COST EUROPEAN COOPERATION IN SCIENCE & TECHNOLOGY

IRACON

COST Action CA15104

Whitepaper on New Localization Methods for 5G Wireless Systems and the Internet-of-Things

COST Action CA15104 (IRACON) aims to achieve scientific networking and cooperation in novel design and analysis methods for 5G, and beyond-5G, radio communication networks. This Deliverable summarizes the expected features and resulting properties of upcoming localization systems exploiting 5G and IoT technologies. It also identifies the important theoretical limitations and practical implementation challenges at hand and recommends potential paths forward towards more accurate, robust, and secure location-based services.

Authors: José A. del Peral-Rosado, Gonzalo Seco-Granados, Ronald Raulefs, Erik Leitinger, Stefan Grebien, Thomas Wilding, Davide Dardari, Elena Simona Lohan, Henk Wymeersch, Jean-Jacques Floch, Andrea M. Tonello, Sarmad A. Shaikh, Thomas Zemen, Troels Pedersen, Thilo Fath, Carles Fernández-Prades, Jordi Vilà-Valls, Reiner Thoma, Marcelo Nogueira, Rudolf Zetik, Wout Joseph, Vittorio Degli Esposti, Andrés Navarro Cadavid, William Arleth Cruz Lopez, Benny Chitambira, Francois Quitin, Monica Nicoli, Rodolfo Oliveira, David Plets, Tuncer Baykas, Biljana Risteska Stojkoska, Kire Trivodaliev, Gloria Soatti, Markus Ulmschneider, Bernard Fleury, Fredrik Tufvesson, Fabian.PonteMueller, Giuseppe Destino, Olivier Renaudin, Norbert Franke, Mohammad Alawieh, Benjamin Sackenreuter

Editors: Klaus Witrisal and Carles Antón-Haro

Date: April 2018

This page is intentionally left blank.

Whitepaper on New Localization Methods for 5G Wireless Systems and the Internet-of-Things

Editors: Klaus Witrisal and Carles Antón-Haro (EWG-LT Chairs, COST IRACON)

Contributors: José A. del Peral-Rosado, Gonzalo Seco-Granados, Ronald Raulefs, Erik Leitinger, Stefan Grebien, Thomas Wilding, Davide Dardari, Elena Simona Lohan, Henk Wymeersch, Jean-Jacques Floch, Andrea M. Tonello, Sarmad A. Shaikh, Thomas Zemen, Troels Pedersen, Thilo Fath, Carles Fernández-Prades, Jordi Vilà-Valls, Reiner Thoma, Marcelo Nogueira, Rudolf Zetik, Wout Joseph, Vittorio Degli Esposti, Andrés Navarro Cadavid, William Arleth Cruz Lopez, Benny Chitambira, Francois Quitin, Monica Nicoli, Rodolfo Oliveira, David Plets, Tuncer Baykas, Biljana Risteska Stojkoska, Kire Trivodaliev, Gloria Soatti, Markus Ulmschneider, Bernard Fleury, Fredrik Tufvesson, Fabian.PonteMueller, Giuseppe Destino, Olivier Renaudin, Norbert Franke, Mohammad Alawieh, Benjamin Sackenreuter
(see affiliations on Page 21)

***Abstract*—Disruptive technologies proposed for 5G wireless systems and the IoT hold promise of providing unprecedented localization capabilities for a wide range of application scenarios and target environments. This whitepaper summarizes the expected features and resulting properties of upcoming localization systems exploiting 5G and IoT technologies. It also identifies the important theoretical limitations and practical implementation challenges at hand and recommends potential paths forward towards more accurate, robust, and secure location-based services.**

***Index Terms*—5G, IoT, Positioning, Application Scenarios, Theoretical Limitations, State-of-the-Art.**

I. Introduction

The use of radio signal for position tracking (positioning) and navigation has a long tradition. Most notably, global navigation satellite systems (GNSS), which originally have been deployed for military purposes, are now widely applied for civilian applications ranging all the way from tracking of cargo containers to gaming. Nevertheless, GNSS suffer from limited coverage in dense urban areas and—in particular—indoors and also from a limited position accuracy.

These limitations rule out most location-based applications that are concerned with the (natural) interaction of humans with their immediate surroundings, the physical environment in which we live, work, and spend our free time. However, GNSS are also too limited to serve the increasing demands on location-awareness, needed for instance for autonomous driving.

K. Witrisal is with the Christian Doppler Laboratory for Location-aware Electronic Systems, Graz University of Technology, Graz, Austria. e-mail: witrisal@tugraz.at

Carles Antón-Haro is with the Centre Tecnpològic de Telecomunicacions de Catalunya (CTTC/iCERCA), Castelldefels (Barcelona), Spain. e-mail: carles.anton@cttc.es

The authors' affiliations can be found on Page 21

Manuscript Timeline: Initial contributions: Jan. 29, 2018; Final Version: March 2018.

The fifth generation (5G) of mobile communication systems and the advent of the Internet of Things (IoT) will provide a range of new, advanced wireless technologies. The purpose of this white paper is to highlight the expected benefits of these new wireless technologies for the purpose of improved positioning.

A. Structure and Scope of this Document

The paper starts with a summary of the most promising future application scenarios for high-accuracy positioning (Section II) followed by a discussion of the technical challenges arising from the applications (Section III). We next illustrate in Section IV the expected features and limitations of 5G and IoT wireless systems with respect to positioning. Section V is an attempt to describe the state-of-the-art of recent scientific and technical progress in the field, highlighting the aspects of radio channel modeling, performance limitations, algorithms, and technical realizations. Positioning testbeds and prototypes are described in Section VI, followed by non-technical challenges such as privacy regulations, recommendations, and conclusions in Sections VII– IX.

This white paper has been authored by members of the Experimental Working Group "Localization and Tracking" of the COST Action IRACON "Inclusive Radio Communication Networks for 5G and Beyond" (www.iracon.org). The aims of this COST Action range from achieving scientific breakthroughs by introducing novel design and analysis methods for the 5th-generation (5G) and beyond-5G radio communication networks, to making available several platforms that will allow testing new solutions in real conditions, and the training of young researchers.

Necessarily, the scope of such a white paper needs to be limited. We'd like to point the interested reader to a number of excellent, recent tutorial and review style articles that have focused on several of the specific issues involved. In particular, [1] envisions mm-wave based, single-anchor positioning systems for indoor applications, [2] identifies the key properties of 5G as they relate to vehicular positioning, [3] is a survey on robustness, security and privacy in location-based services for the future IoT, [4] is a survey of cellular mobile radio localization methods, from 1G to 5G, and [5] is a survey of reliable and accurate indoor positioning system for emergency responders.

B. Standardization Efforts

3GPP has been been working in the past on the standardization of positioning capability for LTE and prior generations and has definite plans for positioning inside future 5G with ambituous performance goals in mind [4]. For the state of discussion on 4th and prior generation positioning, the 3GPP Study on indoor positioning enhancements for UTRA and LTE (TR 37.857) [6] delivers a comprehensive evaluation of achievable performance and possible enhancements within LTE constraints. The study considers techniques directly based on cellular signals as well as techniques external to 3GPP's radio interface (e.g. terrestial beacon systems, use of barometer) that still can deeply be integrated at protocol level. A precise overview on the positioning feature of 3GPP's narrowband IoT technology NB-IOTs that was standardized during release 14 (March 2017) is given in [7]. Explicit standardization of positioning for 5G is yet to start. 3GPP continuously discusses the refinement of its roadmap and explicitely names positioning as one of the tasks for release 16 (starting from June 2018). [8] gives up-to-date insight into working procedures and topics to be tackled during release 16. There will likely be two different paths to pursue work: positioning based on the Uplink and Downlink signals of New Radio (NR), while Device-to-Device (Sidelink) based positioning for Vehicle-to-Everything (V2X) will be treated in a separate work item. Proposals to structure the approach for both are put forward inside 3GPP. [9] shows how companies around Intel imagine NR positioning support and [10] (LG Electronics et al.) is an equivalent view on the upcoming standardization phase of V2X, the first to incorporate NR and high accuracy positioning.

II. New Application Scenarios and End-user Requirements

A. Intelligent Transportation Systems

In the context of ITS, positioning is required, both from the point of view of individual vehicles and from a vehicle network perspective. From the point of view of a single vehicle, ego-positioning has in the past largely been limited to navigation applications, where GPS accuracies were sufficient. With increased levels of automation, more precise positioning is needed to ensure vehicle stay within planned trajectories. Supplemental information of obstacles, vulnerable road users and other vehicles relative position with respect to the vehicle for safe maneuvers is crucial. Vehicles sense their environment and connect to the vehicle network perspective, where both absolute and relative position information of vehicles is needed for completing cooperative maneuvers. In all these scenarios, due to the possibly high mobility, position information must be both timely and accurate. Specific requirements have been listed by 5G automotive [11] for several use cases. These include automated overtake, cooperative collision avoidance, and high-density platooning, which all require 30 cm accuracy with 10 ms delay. In addition vulnerable road user discovery requires 10 cm accuracy, though no delay listed. Accuracy requirements were derived from the physical size of vehicles, people, and roads, but did not account for velocities. The delay requirements is derived from a controller, operating at 10 times the steering frequency (100 Hz). Requirements based on typical velocities were detailed within the EU H2020 HIGHTS project [12], surveying results of known ITS Geolocation requirements. A large number of use cases are listed, of which we here mention those with the tightest requirements in terms of accuracy and delay: intersection coordination (20 cm, 100 ms), vulnerable road user localization (20 cm, 1 s), platooning (10 cm, 20-50 ms), which are similar to those of EU H2020 TIMON project [13]. Finally, the more recent EU H2020 5GCAR project includes among its objectives to propose 5G radio-assisted positioning for vulnerable road users and vehicles. For the former use case, the accuracy requirement is 1 meter, with a latency of 10-50 ms.

We conclude that (i) positioning requirements are less than 1 meter, beyond what can be achieved with current radio technologies; (ii) latency requirements are on the order of 10 ms; (iii) 5G positioning is already being evaluated in European projects.

B. Aerial Vehicles

Unmanned aerial vehicles (UAVs) will play a significant role in both civilian and military applications from remote sensing, search and rescue, to environmental monitoring, to aerial communications and networking [14]. UAV navigation and control requires precise localization and tracking. Traditionally, this is realized with data fusion approaches that exploit inertial sensors and global navigation satellite systems (GNSSs) [15], [16]. However, the availability and reliability of GNSS-based position estimates cannot be always guaranteed, for instance in an urban or sub-urban environment because of severe multipath conditions, blockage of the satellites' signals but also due to the increase of non-intentional or intentional interferences like jamming and spoofing [17]. Navigation of UAVs is even more challenging in indoor environments such as warehouses or GNSS denied environments as forests and mines. Vision based navigation is a possible approach that can partially circumvent these limitations. Potential future autonomous UAV navigation applications need to fulfill stringent precision, latency and safety requirements with the foreseen use of terrestrial radio localization techniques. Both ad-hoc solutions, e.g., based on ultra-wideband (UWB) ranging [18], or opportunistic solutions [19], [20] that exploit existing radio transmissions, e.g., in WiFi or cellular networks, for trilateration or triangulation with antenna arrays, can be developed. Mobile radio network based positioning, e.g., provided by 5G communications, can act as a viable supporting positioning scheme. The applicability of these signals of opportunity as alternative and/or supplement to satellite based navigation signals is currently an area of active research with a special focus on integrity. The increasing threat of cyber-attacks asks among for elaborated anti-spoofing solutions. In the context of airborne applications, operations are usually executed in real-time. Therefore, especially if integrity requirements are not met warning messages have to be communicated with a latency in the order of a few ms only.

C. Industrial Applications

Industrial applications were classified in [21] under three groups: industrial control, factory automation and process automation. The requirements in these groups vary between the applications: Industrial control and factory automation demands precise positioning, low latency and the need to support very high reliability and availability. For example robot positioning applications will require [21] that the positioning accuracy is within 10 cm and the latency is less than 15 ms. These two groups are similar to the intelligent transportation systems in terms of requirements while the operation range is shorter. Industrial process automation targets monitoring and tracking operations of IoT devices (for example tracking valuable tools, containers or electronic equipment). Here massive number of devices are foreseen; in addition, the battery lifetime of the nodes shall operate over multiple years. Requirements on the positioning accuracy are application dependent and can be challenging for this class of devices when targeting below 0.5 m accuracy level inside an industrial plant. Prior solutions for addressing industrial application have been mostly based on RFID tags as low cost solutions. For example applications that rely on dispatching goods by using RFID readers to check them in when they arrive at a logistics center or warehouse, and to check them out again when they leave. An RFID tag provides information during the reading event if the reader is close by the goods. IoT mobile positioning requirements differentiate to others by the low power consumption, the low price of the devices and the needed infrastructure for communications. GNSS-IoT based solutions often fails to acquire a position in an industrial environment or even to sustain the energy consumption constraints of IoT applications.

D. Retail and assisted living

With the rapid growth of location-enabled applications, the potential mass market opportunity for high-accuracy indoor positioning is huge, especially in sectors like retail, marketing, tourism and health-care. In retail, precise indoor navigation can be beneficial for consumers to easily navigate to their desired products, and also for the management to track consumer movement habits and to perform optimal product placement. Moreover, identifying consumers behavior and in-store movements in big shopping malls or airports, can be used for proximity marketing and advertisements [22], [23]. In museums and galleries, such applications track visitors, recognize the artwork in front, and provide the visitors with an automated description about the artworks [24]. For ambient assisted living, location discovery is crucial for context-aware service provisioning, ranging from home entertainment and home automation, to activity detection and elderly monitoring for medical tele-care solutions [25] or inside hospitals [26]. The common requirements of those applications are position accuracy of about the human range, minimal setup efforts, easy usage and low complexity of the algorithms, full coverage, adaptiveness to the environment, low power consumption and scalability, while tolerating latency of a few seconds. Existing solutions based on WiFi or Bluetooth provide latencies between 2–5 seconds [26], with accuracies ranging from 23 cm [27] to 4 m [26] for WiFi and 2–4 m for Bluetooth.

E. 3GPP Approach Towards Positioning Use Cases and Requirements for 5G

3GPP as the joint standardization body of mobile network operators, equipment supplier and chipset manufacturers has been addressing the definition of next generation use cases for 5G from early on. The SMARTER study (Feasibility Study on New Services and Market Technology Enablers) [21] collected already during 3GPP release 14 about 74 use cases grouped into five categories: Enhanced Mobile Broadband, Critical Communications, Massive Machine Type Communications, Network Operation and Enhancement of Vehicle-to-Everything. A great number of the use cases name the need for positioning. Indications on future requirements already make clear that the targets are high, for example sub-meter accuracies and low latency values below 15 ms for positioning results. Requirements have been further studied, for example as collected in the central Study on Scenarios and Requirements for Next Generation Access Technologies TR 38.913 [28]. This document gives for the first time, in Section 9.2, an outlook on the actual realization of 5G positioning. For example the support of hybrid positioning methods (sensor fusion of various RAN-embedded and RAN-external techniques) and the use of high bandwidth and massive antenna systems. Positioning performance shall be scalable to suit different use cases and it shall support a large number of devices. Current work continues during the early stages of release 16 and refines the definition of positioning use cases in the draft version of the “Study on positioning use cases" [29].

III. Technical Challenges

End-user requirements dictate the performance levels needed for any technical system. This section describes a number of challenging demands that have been identified for emerging location-aware services.

a) Heterogeneity: Arising from the wide variety of potential applications, the challenge of heterogeneity has to be discussed. Unlike GNSS and cellular networks, where a single technology platform is capable of supporting an extremely wide range of application scenarios (in case of GPS and GSM, literally with a “global” coverage), a *diversity of (wireless) technologies* will be needed to support location-aware electronic systems with the performance requirements outlined above. Smartphones are a dramatically more powerful platform that already offers a range of wireless interfaces and other sensors supporting localization. Future wireless standards, which are currently being developed under the label of 5G systems, will eventually offer a vastly enhanced localization accuracy and reliability.

Most likely, there will be no single positioning method to satisfy all requirements as stated by [29]. Instead, 5G will serve as an umbrella to combine multiple technologies, such as NR, LTE, and Wifi. Thus, a great diversity of positioning technologies will need to be combined in a data fusion framework. A recent example is the Fine Time Measurement (FTM) Feature of Wifi [30]. Wifi FTM positioning can deliver accurate results in densely populated areas like cities, while GNSS systems are most accurate in open sky conditions. To increase the robustness, other sensors like IMU or magnetic field sensors can be used for dead reckoning. To optimally make use of all available sensors, the LTE Positioning Protocol (LPP) also needs continuous enhancements.

b) Multipath propagation: For radio-based positioning systems, multipath propagation is considered the key physical challenge hindering the implementation of 10 cm-level position accuracy. This applies similarly to indoor systems and to global navigation satellite systems (GNSS)-based vehicular applications. The presence of multiple propagation paths on top of the line-of-sight (LOS) path often degrades the performance of localization algorithms (see Section V-C). Note that, if the propagation paths can be resolved, the presence of multipath can be an asset for localization (Section V-D). However, resolving the propagation paths often requires high-end radio transceivers and large antenna arrays, which are inconsistent with low-cost cellular devices or IoT nodes.

c) Line-of-sight availability: The continuity of service is strongly related to the availability/visibility of infrastructure such as beacon radio signals. In case of radio systems targeting at the 10 cm-accuracy level, even one blocked line-of-sight (LOS) connection may be sufficient to interrupt correctness. Optical systems rely on the availability of map information to facilitate absolute positioning. Changes in the environment may significantly impact on map (and fingerprinting) based techniques, resulting in a poor robustness. Intended (from competing radios or adversaries) and unintended man-made interference signals are another potential threat to be considered [3].

d) Time synchronization: Radio transceivers derive their internal timing reference from independent local oscillators, and because of manufacturing tolerances and temperature variations, these oscillators undergo random phase and frequency drifts over time. Synchronizing the timing reference of independent radio transceivers is therefore an important prerequisite for systems that use propagation delay estimation. The simplest method is to share a common local oscillator through dedicated backbone network [31], [32], but this solution is often expensive and lacking in deployment flexibility. For outdoor systems, GNSS UTC timing references are traditionally used to synchronize different base stations, with accuracies up to 30 parts-per-billion (ppb) [31], [33]. However, GNSS is often unavailable in indoor environments and unreliable for pico-cells placed in dense urban canyons. Network-based synchronization, such as the IEEE 1588 protocol, is currently still in the 1 parts-per-million range [34], an order-of-magnitude below the current requirements in radio networks. Therefore, over-the-air synchronization with minimal bandwidth usage will be an important requirement of future localization systems. Some papers have recently provided tentative prototypes of such timing synchronization systems [35], [36].

