brain implants.

Several solutions have been proposed [146]–[149]. A central aspect is to restrict the centralized processing of neural information and ensure privacy. For that, blockchain-like mechanisms, differential privacy, and federated learning offer promising alternatives. Concurrently, international governments and regulatory bodies should agree on guidelines for the usage of neurotechnology, similar to what has been done for nuclear energy or gene editing applications.

VII. Concluding Remarks and Lessons Learned

This tutorial paper provided an in-depth overview of an interdisciplinary research field at the intersection of neurosciences and wireless communications, as well as signal processing, control theory, and computer sciences. We argue here that an organic encounter between these two research areas has the full potential to take place in future developments of wireless networks, in particular 6G, which will support BTC considering not only its strict requirements but also the particularities of neural signals and brain communication. By revisiting the literature, we have classified the expected benefits of this joint research into two groups, from where we can state the following key research directions.

- *Neurosciences for wireless networks* focuses on how developments in neurosciences will enable new application in the next generation of wireless systems based on BTC, in contrast to HTC and MTC. The key challenges relate to latency, high data rate, and high energy efficiency requirements, which are essential to support QoPE in BTC. Studies on the nature of the neural code, and how to match neural dynamics to behavior, are imperative to shed light on communication protocols. In a complementary effort, future works on materials and biomedical engineering should move toward brain implants with a higher channel density whilst ensuring biocompatibility and security.
- *Wireless networks for neurosciences* focus on how future wireless technologies could support new research and development in neurosciences, potentially including novel wireless-enabled BMIs, and IoBNT, as well as information- and communication-theoretic ways of evaluating brain communications based on their chaotic nature. In this context, the core future developments lie on the strict reliability and latency requirements, considering critical applications, such as BCVs. Furthermore, novel research fields, such as IoBNT, which incorporate molecular-level communications, will increase the demand for high data rates. Finally, having communicating brains in wireless networks bring forth serious ethical and security issues that have to be addressed prior to deployment of any BTC technology.

We illustrated the potential benefits of this proposed research agenda by analyzing a brain-controlled vehicle application.

We expect this contribution to serve as a key reference for researchers from both domains to start building joint activities that are necessary to realize the vision indicated here. The proposed discussions shall point toward a direction full of potential, from basic research to product development, but this can only be realized as a truly interdisciplinary task, similar to the path taken by neuromorphic computing [2]. In particular, a fully integrated smart city society immersed in an ubiquitous wireless computation environment will certainly find its great dilemmas in security, privacy, and ethics, and these topics must underlie any endeavor. In summary, although we are aware that the relation between neurosciences and wireless communications is still not fully established, this tutorial clearly indicates its feasibility if enough efforts are dedicated toward this goal. Our view is that this task needs to be put forth now during the discussions of novel wireless technologies, including 6G, so that BTC enters the agenda of the standardization bodies, indicating the research path for the coming ten years.

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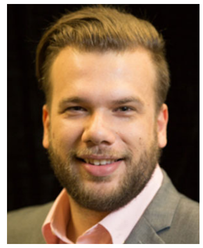

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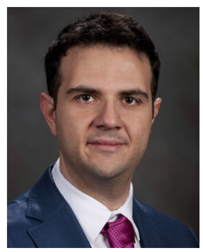

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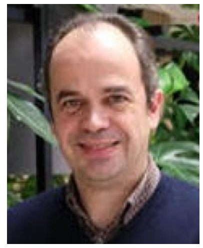

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