Chapter 15

Collaborative Positioning for Urban Intelligent Transportation Systems (ITS) and Personal Mobility (PM): Challenges and Perspectives

Vassilis Gikas[*], Guenther Retscher[†] and Allison Kealy[‡]

[*]*National Technical University of Athens, Athens, Greece,* [†]*Technical University of Vienna, Vienna, Austria,* [‡]*RMIT University, Melbourne, VIC, Australia*

Chapter Outline

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1 INTRODUCTION

In recent years, the fast growth in urban population and in the number of vehicles together with the global trend towards megacities inspires new, smart mobility solutions. Therefore, more sophisticated and integrated modes of transportation and environmental friendly solutions are required to accommodate the rising demands of high livability in modern cities. To this end, fast adaptation and exhaustive use of emerging information and communication technologies (ICT) is vital for enhancing intelligent transportation systems (ITS) (Barbaresso et al., 2015). Overly, four technological trends define the development framework of ITS; namely, cloud computing, big data and analytics, cybersecurity, and cooperative systems.

Cloud-computing facilitates automated and rapid management of the complete spectrum of data gathered within the urban mobility sector, spanning those collected by conventional road ITS terminals through crowd-sourced traffic information. Cloud-computing results in new services that bring important benefits, reducing infrastructure costs while improving road user safety (Arutyunov, 2012). More recently, big data and analytics are being adopted gradually by the transportation sector, and soon are expected to make a profound economic and societal impact in the form of time and fuel savings, as well as carbon emission reduction. However, despite their high potential, big data solutions are still not an important part of the traffic control operation (Borgi et al., 2017). Cybersecurity forms the third critical technological element for the ITS chain. As vehicles become increasingly connected via wireless networks towards ITS-5G, the potential for individuals to cause damage is ever more viable. To this effect, stakeholders and traffic operators need to enforce standards and establish partnerships to minimize evolving threats and keep road users and their data safe (Škorput et al., 2017). Finally, cooperative systems allow vehicles and pedestrians to exchange both status and event information via reliable, high connectivity data communication protocols towards fully automated ITS.

While cooperative systems rely on ICT, the development and efficient operation of an ITS service requires knowledge of the location and kinematics of people or vehicles involved in a scenario. In effect, location awareness is a prerequisite for any ITS application in order to enable effective services to the users including faster, safer, and less costly operations. This paper focuses on the positioning and navigation aspects of urban Cooperative ITS (C-ITS). It examines the role and significance of positioning information for the development and deployment of sustainable, emerging C-ITS services. Furthermore, it discusses the positioning challenges associated with highly demanding, safety-critical ITS applications while it offers future perspectives of the technologies, the techniques and their application for C-ITS. The remainder of this paper is structured as follows. Section 2 provides an overview of C-ITS services in the smart cities concept, while Section 3 deals with the user requirements underlying C-ITS implementation. Sections 4 and 5 offer a review of respective positioning technologies and techniques, followed by a review on collaborative positioning (CP) concepts, algorithms, and techniques. Section 7 presents key examples of emerging C-ITS applications, and finally Section 8 offers a critical discussion on the technical concerns and perspectives relating to positioning aspects for urban C-ITS.

2 C-ITS IN SUPPORT OF THE SMART CITIES CONCEPT

2.1 Scientific and Policy Perspectives of Urban C-ITS

Thanks to the recent developments in ICT and multisensory systems ITS constantly evolve. However, while motorway ITS applications have reached a level of technological maturity with some of them being commercially deployed by the automotive industry and gradually accepted by society, less progress has been made in ITS services for the urban and public transport use cases. In fact, the dynamic character and the high complexity of the megacity environment demands a high level of automation and interoperability of ITS systems that despite past efforts is still not evident (CEN-CENELEC-ETS, 2015; Abdel-Rahim, 2012). This is due to the high traffic volumes, the multifarious traffic conditions and the mixture of multimodal transport means including pedestrians that characterize overly urban scenarios. In response to this need, the EU Commission has been adopted an *Action Plan for the Deployment of ITS in Europe* (EU, 2008), followed by the establishment of the *Expert Group on Urban ITS* (EU, 2010). Also, coordinated actions have been taken between the EU and the USA on the interoperability of the deployment of ITS (Row and Jääskeläinen, 2012). However, despite the substantial progress gained in various technological aspects of ITS, organizational principles to ensure interoperability, such as data management and ownership still remain poorly developed at an international level (Vartis et al., 2016).