Virtual synchronization is another approach that provides accurate positioning estimates for unsynchronized anchors or beacon systems equipped with low quality oscillators. In this approach, at least one reference base station at a known position is required to monitor the time of transmission and clock deviations of each anchor or beacon in a given area. The positioning devices or location server uses these parameters to correct the measurements [37] [38] [39] .

e) Hardware complexity in large antenna array systems: Large antenna array systems can significantly improve the precision of angle-of-arrival based localization systems [40]. However, a number of challenges need to be tackled both at the hardware domain and at the signal processing domain [41]. Firstly, fully digital architectures require the realization of a prohibitively high number of RF-to-Base-Band chains [42]. Thus, novel mixed analog-digital architectures must be devised, for instance exploiting RF switched antenna schemes or phase shifters techniques in analog domain [43], [44]. The cost reduction challenge may lead to increased hardware imperfections, most prominently significant carrier frequency offsets, phase noise and I/Q imbalances [45], [46]. Moreover, higher quantization noise levels are observed by using low-cost A/D converters. Energy consumption is also an issue that is exacerbated in large antenna arrays where a massive amount of data needs to be processed [47]. Furthermore, appropriate antenna configurations have to be studied to meet stringent physical space limitations [46]. Denser antenna arrays introduce mutual coupling, unequal gains and phase response effects that require improved design and calibration techniques [42], [48].

f) Power consumption and computational burden: Power consumption is one of the main technical challenges in mobile devices for IoT applications. These sensors are expected to have a long battery life (e.g. years-long battery life), thus their operational tasks have limited computational burden. Furthermore, their cost has to be very low in order to allow the deployment of thousands of these devices. Given the high amount and low-complexity of IoT devices, the network resources allocated for these devices are also very limited, such as the signal bandwidth. This reduces the number of applicable location methods.

g) MAC: latency and bandwidth usage: 5G networks pose challenging requirements in terms of the design of MAC layer techniques. The need to support a massive number of “always connected" devices that communicate sporadically (e.g. machine-type communications or IoT) is of particular importance. Traditional centralized MAC solutions for cellular systems are based on orthogonal access schemes that are incapable of supporting a massive number of devices due to the large control overhead and severe latency. Random access MAC (RA-MAC) schemes are being proposed for different Low power wide-area networks (LP-WANs) (e.g. LoRa), since they decrease the control overhead and can effectively achieve low latency. However, the schemes proposed so far are not prepared to support high spatial density of devices and their reliability and throughput sharply decreases with the number of devices [49]. To support accurate localization methods future decentralized MAC schemes must also include additional features, such as time guaranteed services to support the positioning anchors' transmission in a reliable and exclusive way. Therefore, future MAC policies must have into account the specific services needs related with low delay and massive number of devices, while optimizing the bandwidth usage to accommodate the specific requirements of the localization methods.

IV. Expected Features and Limitations of 5G and IoT with Respect to Positioning

The expected positioning accuracy in 5G is less than 1 m in urban (and indoor) scenarios and less than 2 m in sub-urban scenarios where the vehicle speeds are up to 100 Km/h [50]. As emphasized in [2], some of the open challenges in 5G positioning are: i) how to optimally combine the cmWave with mmWave positioning; ii) how to design low-cost highly-accurate algorithms through data fusion of 5G with various other sources (cameras, inertial, ...) and through cooperative positioning; iii) how to jointly optimize the communication and positioning targets, which often do not go hand in hand; iv) how to exploit multipath reflections/NLoS scenarios to improve the positioning accuracy; v) how to design synchronization and quantization algorithms for large antenna arrays embedded on moving devices to better support DoA-based positioning. In contrast, IoT technologies aim at providing communications to a massive number of low-power and low-cost devices, with a trend for mesh topologies with simple protocols. As a consequence, the positioning capabilities of IoT systems are limited in order to cope with these challenges. A comparison between 5G and main IoT technologies is illustrated in Fig. 1 in terms of the five criteria discussed in this section, together with the positioning accuracy. The main features and limitations of 5G and IoT positioning aspects are discussed in the next sub-sections.

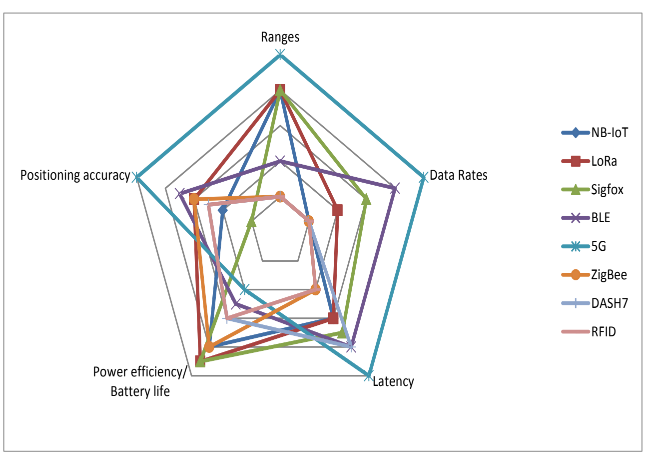

Fig. 1. Comparative aspects of main IoT technologies with 5G.

A. *Features and Limitations of 5G Wireless Systems*

5G is characterized with several disruptive features, which have direct implications to positioning [2]. These features include network densification, mm-Wave and massive MIMO [51], as well as device-to-device communication [52]. In particular, 5G NR will specifically rely on mm-Wave and massive MIMO, while network densification and device-to-device communication are evolutions of 4G systems.

1) Higher bandwidth and new frequency bands: 5G will employ new frequency bands in the mmWave spectrum (above 24 GHz), where large bandwidth are available than in the crowded 6 GHz band. This has a dual effect on positioning. On the one hand, larger bandwidths allow for a higher degree of delay resolution, so that individual multipath components can be estimated and tracked. On the other hand, the large carrier frequency leads to more optical-like propagation, with reduced shadowing, diffraction, and effectively only a few propagation paths [53]. Hence, only few paths must be estimated and tracked and each path has a geometric connection to the physical propagation environment. In the sub-6GHz band, large bandwidths will also be available with carrier aggregation, but more dominant propagation paths will be present.

2) More antennas: With higher carrier frequencies and shorter wavelengths comes the opportunity to pack more antennas into a given area [54]. Above 24 GHz, planar arrays with hundreds of antennas are feasible. To limit costs and power consumption, not all antennas will be equipped with ADCs so that only few streams will be supported by this large number of antennas. Conversion from streams to antennas will occur through a combination of digital and analog beamforming. More antenna elements provides the opportunity to increase the resolution of the channel in the spatial domain (angle of arrival and angle of departure, in azimuth and elevation), providing a new way to separate multipath components (other than in the delay domain). More antenna elements also help in more accurate angle estimation, though this must be balanced with limited precoding capabilities due to having fewer RF chains than antenna elements. Hence, combined with high carriers and large bandwidths, more antennas leads to a high degree of resolvability and high accuracy of estimating multipath components, each with an associated delay, angle of arrival, and angle of departure. This implies that absolute positioning with respect to a single reference transmitter is possible, as well as identification of the sources of each reflected or scattered path.

3) Network densification: Increased area spectral efficiency is obtained from a denser deployment of base stations with a reduced coverage area and aggressive spectral reuse. This requires sophisticated solutions for interference and mobility management [55]. For positioning, ultra-dense networks are beneficial since the distance to reference transmitters is reduced. The reason is two-fold. Firstly, with ranges from 5-50 meters, the probability of having a line-of-sight connection is upward of 50 % [56], which in turn is highly beneficial for localization as the delay and angle information from the optical line-of-sight path provide the most location-relevant information of all multipath components. Secondly, with a dense radio-access network seamless multi-connectivity can be established between terminals and base-station via multi-beam communication. This increases the robustness to line-of-sight obstruction as well as improve localization accuracy.

4) Device-to-device communications: Since LTE Release 12, D2D communication is considered a candidate technology for proximity detection. In 5G, D2D will be native, for high-rate links between nearby users, benefiting from low path loss, low transmit powers, and extremely low latency [57]. Such D2D links also provide an additional source of position information, where well-positioned users can serve as (noisy) location references for users out of direct coverage of base stations. Moreover, D2D links can provide relative position information as well as a mean to develop efficient cooperative positioning schemes for achieving higher accuracy.

B. Features and Limitations of IoT Devices

Different IoT applications require different, and often conflicting, goals in terms of range or coverage, rate or throughput, power consumption, and latency. The current IoT landscape includes both proprietary and standardized solutions, that try to satisfy different requirements in terms of the ideal case of wide-coverage, high-throughput, low-power and low-latency. A general classification of IoT solutions according to the four axes (range, power, rate, latency) is shown in Fig. 2. These IoT solutions can then provide positioning capabilities, which have different limitations depending on the system design.

Range		Power		Rate or Throughput		Latency	
Short	Long	Low	High	Low	High	Low	High
RF-ID BLE ZigBee ANT Z-wave 6LPWA DASH7 ...	LoRa Sigfox LRLP (802.11) ...	ZigBee LoRa Ingenu Sigfox Telensa EC-GSM-IoT NB-IoT DASH7 Wirepas Weightless (N/P/W) ...		ZigBee LoRa Ingenu Sigfox Telensa NB-IoT DASH7 ...	BLE Wirepas ...	DASH7 Wirepas ...	NB-IoT ...

Fig. 2. IoT classification and examples.

1) Long range: Long-range IoT applications include asset tracking, smart city, smart metering, smart farming, smart retail and logistics, etc. Currently, there are two main competing IoT proprietary solutions to achieve *long-range* communications: LoRa and Sigfox. Long Range (LoRa) Wide Area Network is a low-power proprietary technology in ISM band, based on chirp spread spectrum modulation with spreading factor between 7 and 12. LoRa bandwidths range between 125 and 500 kHz and can be adjusted according to the used spreading factor, in order to attain the required trade-off between range and data rates. The spread spectrum modulation used in LoRa enables long-range communications of up to 30 km ranges [58], [59]. Sigfox is also able to reach long-range communications of several tens of km by operating in sub-1GHz bands, currently leading the public deployments of IoT solutions in Europe. It relies on the so-called Ultra Narrow-Band (UNB) modulation (i.e., bandwidths below 1 kHz) which helps in achieving long ranges, as the ultra-narrow receiver filters most of the in-band noise. Field tests with Sigfox in [60] showed achievable Sigfox ranges of up to 25 km.

These proprietary solutions do not have any positioning features specified or included in the standard. Thus, classical positioning approaches, such as fingerprinting based on signal powers, can be applied independently on the system, as long as the designer has access to the received signal power or the backscattered power measurements. However, the performance of these methods is significantly degraded due to the long-range communications. Timing-based schemes can be also implemented, but their performance is greatly reduced for these narrowband signals. Despite the limited studies on the positioning accuracy of these IoT solutions, when no additional GNSS receivers are used, trilateration methods with LoRa timestamps result in a position accuracy of hundreds of meters, as it can be found in [61].

Furthermore, there are two main standard technologies for long-range IoT solutions, which are IEEE 802.11 Long Range Low Power (LRLP) and the 3GPP narrowband technologies, i.e., LTE-M, LTE NB-IoT and EC-GSM-IoT. The IEEE 802.11 LRLP is a relatively new topic interest group, established in 2015 within IEEE 802.11 working group [62] for IoT, M2M, energy management and sensor applications. The 3GPP narrowband technologies are evolving really fast with a major support from the industry. In addition, their positioning capabilities are under standardisation, as it is described in [7]. The main positioning advantage of these standard technologies with respect to proprietary solutions is the use of licensed bands to reduce interference, and the dedication of network resources for positioning, such as pilot signals and positioning protocols.

Following the trend of LTE NB-IoT, the 5G standard is expected to include dedicated pilot signals and protocols for positioning, in order to cover the limited IoT positioning requirements. Still, the narrow bandwidth and the large coverage of IoT communications in 5G are the two main limitations in terms of positioning performance. However, with the advent of large antenna arrays at the base stations new opportunities to accurately estimation the location of NB-IoT devices arise. Various well-established algorithms for angle of arrival estimation can be employed, e.g. [63].

2) Short range and narrowband: Short-range IoT applications, such as smart home, wearables, health and fitness, etc, are typically provided indoors. Examples of short-range IoT technologies are the Radio Frequency Identification (RFID), Bluetooth Low Energy (BLE), and in particularly BLE mesh, ZigBee, ANT and ANT+, DASH7, etc. [64]. These technologies have a low bandwidth, but thanks to the short-range communications, they are able to achieve high-accuracy positioning. The main techniques are based on fingerprinting or proximity techniques, where meter-level accuracies can be achieved, such as with RFID in [65]. Advanced techniques can be based on the use of angle measurements [66]. However, to achieve a high precision, they require large antenna arrays at the receiver side (e.g. readers in RFID technologies), resulting in an increase on the complexity and cost of the IoT system [66].

3) Short range and wideband: Short-range IoT communications can also be based on wideband technologies, such as the IEEE 802.15.4a UWB standard. This standard is based on the direct sequence UWB modulation, which offers spectral efficiency, robustness at low transmit powers, and precise ranging. Thus, thanks to the wide bandwidth, the IEEE 802.15.4a UWB standard is able to achieve centimetre-level accuracies [67]. In addition, these short-range wideband signals result in practically deterministic MPCs, thus they can also be exploited for multipath-assisted localization, as it is shown in [68] with off-the-shelf devices. Using these MPCs, single-anchor localization can be implemented reducing the infrastructure required for the IoT positioning system.

UWB signals can also be implemented in RFID-based systems, as it reviewed in [66]. The use of wideband backscattered signals allows precise ranging measurements, while preserving the system complexity and cost. The main limitations of the UWB-RFID technology are the poor energy efficiency, the short range and the costly ad-hoc infrastructure. Future perspectives of RFID are the exploitation of mmW technologies.

4) Low power and low throughput: Currently, the vast majority of IoT solutions have been designed for low-power low-rate applications, namely with battery life lasting years. Current solutions in IoT range from few years of the battery life on the IoT sensor (e.g., 6LoWPAN/6LPWA, BLE) up to more than 10 years battery life (e.g., NB-IoT, LoRa, Sigfox). Typically, IoT solutions have very low throughputs from few tens of bits per second (bps) up to few hundreds of kbps.

The low-power and low-rate features have a strong impact on the positioning techniques applicable to IoT technologies. Since the transmission time is reduced, the number of positioning measurements is reduced, leading to simple positioning protocols with minimal assistance. Furthermore, the positioning operations on the IoT device need to have a very low-complexity to achieve a low power consumption.

V. Related Work

A. Introduction

In general, position estimation techniques involve a pragmatic two-step process. First, a set of signals are exchanged between one or more mobile nodes to be localized and reference nodes (anchors), located in known positions, from which a number of position-related parameters (observables) are estimated (measurement acquisition). Then, the position of the node(s) is determined based on those signal parameters (localization/tracking) through a proper localization algorithm that accounts for geometric relationships as well as statistical models of measurements.

Every measurable signal which conveys position-dependent information can be in principle exploited to estimate the position of the mobile nodes. When radio signals are considered, useful position-dependent information can be derived by analyzing observables such as received signal strength (RSS), time-of-arrival (TOA), angle-of-arrival (AOA), phase, or combinations of them, depending on the available radio technology and its complexity. The exploited observables affect the choice, complexity, and resulting accuracy of the localization algorithm.

This section summarizes recent work related to the tasks of measurement acquisition and position estimation. It starts with a discussion of radio channel properties and channel modeling considerations (Section V-B), continues with theoretical performance limits derived from the measurement models (Section V-C), and then describes positioning methods and algorithms (Section V-D), following a bottom-up approach. Finally, in Section V-E, selected, recent advances in positioning technologies are summarized.

B. Propagation and Channel Models for Localization

Radio localization relies heavily on knowledge of the interplay between the geometry of the propagation scenario, radiowave propagation and the observables used for localization. As is usual practice in other fields of radio engineering, this knowledge is usually provided in the form of a radio channel model. The term "channel model" is inherited from the field of communications engineering where communications take place via channels. The field of radio channel modeling (for communications) has a long history of development.

1) Purpose of Channel Modeling for Localization: Similarly to communication systems where the channel determines the ultimate performance, in localization systems the accuracy is strongly affected by channel conditions and, in particular, by the presence of multipath components (MPCs). Even more, while in communication the transmitted data are independent of the channel, in localization systems the information associated to the position is embedded in channel parameters such as TOA or RSS. Therefore, there is the need for channel models able to capture such dependence between position and channel properties. Although some overlap in methodology is to be expected when similar radio channels are considered, the models used in communications cannot be expected to completely match the needs of the developer of a localization system [69].

Channel models are needed for a range of different purposes in the development of localization systems, as listed below.

a) Analytical tools in the derivation of localization algorithms: Propagation and channel models are used as analytical tools in the derivation of localization algorithms. To fulfill this purpose a channel model should be analytically tractable, while at the same time should account for the location-dependency of the observables considered while other effects are abstracted away. Such models usually include the connection between observables (e.g. RSS/PDOA, TOA/TDOA, AOA, channel's impulse response, etc.) and location information in some analytically tractable way. Examples of these types of models include range error models used in cooperative localization where the RSS or TOA range-dependance is defined and corresponding ranging errors are accounted for as additive random variables independent of location [70]–[74]. Another example is the simplified modeling of Geometrical

Optics [75] used in multipath-assisted localization methods [1], [76].

b) Performance bounds derivation: Channel models are used as analytical tools to derive theoretical performance limits for localization. To achieve useful bounds, simplistic models are assumed (e.g. [77]–[79]). However, the derived bounds are only valid under the exact conditions for which they are derived. Section V-C describes some recent work on performance bounds.

c) Channel prediction for fingerprinting localization: Deterministic channel models such as ray-based models or electromagnetic models can be used to perform a pixel-based prediction of one or more observables all over the considered domain, in order for an optimization algorithm to determine the mobile location based on the correlation between the measured and predicted observables ("fingerprinting localization", see Section V-D) [67], [80], [81].

d) Link-level localization simulation: Channel models are used for performance simulations of subcomponents of a localization system. Here subcomponents could be e.g. estimators for range or direction based on data for a single communication link. The performance of such estimators is potentially affected by many more effects encountered in the communication channel than those accounted for during their derivation. Therefore, such simulations aim at modeling the link channel in realistic manner to obtain accurate predictions of the subcomponent's performance.

e) System-Level localization simulation: Channel models are used for system wide performance simulations for localization systems. Here it is tested how the subcomponents of the localization system work in combination. The considerations for this type of simulations are similar to the test of subcomponents. However, due to the greater complexity of such tests (possibly encompassing a large number of subcomponents), the requirements in terms of computational complexity of such a model (per link) are more challenging.

Channel modelling is used in c)-e) to replace to time-consuming measurement campaigns.

