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Convergent Communication, Sensing and Localization in 6G Systems: An Overview of Technologies, Opportunities and Challenges

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ABSTRACT Herein, we focus on convergent 6G communication, localization and sensing systems by identifying key technology enablers, discussing their underlying challenges, implementation issues, and recommending potential solutions. Moreover, we discuss exciting new opportunities for integrated localization and sensing applications, which will disrupt traditional design principles and revolutionize the way we live, interact with our environment, and do business. Regarding potential enabling technologies, 6G will continue to develop towards even higher frequency ranges, wider bandwidths, and massive antenna arrays. In turn, this will enable sensing solutions with very fine range, Doppler, and angular resolutions, as well as localization to cm-level degree of accuracy. Besides, new materials, device types, and reconfigurable surfaces will allow network operators to reshape and control the electromagnetic response of the environment. At the same time, machine learning and artificial intelligence will leverage the unprecedented availability of data and computing resources to tackle the biggest and hardest problems in wireless communication systems. As a result, 6G will be truly intelligent wireless systems that will provide not only ubiquitous communication but also empower high accuracy localization and high-resolution sensing services. They will become the catalyst for this revolution by bringing about a unique new set of features and service capabilities, where localization and sensing will coexist with communication, continuously sharing the available resources in time, frequency, and space. This work concludes by highlighting foundational research challenges, as well as implications and opportunities related to privacy, security, and trust.

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INDEX TERMS 6G, beamforming, cmWave, context-aware, IRS, ML/AI, mmWave, radar, security, sensing, SLAM, THz.

I. INTRODUCTION

The fifth generation (5G) new radio (NR) is scheduled for worldwide release by 2020, thus, by now, its development cycle has reached initial maturity and the first networks are under deployment. In fact, there is already a need to prospect for new promising technologies, while identifying significant use cases for the next generation of wireless systems, which have been dubbed sixth generation (6G) communication systems. In the context of such future 6G wireless communication networks, this work focuses on the key aspects of the localization and sensing procedures by: *i*) identifying potential enabling technologies and main features; *ii*) assessing new opportunities of the environment-aware applications; and *iii*) recommending latest trends while posing key research questions.

Typically, wireless networks are praised for their communication features alone, while their inherent localization and sensing benefits are overlooked. In that regard, the 5G NR access interface with its large bandwidth, very high carrier frequency, and massive antenna array offers great opportunities for accurate localization and sensing systems. Moreover, 6G systems will continue the movement towards even higher frequency operation, e.g., at the millimeter wave (mmWave) as well as THz[1] ranges, and much larger bandwidths. In fact, the THz frequency range offers great opportunities, not only for accurate localization but also for high definition imaging and frequency spectroscopy. In [1] the authors provide an overview of the wireless communications and envisaged applications for 6G networks operating above 100 GHz, and then highlight the potential of localization and sensing solutions enabled by mmWave and THz frequencies. Along the same lines, possible directions for the cellular industry towards the future 6G systems are discussed in [2].

The 5G NR supports two distinct frequency bands, namely sub-6 GHz and mmWave operating in the frequency range FR1 (410 to 7125 MHz) and FR2 (24250 to 52600 MHz), respectively [3]. In addition, The NR specifications also feature Standalone (SA) and Non-Standalone (NSA) operation. While the former permits the 5G NR to operate independently of 4G LTE networks, the latter requires the sessions to be first established over the 4G LTE tier with the 5G carrier, which is then added as a secondary layer. The 5G NR Release 16 introduces various enhancements to the current system, for example, advanced beamforming operation, user equipment power saving, dynamic spectrum sharing, dual connectivity, and carrier aggregation. Regarding the overall infrastructure and new deployment scenarios, the 5G NR also incorporates integrated access and backhaul operation, unlicensed spectrum utilization, advanced features for major vertical sectors such as industrial internet of things and ultra-reliable low latency communication (uRLLC), intelligent transportation systems support and vehicle-to-anything communications, as well as positioning capabilities. In fact, the NR systems introduce an advanced positioning architecture which typically consists of the target UE, the radio access network (RAN) and core network (CN) with the respective positioning server and location service client. In the next generation RAN positioning architecture, the location information is exchanged between the target UE, network nodes, and positioning server via signaling in the control plane. From [4], the location information is conveyed using the LTE positioning protocol (LPP) extension, which specifies the signaling exchange between the target UE, the location server, and the location management function (LMF). Equally important, the NR positioning protocol annex (NRPPa) defines procedures to transfer positioning-related information between the next generation RAN nodes and the corresponding LMF [5]. Moreover, the 3GPP standards [6] also define the radio resource control (RRC) protocol to exchange the LPP messages from the core networks (through the NR-Uu interface) to the target UE. It is worth noticing that in this new RAN structure, the LMF sends positioning requests to the serving base stations (either gNB or ng-eNB), which in their turn not only provide positioning information (based on the reference signals measurements) to the target UE, but also carry out measurements on the uplink direction.

In fact, the 5G NR access interfaces put forward a plethora of compelling new use cases that require or benefit from position information. For instance, assets tracking, context-aware marketing, transportation and logistic systems, augmented reality, health care, as well as haptic technologies are emerging IoT applications across various industry verticals. After concluding a Study Item in 2019 to investigate positioning support in upcoming releases of the NR specifications, the 3GPP standardization body is carrying out a Work Item to specify such positioning support for Release 16 and future releases. To begin with, very stringent requirements for the future 3D network-based positioning are defined in [7] whereby the next generation of high accuracy positioning services need to satisfy a level of accuracy less than 1 meter for more than 95% of network area (including indoor, outdoor and urban deployments). The 5G NR establishes distinct radio access technologies for positioning solutions: uplink/downlink time difference of arrival, multi-cell round trip time, uplink angle of arrival and downlink angle of departure. In order to enable these NR positioning approaches, various physical layer measurements are needed [8], the reference signal time difference is already present in LTE networks and is considered as a baseline configuration for the 5G NR, which can be used in conjunction with the beam-based positioning reference signals. Alternatively, the multi-cell round trip time is enabled by UE receiver-transmitter

[1] While the THz terminology is appealing, it is incompatible with the common usage of mmWave; at the same time, the term microwave is ambiguous. A good middle ground is to address the band of interest as "(μuWave)". Here, we use both terminologies interchangeably.

time difference measurements, which are defined for serving and neighboring cells in NR. Within RAN1 discussions, the relative time of arrival is also considered per beam basis in the NR configuration. Finally, the available reference signals, namely channel state information reference signal (CSI-RS) for beam management, CSI-RS for time-frequency tracking, CSI-RS for CSI acquisition, CSI-RS for mobility measurements, phase tracking reference signal (PTRS), demodulation reference signal (DMRS) need to be enhanced so as to support high accuracy positioning in the Rel-16 and upcoming releases [9]. Recently, the technical specification group started discussing the remaining issues for the uplink-/downlink-based positioning. For instance, the standardization body agreed on implementing new measurements on the Uplink direction to support UL relative time of arrival, UL azimuth angle of arrival (AoA), UL zenith angle of arrival (ZoA), UL reference signal received power (RSRP) measurements, as well as new measurement reports including carrier phase estimation at both the serving and neighboring gNBs. In addition, study and work items are focusing on the requirements and deployment issues for the commercial uses cases (including Industrial IoT scenarios) so as to support horizontal and vertical high accuracy, low latency transactions (user and control planes), as well as network and device efficiencies regarding, for example, complexity, scalability, signaling overhead and power consumption [10], [11].

Location and sensing information in mobile communication systems has several applications, ranging from Enhanced 911 (E911) emergency call localization to through-the-wall intruder detection, from personal navigation to personal radar, from robot and drone tracking to social networking. Location side-information can also be a service-enabler for communication network design, operations, and optimization. For instance, in [12] and [13] Taranto *et al.* and Koivisto *et al.* respectively overviewed location-aware communications for 5G networks across different protocol stack layers, and then highlighted promising trends, tradeoffs, and pitfalls. Additionally, the prospects for enhanced network synchronization are highlighted in [14]. In [15], the authors provide a general overview of localization methods for the 5G NR and more specifically for the Internet of Things (IoT) applications, i.e., they initially discuss key enabling technologies and features of 5G networks, and thereafter not only identify important practical implementation challenges, but also recommend potential development paths for localization-based services. In [16], Lohan *et al.* addressed how position side-information can be exploited to improve the operation of high-frequency Industrial IoT (IIoT) deployments. How these concepts, ideas, and services will change in the 6G era forms the core of this contribution.

All in all, it is worth noticing the 5G NR development cycle is now mature, and the research interest is slowly shifting towards the potential 6G technologies and systems, as evidenced by the latest papers, which focus mostly on the communication aspects [2], [17]–[23]. Although a few contributions, such as [19], [20] mention the potential of integrating localization and sensing into the system design or address specific technologies [22], [23] (e.g., IRS and AI/ML, respectively), to the best of our knowledge, our contribution is the first one to focus on the 6G convergent communications, localization and sensing systems by identifying the most promising enabling technologies, discussing on the desired features, new applications, and opportunities, then finally addressing challenges and future directions.

The remainder of this contribution is organized as follows. In Section II, we first identify key enabling technologies for the future mobile communications systems and highlight which desirable features are advantageous to localization and sensing. Thereafter, envisaged applications and opportunities are discussed in Section III. Finally, in Section IV, we summarize our outlook for the future 6G localization and sensing development, while posing fundamental research questions.

II. ENABLING TECHNOLOGIES FOR 6G ENVIRONMENT-AWARE COMMUNICATION SYSTEMS

We can identify four emerging technological enablers for 6G communication networks, as well as localization and sensing systems. These are the use of new frequencies of the radio spectrum, the inclusion of intelligent surfaces, intelligent beam-space processing, in addition to artificial intelligence (AI) and machine learning (ML) techniques. In this section, we cover these enablers in detail while discussing technological challenges and pointing out future opportunities.