Indisputably, the evolution of urban ITS relies both on a policy and a technological perspective. From a policy perspective, the successful deployment of future ITS resides on the integration of urban-related ITS services and sustainable urban mobility plans, such as car sharing services, integrated public transport and multimodal mobility. Furthermore, the rapid increase of user generated information including activity/location data via smartphones, Personal Digital Assistance (PDAs) and other in-vehicle devices, will support further the future of urban mobility through large-scale data analyses and market demand studies (Antoniou et al., 2016; Gikas and Perakis, 2016). However, using such a multifaceted channel of information sources raises openly numerous legal issues including data protection, privacy, and liability. Therefore, further work is required to establish common methodologies, data protocols, and standards for addressing data protection and security issues. Finally, new business models and coordinated efforts on interoperability are required to ensure efficient deployment of ITS at international level.

On the other hand, the solution to efficient urban ITS services from a technological perspective resides on *Cooperative ITS* (C-ITS). C-ITS is the natural evolution of the overall ITS that "*communicates and shares information between ITS stations to give advice or facilitate actions with the objective of improving safety, sustainability, efficiency and comfort beyond the scope of stand-alone systems*" (Schade, 2012). As shown in Fig. 1, the development of C-ITS relies on the application of a number of scientific aspects to the transport sector. *Sensors* provide diverse types of data and parameters ranging from vehicle position and dynamics to road conditions and air quality. *Communication* technologies vary depending on application type. Despite the maturity of wireless communication technologies for vehicular applications (IEEE 802.11p, European Telecommunications Standards Institute (ETSI) ITS-G5) (Rappaport et al., 2013), C-ITS are still facing challenges regarding the communication capacity, data transmission delays, message formats, and contextual information. Regarding *information systems and platforms*, a major concern discussed further in Section 8 relates to limitations of manipulating and analyzing big data volumes in real-time obtained from various information channels. *Data protection*, *security*, and *human-machine interaction* (HMI) aspects are also critical ranging from liability issues through developing efficient interface systems used to inform, assist, and interact information between drivers.

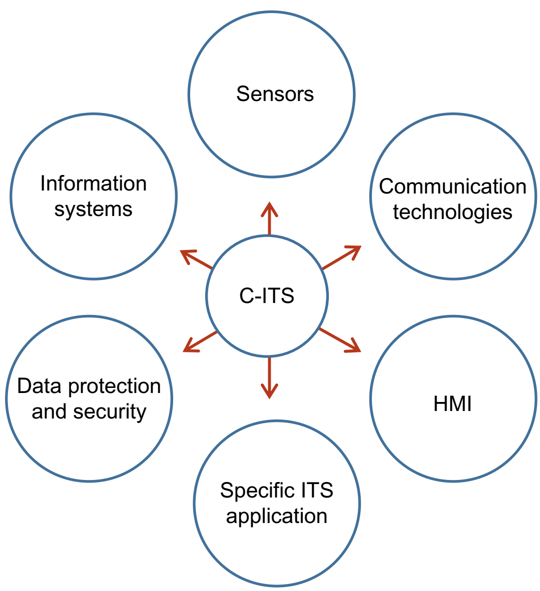

FIG. 1 Scientific aspects defining urban C-ITS.

The origins of current C-ITS go back to the early days of connected vehicles some 15 years ago (Hartman, 2016). Today, C-ITS refer to *vehicle-to-vehicle* (V2V) and *vehicle-to-infrastructure* (V2I) technologies that enable information exchange between vehicles and roadside infrastructure facilitating a wide range of ITS services (Karedal et al., 2011; Jacobi et al., 2015; Mousumi and Gautam, 2015). In the urban environment, V2V and V2I technologies collectively referred to *vehicle-to-everything* (V2X) (Katriniok et al., 2017). V2X is a mesh network in which each vehicle is a node with the ability to transmit, receive, and retransmit messages to other ITS stations. Fig. 2 shows the different types of ITS stations and functionalities involved in urban C-ITS. That is, V2V communications primarily concern with collision avoidance safety systems while V2I systems focus on traffic signal timing and priority information services. Similarly, *vehicle-to-pedestrians* (V2P) systems aim at issuing safety alerts to pedestrians and bicyclists, whereas *vehicle-to-network* (V2N) services aim at providing real-time traffic, routing, and cloud services, respectively.