Purposes d) and e), necessitate to achieve reliable performance assessments considering several possible realistic environments and system configurations (realizations). One approach to achieve this is to simulate some reference cases using site-specific methods. The inherent complexity of site-specific modelling however may limit the number of realizations that can be obtained with this approach.

Another approach is to consider evaluation of the operating characteristics of a component/whole system over a large number (possibly millions) of realizations. In this case, it is important that the model is able to capture the statistical characteristics of the channel, but not necessarily that each realization is completely realistic in all aspects. So-called geometry-based stochastic channel models (GSCMs) fullfill this requirement. A popular example are the cluster-based GSCMs, where clusters of scatter points are used to obtain MPCs with spatially consistent fading properties. The geometry of the clusters and scatter points are randomly generated [82]–[84].

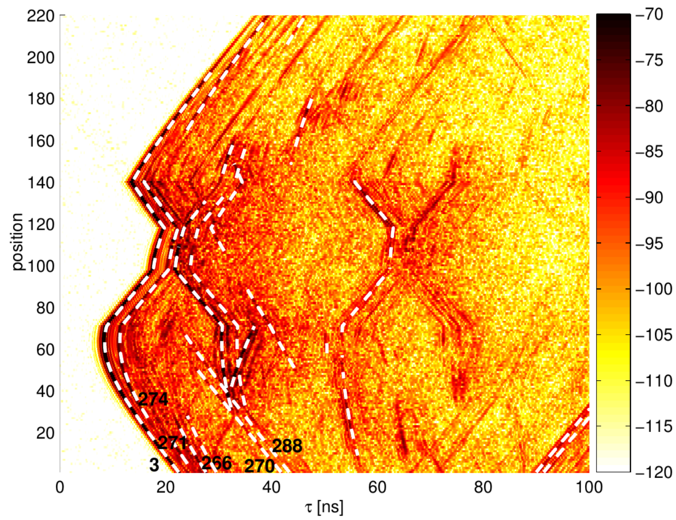

Fig. 3. Measured channel impulse responses with MPCs matched to a simple geometric model representing delays and visibilities (from [85]).

2) Propagation effects: Propagation in real-life environment (and especially urban and indoor environments) is characterized by multipath propagation, i.e. the presence of several propagation paths, including the direct path when the radio link operates in LOS conditions. In variable terms depending on propagation characteristics, system characteristics and the kind of approach, multipath can be divided into two components, which are treated differently within localization systems.

a) Specular, deterministic component: Deterministic specular paths (i.e. likely generated by a few specular reflections and diffractions) whose characteristics (e.g. TOA, AOA) are well defined and depend on the position (goal of the estimation process). In this case, if the dependence between the MPCs characteristic and the position is known through, for example, geometrical optics relationships, then the multipath can be positively exploited to improve the position estimation accuracy. Note that this requires some a priori information about the geometric and electromagnetic characteristics of the environment in order to exploit the dependence between the MPC characteristics and the position. This open the possibility to explore fingerprinting [67], [80], [81] or multipath-assisted localization techniques [1], [76].

b) Diffuse, random component: A high number of diffuse or multiple-bounce paths whose TOA and/or AOA values are very close to each other, the so-called Dense Multipath Component, DMC. Such paths show random characteristics, therefore uncorrelated with the position, or whose relationship with the position is unknown. In this case, MPCs cannot bring further useful information for localization and must be characterized through nuisance parameters related to localization performance degradation and therefore to perfomance bounds [78]. Note that this is different to what happens in communications systems where the DMC can be successfully exploited to increase the communication reliability or rate (e.g. OFDM transmission).

Figure 3 shows measured CIRs from an indoor environment along a trajectory. It also illustrates the hypothetical arrival times of a set of MPCs, computed from a simple mirror-source model. Notice the good match between model and measurement [85], which illustrates the potentially useful information contained in the delay of these MPCs. Inbetween the specular components, the diffuse, random components can be seen.

In real-life radio channels both components are present to some extent: the specular component is relatively more evident than the DMC in LOS or quasi-LOS conditions, simple environments, higher frequencies [86], and when the system has enough bandwidth or antenna elements to resolve a high number of paths. Channel modeling typically need to account for both types of propagation characteristics.

3) Modeling principles: Classical narrowband empirical-statistical models such as Hata-like models [87] only account for average path loss vs. radial distance, multipath is only accounted for through a statistical fading description. Being empirical, they need to be parametrized through calibration measurements.

Other empirical-statistical propagation models are aimed ad describing the temporal characteristics of multipath, including specular and diffuse components, for different kinds of environment, using a parametric tapped-delay-line description [88], [89]. Such models are suitable for characterize TOA measurements and their uncertainty for UWB localization.

Deterministic Ray Tracing and Ray Launching models based on Geometrical Optics can generate a good site-specific description of the specular component for a given environment, provided that the environment (including terminals positions and system configuration) is accurately described through a proper input database [90]. They can be therefore used for localization in fingerprinting methods [80], [91], [92] and multipath-assisted methods [1], [93]. However they fail to describe the DMC and therefore need to be integrated with ray-based diffuse scattering models [94]. In [1], [93], a simple non-stationary Gaussian model has been used to account for the DMC.

So-called Geometry-based Stochastic Channel Models (GSCMs) describe multipath propagation in a statistical way. Typically they make use of clusters of scatter points to obtain aggregate MPCs, somehow including both the specular and the diffuse component, with spatially consistent characteristics and fading properties. Cluster and scatter point positions in either the Euclidean or Angular space are usually randomly generated using proper parameters to describe a given class of environments (e.g. small-indoor, large-indoor, macrocellular, vehicular, etc.) [82]–[84]. Since GSCM are not site-specific they cannot represent a propagation engine for localization algorithms, but they can serve to efficiently simulate the localization performance of different algorithms for an entire class of environments, as already pointed out in the preceding sub-section. Recently, map-based models have been proposed that somehow introduce a more deterministic description into the GSCM paradigm, and therefore can be though of as a combination of GSCM and Ray Tracing models [95], [96].

Channel models based on Graph Theory have been proposed to efficiently simulate multipath radio propagation including the reverberation effect of electromagnetic waves in indoor environments [97]. In this approach scatter points are distributed either randomly or according to the physical characteristics of a given environment and MPCs are generated up to an arbitrary (possibly unbounded) number of bounces. The approach however is more suitable to describe the diffuse component rather than the specular one, and therefore combinations of graph-based and ray-based modeling have been proposed to describe both components in a physically consistent way [98], [99]. The propagation graph framework has recently been extended to include time-varying channels [100] and polarization effects [101]. Depending on how deterministic is the description of the environment such models might be used for localization or for simulation purposes.

C. Theoretical Performance Limits

Theoretical performance limits provide insight into what performance levels can possibly be achieved, based on some given signal model. Provided that the signal model reflects the physical properties of the propagation environment—i.e. the radio channel characteristics—the performance limits can quantify the ultimate performance limits in a certain scenario. The aim of this section is to highlight these performance limits.

1) Performance limits in measurements acquisition:

a) Performance limits on TOA estimation: Distance estimation (ranging) is accomplished from the time-of-flight (TOF) of the transmitted radio signal. For this purpose, it is of fundamental importance to obtain a good estimation of the time-of-arrival (TOA) of the received signal. It is well-known from classic estimation theory that whatever (unbiased) TOA estimator is considered, its root mean square error (RMSE) performance is bounded by the Cramèr-Rao lower bound (CRLB). In simple AWGN channel conditions (only the direct LOS path is present), the CRLB is given as [102]

$$\mathrm{var}\{\hat{\tau}\} \geq \mathrm{CRLB}_{\mathrm{TOA}} = \frac{1}{8\,\pi^2\,\mathrm{SNR}\,\beta^2}\,, \qquad (1)$$

where SNR is the signal-to-noise ratio (SNR) and β is the effective bandwidth of the received signal. This simple expression clearly shows the benefit of having (ultra) wide bandwidth signals and a high SNR.

However, in a realistic multipath channel, the performance will rather be limited by interfering multipath than by AWGN [77]. It has been demonstrated that such interference can be quantified by replacing the SNR in (1) by an (effective) signal-to-interference-and-noise-ratio (SINR) [78], [79]. The SINR characterizes the resulting performance limit and also the detectability of the LOS and other MPCs within the interfering (dense/diffuse) multipath.

An example is given in Fig. 4 (c.f. [78]). It demonstrates that the ranging error bound (REB) scales faster than quadratically with the bandwidth (due to the interfering multipath—for comparison, the REB according to (1) is included) and linearly with the diversity order. (SISO refers to a single-input, single-output channel, while the 16-branch case corresponds e.g. to a 4×4 MIMO configuration.) The detectability of the useful LOS component in dense multipath is evident in the

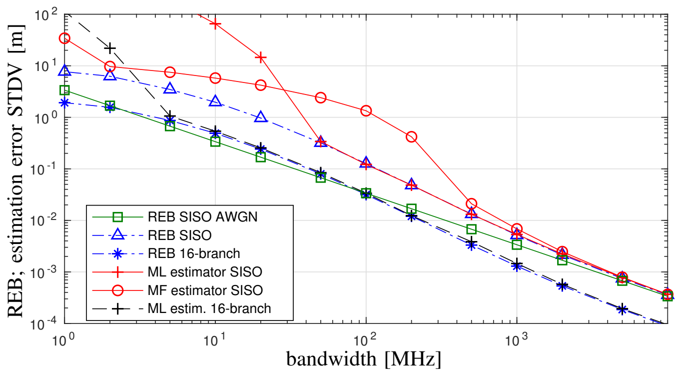

Fig. 4. Ranging error bound (REB) and simulated range estimation (MF, ML) standard deviations (from [78]). Channel and signal parameters: $\mathrm{E_{LOS}}/N_0 = 30$ dB, Ricean K-factor: $K_{\mathrm{LOS}} = 0$ dB, RMS delay spread 17.3 ns; signal: root-raised-cosine pulse, roll-off $R = 0.6$.

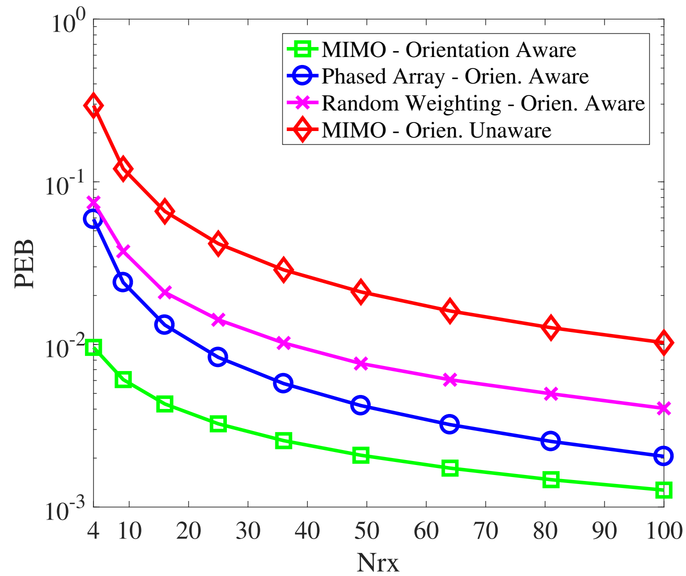

Fig. 5. Position error bound PEB (in meters) in single-anchor localization with massive arrays averaged over RX orientations. $N_{tx} = 25$, N_{rx}: number of transmitting and receiving antennas.

way how the simulated matched filter (MF) and maximum likelihood (ML) estimators diverge from the REBs. The MF estimator suffers from outliers induced by the multipath, while the ML fails at low bandwidth, where the SINR of the LOS drops below a critical threshold. Note that the CRLB does not account for ambiguities and estimation outliers. Other bounds can be of utility for analyzing such effects, as e.g. the Ziv-Zakai bound [67].

b) Impact of clock drift: It is worth mentioning that an accurate TOA estimate is not sufficient to achieve accurate ranging. In fact, time-based ranging requires precise time interval measurements (e.g., with errors in the order of 1 ns or less when centimeter accuracy is required). To this end, nodes are equipped with an oscillator from which an internal clock reference is derived to measure the true time. Numerous physical effects cause oscillators to experience independent frequency drifts which result in large timing errors. In symmetric double-sided two-way ranging, three consecutive range measurements are performed to jointly estimate clock offset, linear clock drift, and distance between two nodes [88]. In time-difference-of-arrival (TDOA) positioning, synchronization is needed between the anchors only and an additional measurement is used to jointly estimate the clock offset of the agent and its position [77]. Joint synchronization and position estimation can also be achieved in cooperative [103] and in multipath-assisted scenarios [79].

c) Performance limits on AOA and RSS estimation: The CRLB for estimating the angle-of-arrival (AOA) can be derived in similar fashion as for the TOA [104], [105]. In an AWGN channel, it scales with the product of SNR and squared carrier frequency and antenna aperture, relating to the fact that the carrier-phase difference among multiple array antenna elements is being exploited. Again, multipath will dictate the practical performance limit.

For RSS based range estimation, a path-loss plus log-normal shadowing channel model can be used to derive the CRLB [106]. The performance depends strongly on the current distance—due to the exponential path-loss model—and on the actual shadowing variance of the channel. Small-scale fading potentially introduces a large among of measurement noise. Fingerprinting methods make an attempt at modeling the large-scale position dependence of the received power, which improves the accuracy [106].

2) Performance limits in Localization/Tracking: Multiple range and/or AOA measurements will be combined to obtain a position estimate. Geometric interpretations of the resulting position error bound have been presented in [77], [105]. Based on these fundamental observations, the performance limits have been analyzed for a range of localization scenarios.

a) Mm-wave, single-anchor, massive array localization: Among the potential advantages of the upcomming millimeter-wave technology and the consequent possibility to pack a large number of antenna elements even in small spaces, the most appealing is the possibility to localize mobiles using a single anchor node [1], [107]. In fact, the use of only one anchor node will allow the exploitation of the same infrastructure used for communications also for positioning purposes [66]. This overcomes the problem of deploying a redundant ad-hoc infrastructure which is, nowadays, a major bottleneck for the widespread adoption of indoor localization systems.

The most intriguing single-anchor scenario in which both the anchor and the mobile node are equipped with an antenna array is studied in [108]–[110]. As expected, the positioning and orientation performance increases as the number of antenna elements increases. In particular, in [110] the differences between MIMO signal processing (using orthogonal waveform at each antenna) and beamforming is investigated. It is shown that while beamforming allows for SNR enhancement, this is beneficial only in particular geometric configurations and does not allow the estimation of the agent orientation on the uplink [108]. On the other hand, the MIMO configuration, thanks to the orthogonality of waveforms, provides a higher number of independent measurements (diversity) which leads to a better performance at the expense of a higher complexity. An example of such behavior is given in Fig. 5 where the theoretical performance in terms of average position error bound (PEB) is reported as a function of the number of antennas N_{rx} at the anchor node. Specifically, these results have been obtained by considering the mobile node at 5 meters from the anchor node transmitting at 60 GHz with an EIRP of 30 dBm (SNR=25 dB) and bandwidth of 1 GHz. The figure also includes the performance attainable using a simple strategy in which the weights of the array are randomly chosen.

The performance of single-anchor position estimators can be additionally improved by exploiting geometry information from deterministic MPCs (c.f. Section V-B). Each deterministic MPC adds useful position information, as discussed in [1], [79], [108], [111].

b) Sub-6 GHz localization: Sub-6GHz cellular deployments are expected to have a higher coverage than mmWave deployments, due the low propagation losses. But the scarce spectrum limits the available bandwidth, resulting in a strong limitation on the achievable positioning performance. The main localization challenges are the visibility of multiple reference stations, the inter-cell interference and the dense multipath in indoor and urban environments [4]. In addition, multilateration techniques require a tight network synchronization.

The performance limits of the vehicular use case have been studied in [112], based only on ranging measurements from LTE vehicle-to-infrastructure (V2I) communications. This vehicular positioning scenario is characterized by a poor geometry, limited bandwidth, and predominant LoS conditions from the serving base station. The LTE network is assumed to transmit the positioning reference signal (PRS), which is a dedicated pilot signal with interference-avoidance mechanisms. The network infrastructure is based on synchronized road-side-units (RSUs) or dedicated BSs at one or both sides of the road. Given an inter-site distance (ISD) equal to 500 m between BSs along the road and 20 MHz of bandwidth, the uplink TDoA position accuracy of the vehicle is in the order of several tens of meters, due the poor geometry and the distance-dependent LoS conditions [112]. The network density and the system bandwidth need to be increased in order to achieve sub-meter accuracy. With an ISD equal to 100 m and a carrier-aggregated bandwidth of 100 MHz, sub-meter accuracy is achieved in 95% of the cases. The poor geometry can be relaxed by combining range and angle measurements, as studied in [113]. The use of multiple antennas at the BSs allows to achieve sub-meter position accuracy in urban environments, with only one or two visible BSs, using an EKF algorithm. However, this solution still requires ultra-dense networks with an ISD around 50 m.

3) Trade-off between position accuracy and communication data-rate: As mm-wave has the anticipated dual use of communication and positioning, it becomes natural to analyze the trade-off arising from the shared time-frequency resources.

In [114]–[116], for instance, it has been assumed that positioning information is acquired during the beam training phase of the mm-wave wireless system. The beam training procedure occurs periodically, introducing a certain overhead and loss of data rate. The positioning accuracy was computed from the CRLB after the beam training phased is completed. On the other hand, the data-rate is calculated by considering the codebook size (related also to the number of antennas), beam training strategy, and the bandwidth taken for an OFDM transmission. A main conclusion is that accurate position and rotation estimation can be achieved using the training signal used for beam alignment only, keeping the overhead at a limited level.

D. Positioning Methods and Algorithms

Methods and algorithms for positioning and position tracking are discussed in this subsection, taking into consideration the propagation characteristics, which relate to the actual observables to be used, and the theoretical performance limits.

1) Multipath-assisted localization: Multipath-assisted localization exploits specular multipath components (MPCs) to obtain additional position information contained in radio signals [1]. It will help to overcome poor channel conditions like obstructed LOS and NLOS propagation situations and it gives diversity that is needed to improve the *robustness* in such cases. As the CLRB in (1) quantifies the ranging-related information contained in the LOS link, the CRLB on the position error for multipath-assisted localization shows that each specular MPC contributes to the position-related information [79].

The cost of this approach lies in the models and algorithms needed to leverage these advantages. A *data association* step is crucial for assigning the MPCs to a geometric model. Of key importance is also the rigorous modeling of the ranging information provided by each MPC (utilizing the CRLB) such that a proper weighting of those contributions can be achieved [76]. A belief propagation based *probabilistic* data association approach has been presented in [117], allowing for "soft" associations and achieving low computational complexity due to a factor graph formulation.