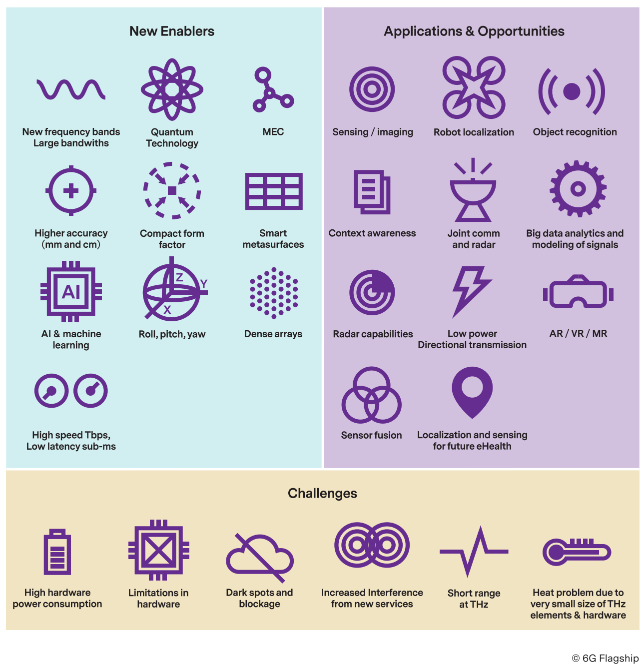
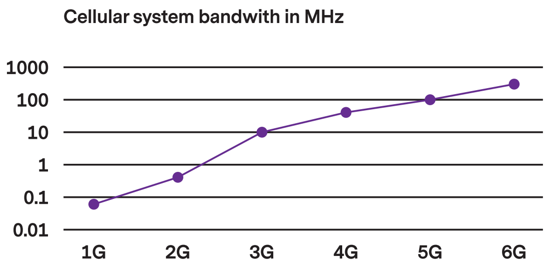


FIGURE 1. Chart relating enabling technologies, 6G new application opportunities and technological challenges.

Figure 1 summarizes key technological enablers and the resulting new opportunities for localization and sensing applications in 6G systems. In addition, the illustration identifies related challenges and open issues that still need to be tackled in order to take advantage of the new opportunities offered by much finer range, Doppler and angle resolutions and to realize the envisaged applications.

A. RF SPECTRUM FOR FUTURE LOCALIZATION AND SENSING SYSTEMS

In this section, we assess the prospect of using new radio frequency (RF) spectrum at high frequency ranges in 6G systems, while discussing the underlying radio propagation features and their impact (advantages and disadvantages) on future localization and sensing applications. We then briefly cover future chip technologies and developments in channel modeling. A detailed discussion on RF and Spectrum allocation for future beyond 5G wireless communication systems is provided in [24].



Frequency Band (GHz)	Contiguous Bandwith (GHz)
116-123	7
174.8-182	7.2
185-190	5
244-246	2
Total	21.2

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FIGURE 2. (top) Growth of channel bandwidth for cellular networks [2]; (bottom) new unlicensed spectrum above 100 GHz proposed by FCC [1].

1) A LEAP IN BANDWIDTH AND CARRIER FREQUENCY

As indicated in Fig. 2, 6G radios will be likely to allocate services across channel bandwidths which are at least five times larger compared to 5G, so as to accommodate ever-demanding data rates, increased reliability needs and demanding new services such as sensing and localization. Taking one step back, in up to fourth generation (4G), only bands below 10 GHz were occupied, whereas 5G NR started implementing several so-called mmWave bands. Towards 6G, then, it is expected that the next-generation radios will thus aim to occupy higher bandwidths, now reaching above 100 GHz. Furthermore, [1] (table reproduced in Fig. 2) indicates the Federal Communications Commission (FCC) is on track to propose several new bands above 100 GHz for unlicensed use. The key goal of doing this is to allow research and development activities towards these frequency bands. Regulatory activity is often indicative of a trend, and it is expected that these bands are likely candidates beyond 5G NR. Practical system and circuit evaluations today (for communications purpose) are already being tested at 140 GHz [1], [2], [25].

Given the expected transition to higher frequencies and thus smaller wavelengths than used for mmWave bands, the term micrometer wave (μmWave) is proposed. The increase in frequency has several important implications: mmWave has a small beam width, typically referred to as a "pencil beam", while μmWave is expected to offer even more beam width reduction, leading to higher positioning accuracy, array gain in the link budget, and imaging capabilities. Depending on the precipitation, the medium and link budget can be effected. There is a significant difference in absorption caused by water vapor in the atmosphere depending on the specific wavelength as illustrated in Fig. 3. Furthermore, the specific absorption of electromagnetic (EM) radiation in atmospheric vapor depends on the specific data and models used for particular types of precipitation, like rain, snow, etc. [26]. However, in general, the EM radiation can reach shorter distance towards higher frequencies, e.g., mmWave and μmWave.

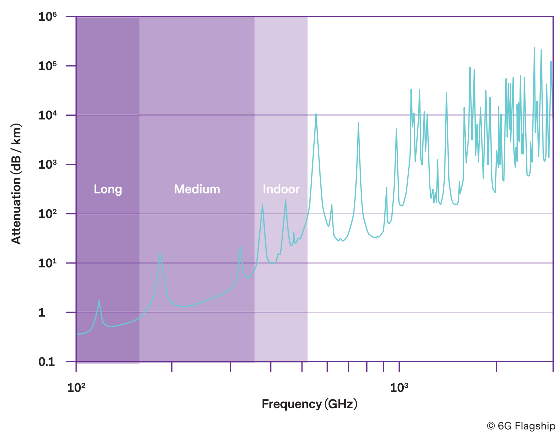

FIGURE 3. Illustration of the relation between frequency range and radio channel propagation effects (reflection, diffraction, scattering) [26].

From a localization and sensing perspective, the transition to THz frequencies has several important benefits. First of all, signals at these frequencies are unable to penetrate objects, leading to a more direct relation between the propagation paths and the propagation environment. Secondly, at higher frequencies, larger absolute bandwidths are available, leading to more resolvable multi-path in the delay domain with more specular components. Third, shorter wavelengths imply smaller antennas, so that small devices can be packed with tens or hundreds of antennas, which will be beneficial for angle estimation. In addition, the high-rate communication links offered by 6G will be able to be leveraged to quickly and reliably share map and location information between different sensing devices. This is beneficial for both active and passive sensing. To harness these benefits, chip technologies must be available that sufficiently support economies of scale. In addition, to support the development of new solutions and algorithms, suitable channel models that properly characterize the propagation of 6G waves over the hardware and the air are needed as well.

2) FUTURE CHIP TECHNOLOGIES

Having defined the broad initial range of relevant (new) spectrum for 6G to be as large as 0.3 - 3 THz, while regulatory bodies have recently started to enable R&D up to 250 GHz, There is a clear need for further development of technology which will able to support the said frequency bands in a cost effective manner. One key aspect is the integration of the required technology. Currently, radio systems operating in the range of multiple 100 GHz typically include antennas and signal processing equipment, for example, which is unreasonably large to integrate into typical user equipment (UE). As we start to migrate towards 5G systems in the world, we see that silicon products for UE purposes have been in development for a few years while the network roll-out has started in a limited geographical scope only during 2019 and 2020. This is in no small part due to the complexity of the added air interface at mmWave frequencies and increased usage of array technology to enable UE-side beamforming. While the development of the front-end and modem chips has taken time, the process technology of choice is now available to enable efficient amplification, down-conversion and further analog processing, even at the large bandwidths. Planar bulk complementary metaloxidesemiconductor (CMOS) technology at 28nm has been able to achieve a so-called transition frequency at least one order of magnitude above the 28 GHz and 39 GHz operational bands. Towards 6G operation, it is expected that a similar hurdle will have to be taken by chip technology. However, this time it is *not* obvious that the process technology can handle the required frequencies. Even at "only" 100 GHz, the same 28 nm planar bulk CMOS process would not be able to achieve the same efficiency e.g., to amplify signals. Hence, alternative technology options must be considered for cost-efficient solutions. Currently, multiple technologies are under study that have the potential to achieve good output power and efficiency at ever-higher frequencies. These include: Gallium Arsenide (GaAs), Gallium Nitride (GaN), Indium Phosphide (InP), CMOS, Silicon Germanium (SiGe), and fully depleted silicon on insulator (FD-SOI) CMOS. Today, the conclusion may be drawn that technically, operation up to 300 GHz should be possible. However, above 300 GHz, even InP will no longer be able to provide efficient amplification and multipliers will have significantly lower output power to drive antennas [27]. Hence, it is an open research question whether further technology development is required and if not, which technology is best suited for the 6G challenge.

3) CONSISTENT CHANNEL MODELS

Electromagnetic wave propagation models are an important component for the proper design, operation, and optimization of wireless communication systems. In fact, when developing new algorithms or deploying new architecture, the simulation of radio channel dynamics and network operation becomes crucial for assessing the overall performance of mobile cellular systems. Propagation models are equally critical to ensure secure and reliable positioning, since it is impossible to design radar, sensing, ranging or direction estimation algorithms without sound hypotheses on how the electromagnetic waves propagate in the vicinity of the sensing device. Models are also critical to predict and benchmark the accuracy achieved by the various sensing and localization approaches. When compared to radio signals at lower frequencies, systems operating at high frequency are more susceptible to weather conditions, and do not propagate properly through materials. These properties are also relevant for sensing. For instance, for radar systems, the radar cross-section of different objects and the clutter properties of different environments must be characterized, and these must be correlated with the propagation models if we want to assess the performance of joint radar and communications systems. As we move into higher frequencies and into spectroscopic analysis, the absorption of electromagnetic waves through different gases and the reflection properties of different materials must be better understood and modeled.

In wireless systems operating at the microwave frequency range, the reflection and diffraction effects dominate the signal propagation and scattering is typically ignored. Differently, at mmWave and THz frequencies the signal wavelength becomes comparable to, or even smaller than, suspended particles in the air (dust, snow and rain) or object surfaces irregularities and roughness. The path components resulting from the scattering may compensate for the radio channel degradation effects mainly as carrier frequencies increase above 30 GHz. Moreover, typical drop-based statistical models [28] fail to capture the targets' motion in highly directive antenna configurations. Thus, it is crucial to develop new channel models able to capture the *consistency* of the propagation features.

- Spatial consistency: A channel model is spatially consistent if its large- and small-scale parameters continuously vary with the target node position and depending on the reference geometry. In other words, nearby target nodes experience correlated large-scale features, while the small-scale parameters of each target (for example, angle or delay information) dynamically change with the position over the network deployment area. The authors in [29] summarized relevant channel modeling considerations and noted that the proper characterization of the radio channel spatial consistency was the most challenging extension to be incorporate into traditional drop-based simulators. In [28], the 3GPP standardization body proposed a spatial consistency procedure for drop-based simulations that can be used with both cluster- and ray- random variables. However, it still misses implementation details related to capturing the correlation distances in highly directive narrow-band antenna arrays, as well as beam steering when considering high resolution scale.