Evidently, while much progress has been made on the technological aspects of urban C-ITS there are still many open issues to face. Investigating the interoperability of different sensors to support efficient data fusion capabilities and integrating sensor systems with communication technologies are only two of them. Other areas that there is a clear need for future research involve studying the effects of coupling between different sensor systems and investigating the reliability and adaptation level to the traffic environment. Among other types of sensing technologies, positioning sensors used for navigation and

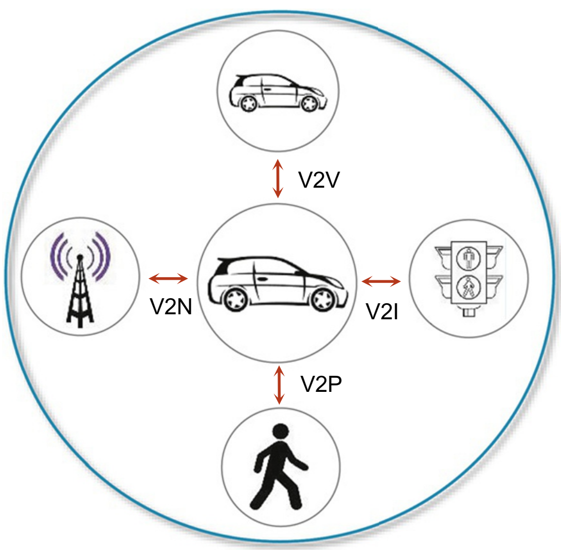

FIG. 2 Relationship among ITS stations present in V2X technologies for smart cities.

geo-referencing purposes are integral to the efficient functioning of ITS and examined in detail in the remainder of this paper.

2.2 Taxonomy of Urban C-ITS Applications

ITS services can be classified in various ways including their field of development or specific characteristics that vary with geographic region. A general classification based on their areas of application includes as a minimum the following categories: traffic and travel information systems, advanced vehicle safety systems, security and emergency systems, payment systems, and freight transport management. Another way of generic classification of ITS applications divides them into two categories: sustainability applications and all remaining ITS types (Row and Jääskeläinen, 2012). In this approach, safety related and other applications are distinguished from use cases aiming to reduce energy consumption, vehicle emissions, and environmental impact at the urban environment.

Other examples of classifying ITS applications are summarized in Table 1. These include the "type of support" they provide, the "driving conditions" when the system operates in respect to a possible crash, their "human-machine interface" and the "type of criticality" with regard to certain aspects of interest (Clausen et al., 2015). For instance, relevant ITS systems concerning a possible crash are *collision avoidance* and *obstacle warning* systems at a precrash stage, *smart restraint systems* during the crash, and *e-call* facilities following the crash (Clausen et al., 2017). Particularly, when the interest goes to the level of services a positioning terminal can support an ITS application, the classification shown in the last column of Table 1 becomes more relevant. For instance, positioning accuracy and integrity measures are more important for *safety-critical systems* (e.g., advance driver assistance systems (ADAS)) than for *security-critical systems* (e.g., transportation of cash) and much less important for *environment and health-critical systems* (e.g., air quality recording or transportation of dangerous goods).

TABLE 1 Ways of Classification of ITS Applications

Type of Support	Driving Conditions	HMI	Type of Criticality
Driving task	Normal driving	Informative	Safety-critical
Information	Crash-system	Warning	Liability-critical
Monitoring	Post-crash system	Intervening	Security-critical
			Environment and health-critical

3 USER REQUIREMENTS FOR URBAN C-ITS

3.1 Requirements Overview

User requirements for urban C-ITS can take several forms and can be analyzed at various levels of detail and rigor, ranging from more relaxed requirements for noncritical applications (e.g., traffic and travel information systems) to more stringent ones for safety-critical and security-critical applications. User requirements can be organized in six generic categories following the classification of the scientific themes contributing to the performance of ITS services discussed in Section 2.1 (see Fig. 1). The relevant categories include requirements for sensors, communication technologies, information systems and platforms, HMI, data protection and security, as well as requirements for specific use cases. Last but not least, cost is an important user requirement that can be assessed in several ways including capital, maintenance, time, and space costs. Clearly, due to the large number of contributing factors in urban ITS, it is not always obvious how to prioritize user requirements, and therefore, a unified approach could only be adopted when based on certified standards and common policies.

As this paper concentrates on the positioning aspects for road C-ITS, the discussion on user requirements focuses on position-sensing technologies and data-processing requirements. Also, requirements concerned with communication technologies and information systems affect vehicle position and dynamics, and thus are also briefly discussed in Section 3.2.