The next issue to be addressed is the acquisition of the geometric model. It can be derived from a given floor plan which defines the location of virtual anchors, mirror images of the physical anchor location [76]. To avoid the difficulty of deriving such a model "by hand", a SLAM algorithm has been developed in [118], which estimates the geometric model simultaneously to the agent localization. In [119], [120] a belief propagation based SLAM algorithm has been developed that uses probabilistic data association. The authors of [121] estimate the locations of virtual anchors without an underlying geometrical model. A corresponding multiple hypothesis data association method has been derived in [122].

2) NLOS Identification and Mitigation: Machine Learning Approach: In localization algorithms it is often assumed that the statistical observation model, which relates the measurements to the position (e.g., TOA), is perfectly know. However the model barely matches the real world.

Because of its critical benefit to localization, NLOS identification research has gain much traction in recent years and several ways of achieving it, have been proposed. Common mechanisms involve considering geometric channel models to estimate the distance traveled by multipath rays, or considering polarization of the signal where every polarization change is

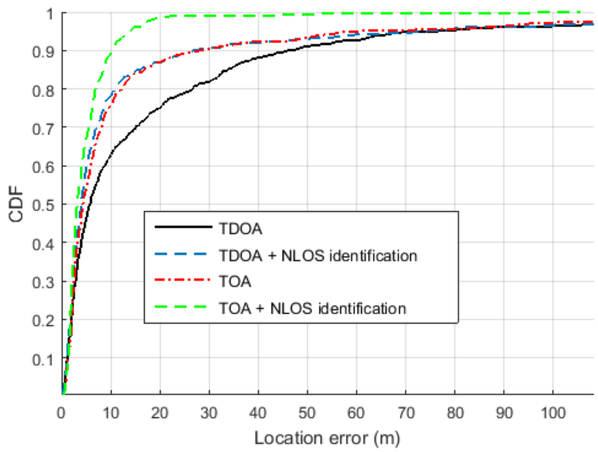

Fig. 6. Location accuracy – effect of NLOS identification. [123]

considered to be a reflection, or also using some statistical characterization [124] [125] [126].

NLOS identification and mitigation techniques that involve hypothetical approaches that require determination of the joint probability distributions of the underlying features, produce heuristic outcomes. Geometric model based approaches assume a maximum of just one reflection or refraction, in the path between the base station and the target [125]. This may not be the case in some environments. A comprehensive survey of NLOS identification and mitigation techniques is discussed in [124].

There are new and promising techniques for NLOS identification based on machine learning techniques. These techniques in the form of support vector machines, are optimization-based approaches that have been demonstrated to be effective in NLOS classification in both outdoor [123] and indoor environments [127]. In both approaches, the Least-squares Support Vector Machine (LSSVM) are used to perform both NLOS identification and mitigation, an approach that does not require any statistical modeling of LOS and NLOS channels, hence can performs both tasks under a common framework. One interesting application is the use of ray-tracing for location specific NLOS identification, to aid outdoor geolocation, whose results demonstrated a best-case scenario of only 1.9% identification error when received signal power, RMS time delay and angle of arrival (AOA) are used as features.

NLOS Mitigation in LSSVM approaches is achieved by estimating the ranging error. Function estimation in the LSSVM, is used to estimate the error in the measured time delay or alternatively, the error in the corresponding range estimate. In the location specific approach, the input space to the support vector machine comprises of the base station position, and selected features or combinations of them, from received signal power, time delay and AOA at base station. The output is the time delay error or alternatively, the range error. The LSSVM is trained to obtain the regressor parameters which are then used to estimate range errors from a separate data set meant to be used for localization. The LS-SVM formulation and detailed options are available from Vapnik's original formulation [128] and in [129]. The effect of NLOS identification is demonstrated in Fig. 6 (from [123]).

3) Crowd-based learning approaches for NLOS mitigation: The model mismatch in real-world situations can be accounted for by incorporating in the model unknown parameters, such as the extra delay due to NLOS conditions, that, in general, are functions of space and that have to be jointly estimated with the location. A way to tackle this problem is to make use of crowd-based learning approaches in which position-dependent unknown parameters are treated as spatial fields of which knowledge is refined by exploiting the presence of a large amount of users (the crowd) that enter the area of interest simultaneously or in different times. Specifically, after a user crosses the area, it takes advantage of the available estimated field obtained from measurements acquired by previous users. In turn, the estimate of this field is updated by the measurements of this user. Thereby, subsequent users can also benefit by using the field for their own localization. This can be termed as an *indirect cooperation approach*. In [130], a learning and spatial representation scheme whose memory and computational burden do not increase with the number of measurements is presented for the tracking of users in indoor scenarios in the presence of NLOS conditions. In this scheme the crowd-based learning process and the tracking process continuously exchange their estimates (NLOS bias field and position, respectively) as new ranging measurements are obtained.

4) NLOS Identification and Mitigation: Classical Fingerprinting and Ray-tracing: TOA- and TDOA-based methods are the most popular schemes used for localization in wireless networks. The studies in [131] have shown the problems faced by compact direction finding antenna array used by AOA sensors and how the performance is affected when integrated into small platforms. However, TDOA localization systems are more affected by multipath propagation and diffraction of rays, since they induce an inherent positive bias which can lead to substantial location errors.

There are several approaches to deal with NLOS propagation conditions in TDOA Systems. In [132], a scattering model together with a matched filter was proposed. In [133], [134], methods are presented that apply a statistical test on the normalized signal residuals for LOS/NLOS identification, assuming that LOS components have a chi-square distribution and the NLOS components a non-central chi-square distribution. Measurements identified as NLOS where not considered for localization in this approaches. NLOS bias mitigation techniques are presented for example in [135] and [136].

It is also possible to obtain the propagation information to deal with NLOS using RF fingerprinting, either by performing extensive measurement campaigns or using ray tracing simulation softwares covering the environment of interest.

In [137], a multipath database was created using a grid of possible emitter positions, where the AOAs (azimuth and elevation) and TOAs were recorded, giving a signature for each possible transmitter location in the area of interest using a ray-tracing software. The received signal of NLOS components is compared with the values in this database, to estimate the emitter position with the same multipath fingerprint.

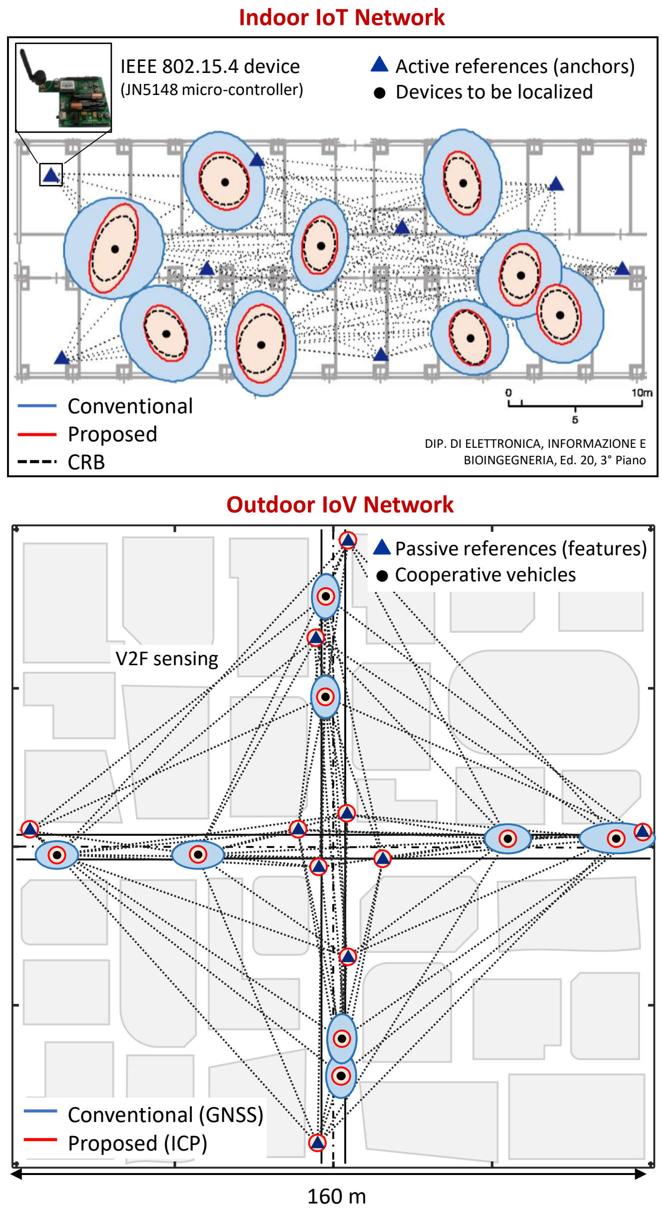

Fig. 7. (top) Indoor IoT network: average location accuracy for the proposed consensus-based method (red ellipse), the conventional approach (light blue ellipse) and CRB (black dashed contour). (bottom) Outdoor IoT network: implicit improvement of the vehicle location accuracy (red ellipse) based on the cooperative localization of features (red ellipse) compared to the GNSS-based approach (light blue contour).

In [91], a ray-tracing-based modified multilateration method was proposed that can cope with NLOS conditions. It uses a discrete approach for emitter location estimation to improve the position accuracy.

5) Cooperative positioning: Distributed techniques for localization in IoT and IoV: In 5G, key application clusters are represented by massive IoT and mission-critical control including in particular VANet for Internet-of-Vehicle (IoV) applications. Both IoT and IoV scenarios envision the deployment of dense networks of devices interconnected by device-to-device (D2D) communications, with decentralized sensing and processing capabilities [138], [139]. These networks call for the adoption of distributed architectures that ensure interoperability, scalability, flexibility and robustness. Network localization is an important issue to support location-based network functionalities in IoT [140], or assisted/automated driving systems in IoV [141]. Distributed techniques have become a key approach in this context as they enable devices to self-localize - also in critical dynamic scenarios - by exploiting communications with neighbors, without the support of any central coordinator, facilitating high-reliability and low-latency operations. Consensus algorithms, in particular, have been proposed to make the devices cooperatively reach an agreement on location-related parameters by relying solely on local data and message exchange with neighbors. This approach was shown to improve both coverage and accuracy of localization in dense network deployments [142].

Fig. 7-(top) shows an example of distributed localization for an indoor IoT scenario (DEIB, Politecnico di Milano) [142], with 17 IEEE 802.15.4 compliant terminals, including 8 anchors acting as reference nodes and 9 devices to be cooperatively localized from D2D received signal strength measurements. A weighted-consensus algorithm is used to enable each device to acquire the whole network topology, by successive refinements of local position estimates and repeated D2D interactions. In the figure, the average location accuracy is represented in terms of error ellipses at 39% confidence plotted around the device locations. The proposed consensus-based method (orange ellipse) is shown to significantly improve the conventional approach (light blue ellipse) and to closely attain the CRB shown as a reference (black dashed contour).

A similar technique is considered in the context of IoV in the example of Fig. 7-(bottom). A novel implicit cooperative positioning (ICP) technique [143] is used to enhance the accuracy of conventional GNSS-based positioning in assisted/automated driving applications by data sharing through vehicle-to-vehicle communications. The scenario includes 8 cooperative vehicles and 10 non-cooperative (passive) features (e.g., people, traffic lights, inactive vehicles), which are cooperatively localized by the vehicles. A consensus-based belief propagation algorithm is implemented by the vehicles to localize, in a fully distributed manner, the jointly sensed features and use them as common noisy reference points (red ellipse) to implicitly enhance their own location accuracy (red ellipse) with respect to the performance of GNSS-based solution (light blue ellipse).

E. Positioning Technologies and Measurement Acquisition

In recent years we assisted to the introduction of a plethora of wireless technologies targeted to different application fields ranging from cellular networks, IoT, and vehicular communications. At the same time new technologies such as massive antenna arrays, mm-Wave, Tera-Hertz and visible light communications are going to be introduced in a pervasive manner. Each of them offers different kind of measurements and hence different opportunities of exploitation for positioning. Especially IoT networks are resource limited, meaning that energy efficient positioning solutions, even battery-less or passive, are of great interest.

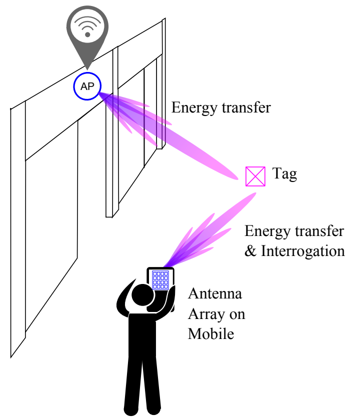

Fig. 8. Opportunities offered by single-anchor localization and massive antenna arrays (from [66]).

In this section we illustrate some recent advances in these directions.

1) Exploiting narrowband measurements for positioning in IoT: Narrowband technologies have very limited positioning capabilities, due to the low power, scarce temporal resolution of signals, and complexity constraints of IoT devices. In addition, interference at unlicensed bands can definitely result in a poor localization performance, but it can be mitigated with coordinated transmission schemes in licensed bands. Therefore, the positioning capabilities of 3GPP narrowband technologies, i.e., eMTC or LTE-M, LTE NB-IoT and EC-GSM-IoT, were studied in Release 14, as it is described in [144]. The main positioning algorithms are enhanced-CID (E-CID), OTDoA and UTDoA. Certainly, the narrow bandwidth, as well as the sparse network density, limits the positioning performance, which is typically desired to fulfill 50 m position accuracy. In order to achieve this requirement, a frequency-hopping (FH) mechanism is studied in [144], by using the flexibility of the narrowband PRS (NPRS) in LTE NB-IoT. The results show that a position accuracy below 50 m can be achieved even in multipath environments, but different impairments still need to be tackled, such as signal acquisition, hardware-induced offsets and cross-correlation ambiguity [144].

Another direction of investigation is the exploitation of the recently introduced public LoRaWAN network. It provides the possibility to perform an alternative way of geo-localization, using TDOA techniques, but with the processing load shifted from the mobile to the back-end network [145], making it much more suitable for localization of resource constrained devices. Recent experimental results, took place around Eindhoven, the Netherlands, considering both pedestrian and vehicular users, indicate that rough positioning accuracies in the order of about 160 meters and 100 meters, respectively, are possible. Such accuracy can be significantly improved to about 70 meters by processing raw TDOA measurements with a road mapping filter making use of the OpenStreetMap database and the approach proposed in [146].

2) Mm-wave and beyond positioning:

a) mm-wave and massive antenna arrays: The future availability of massive antenna arrays at both the mobile device and anchor nodes, thanks to the reduction of the wavelength at mm-wave, will open several opportunities as already discussed in Sec. V-C2a, especially for IoT applications. Among them, very appealing is the possibility to localize mobiles using a single anchor node. This capability is becoming more and more important, especially for indoor environments. In fact, the use of only one anchor will allow the exploitation of the same infrastructure used for communications also for positioning purposes. This overcomes the problem of deploying a redundant ad hoc infrastructure which is, nowadays, the bottleneck slowing the widespread diffusion of indoor localization systems. Moreover it opens new perspectives in infrastructure-less IoT scenarios where the user terminal directly interacts with objects (tags) deployed in the environment by, possibly, powering up via wireless power transfer, communicating, and localizing them relatively to its own position, as discussed in [66] and reported in 8. A single anchor approach is interesting also to support UAVs navigation in critical environments/applications by deploying a ground station equipped with a 2D antenna array that can estimate elevation, azimuth, and distance. Then, this information can be provided to the UAV through an uplink channel [147]–[149].

b) Combined VLC and mm-wave based positioning: Combination of visual light communication (VLC) and radio communication in the unlicensed THz spectrum and mm Wave up/downlink channels in unlicensed 30-300 GHz spectrum is a promising solution which allows wireless communication networks to be deployed in buildings that can provide bit rates greater than 10Gbits/sec, latencies less than 1ms, location accuracy less than 10cm, whilst reducing EMF levels and interference, lowering energy consumption at transmitter/receiver and increasing User Equipment (UE) energy battery lifetime. Such an approach is followed e.g. the H2020 EU Project "Internet of Radio Light" (IORL, https://iorl.5g-ppp.eu). IORL is elaborating a 5G broadband radio-light communication/localization system that provides universal broadband coverage indoors within buildings from remote radio-light heads (RRLHs) that represent access points located within the light roses in buildings.

The mm-Wave based positioning system exploits location relevant parameters that can be estimated either at UE (in the downlink) or at the RRLH controller (in the uplink). The receiver performs measurements and estimates location relevant signal parameters such as the received signal strength (RSS), round-trip times (RTTs), or the time-difference of arrival (TDOA) between different RRLHs. The positioning system based on VLC extends the capabilities of the mm-Wave based system. It uses visible light signals for determining the positioning of target where the signals are transmitted by RRLH lamps (e.g. LEDs) and received by light sensors (e.g. photodiode (PD) or camera), on the target UE as shown in Fig. 9.

The main benefit of such heterogeneous mm-Wave and VLC communication system is the availability of broadband communications services and indoor localization of UEs with an accuracy better than 10cm. Such a high positioning accuracy is to be achieved by combining mm-Wave and VLC technologies in location estimation. The VLC based localization system can

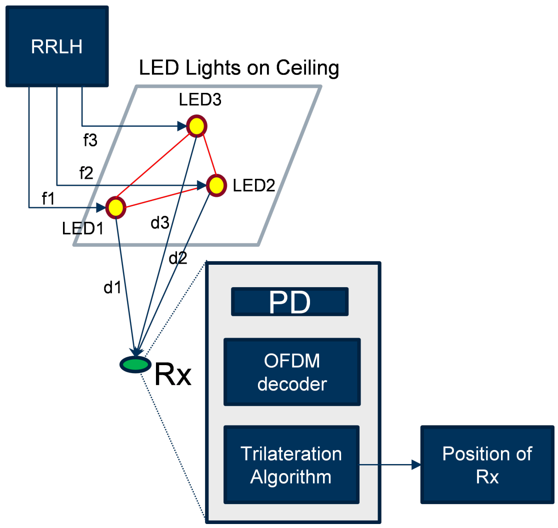

Fig. 9. Concept of the VLC based localization followed by the IORL project.