- Frequency consistency: Consistency across frequency bands is also a desirable feature in channel models; low-frequency signals propagate over a wide area while enabling relatively coarse localization, while the higher frequency bands allow more accurate localization, albeit for a shorter range. This indicates that achieving both long-range and high-accuracy localization will require the joint processing of signals corresponding to widely spaced frequency bands, together with channel models faithfully linking the propagation characteristics across the whole spectrum. A specific model is required for channels involving large transmitting or receiving arrays or surfaces (massive multiple input multiple output (MIMO), distributed MIMO). However, the channel model becomes non-stationary in space since certain parameters, e.g., path loss and angle of arrival (AoA), can not be assumed to be constant between the antennas [30]. Consistency across frequency bands will also be critical for reliable localization in environments where the user might be simultaneously using several bands, e.g., if the network makes use of the control and user plane separation (CUPS) principle.

4) CHALLENGES

Finding the right band for the right frequency to optimize the use of potential new applications is a key challenge. There is also the issue of the technology gap, i.e., how to make cost-effective and scalable systems towards 300 GHz operating frequencies and beyond. Future 6G systems will most probably introduce new use cases and various deployment scenarios which will require developing new (preferably general) dynamic radio channel models capable of capturing the time evolution of relevant metrics (such as channel impulse response) at a fine resolution. At a high frequency range, such channel models need to be consistent across frequencies and space, while capturing radio channel characteristics, material properties as well as features of the radio access interface. However, the channel coherence time will be significantly reduced and thus requires much faster and more frequent updates to properly capture radio changes. Moreover, measurement campaigns to either estimate parameters or validate models become difficult at such high frequencies due to, e.g., long measurement and processing periods, equipment costs and even presence/absence of foliage. In this configuration, ray tracing simulation is a well-known complement to field measurements, although developing accurate ray tracing simulators at a reasonable computational cost, given the necessary fine resolution time, also becomes a challenge.

B. INTELLIGENT REFLECTIVE SURFACES FOR ENHANCED MAPPING AND LOCALIZATION

The radio propagation environment between transmitter and receiver peers has always been perceived as a random (non-controllable) component of wireless communication systems. Toward this end, intelligent reflective surfaces (IRSs)[2] have been recently introduced as a promising solution to control radio channel features such as scattering, reflection, and refraction. In particular, IRSs allow network operators to shape and control the EM response of the environment objects by dynamically adapting parameters such as the phase, amplitude, frequency, and polarization without requiring either complex decoding, encoding, or RF operations [31]. Succinctly, an IRS is an EM surface that is typically implemented through conventional reflective arrays, liquid crystals, or software-defined meta surfaces [32]. Even though IRSs with fixed EM features have been previously employed in radar and satellite communications, it is only recently that they have found applications in mobile communication systems.

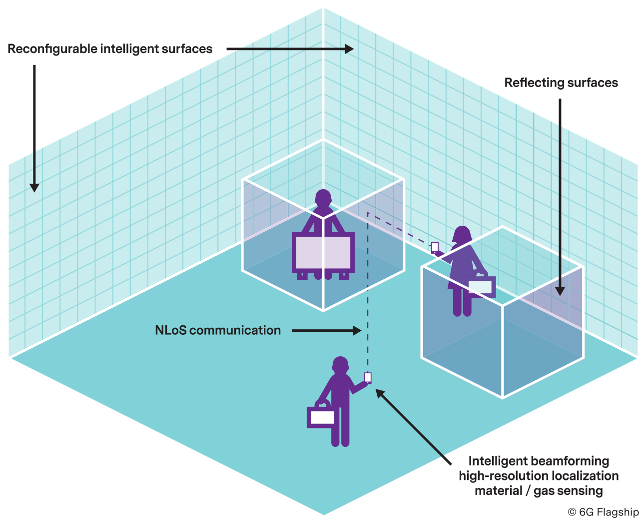

FIGURE 4. Illustration of IRSs in an indoor area, where the IRSs can facilitate the NLOS communication.

IRS-assisted communications have the potential to enable low-complexity and energy-efficient communication paradigms. Figure 4 illustrates prospective application scenarios of IRSs in an indoor setting, where IRSs can extend the wireless communication range and facilitate non line of sight (NLOS) communications. Within IRS varieties, metasurfaces can support much more functionalities than reflect arrays since their elements can be of sub-wavelength size. A metasurface is typically composed of a 2D composite material layer that is devised to control and transform EM waves [33]. Reflections from tiny elements result in scattering in all directions, which collaboratively results in beamforming. In particular, metasurfaces are implemented employing conductive

[2]IRSs go under different names, including reconfigurable intelligent surfaces (RIS) and large intelligent surface (LIS).

patterns that are repeated over a dielectric substrate, capable of implementing programmatically various EM interactions such as wave steering, polarizing, absorbing, filtering, and collimation over distinct spectrum allocations. The resultant programmable wireless environments are expected to be readily incorporated into existing network infrastructures by means of present-day technologies such as software-defined radio.

The advantages of IRS technology over current solutions (e.g., densification and massive MIMO) are discussed in [34]. IRSs can reap the benefits of the mobility and dynamics of the radio environment at a lower energy footprint and without requiring changes to the radio access interfaces of devices. An IRS can reflect signals in precise directions by adjusting the phase shifter arrays, which can be controlled at access points/small-cell base stations (BSs) via smart controller(s). Hence, IRSs are effectively large-scale arrays of phase shifters that do not have their own radio resources. However, an IRS cannot send pilot symbols to help a small-cell BSs to estimate the channel response between small-cell BSs-IRSs. Furthermore, the IRS adds extra complexity to communication systems by significantly increasing the number of parameters and the amount of data needed to design and optimize the operation of such smart radio environments; the control complexity of metasurfaces compared to reflect arrays can further be higher.

The importance of IRSs is particularly emphasized at high frequencies in the context of mmWave/THz communications [35]. With larger path and penetration losses and lower scattering at higher frequencies, the number of naturally occurring propagation paths is low. Furthermore, regular large coherently-operating antenna arrays are difficult to implement at high frequencies (as the size of antenna elements gets smaller), and the relaying technology is also not yet mature. IRS deployments can thus solve these issues, where the addition of controlled scattering can extend the communication range and enhance system performance. Note that electronically-large (large compared to the operating wavelength) IRSs at high frequencies can be realized with very small footprints, which further facilitates their deployment.

The aforementioned intelligent operations of IRSs, alongside the inherent EM features, especially in the mmWave/THz-band, can enhance the performance of localization and sensing. For instance, an IRSs could enable tracking/surveillance applications in NLOS communications and autonomous localization. IRSs can extend high-precision localization techniques for mobile users, especially in Global Positioning System (GPS)-denied indoor environments. Localization performance bounds of IRS-assisted smart radio environments in which a BS infers the position and orientation of a UE are derived in [36]. If the intelligent surfaces are large, the near-field effects provide an opportunity for exploiting the wavefront curvature, which can improve location accuracy and possibly remove the need for explicit synchronization between reference stations [37]. On the other hand, accurate sensing and localization (especially at the THz band) can, in turn, enhance the efficiency of NLOS signals and reflective surfaces, whether intelligent or not (as illustrated in Fig. 4). In particular, intelligent surfaces operating at the THz band can be very small, and hence accurate localization techniques would be required to track their relative location in real-time. Furthermore, the material type of the reflecting surface affects the efficiency of NLOS signals. For example, regular (non-intelligent) smooth surfaces introduce a significant specular reflection component in the THz band. Passive, reflection-based THz sensing can determine the material type of surfaces, which results in intelligent beamforming decisions. This is in line with the concept of leveraging the knowledge of the environment for enhanced communications, sensing, imaging, and localization applications [38].

As addressed in Section II.D, AI/ML techniques can be employed to enhance wireless communications systems' operation across the protocol stack. In this context, AI/ML methods constitute a natural approach to characterize IRS-based deployments, dynamically control EM interaction, and optimize future 6G wireless communication systems' operation. Both classical ML or deep learning techniques can be applied to IRS-based systems [39], providing integrated communication, sensing, and localization capabilities for future networks [40]. Several promising approaches have been proposed recently. Unsupervised subspace methods such as principal components analysis are applied to metasurface-based sensing and imaging [41]. Furthermore, to extract higher-level information, [42] proposes a combination of three parallel convolutional deep neural networks that can be trained to simultaneously sense humans and recognize their gestures and physiological state from the programmable metasurface and Wi-Fi signals. Similarly, [43] represents a learnable EM sensing system by jointly optimizing both the control of the metasurface and a model to perform imaging and recognition of humans and their gestures based on two feedforward deep residual convolutional networks trained within a variational autoencoder framework. In [44], supervised learning is utilized to predict the configuration of IRSs to improve the transmitted signal focusing to UE positions, based on standard multi-layered deep neural networks that are trained on location fingerprint reference data. In non-stationary environments with a lack of labeled datasets, reinforcement learning can be used for online end-to-end learning and control of IRSs and communication systems [39]. For example, in [45], deep reinforcement learning is considered to maximize the downlink received signal to noise ratio (SNR) in IRS-aided communication system.

1) CHALLENGES

Several technological challenges and open issues still need to be addressed to make IRSs a viable alternative in future 6G systems. To carry out research and push the further development of IRSs forward, appropriate models that describe the properties of the constituent materials and the radio propagation features of the incident signal waves are still lacking. Feasible implementations (accounting for hardware and software aspects) of such reconfigurable meta-surfaces are also essential to ascertain their potential gains in wireless communication systems. IRSs also need to collect the channel state information (CSI) between communicating peers to adjust the radio characteristics of the impinging signals properly. Therefore, it is necessary to devise novel energy-efficient methods to estimate the channel properties of the wireless links. When considering the integration of such IRSs into the infrastructure of the wireless systems, it is also be necessary to develop strategies to identify adequate locations for their deployment in the network coverage area. Furthermore, novel signal processing techniques that optimize the performance of IRS-assisted joint communications, sensing, and localization are required. This is especially challenging at high frequencies, where the overall channels tend to be of low-rank, hence carrying less information.