3.2 Positioning Requirements and Parameters Definition

In this study, user requirements concerned with the positioning terminals found in urban C-ITS refer to the relevant performance features. *Global Navigation Satellite Systems* (GNSS) receivers and proximity sensors used for computing longitudinal and lateral positions and inter-vehicle distances respectively are typical cases of positioning terminals. *Position availability*, *accuracy* and *integrity* are considered to be the most critical requirements followed by *coverage*, *continuity*, *update rate*, *system latency* and *data output*.

Position availability refers to the percentage of time (measurement epochs) during which a positioning terminal is available for use at a required performance level of accuracy and/or integrity. Availability usually is affected by random factors, such as communication congestion and other failures. Accuracy should be regarded as a key driver to the performance of an ITS. It describes the conformance of an estimated (measured) position to the statistical figures of merit of position or velocity error. Accuracy is expressed for the horizontal or vertical components (*horizontal position error*, HPE; *vertical position error*, VPE) usually at 95% confidence level. Particularly, for road ITS applications a statistical characterization of HPE relies usually on the 50th, 75th or 95th percentiles of the error *cumulative distribution function* (CDF) (Fig. 3, left). In order an accuracy

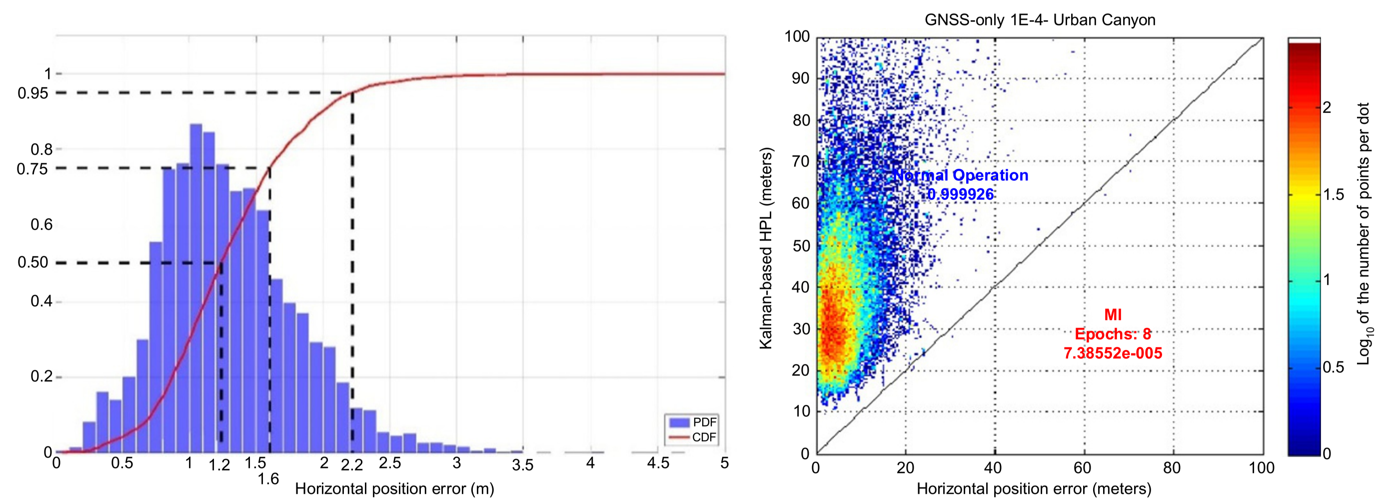

FIG. 3 Accuracy metrics realized via probability density and cumulative distribution function of horizontal position GNSS data (left), and integrity metric representing protection level versus GNSS horizontal position error (right). *(Source: Peyret, F., Bétaille, D., Engdahl, J., Gikas, V., et al., 2017. Assessment of positioning performance in ITS applications. In: COST Action: TU1302-SaPPART Handbook, TMI. IFSTTAR.)*

measure to be meaningful, it is assumed that systematic measurement errors have been adequately modeled and sensors have been properly calibrated.