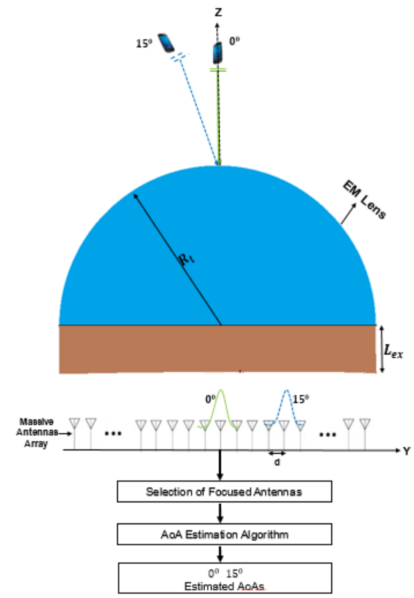

Fig. 10. System model for the EM lens assisted massive antennas array based localization.

be installed inexpensively since it utilizes existing illumination systems with only few modifications. It can be used in RF-inappropriate environments, like hospitals, underground mines and gas stations. Another advantage of VLC-IPS is that there is less effect of multipath on visible light than on RF signal, so the position estimation could be more accurate.

c) EM Lens Antennas for Localization: The resolution of localization techniques based on AoA estimation can be improved with the usage of massive antennas array (MAA) systems as discussed in [40], [150], [151]. However, as we mentioned in Section III, this approach may increase both the hardware (RF chains) and the computational complexities, especially when subspace based algorithms, such as MUSIC or ESPRIT, are deployed. An approach to reduce complexity consists of the deployment of electromagnetic (EM) lens [41], [152].

The EM lenses have recently attracted a renewed interest by the wireless communications community because of the interest in developing mm-Wave systems, where the lens physical dimensions have acceptable size [153]. EM lenses have been studied mostly for beam forming to enhance data rates in massive MIMO [154]. Their ability to focus the impinging wave energy in a small subset of the array elements, makes them attractive in AoA estimation applications as well. Thus, only a small subset of array elements (depending on the AoA) needs to be processed, which contributes to significantly reduce hardware and associated signal processing complexity [155]–[157]. The focusing ability is also beneficial for separating the multipath signal components arriving from different directions and reducing the signal interference [155]. As a result, enhanced AoA resolutions can be attained as compared to the system without lens, despite the reduced complexity.

The localization system depicted in Fig. 10, shows that the system comprises the EM lens (with radius R_l and/or extension length L_{ex}) combined with a massive ULA, a block that detects the focused subsets of antennas, and a block that implements fine AoA digital estimation. A fully digital or a mixed analog-digital architecture can be realized aiming at increasing precision and simplifying the system further. In this regard, one can consider a fully digital localization system by applying for instance the subspace algorithms, i.e., MUSIC, on the selected subset of array elements in baseband [155], [156]. Moreover, simpler analog signal processing methods can also be envisioned i.e., the sum-difference patterns technique proposed in [157]–[159] that exploits RF couplers.

3) Energy Autonomous Positioning for IoT:

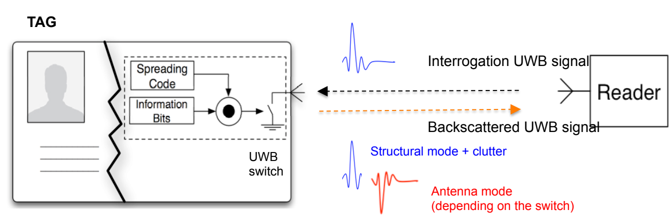

Fig. 11. UWB backscatter communication principle.

a) Localization of battery-less tags: In the new scenarios foreseen by the IoT, industrial and consumer systems will be required to detect and localize tagged items or goods with high accuracy using cheap, energy autonomous (battery-less), and disposable tags.

Current UHF-RFID technology, designed for detecting battery-less tags, does not include a standard feature for high accuracy positioning as requested by many emerging applications (e.g., augmented reality, logistics). In specific controlled conigurations, carrier phase information can be exploited to achieve high accuracy positioning [66], [160], [161]. Another possibility for high accuracy localization of passive RFID tags is to modulate a direct sequence spread spectrum signal onto the interrogation signal of a standard UHF-RFID reader [162]. Coherent combining of the spreading signal is possible by utilizing the known RN16 response of the RFID tag, leading to sub-meter positioning accuracy with COTS-available RFID tags [163], [164].

To achieve even higher positioning accuracies, a combination of UWB backscattering for communication/localization purposes [165]–[167] and UHF for "on demand" powering of battery-less tags [168] is needed. Here power transfer is done through the UHF link since the strict regulations on power emission mask in the UWB band do not allow for a sufficient energy accumulation in the tag. The same link can be used to address the tag (wake-up). Once addressed, the intended tag starts switching the load of its UWB antenna between short and open circuit, according to a proper coded sequence, thus modifying (modulating) the way the UWB signal emitted by the interrogating node is backscattered by the tag (see Fig. 11). By analyzing the backscattered signal and measuring the total round-trip time, the interrogating node can detect the tag and determine its distance with high accuracy (ranging). It is worth to note that no UWB receiving and transmitting circuits are needed in the tag which thus can be made extremely energy efficient and small. In Sec. VI-D examples of implementations and tests of UWB-RFID localization systems with battery-less tags in real scenarios is presented.

b) Passive Localization using 5G signals: With its increased bandwidth and its envisioned usage for vehicular communication, 5G new radio signals might be exploited for road surveillance in automotive environments, thus, enabling extended awareness including non-cooperative road users as for instance pedestrians, cyclists and non-equipped vehicles. In particular, arrays of widely separated 5G road-side units can be used to probe reflected signals of moving objects in order to classify them and determine their position and velocity (passive localization). An example of this application is given in [169] where authors present a road surveillance system based on 5G signals and discuss an appropriate waveform design for determining range and Doppler of a moving object. Measurements with a static antenna array in [170] showed that different objects can be classified on behalf of its reflected power and can be tracked by the signals they scatter. The measurements demonstrate the capability of RF sensor networks for positioning and velocity estimation of non-cooperative road users.

VI. Testbeds and Prototyping Activities

In order to conduct experimental research, companies and institutions build *testbeds*, which are new product development platforms and environments for conducting rigorous, transparent, fair and reproducible testing of scientific theories, new concepts and technologies, as well as for the rapid development and assessment of prototypes.

A. Bridging the gap between simulation and real test with standardized testing approaches

1) Need for a common real test procedure: Evaluating options for positioning techniques during standardization in 3GPP is performed trough simulations based on jointly agreed parameter set and assumptions. Often the simulation environments parameters are based on data communication and are common for evaluating different techniques within predefined scenarios. The results give a strong indication on the expected performance however the positioning performance can only be concluded with tests in real environments. As another aspect, tracking systems datasheets are often not comparable due to different and not standardized testing methods of vendors. To predict the performance without disturbing for example the production process, pseudo-real environment measurements will help to prevent expensive test installations on the user side. 5G positioning will evaluate various positioning technologies which are targeting different environments and designed for special purposes and applications. Whether evaluating the performance of single techniques or hybrid solutions defining standard test procedures is essential for drawing irrefutable results.

2) Test approach : The need for industry accepted methodologies for testing positioning performance was identified in [171] for evaluating positioning system that can fulfill the E911 accuracy requirements. It attempted also to set a baseline standard for indoor positioning testing. Within 5G, the applications extend further to target more scenarios like in industrial and automotive applications. Hence, for testing the performances or for validation if requirements are fulfilled, this requires the definition of standardized test approaches.

Three kinds of tests can be distinguished, namely: basic performance tests, pseudo-real tests and real live tests. The former is generally applied, when the basic performance of a system is requested. This comprises a static point test, where points within a specific area are examined, and a driven trajectory, which can be achieved by a robot platform. Pseudo-real tests consist of environmental setups, where the specific characteristics of the examined application are simulated.

3) Testbeds: Testbeds are needed that implement the above and are available to involved parties. While having the required measurement capabilities, the advantage of such a test center is the feasibility of setting up the test scenario with reproducible environmental conditions supporting high dynamics and seamless indoor/outdoor measurements. For indoor industrial applications for example, a setup like in Fig. 12 is defined for evaluating the radio performance inside a working cell of a production environment. Proof-of-Concept-Setups of potential 5G tracking technologies like dense deployments or and multiple antenna systems can be set up and multiple frequency ranges including millimeter-wave bands can be covered. One existing example to address the issue of characterizing systems is Fraunhofer IIS's test center in Nuremberg, Germany [172].

B. GNSS-based Testbeds

The swiftly evolving landscape of GNSS signals and systems demands rapid prototyping tools in order to explore receivers' full capability, including radically new uses of those signals. That flexibility is hard to find in today's GNSS receiver technology, mainly driven by application-specific integrated circuits (ASIC) and system-on-chip (SoC) implementations with high development costs and very limited degree of reconfigurability, thus hampering experimentation and fair

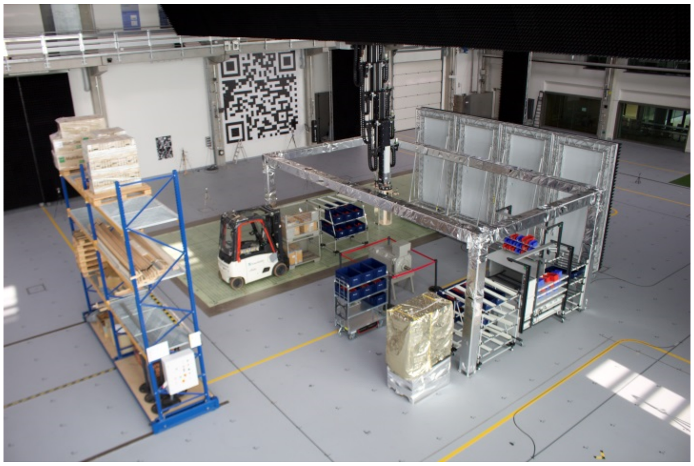

Fig. 12. Test and Application Centre L.I.N.K. (industry 4.0 setup with automatic robot).

(a) Antenna platform. (b) Laboratory rack.

Fig. 13. GESTALT® Testbed for the experimentation with GNSS signals. It includes a set of antennas and RF front-ends, and a host server running instances of an open source software-defined GNSS receiver.

trials of new approaches. Manufacturers are incorporating new features to their commercial receivers at steady pace: most low-cost, mass-market GNSS receivers are already multi-constellation (GPS and GLONASS) but still not multiband. In contrast, professional receivers are mostly dual-band, with some triple-band model (Novatel's OEM628) already available, and allow for access to observables via RINEX files or RTCM stream messages.

In all cases, modern GNSS receivers' performance heavily relies on assistance data from external systems (e.g., cellular and WiFi networks) in order to shorten the time-to-first-fix or enhance their navigation performance via the application of high-accuracy algorithms such as Real Time Kinematics (RTK) or Precise Point Positioning (PPP). The interplay between GNSS receivers and 5G networks is expected to have a growing importance in the provision of new positioning services, specifically on those requiring high levels of accuracy, precision and reliability.

An example of testbed aimed to the research on Global Navigation Satellite Systems signals is GESTALT® (a loose acronym for GNSS Signal Testbed), a facility located at CTTC's headquarters (Castelldefels, Spain). The installation includes hardware, software and networking components, constituting a state-of-the-art facility for research and development of next-generation's GNSS receivers. The presented facility (see Fig. 13) is equipped with an assortment of GNSS antennas; GNSS signal generators for controlled experiments; state-of-the-art radio-frequency front-ends able to work concurrently in three GNSS frequency bands, with configurable bandwidth, frequency downshifting and filtering; digitation working at sample rates as high as 80 MSps with 8-bit, coherent I/Q samples; high-speed interfaces to a host computer; and an open source GNSS software receiver in charge of signal processing and generation of suitable outputs in standard formats.

A key GESTALT® feature is its openness. In addition to the fact that it can be fully operated remotely, the core software receiver engine in charge of all the digital signal processing chain is a free and open source project with a lively community of users and developers (check the website at http://gnss-sdr.org). Accordingly, a partial testbed replication can be done on a limited budget with commodity computers and low cost, over-the-counter antennas and radio-frequency front-ends. This allows for the practical implementation of new concepts, reproducible research and short assessment and validation times, ultimately shortening the gap between ideas for new uses of GNSS signals and user-driven, market-ready products and services.

A network of software-defined GNSS receivers executed in the cloud could be a solution to overcome the limited computational resources of IoT node. In this solution, the GNSS receiver is no longer a physical device but a virtualized function provided as a service. In [173], authors proposed a system architecture based on optical networks and automated orchestration tools to deliver continuous service with high-accuracy performance to users with high-bandwidth connectivity, which could be provided by 5G networks.

Virtualisation technologies also offer a convenient solution for security-related applications (e.g. GPS M code, Galileo PRS), since the encryption module remains on the service provider's premises, and there is no need for a security module in the receiver equipment. This approach may enable the widespread use of restricted/authorised signals by the civilian population.

C. *Localisation for Massive MIMO Testbeds*

Massive MIMO provides an opportunity for superior positioning schemes based on the highly accurate AOA/AOD information that can be obtained via the use of massive antenna arrays. In particular, it presents an opportunity for a simple, single BS localisation by utilizing the LOS AOA and mobile station range information. Massive MIMO challenges are discussed in [174] and [175]. User/mobile detection is usually done as a first step in modern wireless systems. If full localisation can be performed at the same time, there are potential benefits that such an approach can bring to the next-generation wireless systems as discussed in [176].

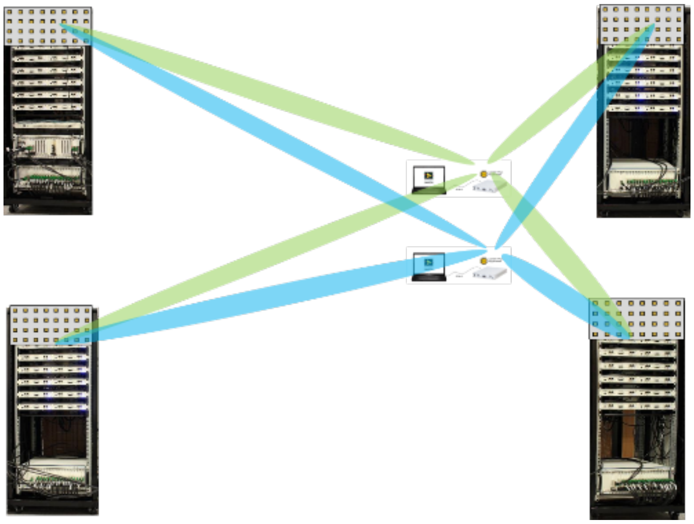

Fig. 14. Bristol Massive MIMO testbed

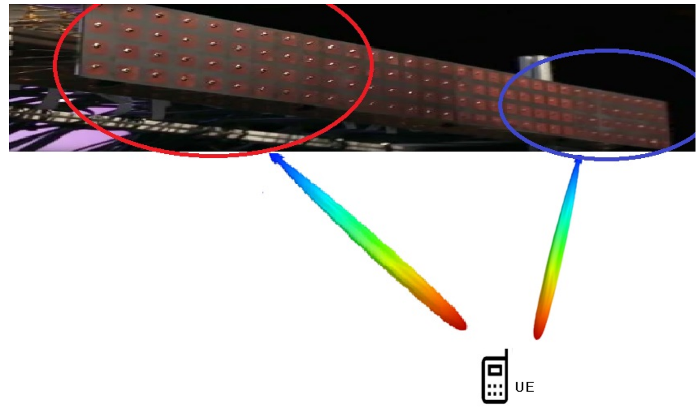

Fig. 15. Localisation using a single BS with a large antenna array

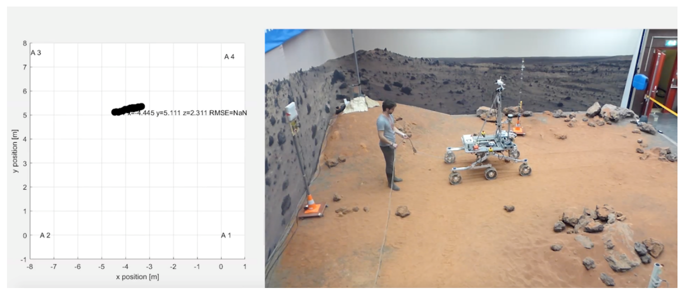

Fig. 16. Test of the UWB-RFID battery-less localization system on the Mars Rover prototype in the Automation and Robotics Laboratories at ESA.

An overview of the University of Bristol's Massive MIMO testbed can be found in [176]. Fig. 14 shows the distributed system, each cabinet with radios driving a 32-element sub array, to act as a base station. The two Universal Software Radio Peripherals (USRPs) and a laptop shown on the figure, are the user equipment. The testbed is currently being used in the development, test and validation of DOA and localization strategies.

Localisation schemes that employs DOA estimation can be approached in two different ways, when massive MIMO arrays are considered. One way is to perform DOA on individual, separate base stations, and then use tri-angulation to get the location of the target or user equipment (UE). Another way is to take advantage of the large geometries of linear or rectangular arrays to perform DOA using different subsets of antennas on the array. This allows DOA estimation and subsequently triangulation, to be performed using just a single BS. This approach however, depends on array size and geometry. It is suitable for LOS scenarios with smaller coverage areas, like indoor environments. Linear or rectangular arrays will suffer from the Geometric Dilution of Precision (GDOP) problem, but use of subarrays for DOA estimation allows localisation algorithms to have a choice over the selection of best DOA estimates, based on predetermined confidence criterion. Fig. 15 shows how subarrays on a rectangular array may be used for DOA estimation to achieve localization using a single base station. A major challenge with most DOA approaches is the calibration of the antenna arrays. Super resolution AOA requires multiple antennas at each base station, which is well provided for by massive MIMO, but calibrating those hundreds of radio chains is a challenge.

D. Testbeds of Localization systems based on battery-less tags

Here we briefly describe some implementation and test beds of battery-less localization systems based on the UWB-RFID concept explained in Sec. V-E3.

In [168] and references therein, most of the aspects related to the design of UWB-RFID systems based on backscatter modulation are discussed such as the design of dual-band UWB/UHF rectenna, energy harvesting circuits, and signal processing techniques. The experimental campaign described carried out in a real environment indicates that an accuracy of about 4 cm in a 5x5 area. Another test bed is that described in [177] where the same technology was applied to order luggage in airports when items are as close each other as less then 20 cm.

Better performances have been obtained within the "LOST" project funded by the European Space Agency by a team composed by the University of Bologna and the University Catholique of Louvain. The main objective of the project was to study radio technologies able to localize with centimeter-level accuracy battery-less tags inside the International Space Station (ISS), which is a quite challenging "indoor" scenario. Differently from the previous test bed, here the tag accumulates the energy from the UHF link and once addressed sends out a train of UWB pulses through a small energy efficient UWB pulse generator. In this way longer ranges have been obtained with the same accuracy, in particular more than 10 meters both in wireless power transfer and UWB localization. The functionality and performance of the LOST system have been successfully tested directly on the Mars Rover prototype in the Automation and Robotics Laboratories at ESA as shown in Fig. 16.