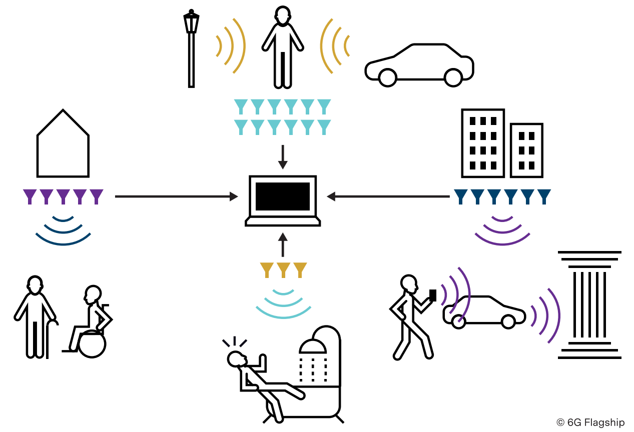

FIGURE 5. Illustration of the beamspace domain/processing for accurate positioning. This figure depicts the collaborative multi-antenna systems deployed in target space with distributed topology for managing hybrid beamspace and localizing passive and active targets; the link ensured between the multi-antenna systems and the active target could be the LOS and NLOS paths and could be blocked by moving background objects.

C. BEAMSPACE PROCESSING FOR ACCURATE POSITIONING

Beamspace is one of the promising enablers for localization and sensing in 6G. The beamforming at mmWave and μmWave is essentially the transmission of coherent signals thus forming a concentrated field in a certain direction to increase the signal-to-noise ratio or throughput as a beamforming gain. Enhanced beamforming capacity in three-dimensional (3D) space is advantageous to overcome the high path loss in mmWave and μmWave bands and to mitigate the interference from different directions by forming very narrow beams. A beamspace channel response collected by a monostatic or multistatic transmitter and receiver contains spatial information of not only the link ends but also the interacting objects/humans in between, which can be processed for localization and sensing purpose. Beamforming can be categorized into analog, digital, and hybrid beamforming [46], where the former supports a single stream and phase shifters allow directional transmission (depending on the aperture), while the second option allows multiple streams in different directions. Beamspace processing relies on advances in channel estimation, including angular and delay domain profiles, needed for localization and sensing algorithms. The channel estimation is particularly critical in unfavorable NLOS and high mobility scenarios. As illustrated in Fig. 5, in the case of localizing and tracking active mobile users in a changing environment, the beams are managed dynamically as the channel estimation of the angle of arrival (AoA) or angle of departure (AoD). There exist a plethora of methods for AoA or AoD estimation, with varying degrees of complexity and performance.

In terms of the localization of active mobile users who can be connected with the base station by a line of sight (LOS) path, or strong NLOS path such as specular reflection, accurate and fast AoA or AoD estimation of the major multipath is sufficient. In the uplink direction, AoA estimates from LOS links allow to infer the location of the active user directly, while NLOS links, resulting from multipaths of the signal transmitted by an active user bouncing off scatters and then arriving at the base station, allow to estimate the location of a scatterer (interacting object). In the case of the latter, i.e., the NLOS scenarios, in order to trace down the location of the user, both AoA and AoD estimations are needed.

In addition to beamspace processing for the localization of active users in LOS and NLOS scenarios, it is even more challenging if the target does not carry or wear any device, i.e., device-free localization [47] or sensing. In this case, there is a need for additional environment indications where the spatial characterization of the target(s) can be distinguished from the background objects. This is especially challenging when multiple targets are present [48] and the identification of the targets [49] is needed as well. With a pencil-like beam operating at mmWave and μmWave frequency bands, the spatial resolution is very high. At the ultra-wide bandwidth, the delay resolution is also very high. The combined angular-delay profiles of beamspace channels serve to localize and sense passive targets. The beamspace channels can be collected continuously and in this case the instantaneous beamspace can be compared with a reference (collected off-line to represent the static environment) to sense a passive target, and compared with a previous sample (on-line or real-time) to track a moving target. The identification of targets needs the help of learning algorithms to distinguish the angular-delay profile variations of different target (present in different size, dielectric properties, etc.). Dedicated beamforming signals and the deployment of strategic monostatic/multistatic multi-antenna system (MAS) could support maximum accuracy for the localization and sensing of scattering targets.

1) CHALLENGES

An important challenge in beamspace processing is blockage, e.g., due to high mobility background objects cause deep fading and thus influence the localization accuracy. In case of deep fading, the localization and sensing function of a current serving MAS may be temporally switched to another MAS. In order to coordinate the available MASs deployed in a target area for real-time localization and tracking, the prevention of blockage from moving background objects which can cause dramatic degradation of beamspace signal quality is necessary. This could be achieved through image-based mobility-behavior prediction, geometrical domain environmental identification and radio channel simulation, ideally in a runtime in the order of milliseconds. In high mobility scenarios, the observation of moving background objects which could potentially block the beamspace could be implemented, e.g., using a depth camera; the learning and prediction of its moving trajectory can be conducted in real-time; the potential influence on the beamspace channels could also be predicted by ray tracing simulations or a hybrid method of ray tracing and a propagation graph [50]. Additional practical challenges include the following. First, with beamforming at higher frequencies more than 40 GHz (post-5G frequencies), there are risks of increased phase noise and non-linearity of systems, which could affect the signal quality and result in channel estimation errors and hence influence the functionality. Second, when the target is in the near-field of a multi-antenna station, It will be necessary to devise direction estimation algorithms for beamspace channels for a robust estimation. Third, how the beamspace separation influences the accuracy of identifying multiple targets that are closely located together is yet to be investigated thoroughly. Fourth, the AI-enabled precoding for digital beamforming combined with a dynamic multipath simulator with environment information could add constructively for even sounder system attributes. Nevertheless, the trade-off between the algorithm complexity, the hardware capability and the time consumption needs to be balanced. A combination with learning algorithms for target recognition is promising; For this purpose, comprehensive performance evaluation matrices, current and foreseeing localization accuracy, and the Cramér-Rao bound on estimation accuracy need to be defined with the specifications of the system configuration.

D. MACHINE LEARNING FOR INTELLIGENT LOCALIZATION AND SENSING

AI techniques are becoming ever more important moving towards the data-rich 6G era. Studying how to build intelligent systems and agents which are able to achieve rational goals based on logical and probabilistic reasoning, planning and optimal decision making, possibly in uncertain environments is a broad field. Modern AI systems are typically based on ML [51], which provides data-driven multidisciplinary approaches to learn models beyond explicitly programmed rules. 6G systems and beyond will rely on such data-driven algorithms, providing new opportunities not only for wireless communication but also for advanced localization and sensing techniques operating at the mmWave and μmWave frequency ranges. The interested reader is also referred to [52] for a detailed discussion on Machine Learning solutions for 6G Wireless Communication Networks.

1) LOCALIZATION

ML methods in localization mainly focused on fingerprinting and the usage of regression and classification methods [53]–[55]. In data-rich and complex localization applications, especially for the Global Navigation Satellite System (GNSS) poor indoor and urban outdoor channel conditions, we expect a more widespread use of ML, since traditional mathematical models and signal processing techniques are not alone able to solve challenging problems where we have a large number of multi-modal, indirect and noisy observations, and the physical properties of non-linear signal characteristics of the system are possibly unknown or difficult to model. Instead, we can utilize AI methodologies to model how the system behaves, including sensor noise and different uncertainties of the system. Furthermore, in many cases, to realize high-level sensing and localization from possibly high-dimensional low-level raw measurements, e.g., CSI in massive MIMO systems, predictive models and pattern recognition based on ML techniques are essential. Hence, the use of statistical AI methods to simultaneously model complex radio signal characteristics and fuse many complementary yet noisy sensors will become more important in future localization and mapping systems. These will be likely to be supported by hybrid models combining traditional physics-based models of signal propagation with data-driven learning approaches and sequential Bayesian state-space models [51]. Furthermore, as the predictive function of mapping low-level measurements to high-level target concepts becomes extremely complicated, it will be impossible to build the mathematical model by hand. Machine learning provides an alternative framework which is able to learn from data by optimizing or inferring unknown free parameters (or latent variables) of the model to build more flexible and accurate approaches to 6G localization and sensing, based on state-of-the-art deep learning and probabilistic methods [51], for instance.

2) SENSING

RF-based sensing at high carrier frequencies will provide more accurate techniques to measure the environment, detect and recognize objects, and the wider spectral range will provide opportunities to sense and identify new kinds of targets and variables which are not detectable in currently used frequency bands [1]. As data becomes more highly-dimensional and complex, AI- and ML-aided, together with these novel sensing capabilities, will provide opportunities not seen before. New kinds of high-level information and patterns hidden in the raw data will be extracted and many weak and noisy signals will be integrated temporarily and spatially to realize novel sensing approaches. On the one hand, extracted patterns and (latent) variables can be seen as a virtual sensor, providing an intermediate step to performing higher-level reasoning, for example, to realize more precise target localization. On the other hand, ML algorithms can be trained directly to predict the characteristics of a dynamic environment. For example, this may be applied to detecting and classifying objects in variable conditions [56] or identifying users [57] and recognizing user behavior and contexts to enable future wireless communication networks as well as novel services and applications using passive sensing (cf. Section III-C).

Target applications of ML aided localization and sensing can thus vary from low-level feature extraction and pattern discovery to object detection and recognition, location tracking and prediction, environmental mapping, cooperative localization, channel charting (see Section III-E), and autonomous navigation and planning, for instance. Fig. 6 illustrates the AI and ML landscape of general supervised, unsupervised, and reinforcement learning concepts and their relations. Furthermore, a set of methods and models in each concept relevant to the localization and sensing as enabling technologies are shown as well as typical challenging and opportunistic data types and applications arising from the area of future 6G systems.

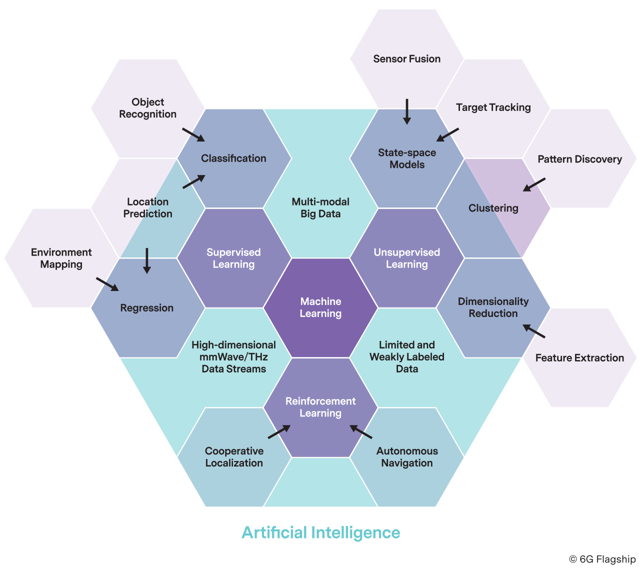

FIGURE 6. Landscape of the AI- and ML-based approaches for the localization and sensing solutions.