Integrity is a quality metric used to assess unambiguously the performance of a system even if high accuracy is observed, and thus is important for safety related applications. Particularly, integrity refers to the trust a user can have in the delivered value of a computed position or velocity, and therefore, corresponds to the confidence that can be placed in the output of a system. For civil aviation, integrity refers to the probability (*risk*) of failure of a system for which the user is not informed within a preset period of time (*time-to-alarm*). For road transport applications two distinct features define integrity. Firstly, *integrity risk* (IR) refers to the probability that a position or velocity error exceeds a protection level computed by the positioning terminal supposed to over bind the actual error. Secondly, a *horizontal protection level* (HPL) is a statistical bound of the HPE computed so as to guarantee that the probability of the actual position error exceeding said number is smaller than or equal to the target integrity risk (Peyret, 2013; Peyret et al., 2017).

Fig. 3 right, shows the HPL as a function of HPE obtained for a kinematic GNSS data set realized in an urban canyon using the so-called "Stanford plot". On this plot, the bisecting line $x = y$ divides the "safe" region from the "unsafe" one assuming a 50th percentile HPL. Therefore, the data in the bottom right part of the plot highlight a limited number of instants (eight epochs) during which the system failed to fulfill the preset target integrity risk, and this data are called misleading information.

Generally, defining positioning requirements for ITS is a rather complicated task. It requires thorough investigation of specific application requirements for different operating scenarios and extensive testing of sensors. As an example, here the field and laboratory simulation testing and "*record and replay*" analysis is mentioned here for GNSS receiver assessment (Cristodaro et al., 2017). For this purpose extensive collaboration between organizations and stakeholders is required to ensure interoperability at a development and deployment phase.

4 POSITIONING TECHNOLOGIES FOR URBAN ITS

Table 2 provides an overview of the major technologies currently applied for vehicle and pedestrian positioning in combined out-/indoor environments. These can be classified in four major categories based on their principle of operation; namely, *radio frequency* (RF), *inertial*, *optical* and other technologies. In the following subsections, the most important technologies with use in ITS applications are examined in detail, whereby a special emphasis is led on wireless options and low-cost inertial systems.

TABLE 2 Characteristics and Specifications of Current Localization Techniques and Systems

Signal	System	Technique	Method	Costs	Navigation Information	Typical Accuracy
Radio frequency (RF)	GPS (SPP[1])	Lateration	TOA	Low	*X*, *Y*, *Z*	<13 m
	DGNSS	Lateration	TOA	Low	*X*, *Y*, *Z*	0.5–3 m
	A-GNSS (assisted-GNSS)	Lateration	TOA	Low	*X*, *Y*	>10 m
	Pseudolites (e.g., Locata)	Lateration	TOA	High	*X*, *Y*, *Z*	0.1–3 m
	Cellular network	Proximity, lateration, hyperbolic lateration, angulation	COO TDoA AoA	Low	*X*, *Y*, (*Z*)	>50 m
	Wi-Fi (wireless fidelity)	Fingerprinting, lateration	RSSI	Low	*X*, *Y*, (*Z*)	1–5 m
	ZigBee	Proximity, lateration	CoO SSI	High	*X*, *Y*, *Z*	1–10 m
	Bluetooth	Proximity, lateration	CoO RSSI ToA	Medium	*X*, *Y*, (*Z*)	5–20 m
	UWB (ultra-wideband)	Lateration, hyperbolic lateration, angulation	ToA TDoA AoA	High	*X*, *Y*, *Z*	0.1–1 m
	Radio frequency identification (RFID)	Proximity, lateration, fingerprinting	CoO RSSI	Medium (active) low (passive)	*X*, *Y*, (*Z*)	1–5 m
	FM radio	Lateration	RSSI	Low	*X*, *Y*, (*Z*)	1–10 m
	Digital television	Fingerprinting	RSSI	Low	*X*, *Y*, (*Z*)	10–20 m

Inertial	Odometer	Dead reckoning	Relative positioning	Medium	Distance travelled d	0.01%–0.1%
	MEMS-based accelerometer[2]	Dead reckoning	Relative positioning	Low	Accelerations a_{tan}, a_{rad}, a_z	$<0.03\,m/s^2$
	MEMS-based gyroscope[3]	Dead reckoning	Relative positioning	Low	Heading, pitch and roll ϕ, psi, eta	0.5° to 3°
Optical	Video scene analysis	Scene analysis, angulation	Computer vision	High	Pan and tilt α, β	0.1° to 1°
	2D image-based	Scene analysis, angulation	Computer vision	Low	Pan and tilt α, β	0.01° to 0.1°
	Multi 2-D image-based	Scene analysis, angulation	Computer vision	Low	X, Y, Z Orientation angles ω, ψ, κ	0.1 m (image scale) 0.01° to 0.1°
	3D image-based	Scene analysis, angulation	Computer vision	Low	X, Y, Z Orientation angles ω, ψ, κ	0.01–1 0.01° to 0.1°
	Optical sensor network	Scene analysis, angulation	Computer vision	Low	X, Y, (Z)	1–5 m
	Laser	Lateration, angulation	TOA AoA	High	X, Y, Z	0.01–0.1 m