VII. Non-technical Challenges

The successful deployment of advanced localization services in future wireless networks can also be hampered by a number of non-technical challenges (in addition to the aforementioned technical ones). To start with, regulations on the privacy of geolocation information have a very important role to play. In the US, where such regulations are mostly addressed at the state (rather than federal) level, there exist multiple bills aiming for a tighter use of geolocation data. For example, the Location Privacy Protection Act would "prohibit companies from collecting or disclosing geolocation information from an electronic communications device without the user's consent". Still, it provides exceptions for parents tracking their children, emergency services, law enforcement, and other cases. In Europe, the Directive on Privacy and Electronic Communications dictates that location data can only be used if anonymized. If not, (i) users must give their consent for their location data to be used and accessed; and (ii) the service provider must inform the user about what location data is collected, processed, for which purpose, and whether it will be transmitted to any third parties. Besides, users are allowed to opt out at any time. Clearly, all the above puts stringent limits to the collection and/or use of location data by e.g., network operators.

Another issue is the lack of suitable business models for many application scenarios. This is partly due to the fact that most location services offered today by wireless networks are driven by regulatory requirements. Take, for instance, the 112 number for emergency services. Knowing the exact location of people calling the 112 emergency number is very important for emergency services. This knowledge ensures, inter-alia, timely interventions, or verification of genuine calls. But, again, this is not the result of any underlying business model. Instrumental towards the definition of business models is the identification of the various players in the value chain, their roles, strategies and responsibilities. For instance, in order to address automotive applications, mobile network operators, road operators (public or private sector entities) and the automotive industry need to form alliances. This process has started in e.g., the 5G Automotive Association (5GAA) but needs to continue at a wider scale.

The access to the location information gathered by future mobile networks also deserves some attention. Nowadays, a vast majority of location-based apps running on mobile phones and handheld devices (e.g., apps for navigation, fitness-tracking, etc.) just require access to GNSS, IMU or Wi-Fi measurements (i.e., over-the-top). End-users are generally inclined to grant access to such data. But, will the new built-in positioning capabilities of 5G might be equally accessible to all parties? Or just to certain parties such as the mobile network operator. Or, perhaps, will the cost of getting access to location data be prohibitively high in an attempt to reap part of the benefits of over-the-top offerings?

VIII. Recommendations

Localization and tracking techniques are finding their way as an integral part of future wireless communication systems like 5G. Despite of the attention raised among the research community, many open issues at the scientific, technological and regulatory levels still remain. Besides, the impact of a widespread adoption of network-based localization in a number of verticals (e.g., transportation, healthcare, tourism), society (e.g,, enhanced road safety, emergency management, etc), and communication networks themselves (e.g., reduced CAPEX/OPEX for network optimization) is very large. All the above, calls for an increased and more coordinated effort in the years to come.

To that aim, we propose the following recommendations and way forward:

1) **Additional research efforts** in areas such as (i) synchronization mechanisms and requirements for different environments, such as indoor, urban, sub-urban and rural.; (ii) cooperative positioning; (iii) data fusion: the combination of heterogeneous measurements from multiple sources (wireless networks including 5G, cameras, inertial systems, VLC) and frequency bands (cm-wave, mm-wave); (iv) joint optimization of the (often contradictory) communications and positioning targets; (v) the exploitation of multi-path propagation/NLOS scenarios in localization algorithms; (vi) the derivation of suitable channel models, in particular for higher frequency bands and/or massive MIMO settings; (vii) low energy consumption and complexity reduction in large antenna arrays and/or IoT devices; and, last but not least, (ix) the derivation of (asymptotic) performance limits for the benchmarking of actual systems.
2) **A closer interaction among the signal processing, channel modeling, network protocol, radiofrequency and microelectronic design communities** in order to overcome the aforementioned technological problems related with localization and tracking functionalities in future wireless networks .
3) **Continuous monitoring of, and provision of inputs to, standardization bodies** (notably 3GPP, IEEE) and industry fora, along with interaction with regulatory bodies for the purpose of ensuring global impact and economies of scale of localization technologies.
4) **Broader and sustained support from publicly-run research funding programs** (Horizon 2020, GSA), in order to underpin the aforementioned research and standardization efforts.
5) **Identification of novel application scenarios** (e.g., intelligent transportation systems, industrial environments, retail) and use cases potentially benefiting from the increased localization accuracy and reliability of 5G and future communication systems can offer.
6) **Increased efforts in experimental research and prototyping activities**, aimed to help bridge the gap between theoretical research and commercial exploitation, with emphasis in the usage of open-source testbeds, for reproducibility.

IX. Conclusions

Localization technologies are called to play a central role in the design of 5G communication systems and IoT wireless technologies. This whitepaper, which has been authored by members of the Experimental Working Group "Localization and Tracking" of the COST Action IRACON, is aimed to highlight this.

The paper has started with a summary of the most promising future application scenarios for high-accuracy positioning. This includes intelligent transportation systems, unmanned aerial vehicles, industrial applications like system control, or factory and process automation; retail (e.g., for indoor user navigation to desired products or proximity marketing), or ambient assisted living. Except for the last two scenarios, submeter accuracies and latency values below 10 ms are needed for positioning. And, clearly, those requirements cannot be met by today's wireless communication systems.

The review of future application scenarios has been followed by a discussion of the technical challenges arising from them. To start with, a variety of heterogeneous (wireless) technologies will be needed to support such variety of applications and performance requirements. Besides, efficient methods to mitigate/exploit multipath propagation, the detection of line-of-sight availability or time synchronization schemes for independent radio transceivers must be developed. Despite that large antenna array systems (likely to be used in future 5G systems) can significantly improve the precision of angle-of-arrival based localization systems, particular attention has to be paid to hardware complexity and cost complexity considerations; whereas power consumption and computational burden turn out to be key challenges for IoT-based localization.

Next, we have illustrated the expected features and limitations of 5G and IoT wireless systems with respect to positioning. The larger bandwidths in 5G systems, on the one hand, allow for a higher degree of delay resolution. On the other, higher carrier frequencies result into fewer propagation paths and the possibility to pack more antennas into a given area. All the above, clearly, leads to a high degree of resolvability of multipath signals and, in turn, enhanced positioning accuracy. Network densification is also beneficial in that it maximizes the probability of having LOS condition with, possibly, multiple base stations. Along with that, the availability of device-to-device links also provides an additional source of positioning information. The narrow bandwidth and large coverage of long range IoT solutions (LoRa, Sigfox, LRLP, NB-IoT, etc.), on the contrary, limit to a large extent their achievable positioning performance. For short-range and narrowband systems like Bluetooth Low Energy or RFID, however, fingerprinting-based or proximity techniques can achieve meter-level accuracies. Complementarily, short-range wideband systems (e.g., IEEE 802.15.4a UWB standard) allow for centimeter-level accuracies.

This white paper has also attempted to describe the state-of-the-art of recent scientific and technical progress in the field. Since in localization systems the information associated to the position is embedded in channel parameters such as TOA or RSS, there is a pressing need to derive channel models able to capture such dependencies. A non-exhaustive list of channel model families includes classical narrowband ones such as Hata-like models, deterministic ray-tracing and ray-launching models, geometry-based stochastic models, and models based on graph theory. On a different key, theoretical performance limits provide insight into what performance levels can possibly be achieved, based on some given signal model. Therefore, we have discussed and presented some recent research results concerning performance limits in measurement acquisition (TOA, AOA or RSS estimation; impact of clock drift, etc), localization and tracking, for a range of localization scenarios like mm-wave, single-anchor massive arrays, and sub-6 GHz cellular systems. Besides, we have analyzed the inherent trade-offs between positioning accuracy and achievable communication data rate, since the available time-frequency resources must be shared between both tasks. We have also reviewed a number of advanced methods and algorithms for positioning and tracking. On the one hand, we have focused our attention on novel multipath-assisted localization techniques exploiting (rather than attempting to mitigate) specular multi-path components in order to improve robustness in NLOS scenarios. On the other, we have also discussed NLOS identification schemes based on machine learning techniques (e.g., support vector machines); approaches for NLOS mitigation by incorporating extra parameters in the channel model accounting for the extra delay; or cooperative positioning techniques for IoT and IoV scenarios, enabling devices to self-localize by exploiting communication with their neighbors (via consensus algorithms, for instance). To conclude this part, we have also provided an overview of recent advances in the exploitation of narrowband measurements for positioning in IoT. This includes resorting to coordinated transmission schemes in licensed bands or shifting the processing load from the (resource constrained IoT device) to the back-end network, like in LoRaWAN networks. We have also discussed combined VLC and mm-wave based positioning schemes allowing for (very) broadband communication services and indoor localization services of UEs with an accuracy below 10 cm; and the use of electromagnetic lens antennas to focus impinging waves on a subset of elements in a large array (and, by doing so, minimize hardware costs and computational complexity).

In order to bridge the gap between theoretical advances and product development, experimental research and prototyping activities are key. In this context, testbeds play a very prominent role. For this reason, we have brought to the reader's attention the availability of GNSS-based testbeds like GESTALT. This is a software-defined receiver and open-source project which allows for the practical implementation of new concepts, to investigate e.g, the interplay of GNSS receivers and 5G networks for the provision of new localization services. Complementarily, we have also reported on a number of experimental activities on localization for massive MIMO testbeds; and testbeds of battery-less (tags) localization systems based on UWB-RFID concepts.

Finally, we have outlined a number of non-technical challenges hindering the successful deployment of advanced localization services. This includes privacy regulations on geolocation information, the lack of suitable business models for many application scenarios, or the need to identify the various players in the value chain. To close this white paper, we have put forward a number of recommendations to facilitate a widespread adoption of (network-based) localization services: additional research and funding efforts; a closer interaction of a number of research communities, tighter interaction with relevant standardization bodies, identification of novel application scenarios and, last but not least, increased efforts in experimental research and prototyping activities.

Acknowledgements

We acknowledge COST Action CA15104 "IRACON" for bringing together an exciting research community dealing with "Inclusive Radio Communications for 5G and Beyond". This White Paper has been edited by members of this COST Action. We also acknowledge the support by the authors' institutions, which are listed in the footnote.[1]

References

[1] K. Witrisal, P. Meissner, E. Leitinger, Y. Shen, C. Gustafson, F. Tufvesson, K. Haneda, D. Dardari, A. Molisch, A. Conti, and M. Z. Win, "High-accuracy localization for assisted living: 5G systems will turn multipath channels from foe to friend," *IEEE Signal Process. Mag.*, vol. 33, no. 2, pp. 59–70, Mar. 2016.

[2] H. Wymeersch, G. Seco-Granados, G. Destino, D. Dardari, and F. Tufvesson, "5G mm-Wave positioning for vehicular networks," *Wireless Communications Magazine*, vol. XX, no. YY, p. ZZ, 2018.

[3] L. Chen, S. Thombre, K. Jarvinen, E. S. Lohan, A. K. Alen-Savikko, H. Leppakoski, M. Z. H. Bhuiyan, S. Bu-Pasha, G. N. Ferrara, S. Honkala, J. Lindqvist, L. Ruotsalainen, P. Korpisaari, and H. Kuusniemi, "Robustness, security and privacy in location-based services for future IoT: A survey," *IEEE Access*, vol. 5, pp. 2169–3536, Apr. 2017.

[4] J. A. del Peral-Rosado, R. Raulefs, J. A. López-Salcedo, and G. Seco-Granados, "Survey of cellular mobile radio localization methods: from 1G to 5G," *IEEE Commun. Surveys Tuts.*, vol. XX, no. XX, p. XX, Dec. 2017.

[1]C. Antón-Haro (Editor, Section Editor), C. Fernández-Prades (Section Editor), and Jordi Vilà-Valls are with the Centre Tecnològic de Telecomunicacions de Catalunya (CTTC/iCERCA), Spain.
K. Witrisal (Editor, Section Editor) and S. Grebien are with Graz University of technology, Austria, and the Christian Doppler Laboratory for Location-aware Electronic Systems.
T. Wilding is with Graz University of Technology, Austria.
J. A. del Peral-Rosado (Section Editor) and G. Seco-Granados are with the Universitat Autònoma de Barcelona (UAB), Spain
R. Raulefs (Section Editor), M. Ulmschneider, F. PonteMueller, and M. Schmidhammer are with the Deutsches Zentrum fÃijr Luft- und Raumfahrt (DLR), Germany
D. Dardari (Section Editor) and V. Degli Esposti are with the Università di Bologna, Italy.
E. Leitinger (Section Editor) is with Lund University, Sweden and with Graz University of Technology, Austria
E.S. Lohan is with the Tampere University of Technology (TUT), Finland.
H. Wymeersch (Section Editor) is with Chalmers, Sweden.
J.J. Floch and T. Fath are with Airbus Defence and Space GmbH, Germany.
R. Thomae and M. Nogueira are with TU Ilmenau, Germany.
W. Joseph and D. Plets are with U. Ghent, Belgium.
A.M. Tonello and S.A. Shaikh are with the University of Klagenfurt, Austria.
T. Pedersen and B. Fleury are with Aalborg University, Denmark.
A. Navarro Cadavid and W.A. Cruz Lopez are with Universidad Icesi, Colombia.
T. Zemen and O. Renaudin are with the Austrian Institute of Technology (AIT), Austria.
M. Nicoli and G. Soatti are with Politecnico di Milano (POLIMI), Italy.
R. Zetik, N. Franke, M. Alawieh and B. Sackenreuter are with the Fraunhofer IIS, Germany.
F. Quitin (Section Editor) is with the Université Libre de Bruxelles (ULB), Belgium.
G. Destino is with the University of Oulu, Finland.
K. Trivodaliev and Biljana Risteska Stojkoska are with the Ss Cyril and Methodius University, Macedonia.
F. Tufvesson is with Lund University.
T. Baykas is with Medipol University, Turkey.
B. Chitambira is with the University of Bristol, UK
R. Oliveira is with Instituto de TelecomunicaÃğÃţes and Universidade Nova de Lisboa, Portugal.

[5] A. F. G. Ferreira, D. M. A. Fernandes, A. P. Catarino, and J. L. Monteiro, "Localization and positioning systems for emergency responders: A survey," *IEEE Communications Surveys Tutorials*, vol. 19, no. 4, pp. 2836–2870, Fourthquarter 2017.

[6] 3GPP, "3GPP TR 37.857: Study on indoor positioning enhancements for UTRA and LTE (Release 13)," ETSI, Tech. Rep., 12 2015.

[7] X. Lin, J. Bergman, F. Gunnarsson, O. Liberg, S. M. Razavi, H. S. Razaghi, H. Rydn, and Y. Sui, "Positioning for the internet of things: A 3gpp perspective," *IEEE Communications Magazine*, vol. 55, no. 12, pp. 179–185, 2017.

[8] 3GPP, "3GPP RP-172795: Handling new SI/WI proposals in RAN," ETSI, Tech. Rep., 12 2017.

[9] I. et al., "3GPP RP-172397: New SID: Study on NR positioning support," ETSI, Tech. Rep., 12 2017.

[10] L. E. et al., "3GPP RP-172502: New SI proposal: Study on 3GPP V2X phase 3 based on NR," ETSI, Tech. Rep., 12 2017.

[11] "5G Automotive Vision," 5G Public Private Partnership, Oct. 2015.

[12] "D2.1 Use cases and Application Requirements ," HIGHTS Deliverable, March 2016.

[13] "TIMON - Enhanced real time services for optimized multimodal mobility relying on cooperative networks and open data," H2020 Project. Grant Agreement No. 636220, 2017, Aceessed: March 16, 2018. [Online]. Available: https://www.timon-project.eu/

[14] L. Gupta, R. Jain, and G. Vaszkun, "Survey of important issues in UAV communication networks," *IEEE Communications Surveys Tutorials*, vol. 18, no. 2, pp. 1123–1152, Secondquarter 2016.

[15] B. Salamat and A. M. Tonello, "Novel trajectory generation and adaptive evolutionary feedback controller for quadrotors," in *Proc. of IEEE Aerospace*, [To be appeared] 2018.

[16] A. Papaiz and A. M. Tonello, "Azimuth and elevation dynamic tracking of uavs via 3-axial ULA and particle filtering," *International Journal of Aerospace Engineering*, vol. 2016, p. 9 pages, 2016.

[17] A. Nemra and N. Aouf, "Robust INS/GPS sensor fusion for UAV localization using SDRE nonlinear filtering," *IEEE Sensors Journal*, vol. 10, no. 4, pp. 789–798, Apr. 2010.

[18] K. Guo, Z. Qiu, C. Miao, A. H. Zaini, C.-L. Chen, W. Meng, and L. Xie, "Ultra-wideband-based localization for quadcopter navigation," *Unmanned System, World Scientific Publishing Company*, vol. 4, no. 1, pp. 23–34, Feb. 2016.

[19] A. Papaiz and A. M. Tonello, "Particle filtering with weight reshaping for opportunistic angle of arrival estimation in a vehicular scenario," in *2015 IEEE 5th International Conference on Consumer Electronics - Berlin (ICCE-Berlin)*, Sep. 2015, pp. 145–149.

[20] R. K. Martin, J. S. Velotta, and J. F. Raquet, "Bandwidth efficient cooperative TDOA computation for multicarrier signals of opportunity," *IEEE Transactions on Signal Processing*, vol. 57, no. 6, pp. 2311–2322, June 2009.

[21] 3GPP, "3GPP TR 22.891: Technical Specification Group Services and System Aspects; Feasibility Study on New Services and Markets Technology Enablers; Stage 1; (Release 14)," ETSI, Tech. Rep., 03 2016.

[22] A. Yaeli, P. Bak, G. Feigenblat, S. Nadler, H. Roitman, G. Saadoun, H. J. Ship, D. Cohen, O. Fuchs, S. Ofek-Koifman *et al.*, "Understanding customer behavior using indoor location analysis and visualization," *IBM Journal of Research and Development*, vol. 58, no. 5/6, pp. 3–1, 2014.

[23] H. Hwangbo, Y. S. Kim, and K. J. Cha, "Use of the smart store for persuasive marketing and immersive customer experiences: A case study of korean apparel enterprise," *Mobile Information Systems*, vol. 2017, 2017.

[24] S. Alletto, R. Cucchiara, G. Del Fiore, L. Mainetti, V. Mighali, L. Patrono, and G. Serra, "An indoor location-aware system for an iot-based smart museum," *IEEE Internet of Things Journal*, vol. 3, no. 2, pp. 244–253, 2016.

[25] E. Ahvar, N. Daneshgar-Moghaddam, A. M. Ortiz, G. M. Lee, and N. Crespi, "On analyzing user location discovery methods in smart homes: A taxonomy and survey," *Journal of Network and Computer Applications*, vol. 76, pp. 75–86, 2016.

[26] T. Haute, E. Poorter, P. Crombez, F. Lemic, V. Handziski, N. Wirström, A. Wolisz, T. Voigt, and I. Moerman, "Performance analysis of multiple indoor positioning systems in a healthcare environment," *International journal of health geographics*, vol. 15, no. 1, p. 7, 2016.

[27] F. Zafari, A. Gkelias, and K. Leung, "A survey of indoor localization systems and technologies," *arXiv preprint arXiv:1709.01015*, 2017.