3) CHALLENGES

The present-day AI and machine learning toolbox already provide a variety of techniques to extend traditional localization and sensing, for example, based on uncertainty-aware probabilistic learning and reasoning methods and deep neural networks [51]. However, many of these well-established techniques have their limitations because they are data-hungry, requiring a large amount of labeled training data and computing power. To be able to learn from limited, arbitrary structured, and noisy data, novel hierarchical models and advanced inference techniques need to be developed and combined in clever ways. To overcome the cost of collecting labeled training data, several recent approaches could be further developed. Semi-supervised learning combines a small number of labeled data points with a large number of inexpensive unlabeled data points to refine a supervised solution. Furthermore, the characteristics of localization and sensing in next-generation communication systems will be more autonomous, often non-stationary and time-evolving, requiring online adaptive ML techniques. For instance, federated learning-based crowd-sourcing [58] and reinforcement learning-based cooperative localization [59] could help to overcome the challenges of limited data and adaptive environments. To be able to apply AI and ML techniques successfully as an enabler for the next-generation highly dynamic large-scale localization and sensing systems, solving these challenges will become essential.

III. LOCALIZATION AND SENSING OPPORTUNITIES FOR FUTURE 6G SYSTEMS

In this section, we discuss new localization and sensing opportunities, which are enabled by the aforementioned key technologies and are tailored for the upcoming 6G wireless communication systems. In this context, it is worth emphasizing that localization, sensing and communication must all coexist, sharing the same time-frequency-spatial resources in the envisioned 6G systems. There are different mechanisms to enable such sharing, including: coexistence, cooperation, and co-design [60]. In this sort of sharing, mutual interference can be a challenge if not properly addressed. While any form of sharing can be interpreted as reducing the performance of at least one functionality, the interplay is not necessarily a zero-sum game: sensing and location information can guide communication (e.g., for beamforming or for hand-overs), while communication can support localization and sensing by sharing map information between devices. Sharing is not limited to the resources but can also exist at a waveform or hardware level. In terms of waveforms, communication waveforms may have undesirable properties from a localization or sensing point of view and vice versa. The design of joint parameterized waveforms will alleviate this problem. In terms of hardware, the same resources will be used for all three functionalities of localization, sensing, and communication.

User requirements and key performance indicator (KPI) defined for 5G positioning services are equally important and have been under active discussion in the 3GPP releases 16 and 17. However, it is worth noticing that there is a significant gap between the most stringent requirements of the use cases, as described in [61], [62], and what has been effectively achieved in the current 3GPP standards, in particular, in Release 16 [9], [63]. This gap between the requirements of the envisaged use cases and the performance targets in Release 17 may become a clear objective to be attained by the future 6G systems. Furthermore, 6G should include KPIs related to the new functionalities that it will include. In particular, the UE orientation and the map or features of the environment should be captured in the corresponding accuracy metrics.

In addition to 5G NR traditional figures such as capacity, coverage, (peak) data rate, energy consumption, deployment/operational cost, (E2E) latency, reliability, 6G should also consider KPIs related to the new functionalities that will be incorporated. Having said that, it thus becomes relevant to discuss the benefits of integrated computation, intelligence and sensing capabilities into the network and how that will improve the overall system performance, for example in terms of capacity, coverage and achievable data rates. Particularly, the UE orientation and mapping features of the environment should be captured in the corresponding accuracy metrics. KPI characterizing the power consumption per position fix should also be considered since this is an essential aspect for positioning in the (industrial) IoT context. In addition, new societal indicators need to be also taken into consideration so as to account for the sustainable development goals established by the United Nations, as well as the human component when considering the ongoing convergence between digital and physical worlds. Besides flexibility and availability, 6G systems/protocols/signals should be designed so that the user equipment performing or supporting localization using 6G should also be able to continuously monitor integrity (to detect, isolate, and exclude signals from faulty transmitters or those heavily affected by multipath). In this context, some KPIs similar to legacy definitions of integrity monitoring such as time-to-alarm, false alarm rate, the maximum number of false transmitters that can be detected, etc. should be considered.

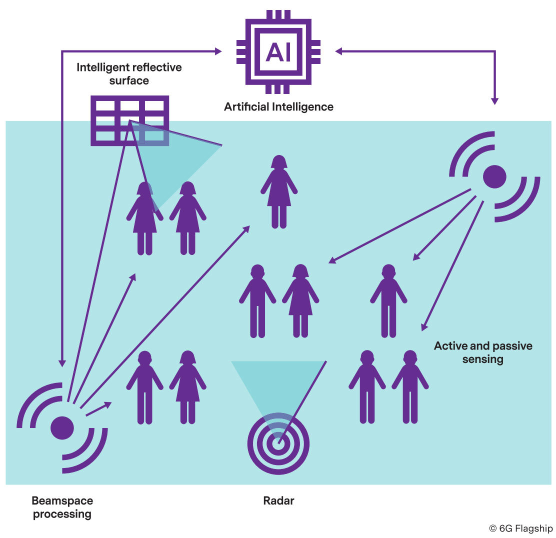

FIGURE 7. Illustration of the envisaged 6G opportunities and applications.

Figure 7 illustrates future deployment scenarios wherein the aforementioned technological enablers are employed to create exciting new opportunities for localization and sensing applications. In the following sections, we go into details and discuss various such application and service opportunities which will become a reality in the convergent 6G communication, localization and sensing systems.

A. THz IMAGING

The higher frequency bands, encompassing the mmWave and THz bands, offer unique opportunities for sensing because they allow very fine resolution in all physical dimensions: range, angle and Doppler. Both active and passive sensing and imaging are possible, where a passive sensor exploits the emissivity or the natural reflection of surfaces and uses an array of imager pixels to capture the image, in a non-coherent way, just like a conventional camera but in a much lower part of the electromagnetic spectrum. In contrast, an active sensor transmits a carefully designed sounding waveform and processes the echoes coherently to extract range, Doppler and angle information at a high accuracy and resolution. Both will now be discussed in more detail, followed by an introduction to an emerging application area: biomedical sensing and imaging.

1) PASSIVE IMAGING

The THz imaging state of the art reports two main competing categories of THz two-dimensional (2D)-array image sensors. On the one hand, there is the above-IC bolometer[3] based THz image sensors based on a classical infrared (IR) sensor, which offers high sensitivity and currently has a good maturity [64]. However, using two circuits (the sensor layer and the CMOS circuit for the data extraction) and the necessary above-IC technology for assembling the layers make bolometer based image sensors expensive. On the other hand, monolithic CMOS-based THz imagers have recently emerged as a low-cost competitor [65], [66]. For these images, two kinds of architecture exist. First, the THz detection can be carried out by heterodyne demodulation. However, due to the pixel architecture and its high power consumption, such an imaging pixel cannot be used in a 2D-array sensor, and its use is limited to raster scanning techniques. The other possibility is to use incoherent (or direct) detection using a simple MOS transistor, resulting in a pixel with low complexity and power consumption. The THz antenna and its MOS detector provide a low-frequency output signal, proportional to the THz wave, which is amplified prior to readout. This property allows using a quasi-classic image sensor readout scheme which is fully compatible with 2D-array sensors. Even with their poor current sensitivity (1000 times less than bolometer-based sensor), this MOS-based THz image sensors have proven to be a viable cost-effective alternative to bolometer-based imagers.

2) ACTIVE IMAGING

We envision two distinct application areas for active imaging: active radar and material sensing.

Active radar imaging makes it possible to add the range and even Doppler dimensions to the image (3D or four-dimensional (4D) imaging). On the lower edge of the

[3] A bolometer is a device that measures the power of incident EM radiation via the heating of a material with a temperature-dependent electrical resistance.

spectrum, in the mmWave and low THz bands, radar imaging is evolving fast to satisfy the requirements of advanced driver assistance systems (ADAS) and autonomous driving. This trend resorts to MIMO techniques whereby a virtual antenna array is created with a size equal to the product of the number of transmitting and receiving antennas. 79 GHz radar imaging with a wide field-of-view, resolutions of 1 deg and a cm-scale range resolution is experimentally feasible today, and radars with a wide field-of-view and light detection and ranging (LIDAR)-like resolutions are an active field of applied research. Using higher carrier frequencies such as 140 or 300 GHz is a longer-term trend, resulting in a smaller form factor or better angular and range resolutions, thanks to the wider bandwidths. Some experimental systems already show the potential of CMOS in the low THz regime (140 GHz) [67]. Active radar imaging has interesting applications beyond automotive radar such as body scanning for security, smart shopping and gaming. For shorter range applications, antennas can even be integrated on-chip [67] in bulk CMOS for ultra-low form factor gesture recognition, vital sign monitoring and person detection and counting. It is expected that SiGe or III-V compounds will complement CMOS for the RF part when the carrier frequency is higher than about 200 GHz [68], [69].

In addition to active radar sensing, the vastly wider channel bandwidths, narrow beams and compact antenna arrays at the THz band also enable material sensing. Fundamentally, it is the THz-specific spectral fingerprints that many biological and chemical materials possess that brings a great deal of potential to THz wireless sensing. For instance, THz rays can be used to study water dynamics by analyzing molecular coupling with hydrogen-bonded networks, as well as to monitor gaseous compositions via rotational spectroscopy. THz time domain spectroscopy (TDS) is typically used in such sensing applications, which consists of probing a material/medium with short pulses, the frequency response of which covers the entire frequency band, and recovering the absorption or transmission coefficients at the receiver. Following signal acquisition, a variety of signal processing and ML techniques can be used to pre-process the received signals, extract characteristic features, and classify the observations.