Continued

TABLE 2 Characteristics and Specifications of Current Localization Techniques and Systems—cont'd

Signal	System	Technique	Method	Costs	Navigation Information	Typical Accuracy
Others	Digital compass/ magnetometer	Dead reckoning	Relative positioning	Low	Heading ϕ	0.5° to 3°
	Barometric pressure sensor	Dead reckoning	Relative altitude determination	Low	Delta Z	1–3 m
	Temperature sensor[3]	n/a	Relative altitude determination	Low	T	0.2° to 0.5° [C]
	Ambient geomagnetic field	Fingerprinting	Pattern recognition	Low	X, Y, Z	1–5 m

[1] *Single Point Positioning with C/A code with positioning accuracies as specified in the GPS interface document.*
[2] *Sensors in modern smartphones.*
[3] *Requirement for barometric altitude determination.*

Extracted, Adapted, and Updated From Kealy, A., Retscher, G., Toth, C., Hasnur-Rabiain, A., Gikas, V., Grejner-Brzezinska, D.A., Danezis, C., Moore, T., 2015. Collaborative navigation as a solution for PNT applications in GNSS challenged environments—report on field trials of a joint FIG/IAG working group. J. Appl. Geod. 9(4), 1862–9016, 244–263, https://doi.org/10.1515/jag-2015-0014; Retscher, G., 2016. Indoor navigation (Chapter 9-1). In: Grafarend, E.W. (Ed.), Encyclopedia of Geodesy, Earth Sciences Series. Springer International Publishing: Switzerland, 978-3-319-02370-0 (Online), https://doi.org/10.1007/978-3-319-02370-0_9-1, 7 pp.; With Specifications Based on Faragher, R., Harle, R., 2014. An analysis of the accuracy of Bluetooth Low Energy for indoor positioning applications. In: Proceedings of 27th International Technical Meeting of The Satellite Division of the Institute of Navigation ION GNSS+ 2014. Institute of Navigation, USA, pp. 201–210; Hightower, J., Boriello, G., 2001. A Survey and Taxonomy of Location Systems for Ubiquitous Computing. Technical Report, University of Washington, Department of Computer Science and Engineering; Liu, H., Darabi, H., Banerjee, P., Liu, J., 2007. Survey of wireless indoor positioning techniques and systems. IEEE Trans. Syst. Man Cybern. C: Appl. Rev. 37(6), 1067–1080; Mautz, R., 2012. Indoor Positioning Technologies. Swiss Geodetic Commission, Geodetic-Geophysical Reports of Switzerland, 86, 134 p; Stojanović, D., Stojanović, N., 2014. Indoor localization and tracking: methods, technologies and research challenges. Facta. Univ. Ser. Mech. Autom. Control Robot, vol. 13(1), pp. 57–72.

4.1 Radio Frequency-Based (RF) Technologies

4.1.1 Global Navigation Satellite Systems (GNSS)

GNSS positioning is the key technology for localization in ITS. When satellite positioning is mentioned, usually reference is made to the *US Navigation Satellite Time and Ranging system, Global Positioning System* (NAVSTAR GPS). However, since 2011 the *Russian Global Orbiting Navigation Satellite System* (GLONASS) is also in full operation while other GNSS under development include the Chinese Beidou and the European Galileo. Despite the fact that the overall system design (i.e., the signal structure, the orbit and clocks, the satellite configuration design, etc.) differs among GNSS, their operation is similar and contemporary receivers can facilitate satellite signals from different systems. Table 2 provides the specifications of the commonly applied GNSS solutions in navigation. GNSS *Single Point Positioning* (SPP) for standalone navigation delivers positioning accuracies on the several meter level. An improvement in terms of positioning accuracy is achieved with *Differential GNSS* (DGNSS). Furthermore, *Satellite-based Augmentation Systems* (SBAS), such as the *Wide Area Augmentation System* (WAAS) over America and the *European Geostationary Overlay System* (EGNOS) in Europe, provide differential corrections and position integrity information. Thereby, SBAS solutions render GNSS a suitable technology for ITS, particularly for noncritical ITS applications such as car navigation. With the help of assistance data, such as position and time aiding as well as satellite orbit data obtained from cellular phone networks, navigation with mobile devices could be facilitated even in challenging environments. Using this *so-called Assisted GNSS* (A-GNSS) technology, faster position fixes are achieved effectively enabling higher sensitivity and stronger performance.