[28] 3GPP, "3GPP TR 38.913: Study on Scenarios and Requirements for Next Generation Access Technologies; (Release 14)," ETSI, Tech. Rep., 06 2017.

[29] ——, "3GPP TR 22.872: Study on positioning use cases; Stage 1 (Release 16)," ETSI, Tech. Rep., 11 2017.
[30] "IEEE Std 802.11-2016 (Revision of IEEE Std 802.11-2012)," pp. 1–3534, Dec 2016.
[31] V. Jungnickel, T. Wirth, M. Schellmann, T. Haustein, and W. Zirwas, "Synchronization of cooperative base stations," in *IEEE International Symposium on Wireless Communication Systems (ISWCS)*, 2008.
[32] A. Forenza, S. Perlman, F. Saibi, M. D. Dio, R. van der Laan, and G. Caire, "Achieving large multiplexing gain in distributed antenna systems via cooperation with pCell technology," in *2015 49th Asilomar Conference on Signals, Systems and Computers*, 2015.
[33] J. Pratt, P. Axelrad, K. M. Larson, B. Lesage, R. Gerren, and N. DiOrio, "Satellite clock bias estimation for igps," *GPS Solutions*, vol. 17, no. 3, pp. 381–389, 2012.
[34] G. Giorgi and C. Narduzzi, "Performance analysis of kalman filter-based clock synchronization in IEEE 1588 networks," in *International IEEE Symposium on Precision Clock Synchronization for Measurement, Control, and Communication*, 2009.
[35] H. Balan, R. Rogalin, A. Michaloliakos, K. Psounis, and G. Caire, "Achieving high data rates in a distributed MIMO system," in *Proceedings of the 18th annual international conference on Mobile computing and networking, (MobicomâĂŹ12)*, 2012.
[36] F. Quitin, M. Rahman, R. Mudumbai, and U. Madhow, "A scalable architecture for distributed transmit beamforming with commodity radios: design and proof of concept," *IEEE Transactions on Wireless Communications*, vol. 12, no. 3, 2013.
[37] L. Patino-Studencka, A. Eidloth, and J. Thielecke, "Modelling of free-running clocks for a virtually synchronized microwave locating system," in *Positioning, Navigation and Communication, 2009. WPNC 2009. 6th Workshop on*. IEEE, 2009, pp. 151–155.
[38] M. Alawieh, L. Patino-Studencka, and D. Dahlhaus, "Stochastic modeling of pseudolite clock errors using enhanced ar methods," in *Communication Systems Networks and Digital Signal Processing (CSNDSP), 2010 7th International Symposium on*. IEEE, 2010, pp. 178–183.
[39] M. Leng, F. Quitin, W. P. Tay, C. Cheng, S. G. Razul, and C. M. S. See, "Anchor-aided joint localization and synchronization using soop: Theory and experiments," *IEEE Transactions on Wireless Communications*, vol. 15, no. 11, 2016.
[40] R. Shafin, L. Liu, and J. Zhang, "DoA estimation and RMSE characterization for 3D massive-MIMO/FD-MIMO OFDM system," in *Proc. of IEEE Global Communications Conference (GLOBECOM)*, Dec. 2015, pp. 1–6.
[41] S. A. Shaikh and A. M. Tonello, "Localization based on angle of arrival in EM lens-focusing massive MIMO," in *Proc. of IEEE 6th International Conference on Consumer Electronics (ICCE), Berlin, Germany*, Sep. 2016, pp. 127–131.
[42] F. Rusek, D. Persson, B. K. Lau, E. G. Larsson, T. L. Marzetta, O. Edfors, and F. Tufvesson, "Scaling up MIMO: Opportunities and challenges with very large arrays," *IEEE Signal Processing Magazine*, vol. 30, no. 1, pp. 40–60, Jan. 2013.
[43] A. Papaiz and A. M. Tonello, "Single-receiver switched opportunistic approach to AoA estimation in hardware impaired scenarios," in *SCC 2017; 11th International ITG Conference on Systems, Communications and Coding*, Feb. 2017, pp. 1–6.
[44] A. Lu and V. Lau, "Phase only RF precoding for massive MIMO systems with limited RF chains," *IEEE Transactions on Signal Processing*, vol. 62, no. 17, pp. 4505–4515, 2014.
[45] D. Inserra and A. M. Tonello, "Characterization of hardware impairments in multiple antenna systems for DoA estimation," *Journal of Electrical and Computer Engineering*, vol. 2011, p. 10 pages, 2011.
[46] E. Larsson, O. Edfors, F. Tufvesson, and T. Marzetta, "Massive MIMO for next generation wireless systems," *IEEE Communications Magazine*, vol. 52, no. 2, pp. 186–195, Feb. 2014.
[47] E. BjÃűrnson, J. Hoydis, M. Kountouris, and M. Debbah, "Massive MIMO systems with non-ideal hardware: Energy efficiency, estimation, and capacity limits," *IEEE Transactions on Information Theory*, vol. 60, no. 11, pp. 7112–7139, Nov. 2014.
[48] D. Inserra and A. M. Tonello, "Performance analysis of a novel antenna array calibration approach for direction finding systems," *Transactions on Emerging Telecommunications Technologies*, vol. 23, no. 8, pp. 777–788, Sep. 2012.
[49] O. Georgiou and U. Raza, "Low power wide area network analysis: Can lora scale?" *IEEE Wireless Communications Letters*, vol. 6, no. 2, pp. 162–165, April 2017.
[50] G. Forum, "5G New Wave - Towards future societies in the 2020S," kani.or.kr/5g/whitepaper/2015\%205G_Forum_White_Paper_Service.pdf, accessed Jan 2018, March 2015.
[51] J. G. Andrews, S. Buzzi, W. Choi, S. V. Hanly, A. Lozano, A. C. Soong, and J. C. Zhang, "What will 5g be?" *IEEE Journal on selected areas in communications*, vol. 32, no. 6, pp. 1065–1082, 2014.
[52] F. Boccardi, R. W. Heath, A. Lozano, T. L. Marzetta, and P. Popovski, "Five disruptive technology directions for 5g," *IEEE Communications Magazine*, vol. 52, no. 2, pp. 74–80, 2014.
[53] T. S. Rappaport, G. R. MacCartney, M. K. Samimi, and S. Sun, "Wideband millimeter-wave propagation measurements and channel models for future wireless communication system design," *IEEE Transactions on Communications*, vol. 63, no. 9, pp. 3029–3056, 2015.
[54] S. Sun, T. S. Rappaport, R. W. Heath, A. Nix, and S. Rangan, "Mimo for millimeter-wave wireless communications: Beamforming, spatial multiplexing, or both?" *IEEE Communications Magazine*, vol. 52, no. 12, pp. 110–121, 2014.
[55] N. Bhushan, J. Li, D. Malladi, R. Gilmore, D. Brenner, A. Damnjanovic, R. Sukhavasi, C. Patel, and S. Geirhofer, "Network densification: the dominant theme for wireless evolution into 5g," *IEEE Communications Magazine*, vol. 52, no. 2, pp. 82–89, 2014.
[56] J. Li, "Los probability modeling for 5g indoor scenario," in *2016 International Symposium on Antennas and Propagation (ISAP)*, Oct 2016, pp. 204–205.
[57] M. N. Tehrani, M. Uysal, and H. Yanikomeroglu, "Device-to-device communication in 5g cellular networks: challenges, solutions, and future directions," *IEEE Communications Magazine*, vol. 52, no. 5, pp. 86–92, 2014.
[58] U. Raza, P. Kulkarni, and M. Sooriyabandara, "Low power wide area networks: An overview," *IEEE Communications Surveys Tutorials*, vol. 19, no. 2, pp. 855–873, Secondquarter 2017.
[59] J. Petajajarvi, K. Mikhaylov, M. Hamalainen, and J. Iinatti, "Evaluation of lora lpwan technology for remote health and wellbeing monitoring," in *2016 10th International Symposium on Medical Information and Communication Technology (ISMICT)*, March 2016, pp. 1–5.
[60] K. E. Nolan, W. Guibene, and M. Y. Kelly, "An evaluation of low power wide area network technologies for the internet of things," in *2016 International Wireless Communications and Mobile Computing Conference (IWCMC)*, Sept 2016, pp. 439–444.
[61] B. C. Fargas and M. N. Petersen, "GPS-free geolocation using LoRa in low-power WANs," in *2017 Global Internet of Things Summit (GIoTS)*. IEEE, jun 2017, pp. 1–6. [Online]. Available: http://ieeexplore.ieee.org/document/8016251/
[62] I. P802.11, "Lrlp topic interest group," http://www.ieee802.org/11/Reports/lrlp_update.htm, accessed Jan 2018.
[63] R. O. Schmidt, "Multiple emitter location and signal parameter estimation," *IEEE Transactions on Antennas and Propagation*, vol. 34, pp. 276–280, Mar. 1986.
[64] S. Al-Sarawi, M. Anbar, K. Alieyan, and M. Alzubaidi, "Internet of things (iot) communication protocols: Review," in *2017 8th International Conference on Information Technology (ICIT)*, May 2017, pp. 685–690.
[65] T. Liu, Y. Liu, L. Yang, Y. Guo, and C. Wang, "Backpos: High accuracy backscatter positioning system," *IEEE Transactions on Mobile Computing*, vol. 15, no. 3, pp. 586–598, March 2016.
[66] D. Dardari, N. Decarli, A. Guerra, and F. Guidi, "The future of Ultra-Wideband localization in RFID," in *2016 IEEE International Conference on RFID (RFID) (IEEE RFID 2016)*, Orlando, USA, May 2016.
[67] D. Dardari, A. Conti, U. Ferner, A. Giorgetti, and M. Z. Win, "Ranging with ultrawide bandwidth signals in multipath environments," *Proc. IEEE*, vol. 97, no. 2, pp. 404–426, Feb 2009, special Issue on UWB Technology & Emerging Applications.
[68] J. Kulmer, S. Hinteregger, B. GroÃ§windhager, M. Rath, M. S. Bakr, E. Leitinger, and K. Witrisal, "Using decawave uwb transceivers for high-accuracy multipath-assisted indoor positioning," in *Proc. ICC Workshops*, May 2017, pp. 1239–1245.
[69] T. Pedersen, "Contributions in radio channel sounding, modeling, and estimation," Ph.D. dissertation, Aalborg University, Jan. 2009.
[70] L. J. Greenstein, V. Erceg, Y. S. Yeh, and M. V. Clark, "A new path-gain/delay-spread propagation model for digital cellular channels," *IEEE Transactions on Vehicular Technology*, vol. 46, no. 2, pp. 477–485, May 1997.
[71] N. Patwari, J. N. Ash, S. Kyperountas, A. O. Hero, R. L. Moses, and N. S. Correal, "Locating the nodes: cooperative localization in wireless sensor networks," *IEEE Signal Processing Magazine*, vol. 22, no. 4, pp. 54–69, Jul. 2005.
[72] B. Alavi and K. Pahlavan, "Modeling of the distance error for indoor geolocation," in *IEEE Wireless Communications and Networking (WCNC '03)*, vol. 1, March 2003, pp. 668âĂŞ–672.

[73] C. Pedersen, T. Pedersen, and B. H. Fleury, "A variational message passing algorithm for sensor self-localization in wireless networks," in *2011 IEEE International Symposium on Information Theory Proceedings*, Jul. 2011, pp. 2158–2162.

[74] S. Begusic, D. N. Urup, J. Kolonic, H. H. Pedersen, W. Wang, R. Raulefs, M. L. Jakobsen, G. Steinböck, and T. Pedersen, "Wireless indoor positioning relying on observations of received power and mean delay," in *2013 IEEE International Conference on Communications Workshops (ICC)*, Jun. 2013, pp. 74–78.

[75] C. A. Balanis, *Advanced Engineering Electromagnetics*. New York, NY: John Wiley & Sons, 1989.

[76] P. Meissner, E. Leitinger, and K. Witrisal, "UWB for robust indoor tracking: Weighting of multipath components for efficient estimation," *IEEE Wireless Comm. Lett.*, vol. 3, no. 5, pp. 501–504, Oct. 2014.

[77] Y. Shen and M. Win, "Fundamental limits of wideband localization; Part I: A general framework," *IEEE Trans. Inf. Theory*, vol. 56, no. 10, pp. 4956–4980, Oct. 2010.

[78] K. Witrisal, E. Leitinger, S. Hinteregger, and P. Meissner, "Bandwidth scaling and diversity gain for ranging and positioning in dense multipath channels," *IEEE Wireless Commun. Lett.*, vol. 5, no. 4, pp. 396 – 399, Aug. 2016.

[79] E. Leitinger, P. Meissner, C. Ruedisser, G. Dumphart, and K. Witrisal, "Evaluation of position-related information in multipath components for indoor positioning," *IEEE J. Sel. Areas Commun.*, vol. 33, no. 11, pp. 2313 – 2328, Nov. 2015.

[80] K. Pahlavan, F. O. Akgul, M. Heidari, A. Hatami, J. M. Elwell, and R. D. Tingley, "Indoor geolocation in the absence of direct path," *IEEE Wireless Communications*, vol. 13, no. 6, pp. 50–58, Dec 2006.

[81] C. Steiner and A. Wittneben, "Low complexity location fingerprinting with generalized UWB energy detection receivers," *IEEE Trans. Signal Process.*, vol. 58, no. 3, pp. 1756 – 1767, Mar. 2010.

[82] M. DÃűttling, W. Mohr, and A. Osseiran, *WINNER II Channel Models*. Wiley Telecom, 2010, pp. 624–. [Online]. Available: http://ieeexplore.ieee.org/xpl/articleDetails.jsp?arnumber=8045088

[83] A. F. Molisch, H. Asplund, R. Heddergott, M. Steinbauer, and T. Zwick, "The cost259 directional channel model-part i: Overview and methodology," *IEEE Transactions on Wireless Communications*, vol. 5, no. 12, pp. 3421–3433, December 2006.

[84] S. Wu, C. X. Wang, e. H. M. Aggoune, M. M. Alwakeel, and X. H. You, "A general 3d non-stationary 5g wireless channel model," *IEEE Transactions on Communications*, vol. PP, no. 99, pp. 1–1, 2017.

[85] P. Meissner, E. Leitinger, M. Froehle, and K. Witrisal, "Accurate and robust indoor localization systems using ultra-wideband signals," in *European Conference on Navigation (ENC)*, Vienna, 2013.

[86] S. Salous, V. D. Esposti, F. Fuschini, R. S. Thomae, R. Mueller, D. Dupleich, K. Haneda, J. M. M. Garcia-Pardo, J. P. Garcia, D. P. Gaillot, S. Hur, and M. Nekovee, "Millimeter-wave propagation: Characterization and modeling toward fifth-generation systems. [wireless corner]," *IEEE Antennas and Propagation Magazine*, vol. 58, no. 6, pp. 115–127, Dec 2016.

[87] M. Hata, "Empirical formula for propagation loss in land mobile radio services," *IEEE Transactions on Vehicular Technology*, vol. 29, no. 3, pp. 317–325, Aug 1980.

[88] IEEE P802.15.4a-2007 (Amendment 1), *802.15.4: Wireless Medium Access Control (MAC) and Physical Layer (PHY) Specifications for Low-Rate Wireless PANs*, Std., 2007.

[89] D. Cassioli, M. Z. Win, and A. F. Molisch, "The ultra-wide bandwidth indoor channel: from statistical model to simulations," *IEEE Journal on Selected Areas in Communications*, vol. 20, no. 6, pp. 1247–1257, Aug 2002.

[90] F. Fuschini, E. M. Vitucci, M. Barbiroli, G. Falciasecca, and V. Degli-Esposti, "Ray tracing propagation modeling for future small-cell and indoor applications: A review of current techniques," *Radio Science*, vol. 50, no. 6, pp. 469–485, June 2015.

[91] J. Schmitz, F. SchrÃűder, and R. Mathar, "Tdoa fingerprinting for localization in non-line-of-sight and multipath environments," in *2015 International Symposium on Antennas and Propagation (ISAP)*, Nov 2015, pp. 1–4.

[92] M. Raspopoulos, "Multidevice map-constrained fingerprint-based indoor positioning using 3-d ray tracing," *IEEE Transactions on Instrumentation and Measurement*, vol. 67, no. 2, pp. 466–476, Feb 2018.

[93] P. Meissner, M. Gan, F. Mani, E. Leitinger, M. FrÃűhle, C. Oestges, T. Zemen, and K. Witrisal, "On the use of ray tracing for performance prediction of uwb indoor localization systems," in *2013 IEEE International Conference on Communications Workshops (ICC)*, June 2013, pp. 68–73.

[94] V. Degli-Esposti, F. Fuschini, E. M. Vitucci, and G. Falciasecca, "Measurement and modelling of scattering from buildings," *IEEE Transactions on Antennas and Propagation*, vol. 55, no. 1, pp. 143–153, Jan 2007.

[95] G. SteinbÃűck, A. Karstensen, P. KyÃűsti, and A. Hekkala, "A 5g hybrid channel model considering rays and geometric stochastic propagation graph," in *2016 IEEE 27th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC)*, Sept 2016, pp. 1–6.

[96] A. Hekkala, P. KyÃűsti, J. Dou, L. Tian, N. Zhang, W. Zhang, and B. Gao, "Map-based channel model for 5g wireless communications," in *2017 XXXIInd General Assembly and Scientific Symposium of the International Union of Radio Science (URSI GASS)*, Aug 2017, pp. 1–4.

[97] T. Pedersen, G. Steinbock, and B. H. Fleury, "Modeling of reverberant radio channels using propagation graphs," *IEEE Transactions on Antennas and Propagation*, vol. 60, no. 12, pp. 5978–5988, Dec 2012.

[98] G. SteinbÃűck, M. Gan, P. Meissner, E. Leitinger, K. Witrisal, T. Zemen, and T. Pedersen, "Hybrid model for reverberant indoor radio channels using rays and graphs," *IEEE Transactions on Antennas and Propagation*, vol. 64, no. 9, pp. 4036–4048, Sept 2016.

[99] L. Tian, V. Degli-Esposti, E. M. Vitucci, and X. Yin, "Semi-deterministic radio channel modeling based on graph theory and ray-tracing," *IEEE Transactions on Antennas and Propagation*, vol. 64, no. 6, pp. 2475–2486, June 2016.

[100] K. Stern, A. Fuglsig, K. Ramsgaard-Jensen, and T. Pedersen, "Propagation graph modeling of time-varying radio channels," in *Proc. EuCAP2018*, 2018.

[101] R. Adeogun and T. Pedersen, "Propagation graph based model for polarized multiantenna wireless channels," 4 2018.

[102] S. Kay, *Fundamentals of Statistical Signal Processing: Estimation Theory*. Prentice Hall Signal Processing Series, 1993.