As an alternative to THz-TDS, and with the advent of THz technology, carrier-based sensing setups can be used, assisted by ultra-massive MIMO configurations. For example, each subset of antennas that is fed by a single RF chain can generate a narrow and directed beam at a specific target frequency. With such fine-tuning capabilities, only a select few carriers can investigate the components of a medium by selecting these carriers to be close to the resonant frequencies of target molecules, for example. In such a carrier-based setup, THz sensing can be piggybacked onto THz communications [38]. However, many challenges need to be addressed, from a signal processing perspective to enable efficient joint THz sensing and communications.

3) BIOMEDICAL APPLICATIONS

Thanks to advances in semiconductor technology, packaging and signal processing, THz imaging is gaining interest in a number of application areas [70]. Healthcare has the potential to be transformed by digital health technologies, including highly compact and wearable biosensors, which are garnering substantial interest due to their potential to provide continuous, real-time physiological information via dynamic, non-invasive, contactless measurements. microelectromechanical systems (MEMS) sensors (e.g., inertial measurement units, pressure and temperature sensors) are now widespread in consumer devices (e.g. smart phones and smart watches), and both these and heart rate sensors are becoming more widely used in medical applications. However, there is a need for more radical mobile sensor technology to provide passive, continuous, home-based monitoring of biochemical markers in biofluids, such as sweat, tears, saliva, peripheral blood and interstitial fluid. THz imaging and spectroscopy has the potential to provide such a data source for future digital health technologies. For example, the measurement of chemicals in sweat has great potential to impact diverse medical applications, including wound healing, metabolic activity, inflammation and pathogens, and proteomics. Current commercial and research THz systems which are suitable for biomedical applications (such as Teraview [71] and Terasense [72]) have a high cost and use bulky optical components. THz integrated CMOS design trends including the source and essential capability of beam steering in a module or by extension a system in package (SIP), will provide highly compact sources that leverages existing advanced electronic manufacturing processes to deliver a product at a small fraction of current production price points. The compact size of the sources would also reduce other product costs including distribution and installation.

4) CHALLENGES

THz sensing and imaging target small defects in materials thanks to the small wavelength of THz frequencies for industry market; clinical, bio and agro-food analysis thanks to O_2 or H_2O peaks of absorption in the spectrum. The technology is also useful for security imaging thanks to the contrast between water-based tissues and other materials. This poses specific challenges for the transmitters and the receivers.

Challenges for transmitters: Specific H_2O absorption peaks are at THz frequencies, except the one at 180 GHz. To create contrast, the radio source must provide radiated power and a focused beam. The available power gain depends on the Fmax value (which yields the frequency when the transistor power gain is 0 dB) of the technology, and the available power output depends on the breakdown voltage of the transistors; the trade-off between these characteristics must be solved by silicon technologies to reduce the size and cost of applicative solutions. The focused beam can be obtained by antenna arrays, but the integration of these objects is

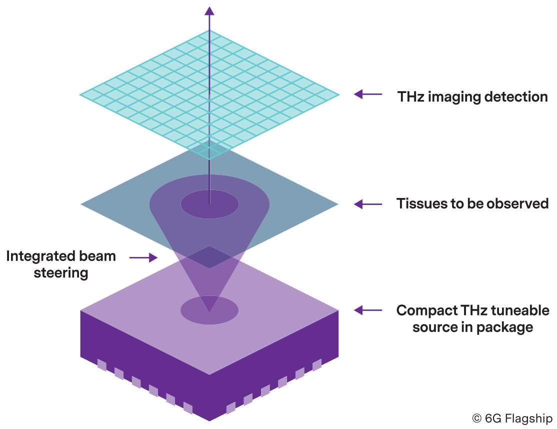

FIGURE 8. Direct THz imaging.

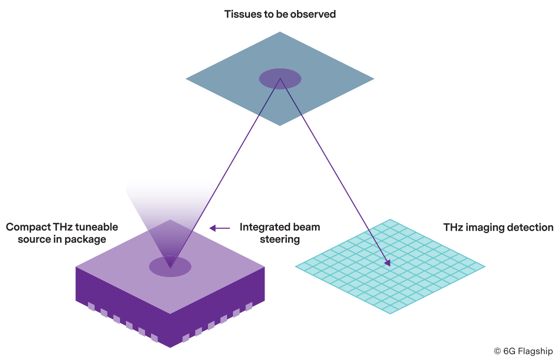

FIGURE 9. Reflected THz imaging.

a challenge. In addition, the orientation of the beam requires phase array functions, which at THz frequencies, requires either active solutions, and we come back to the Fmax-BV (Breakdown voltage represents the maximum DC voltage before the breakdown of the transistor) trade-off, or passive solutions using a new material phase shifter, with through path loss and integration challenges.

Challenges for receivers: The sensitivity of passive imagers, based on the illumination of MOS passive transistors, is not optimized. The technological challenge in the next years will be to optimize the sensitivity of the transistors to THz sources, and to reduce the size of these transistors, in order to increase the image definition and contrast. The sensitivity of coherent receivers (active), mainly for radar applications, is also a big challenge. This is defined by the Noise Figure Min (NFmin) of the technology, and the local oscillator (LO) phase noise at THz frequencies. The process technology NFmin must be reduced at very high frequencies, while the design challenge will focus on the LO generation, even if the technology selection determines the $1/f$ cut frequency.

B. SIMULTANEOUS LOCALIZATION AND MAPPING

In simultaneous localization and mapping (SLAM), mobile devices are considered as sensors, with time-varying states

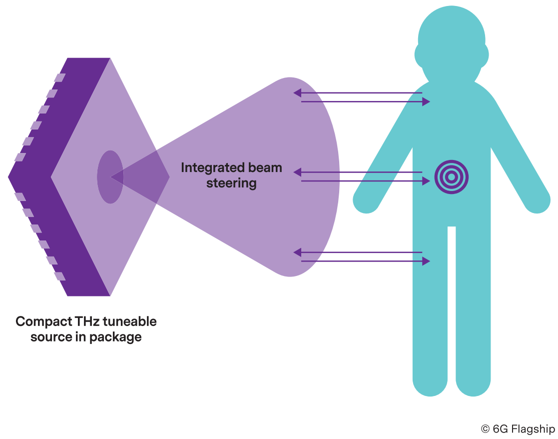

FIGURE 10. Radar application.

(position, pose, as well as their derivatives), and landmarks (object), with fixed or slowly changing states. Both sensor states and landmark states are a priori unknown. A sensor moves through the environment and collects measurements in its local frame of reference related to the landmarks. These measurements may be from 6G radar-like signals originating from the mobile device or from fixed infrastructure. The sensor has an associated mobility model, describing the evolution of the sensor state statistically as it moves. SLAM algorithms aim to recover estimates of the sensor state (including the entire sensor state trajectory) as well as state estimates of the landmarks. SLAM methods differ in their measurement models, as well as the way they process (online or in a batch) and represent state statistics (e.g., parametric distributions or particles). The most common batch-based method is GraphSLAM [73], which constructs a factor graph, with vertices that correspond to the poses of the sensor at different points in time and edges that represent measurements. A global optimization is then run to recover the sensor's poses and localize the sensor within the map. It should be noted that beside SLAM, the factor graphs running message passing algorithm with the use of various EM properties such as AoA, time of arrival (ToA), time difference of arrival (TDoA), received signal strength (RSS) and differential received signal strength (DRSS) for localization, as well as extended Kalman filter (EKF) for tracking purpose, have been employed in the past two decades [74]. The online methods vary from simple EKF-SLAM to sophisticated methods based on random finite set theory [75]. All these methods must account for unknown data associations between the measurements and landmarks, leading to a high computational complexity.

Performing SLAM using 6G radio signals instead of laser or camera measurements is more challenging than conventional SLAM systems because the range and angle measurements are much less accurate and might be subjected to strong outliers because of the non-ideal antenna radiation pattern (sidelobes) and multipath. Therefore, ad hoc measurement models tailored to radio propagation characteristics need to be developed. In particular, the measurements are expected to be rich, comprising angle and delay information, while at the same time the state model is likely to be complex, treating a sensor not as a point with a 3D location, but also with an orientation in 3D (with a specific pitch, roll, and yaw angle) [76]. Moreover, the higher resolution of measurements leads to a fine-grained view of the landmarks in the environment. Hence, refined state models must be considered, e.g., including the EM properties of objects, their size and orientation, as is currently done in radar [77]. More specifically, leveraging the geometry side information captured by THz imaging [1], the gap between LIDAR-based and radio-based SLAM will be reduced by opening new appealing perspectives such as the possibility to construct and update automatically accurate maps of indoor environments taking advantage of the pervasiveness of end-user devices, including smartphones and smart glasses, as well as other cross reality (XR)-tailored devices in the 6G era. In fact, user devices could act as *personal radar* devices that scan the surrounding environment obtained from the radio signal range and angle measurements. These raw ''radio images'' measurements can be shared according to the crowd-sensing paradigm and used as input for SLAM algorithms. The automatic generation and update of indoor maps will enable new services such as infrastructure-less and map-less localization [78]. 6G SLAM methods will also find applications in augmented reality (AR) / virtual reality (VR) / mixed reality (MR) and the localization of autonomous vehicles and drones.

1) CHALLENGES

The main challenges in 6G SLAM will be the development of novel models for the landmark state and the derivation of powerful, but low complexity algorithms that can run on mobile devices, possibly supported by distributed mobile edge computing (MEC). Due to the extremely high data rates, hardware impairments are expected to be a major limitation. On the other hand, as SLAM deals with the movement of objects on slow time scales, e.g., m/s and rad/s, there is plenty of time during which the environment is practically frozen to process and collect the measurements.

C. PASSIVE SENSING USING TRANSMITTERS OF OPPORTUNITY

Passive sensing (sometimes referred to as passive radar or passive coherent location) is an emerging technology by which the energy reflected by static or moving reflectors is received and processed by a receiver device to extract information about the objects. It is passive in the sense that no signal is transmitted for this purpose: the receiver opportunistically uses radio waves (usually wireless communication signals) transmitted for other uses such as cellular, Wi-Fi, TV or radio broadcasting signals. It can be viewed as a bi-static radar where the transmitter is not ''controlled by'' or ''synchronized with'' the receiver. The receiver typically uses prior knowledge of the physical layer and frame structure of the wireless standard in use to extract information about the environment. Although not strictly necessary, it is easier for the processing receiver if it uses a separate antenna channel to receive the LOS signal from a wireless transmitter. Signals from stationary transmitters (BS, access point (AP) or broadcast antennas) are preferred since echoes from static reflectors then have zero Doppler, although static clutter removal may be challenging [79]. Passive sensing is also non-cooperative in nature since detected objects and targets do not communicate with the receiver, nor do they carry special reflectors or transponders to help the receiver. For moving targets, passive sensing allows several interesting applications such as vital sign monitoring, fall detection, presence detection, intruder detection, human activity recognition, localization and more [80]. In addition, passive sensing could potentially help to create maps of the static environment. Passive sensing has also been reported in through-the-wall detection/imaging.