4.1.2 Cellular Phone Networks

Different methods and approaches can be employed to locate cellular phones using wireless network signals either from the mobile station or from existing infrastructure. A comprehensive discussion on positioning technologies for cellular phones is given in Drane et al. (1998). Technical solutions range from handset-based and network systems that employ specialized software to satellite navigation. In the handset-based positioning technique a mobile phone user estimates its own position through synchronized signal transmissions from the available surrounding network *Base Tranceiving Station*s (BTSs). On the other hand, network-based positioning is a form of remote positioning whereby the transmissions of a mobile phone are used to obtain the position fix. The technique requires synchronized clocks at the BTSs locations if a (tri)lateration approach is employed. Also, hybrid positioning architectures combine different aspects of remote- and self-positioning.

Cellular localization can be accomplished using the *cell-of-origin* (CoO) technique or other commonly used principles for absolute positioning based on transmitter signal strength, such as the *time-of-arrival* (TOA) and *difference-time-of-arrival* (DTOA) techniques. A further discussion of these methods is provided in Section 5.1.2 (see also Table 3). Achievable positioning accuracies can be quite different depending on the method and conditions of operation. It is difficult, however, to generally give numbers for them as they depend very much on the environmental conditions and on other major influencing factors (Kealy and Retscher, 2017). In rural environments, network cells can be very large providing only low positioning accuracies due to the limited number of BTSs available in proximity. Thus, localization performs generally better in urban environments when the TOA lateration or time difference of arrival (TDoA) hyperbolic lateration are employed. In this case, positioning accuracies are of the order of 50–150m unless pico-cells are employed. The latter have an effective radius coverage up to 10m and usually are found indoors. Finally, latency in signal transmission is a major issue in cellular networks affecting also positioning accuracy (Drane et al., 1998).

4.1.3 Wi-Fi, Bluetooth, ZigBee

The most prominent signal-of-opportunity for positioning is Wi-Fi. Wi-Fi (IEEE 802.11) is a flexible short-range data communication protocol that is mainly used to extend or substitute a wired local area network (LAN), such as Ethernet (Wang et al., 2006). It does not require dedicated infrastructure installations except for a number of *access points* (APs) which are usually available in the environment (Kealy and Retscher, 2017). Typically, it is deployed as an ad-hoc network in a hot-spot fashion in the areas where a wireless Internet access is needed. In the infrastructure topology, the AP is a central control point which forwards traffic between terminals of the same cell and bridges traffic to wired LAN. APs transmit beacons periodically according to the beacon interval parameter. A synchronization function is defined that keeps timers of all terminals synchronized to the AP clock by using the timestamp information of the beacon frames. The IEEE 802.11 Media Access Control (MAC) protocol utilizes carrier sensing-based contention which relies on energy detection or signal quality. The standard specifies the *Received Signal Strength Indication* (RSSI) that measures RF energy by the radio. RSSI of up to 8 bits (256 levels) are supported; however, the absolute accuracy is not specified (Kotanen et al., 2003). The RSSIs and MAC addresses of the APs are location-dependent information that can be adopted for positioning purpose. An observable associated with a MAC address of an AP consist of the following information: (1) the unique MAC address of the RF transmitter, (2) the location of the RF transmitter, and (3) the effective range of the signal, or the size of the signal coverage area of the RF transmitter (Chen, 2012). For localization purposes, most commonly, fingerprinting or (tri)lateration is employed (see Section 5.1). Regarding urban

TABLE 3 Comparison of Most Commonly Used Position Estimation Methods and Measurement Models

Method	No. of Base Stations Required	Time Synchronization	LoS	Accuracy	Advantage	Disadvantage
COO	1	Not required	No	Depending on cell size	Simple algorithm	Discrete positions
TOA	≥3	Mobile object and all receivers	Yes	dm – m	Continuous positioning; no training phase required	Poor accuracy may occur caused by environmental effects
TDoA	≥3	All receivers	Yes	dm – m	Increased accuracy than TOA due to hyperbolic lateration; no training phase required	Poor accuracy may occur caused by environmental effects
AoA	>2 with antenna array	Not required	Yes	Several m	Simple intersection method; no training phase required	False measurement to reflected signals cause large errors
RSSI fingerprinting	≥3	Not required	No	Several m	Continuous positioning; environmental effects are considered in training phase	Poor accuracy in dynamic environments

ITS applications, Wi-Fi can serve primarily as a data communication means while its use for localization purposes is complementary to other positioning systems (Antoniou et al., 2017).