[103] B. Etzlinger, F. Meyer, F. Hlawatsch, A. Springer, and H. Wymeersch, "Cooperative simultaneous localization and synchronization in mobile agent networks," *IEEE Trans. Signal Process.*, vol. 65, no. 14, pp. 3587–3602, July 2017.

[104] A. Mallat, J. Louveaux, and L. Vandendorpe, "Uwb based positioning in multipath channels: Crbs for aoa and for hybrid toa-aoa based methods," in *Communications, 2007. ICC'07. IEEE International Conference on*. IEEE, 2007, pp. 5775–5780.

[105] Y. Han, Y. Shen, X.-P. Zhang, M. Z. Win, and H. Meng, "Performance limits and geometric properties of array localization," *IEEE Trans. Inf. Theory*, vol. 62, no. 2, pp. 1054–1075, 2016.

[106] F. Gustafsson and F. Gunnarsson, "Mobile positioning using wireless networks: possibilities and fundamental limitations based on available wireless network measurements," *IEEE Signal Process. Mag.*, vol. 22, no. 4, pp. 41–53, Jul. 2005.

[107] A. Shahmansoori, G. E. Garcia, G. Destino, G. Seco-Granados, and H. Wymeersch, "Position and orientation estimation through millimeter wave mimo in 5g systems," *arXiv preprint arXiv:1702.01605*, 2017.

[108] Z. Abu-Shaban, X. Zhou, T. Abhayapala, G. Seco-Granados, and H. Wymeersch, "Error bounds for uplink and downlink 3d localization in 5g mmwave systems," *arXiv preprint arXiv:1704.03234*, 2017.

[109] N. Garcia, H. Wymeersch, E. G. Larsson, A. M. Haimovich, and M. Coulon, "Direct localization for massive mimo," *IEEE Trans. Signal Process.*, vol. 65, no. 10, pp. 2475–2487, 2017.

[110] A. Guerra, F. Guidi, and D. Dardari, "Single-anchor localization and orientation performance limits using massive arrays: MIMO vs. beamforming," *arXiv preprint arXiv:1702.01670*, 2017, under revision for IEEE Trans. Wireless Commun.

[111] Y. Shen and M. Win, "On the use of multipath geometry for wideband cooperative localization," in *IEEE Global Telecommun. Conf., GLOBECOM*, 2009.

[112] J. A. del Peral-Rosado, M. A. Barreto-Arboleda, F. Zanier, G. Seco-Granados, and J. A. López-Salcedo, "Performance limits of V2I ranging localization with LTE networks," in *Proc. WPNC*, Oct 2017, pp. 1–5.

[113] M. Koivisto, M. Costa, J. Werner, K. Heiska, J. Talvitie, K. LeppÃď-nen, V. Koivunen, and M. Valkama, "Joint device positioning and clock synchronization in 5G ultra-dense networks," *IEEE Trans. Wireless Commun.*, vol. 16, no. 5, pp. 2866–2881, May 2017.

[114] G. Destino and H. Wymeersch, "On the Trade-off Between Positioning and Data-Rate for mm-Wave Communications," in *IEEE International Conf. on Communications Workshops, ICCW*, May 2017.

[115] J. Saloranta, G. Destino, and H. Wymeersch, "Comparison of Different Beamtraining Strategies from A Rate-positioning Trade-off Perspec-

tive," in *European Conference on Networks and Communications*, Jun. 2017, pp. 1–5.

[116] J. Saloranta and G. Destino, "Reconfiguration of 5g radio interface for positioning and communication," in *European Signal Processing Conference*, Aug. 2017, pp. 898–902.

[117] E. Leitinger, F. Meyer, P. Meissner, K. Witrisal, and F. Hlawatsch, "Belief propagation based joint probabilistic data association for multipath-assisted indoor navigation and tracking," in *Proc. ICL-GNSS-16*, Barcelona, Spain, Jun. 2016.

[118] E. Leitinger, P. Meissner, M. Lafer, and K. Witrisal, "Simultaneous localization and mapping using multipath channel information," in *Proc. IEEE ICC-15*, London, UK, Jun. 2015, pp. 754–760.

[119] E. Leitinger, F. Meyer, F. Hlawatsch, K. Witrisal, F. Tufvesson, and M. Z. Win, "A scalable belief propagation algorithm for radio signal based SLAM," *Corr*, vol. arXiv:1801.04463, 2018.

[120] E. Leitinger, F. Meyer, F. Tufvesson, and K. Witrisal, "Factor graph based simultaneous localization and mapping using multipath channel information," in *Proc. IEEE ICC-17*, Paris, France, Jun. 2017.

[121] C. Gentner, T. Jost, W. Wang, S. Zhang, A. Dammann, and U.-C. Fiebig, "Multipath assisted positioning with simultaneous localization and mapping," *IEEE Trans. Wireless Commun.*, vol. 15, no. 9, pp. 6104–6117, September 2016.

[122] M. Ulmschneider, C. Gentner, T. Jost, and A. Dammann, "Multiple hypothesis data association for multipath-assisted positioning," in *14th Workshop on Positioning, Navigation and Communications (WPNC)*, October 2017.

[123] B. Chitambira, S. Armour, S. Wales, and M. Beach, "Nlos identification and mitigation for geolocation using least-squares support vector machines," in *2017 IEEE Wireless Communications and Networking Conference (WCNC)*, March 2017, pp. 1–6.

[124] J. Khodjaev, Y. Park, and A. Saeed Malik, "Survey of NLOS identification and error mitigation problems in UWB-based positioning algorithms for dense environments," *annals of telecommunications - annales des tÃl'lÃl'communications*, vol. 65, no. 5, pp. 301–311, 2010. [Online]. Available: http://dx.doi.org/10.1007/s12243-009-0124-z

[125] X. Wei, N. Palleit, and T. Weber, "Aod/aoa/toa-based 3d positioning in nlos multipath environments," in *2011 IEEE 22nd International Symposium on Personal, Indoor and Mobile Radio Communications*, Sept 2011, pp. 1289–1293.

[126] I. Guvenc and C. C. Chong, "A survey on toa based wireless localization and nlos mitigation techniques," *IEEE Communications Surveys Tutorials*, vol. 11, no. 3, pp. 107–124, rd 2009.

[127] S. Marano, W. M. Gifford, H. Wymeersch, and M. Z. Win, "Nlos identification and mitigation for localization based on uwb experimental data," *IEEE Journal on Selected Areas in Communications*, vol. 28, no. 7, pp. 1026–1035, September 2010.

[128] "V. N. Vapnik, The Nature of Statistical Learning Theory," New York, NY, USA, 1995.

[129] J. A. K. Suykens and J. Vandewalle, "Least Squares Support Vector Machine Classifiers," *Neural Processing Letters*, vol. 9, no. no. 3, pp. 293–300, 1999.

[130] E. Arias-de-Reyna, D. Dardari, P. Closas, and P. M. Djurić, "Enhanced indoor localization through crowd sensing," in *2017 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, March 2017, pp. 2487–2491.

[131] M. G. Pralon, G. D. Galdo, M. Landmann, M. A. Hein, and R. S. ThomÃd', "Suitability of compact antenna arrays for direction of arrival estimation," *IEEE Transactions on Antennas and Propagation*, vol. PP, no. 99, pp. 1–1, 2017.

[132] S. Al-Jazzar and J. Caffery, "Ml and bayesian toa location estimators for nlos environments," in *Proceedings IEEE 56th Vehicular Technology Conference*, vol. 2, 2002, pp. 1178–1181 vol.2.

[133] Y.-T. Chan, W.-Y. Tsui, H.-C. So, and P. chung Ching, "Time-of-arrival based localization under nlos conditions," *IEEE Transactions on Vehicular Technology*, vol. 55, no. 1, pp. 17–24, Jan 2006.

[134] M. P. Wylie and J. Holtzman, "The non-line of sight problem in mobile location estimation," in *Proceedings of ICUPC - 5th International Conference on Universal Personal Communications*, vol. 2, Sep 1996, pp. 827–831 vol.2.

[135] I. Guvenc and C. C. Chong, "A survey on toa based wireless localization and nlos mitigation techniques," *IEEE Communications Surveys Tutorials*, vol. 11, no. 3, pp. 107–124, rd 2009.

[136] B. Y. Shikur and T. Weber, "Tdoa/aod/aoa localization in nlos environments," in *2014 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2014, pp. 6518–6522.

[137] B. R. Phelan, E. H. Lenzing, and R. M. Narayanan, "Source localization using unique characterizations of multipath propagation in an urban environment," in *2012 IEEE 7th Sensor Array and Multichannel Signal Processing Workshop (SAM)*, June 2012, pp. 189–192.

[138] J. Predd, S. R. Kulkarni, and H. V. Poor, "Distributed Learning in Wireless Sensor Networks," *IEEE Signal Processing Magazine*, vol. 23, no. 4, pp. 56–69, Jul. 2006.

[139] R. Olfati-Saber, J. A. Fax, and R. M. Murray, "Consensus and Cooperation in Networked Multi-Agent Systems," *Proceedings of the IEEE*, vol. 95, no. 1, pp. 215–233, 2007.

[140] A. Al-Fuqaha, M. Guizani, M. Mohammadi, M. Aledhari, and M. Ayyash, "Internet of Things: A Survey on Enabling Technologies, Protocols, and Applications," *IEEE Communications Surveys Tutorials*, vol. 17, no. 4, pp. 2347–2376, Fourthquarter 2015.

[141] M. During and K. Lemmer, "Cooperative Maneuver Planning for Cooperative Driving," *IEEE Intelligent Transportation Systems Magazine*, vol. 8, no. 3, pp. 8–22, Fall 2016.

[142] G. Soatti, M. Nicoli, S. Savazzi, and U. Spagnolini, "Consensus-based Algorithms for Distributed Network-State Estimation and Localization," *IEEE Transactions on Signal and Information Processing over Networks*, vol. 3, no. 2, pp. 430–444, Jun. 2017.

[143] G. Soatti, M. Nicoli, N. Garcia, B. Denis, R. Raulefs, and H. Wymeersch, "Implicit Cooperative Positioning in Vehicular Networks," *IEEE Transactions on Intelligent Transportation Systems*, (to appear) 2018.

[144] J. A. del Peral-Rosado, J. A. López-Salcedo, and G. Seco-Granados, "Impact of frequency-hopping NB-IoT positioning in 4G and future 5G networks," in *Proc. ICC Workshops*, 2017, pp. 815–820.

[145] R. Kaune, "Accuracy studies for tdoa and toa localization," in *2012 15th International Conference on Information Fusion*, July 2012, pp. 408–415.

[146] J. Trogh, D. Plets, L. Martens, and W. Joseph, "Advanced real-time indoor tracking based on the viterbi algorithm and semantic data," *International Journal of Distributed Sensor Networks*, vol. 11, no. 10, 2015. [Online]. Available: http://dsn.sagepub.com/content/11/10/271818.abstract

[147] Z. Becvar, M. Vondra, P. Mach, J. Plachy, and D. Gesbert, "Performance of mobile networks with uavs: Can flying base stations substitute ultra-dense small cells?" in *Proceedings of European Wireless 2017; 23th European Wireless Conference*. VDE, 2017, pp. 1–7.

[148] J. Chen and D. Gesbert, "Optimal positioning of flying relays for wireless networks: A los map approach," in *2017 IEEE International Conference on Communications (ICC)*. IEEE, 2017, pp. 1–6.

[149] ——, "Local map-assisted positioning for flying wireless relays," *arXiv preprint arXiv:1801.03595*, 2018.

[150] V. Savic and E. Larsson, "Fingerprinting-based positioning in distributed massive MIMO systems," in *Proc. of IEEE Vehicular Technology Conference (VTC Fall), Boston, MA*, Sep. 2015, pp. 1–5.

[151] A. Wang, L. Liu, and J. Zhang, "Low complexity direction of arrival (DoA) estimation for 2D massive MIMO systems," in *Proc. of IEEE Globecom Workshops*, Dec. 2012, pp. 703–707.

[152] F. Guidi, "AOA estimation with EM lens-embedded massive arrays," in *Proc. IEEE 87th Veh. Technol. Conf. (VTC2018-Spring)*, Porto, Portugal, Jun. 2018.

[153] J.Thornton and K. Huang, "Modern lens antennas for communications engineering." IEEE Press, John Wiley and Sons, Inc., Hoboken, New Jersey, 2013.

[154] Y. Zeng, R. Zhang, and Z. N. Chen, "Electromagnetic lens-focusing antenna enabled massive MIMO performance improvement and cost reduction," *IEEE Journal on Selected Areas in Communications*, vol. 32, no. 6, pp. 1194–1206, Jun. 2014.

[155] S. A. Shaikh and A. M. Tonello, "DoA estimation in EM lens assisted massive antenna system using subsets based antenna selection and high resolution algorithms," *International Journal of Radioengineering*, [To be appeared] 2018.

[156] ——, "EM lens-clustering based direction of arrival estimation in massive antenna systems," in *Proc. of IEEE International Conference on Smart Systems and Technologies (SST), Osijek, Croatia*, Oct. 2017, pp. 127–131 [to appear on].

[157] ——, "Complexity reduced direction finding massive MIMO system using EM lens," in *IRACON-COST International Workshop on Dependable Wireless Communications and Localization for the IoT, TU Graz University, Graz, Austria*, Sep. 2017, pp. 1–3.

[158] ——, "Performance analysis of 180 degree HRR coupler used for direction finding with an antenna array," *International Journal of Online Engineering (iJOE)*, vol. 13, no. 10, pp. 86–102, Oct. 2017.

[159] S. A. Shaikh and I. Tekin, "Two Axis Direction Finding Antenna System using Sum-Difference Patterns in X-Band," *Microwave and Optical Technology Letters*, vol. 57, no. 9, pp. 2085–2092, Sep. 2015.

[160] A. Costanzo, D. Masotti, T. Ussmueller, and R. Weigel, "Tag, you're it: Ranging and finding via RFID technology," *IEEE Microwave Magazine*, vol. 14, no. 5, pp. 36–46, July-Aug 2013.
[161] M. ScherhÃd'ufl, M. Pichler, and A. Stelzer, "UHF RFID localization based on phase evaluation of passive tag arrays," *IEEE Trans. Instrum. Meas.*, vol. 64, no. 4, pp. 913–922, Apr. 2015.
[162] H. Arthaber, T. Faseth, and F. Galler, "Spread-spectrum based ranging of passive UHF EPC RFID tags," *IEEE Commun. Lett.*, vol. 19, no. 10, pp. 1734–1737, Oct. 2015.
[163] F. Galler, S. Grebien, T. Faseth, K. Witrisal, G. Magerl, and H. Arthaber, "Extension of an SDR UHF RFID testbed for MIMO and monostatic time of flight based ranging," *IEEE Journal of Radio Frequency Identification*, vol. 1, no. 1, pp. 32–38, March 2017.
[164] S. Grebien, J. Kulmer, F. Galler, M. Goller, E. Leitinger, H. Arthaber, and K. Witrisal, "Range estimation and performance limits for UHF-RFID backscatter channels," *IEEE Journal of Radio Frequency Identification*, vol. 1, no. 1, pp. 39–50, March 2017.
[165] D. Dardari, R. D'Errico, C. Roblin, A. Sibille, and M. Z. Win, "Ultrawide bandwidth RFID: The next generation?" *Proc. IEEE*, vol. 98, no. 9, pp. 1570 –1582, Sep 2010, special Issue on RFID - A Unique Radio Innovation for the 21st Century.
[166] N. Decarli, F. Guidi, and D. Dardari, "Passive UWB RFID for tag localization: Architectures and design," *IEEE Sensors J.*, vol. 16, no. 5, pp. 1385–1397, March 2016.
[167] D. Arnitz, U. Muehlmann, and K. Witrisal, "UWB ranging in passive UHF RFID: proof of concept," *Electronics Letters*, vol. 46, pp. 1401–1402(1), September 2010.
[168] A. Costanzo, D. Dardari, J. Aleksandravicius, N. Decarli, M. D. Prete, D. Fabbri, M. Fantuzzi, A. Guerra, D. Masotti, M. Pizzotti, and A. Romani, "Energy autonomous UWB localization," *IEEE Journal of Radio Frequency Identification*, vol. 1, no. 3, pp. 228–244, Sept 2017.
[169] M. Schmidhammer, S. Sand, M. Soliman, and F. de Ponte Müller, "5G Signal Design for Road Surveillance," in *2017 14th Workshop on Positioning, Navigation and Communications (WPNC)*, Oct 2017, pp. 1–6.
[170] M. Schmidhammer, F. de Ponte Müller, S. Sand, and R. Rashdan, "Detection and Localization of Non-Cooperative Road Users based on Propagation Measurements at C-Band," in *2018 12th European Conference on Antennas and Propagation (EuCAP)*, Apr 2018, pp. 1–5.
[171] "Indoor Location Test Plan," CSRIC-WG3, September 2012.
[172] F. IIS, "Test and application centre l.i.n.k," https://www.iis.fraunhofer.de/en/ff/lv/lok/test/link.html, accessed Jan 2018.
[173] C. Fernández-Prades, C. Pomar, J. Arribas, J. Fàbrega, J. Vilà-Valls, M. Svaluto Moreolo, R. Casellas, R. Martínez, M. Navarro, F. Vílchez, R. Muñoz, R. Vilalta, L. Nadal, and A. Mayoral, "A cloud optical access network for virtualized GNSS receivers," in *Proc. 30th Int. Tech. Meeting Sat. Div. Inst. Navig.*, Portland, OR, Sep. 2017, pp. 3796–3815.
[174] T. L. Marzetta, "Noncooperative cellular wireless with unlimited numbers of base station antennas," *IEEE Transactions on Wireless Communications*, vol. 9, no. 11, pp. 3590–3600, November 2010.
[175] E. G. Larsson, O. Edfors, F. Tufvesson, and T. L. Marzetta, "Massive mimo for next generation wireless systems," *IEEE Communications Magazine*, vol. 52, no. 2, pp. 186–195, February 2014.
[176] P. Harris, W. Hasan, H. Brice, B. Chitambira, M. Beach, E. Mellios, A. Nix, S. Armour, and A. Doufexi, "An overview of massive mimo research at the university of bristol," vol. 2016, no. 5. Institution of Engineering and Technology, 2016, cited By 0. [Online]. Available: https://www.scopus.com/inward/record.uri?eid=2-s2.0-85007438921&doi=10.1049%2fic.2016.0064&partnerID=40&md5=de0bc949b49e06687a5d09293fffafe4
[177] F. Guidi, N. Decarli, D. Dardari, F. Natali, E. Savioli, and M. Bottazzi, "A low complexity scheme for passive UWB-RFID: Proof of concept," *IEEE Communications Letters*, vol. 20, no. 4, pp. 676–679, April 2016.