We foresee an increased interest in and deployment of passive sensing, supported by the progress in signal processing, compressive sensing and machine learning. Going in this direction, the IEEE 802.11 Working Group created the ''WLAN Sensing Study Group'' that is studying the creation of a Task Group to draft the 802.11 standard for WLAN sensing [81]. Very advanced examples include the use of Wi-Fi signals to to carry out through-the-wall imaging [82], the use of digital video broadcasting signals to carry out 2D passive radar imaging with inverse synthetic aperture radar (ISAR) techniques [83] and [84] and the use of 5G signals to locate road users [85]. Signal processing for passive sensing borrows much from radar signal processing. A major difference is in the waveform design since chirp-based waveforms are not common in wireless communications, and the wireless modulation is typically not optimized for the (range-Doppler) ambiguity function. Therefore, the matched filter processing is usually different. Building range-Doppler maps and range-Doppler-angle radar data cubes is the ultimate goal of passive sensing, and this goal is often not achieved with the same quality and SNR as for conventional active radars. The whole arsenal of ML methods (see Section II-D), including hand-crafted feature extraction, deep learning and even spiking neural networks, could be adapted to passive sensing.

1) CHALLENGES

Because of its opportunistic nature and the impossibility to control the transmission, passive sensing will almost always achieve a lower degree of performance than a conventional active radar. The challenges that must be addressed to improve the performance of passive sensing in 6G networks are numerous: improving the quality (SNR, multipath-free) of the reference signal; maintaining the coherence-on-receive over long observation times towards fine Doppler resolution; removing the static clutter and coping with multipath reflections which create ghosts; accommodating the limited bandwidth, and hence the range resolution of the wireless signals (e.g. a 20 MHz signal translates into a range resolution of 15 m); in the spatial dimension, improving the angular resolution and coping with the non-uniform illumination due to the environment and transmitter beamforming. The implementation of low-cost, low-power terminals involves several challenges, such as carefully balancing the use of data-aided (i.e., preamble) and non-data aided (i.e., communication payload) signals and reusing existing RF and digital hardware.

D. ACTIVE SENSING WITH RADAR AND COMMUNICATIONS CONVERGENCE

The use of radar was for a very long time limited to applications in the military, aviation, law enforcement and meteorology using large and expensive antennas and equipment. However, more recently, advances in semiconductor technology, antenna design and signal processing [86], [87] have made low-cost integrated radars readily available. On account of this, radar usage has also exploded in the consumer market, particularly in the automotive industry, where features such as adaptive cruise control, lane change assistance and cross-traffic alerts rely on radar sensing. Beyond this, new applications are emerging, such as intruder detection, gesture recognition, and heart rate and respiration rate monitoring, among many others. Radar detects the range, angle and velocity of objects based on the propagation of EM waves, which are reflected by these objects, and, as such, rely on the same physical phenomena as wireless communications. In spite of this, current radar systems use dedicated chipsets and antennas, and have reserved frequency bands, for instance, in the ultra wideband (UWB), 24 GHz and 76-81 GHz bands. However, wireless communication technologies are converging towards the requirements of radar systems, with the increasing usage of directive antenna patterns through beamforming and transmission at higher frequencies with wider bands, which are required for angle and range resolution. The rise of new applications and market demand, together with technological developments both in the radar and in the wireless communications industry, make the integration of both technologies in a single system desirable and feasible in the near future.

There are several ways in which radar and communications may operate in the same spectrum: coexistence, cooperation, and co-design. Coexistence uses cognitive-radio techniques and beamforming is used to avoid interference in time and space domains [88]. This is a good approach when large-scale radar systems, such as aeronautical or meteorological radars are considered, but not for more dynamic scenarios and applications, as in the automotive branch or in the consumer market. In such cases, cooperation is an option, whereby the radar and communication sub-systems operate largely independently, but exchange information to support each other, in particular for interference mitigation. For instance, in-band communications may also help radar detection, in that it allows the exchange of information between different sensors, and, on the other hand, radar may help communications, for instance, by gathering information about obstacles and reflectors, that may aid beam tracking. As a third alternative, co-design is a more promising approach, in which a single

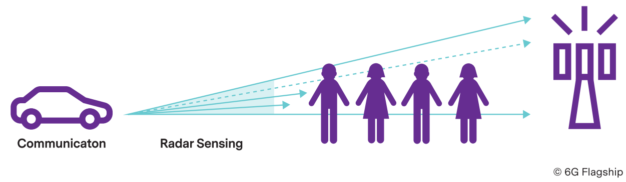

FIGURE 11. Interplay between communications and radar.

waveform is employed both for radar and communications. This is likely to be the path taken in 6G systems, and it brings about advantages and opportunities, such as more efficient and flexible use of spectrum for different purposes, as well as lower costs through hardware reuse and integration and lower energy consumption than in two separate systems. The concept of a joint radar and communications system is depicted in Fig. 11.

As already mentioned in Section III-A and Section III-C, 6G systems will probably rely on both passive and active radar principles. In active radar, as we can leverage the knowledge of the transmitted signal as a reference, more precise and accurate results can be expected, but some hardware and signal-processing challenges may arise, particularly to deal with a strong self-interference at the radar receiver. Both passive and active radars are likely to be employed simultaneously, and the information provided by both can be combined by means of sensor fusion to provide a rich and accurate mapping of the environment. In any case, with new applications and requirements in mind, the 6G waveform will need to be designed so that the following features are enabled: (i) good radar performance in terms of range and resolution in 4D (range, velocity, azimuth and elevation angle); (ii) good communication performance in terms of spectral and power efficiency; (iii) flexibility between communications and sensing needs as well as for different radar needs (e.g., short-range/long-range and different resolutions).

1) CHALLENGES

While communicating and sensing with the same waveform promises many advantages, there are some significant challenges to be solved. The waveform design must satisfy tradeoffs between the communications and radar requirements listed above. Improved radar detection and estimation algorithms are needed for wireless communications scenarios, which are characterized by high mobility, multiple targets and clutter. Techniques employing compressed sensing and ML may be required. Additionally, suitable hardware architecture is needed, including antenna design, duplexing, analog-to-digital conversion, mixers, accounting for different radar and communications receivers. Interference is likely to be a difficulty. Self-interference is a significant issue in active radars. In-band full-duplexing is de-facto needed, and the antenna, waveform and signal processing have to be designed to minimize its impact as much as possible.

The increased usage of radar for different applications will also result in higher interference levels between

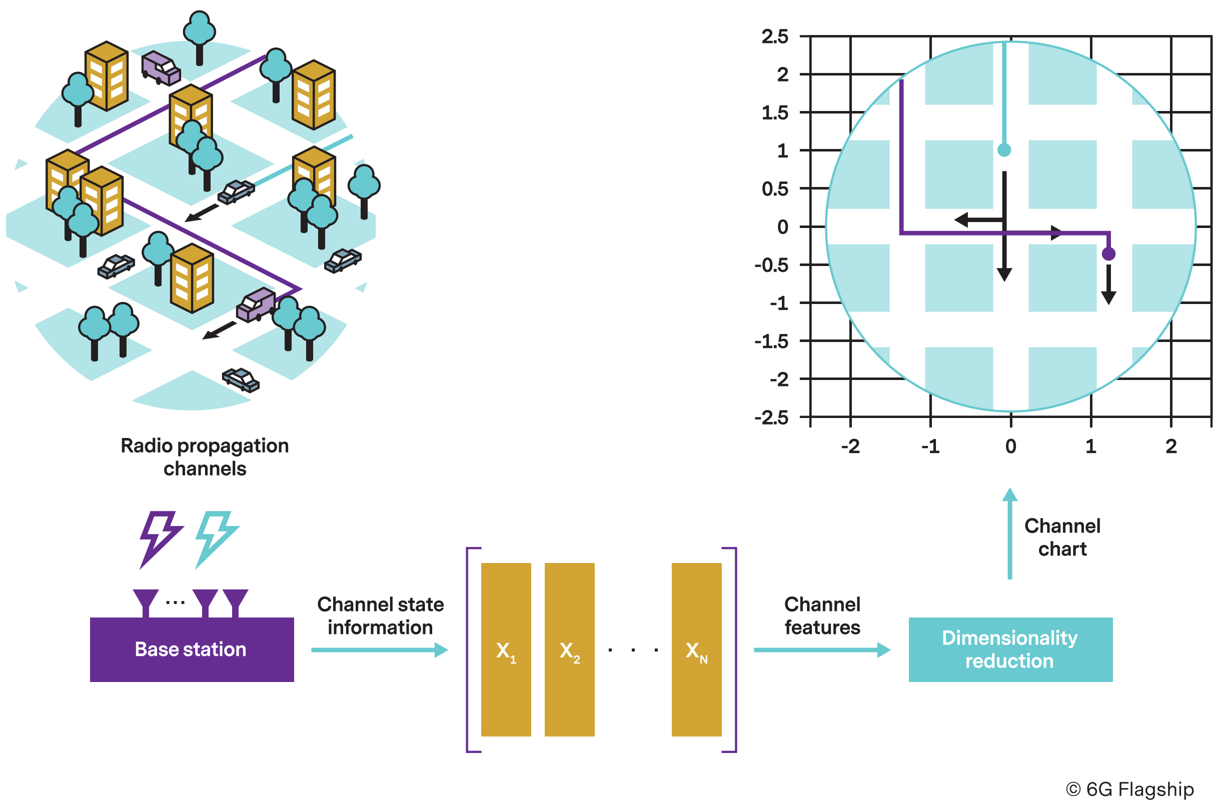

FIGURE 12. **Channel charting uses dimensionality reduction techniques to generate a pseudo-map of the wireless propagation channel, and associates the user CSI to a pseudo-location which can be tracked consistently across the users and over time.**

different users. Interference management and cancellation techniques will be needed, although the large difference in transmission powers needed for communication and reliable radar detection will make this challenging. However, the challenges are not all related to signal processing and the physical layer. New medium access control (MAC) protocols and radio resource management (RRM) algorithms will be needed to allocate the radio resources according to the needs of different radar and communication services. A better understanding of the trade-offs between radar and communications KPIs may be necessary. A few preliminary works bring some insight on these performance trade-offs. For instance, in [89] the authors derive some fundamental theoretical bounds for the co-existence of radar and communications, and in [90] analytical results are obtained following an ALOHA approach.

The design of a full protocol stack and network architecture for a joint communications and sensing system is however a more complicated problem, in which we must consider systems with multiple cells and beams, as well as use cases with widely different requirements. This problem has been already extensively addressed in communications, in which the network, protocols and RRM algorithms are designed to accommodate different services, like mobile broadband, URLLC and mMTC. In the future, however, similar issues will apply for radar sensing, in which the requirements can be very different, for instance between indoor imaging and vehicular collision avoidance, just to name two applications, and a sensing QoS will have to be defined. The integration of localization and sensing cannot be forgotten either, and the requirements in outdoor and indoor use cases are likely to be widely different. Signalling overhead will have to be kept in check, and, additionally, network concepts like slicing will have to be extended to include radar sensing and localization services. Protocol and network design beyond the physical layer remains however an open issue, and, to the best of our knowledge, there is little to no literature in this subject.

E. CHANNEL CHARTING

Channel charting [91] is a baseband processing approach involving applying classical unsupervised dimensionality reduction methods from machine learning to CSI. Based on a large dataset of CSI samples acquired in a given environment, it creates a virtual map (known as a *chart*) in an unsupervised manner, on which the users can be located and tracked. Due to the unsupervised nature of the approach, channel charting is applicable to situations where there is not enough information available about the geometric properties of the scattering environment to build a faithful geometric model of the user's environment and location. Despite the fact that a position on the chart cannot be readily mapped to a user location, it provides a real-time pseudo-location within the cell, which is consistent across the users and over time (Fig. 12), without the need for expensive dedicated measurement campaigns to obtain a labeled CSI dataset as required by fingerprinting methods, for example. The tracking of the pseudo-location on the chart can be used to enhance numerous network functionalities, e.g., for predictive RRM and rate adaptation, handover between cells, mmWave beam association and tracking and UE pairing or grouping in device to device (D2D) scenarios.

Although it does not replaces a true position in location-based applications, the use of a pseudo-location has certain benefits. First, the unsupervised nature of channel charting allows some form of self-configuration that does not involve any prior information (such as an area map, or knowledge about the geometry of the surrounding buildings); this is a handy feature for the deployment of temporary or emergency networks. Pseudo-location can also be seen as a privacy protection feature, allowing applications such as contact tracing to be implemented without ever requiring the actual user position to be estimated.

1) CHALLENGES

Channel charting has been developed initially within the massive MIMO paradigm, where scattering is rich and prominent RF propagation features are expected to be stable (or evolve slowly) over time. Applying this approach to higher frequency bands (where LOS propagation dominates) will be likely to require extending it to jointly process signals from multiple transmission points. Other open questions associated with charting stem directly from the ML roots of channel charting, such as the ability to implement life-long learning, or optimal feature design for CSI signals.

F. CONTEXT-AWARE LOCALIZATION SYSTEMS

6G should allow for the phenomenological interpretations of ''context'', i.e., it should allow for the interpretation of the situation of entities through action. Physical, cultural and organizational contexts shape actions and create the conditions for humans to interpret and understand their actions. This is done not only by the measurable characterization of entities such as a person, place or object, but also by combining this with the understanding of the activity and temporal aspect of the behavior. Context-awareness is equally important in detecting the contextual factors of devices, and humans [92].

6G applications will be able to benefit from context-awareness in several ways. Applications will consume less energy because an application knows when it is ideal to communicate. Context-awareness allows intelligent prediction of data transmission, which can allow better throughput on demand. Context-awareness can be used to move personalization algorithms and sensor data intelligently into parts of the network where storage and computation are fast and feasible, which would allow the hyper-personalization of services. Intelligent storage and distributed processing capabilities will allow the fusion of sensor data for detecting trends and deviations, which are essential for example in healthcare scenarios [92], [93]. Context-awareness also allows multi-modal localization, where mobile devices can switch between different channels and communication technologies depending on the current location or context. Multi-modality enables devices to reduce their power consumption, increase the quality of service, and select local or private technologies versus national or public technologies. As a consequence of these differences in communication modalities, different localization methodologies must be implemented as well, based on context-awareness [94]. 6G can also boost the following specific trends in context-awareness. First of all, it will be able to detect trends and deviations, i.e., understand the temporary aspects of context through storage of context history, and processing of temporal context data. This is needed, for example, in hyper-personalization, where real-time deviations of a person's status are detected. Secondly, advanced temporal context detection algorithms have special security concerns as they combine highly personal data (such as physiological measures of humans) with open, public data (such as weather conditions). Storing and processing this data in different parts of the infrastructure requires intelligent security solutions. Finally, distributed context-awareness requires a high level of standardization of context parameters. Without standardized interpretation rules for context parameters, it will be impossible to build connectivity infrastructures that can translate the context into assets for applications.

1) CHALLENGES

Challenges to implement and adopt such context-aware features include, the standardization of context parameters and operating principles for fair data economy facilitating flow and combinations of different data sources governed by a heterogeneous ecosystem.

G. SECURITY, PRIVACY AND TRUST FOR LOCALIZATION SYSTEMS

It is expected that more and more stakeholders will be involved in the 6G positioning chain, i.e., virtual network operators, and that there will be an increased number of location-based service providers due to the developing new applications and services. There will also be multi-user devices supporting cooperative and opportunistic services. All such stakeholders in the positioning chain will be able to benefit from the availability of new security, privacy, and trust solutions for localization systems. For instance, secure location information will be able to be increasingly used as a security parameter for digital interactions in more general contexts, for example, automated driving, health monitoring, social media, surveillance systems, etc. In order to reduce the power consumption of user devices and to enable massive location-based IoT connectivity, it is likely that network- and cloud-based localization solutions will become much more widespread than device- and edge-based localization solutions. This raises the questions of trust in the network- and cloud-service providers, as well as in the location-lased service providers. A detailed discussion on the research challenges for trust, security and privacy in future 6G systems is provided in [95].

1) CHALLENGES

Service providers' vulnerabilities could be exploited by possible attackers to extract user's location patterns and to misuse the information for identity thefts, burglaries, toll avoidance, stalking, etc. [96], [97]. Privacy concerns due to the future use of THz communications on hand-held devices and wearables have been already raised, e.g., in [38]. An attacker or a malicious device could conduct THz-based remote sensing and see-through imaging that could be privacy-invasive. Radar-like localization solutions are also emerging based on 4G and 5G signals and advances in full-duplex communications [98]–[100], and it is likely to be expanded beyond 5G as well. High-resolution imaging combined with machine learning techniques could be invasive of privacy; for example, radio frequency fingerprinting (RFF) [101], [102] can identify user devices even in the absence of transmitting a device identity.

IV. SUMMARY AND RESEARCH QUESTIONS

Herein, we identified not only several key technological enablers toward 6G localization and sensing systems but also novel applications and service opportunities. These enablers correspond to the new RF spectrum at the high-frequency range, especially above 100 GHz and beyond; the introduction of intelligent reflective surfaces which allow network operators to shape and control the EM response of the environment; advanced beam-space processing to track users and objects, as well as map the environment; the pervasive use of artificial intelligence leveraging the unprecedented availability of data and computing resources to tackle fundamental problems in wireless systems; and advances in signal processing to support novel convergent communication and radar applications. In turn, these enablers will lead to new opportunities in the 6G era. The opportunities highlighted in this work were imaging for biomedical and security applications; applications of simultaneous localization and mapping to automatically construct maps of complex indoor environments; passive sensing of people and objects; using location information as a big data source, guiding and predicting the human-digital ecosystem; the coexistence and cooperation between sensing, localization and communication, leading to one device with this three-fold functionality; and finally, the use of location information to boost security and trust in 6G connectivity solutions.

A joint effort across a large number of scientific disciplines will be required to achieve these goals, much more than the effort required in any previous mobile communication generation. In order to realize these opportunities, fundamental research questions need to be properly addressed. Below are a selection of key questions to be addressed:

1) How can high-accuracy cm-level positioning and high-resolution 3D sensing/imaging be achieved by taking advantage of the 6G key technology enablers?
2) How can novel waveform designs be devised so as to enable convergent communication, localization and sensing systems which efficiently share resources in time, frequency and space domains?
3) How can energy-efficient high-accuracy localization and high-resolution sensing/imaging solutions be devised while operating at a high frequency range and supporting mobility of the communicating objects?
4) How can real-time energy-efficient AI/ML techniques be developed to achieve high-accuracy localization and high-resolution sensing, while leveraging the unprecedented availability of data and computing resources?
5) How can the quality and accuracy gap between passive sensing and active sensing be bridged?

Finally, there are also open questions related to how a convergent communication, localization and sensing 6G ecosystem would look like. We can foresee three levels of convergence:

1) Localization and sensing deeply integrated into 6G wireless communications networks:
   a) Uses the same infrastructure, tailor-made localization and sensing signals that are part of the 6G air interface design, sensing reusing the communications signals, or potentially even jointly designed agile signals for concurrent communication, localization and sensing.
   b) Various kind of mobile networks operators could be the provider of these kind of convergent 6G (public or private) networks.
2) Sensing enabled by 6G connectivity, but where the sensing part is not co-designed with the 6G air interface.
   a) Cooperative sensing that inherently needs 6G connectivity capabilities between the cooperative sensors (e.g. advanced cooperative radar systems).
   b) Sensing whose data is (ML/AI) processed in a cloud, in particular when low latency/high capacity/very reliable wireless connectivity is needed for the cloud access. A typical scenario would be when tight control on the communications and computing in the (distributed) cloud is required for the sensing system.
3) Non-connected sensing/ sensing not connected via 6G, that benefits from the hardware and software developments in the 6G ecosystem.
   a) Localization and sensing systems benefiting from the R&D and efficient manufacturing and testing capabilities of the (3GPP) 6G ecosystem.
   b) 6G could drive availability of low cost and high performing hardware, specially at THz frequencies, enabling sensing in so far not economically viable application domains (including new experimental science domains). To this end, broad research initiatives would be needed to across these borders to maximize the potential of

a convergent communication, localization and sensing 6G ecosystem.

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