Bluetooth (IEEE 802.15.1) has become popular for positioning mainly indoors. It is a wireless protocol that is used for short-range communication that uses the 2.4 GHz, 915 MHz, and 868 MHz industrial, scientific and medical (ISM) radio bands to communicate at 1 Mbit between up to eight devices. It is considered a cable replacement for mobile devices and is mainly designed to maximize the ad-hoc networking functionality (Wang et al., 2006). Compared to Wi-Fi, it supports a lower gross bit rate (1 Mbps) and a shorter operating range (typically around 10 m). It is a "lighter" standard, highly ubiquitous (embedded in most mobile devices) and supports several other networking services in addition to internet protocol (IP). For positioning either tags or Bluetooth low energy (LE), iBeacons are common. Bluetooth tags are small size transceivers and as any other Bluetooth device, each tag has a unique ID. This ID can be used for localization of the tag (Prasithsangaree et al., 2002). Localization is based on proximity-sensing and cell-based solutions (compare Table 1) (Kealy and Retscher, 2017).

Lastly, ZigBee is an IEEE 802.15.4-based specification that suites high-level communication protocols used to create personal area networks with small, low-power digital radios. ZigBee operates in the ISM radio bands (usually 2.4 GHz) spanning data rates from 20 kbit/s (868 MHz band) to 250 kbit/s (2.4 GHz band). Owing to its low power consumption and simple networking configuration, ZigBee is best suited for intermittent data transmissions from a sensor or input device. Operating distances are limited from 10 to 100 m in *line-of-sight* (LoS) conditions, depending on power output and environmental characteristics. ZigBee localization techniques usually utilize the measurement of the RSSI in conjunction with (tri)lateration and fingerprinting (Kealy and Retscher, 2017).

4.1.4 Ultra-wideband (UWB)

Ultra-wideband (UWB) is a radio-technology developed primarily for high (>500 MHz) bandwidth communication. Nevertheless, today, it becomes a rapidly evolving ranging technology used for precise positioning and object-tracking applications. Position fixing is accomplished using lateration and hyperbolic lateration as well as angulation techniques (see Section 4.2.1). Compared to other radio-based technologies, such as Radio Frequency Identification (RFID) and Wi-Fi, which are subject to deep fading and inter-symbol interference, a major benefit of UWB is their immunity to multipath fading leading to low range uncertainty (<10 cm) even at long (up to hundreds of meters) ranges (Gikas et al., 2017). Also, the bandwidth characteristics of UWB offer remarkable Non-Line-of-Sight (NLoS) functionality which is of great importance for complex hybrid and indoor environments. Despite the high accuracy potential of UWB, the relatively high cost limit their usage for applications where high-precision localization and tracking is required, such as positioning and guidance of robots in indoor environments. However, it is anticipated that as production costs of UWB systems reduce gradually with time, their penetration in urban ITS will increase steadily, especially for ADAS applications.

4.1.5 Radio Frequency Identification (RFID)

RFID is another wireless option for positioning. It was originally developed for automatic identification of objects (see e.g., Finkenzeller, 2012) and is applied in transportation and logistics. A typical RFID system consists of three components, namely the tag, an interrogator or reader which receives the information from the tags and a control unit which operates the system and processes the information. In general, RFID tags can be distinguished in active and passive depending upon the signals transmitted and the tag's structure as well as their communication range. Long-range active tags achieve reading ranges up to several hundreds of meters while passive ones can operate only up to a few meters. However, passive tags are low-cost and do not require an electronic power source to operate. The range of passive tags may be increased by using larger antennae at the tag and reader. A comprehensive introduction on the use of RFID for positioning and the useable location methodologies can be found in Retscher et al. (2012). In general, two approaches can be distinguished, known as the direct and reverse approach. The direct approach involves RFID tags fixed at known positions and moving readers. The selection of the best approach depends on implementation costs as dictated by an individual application. For cases that a large number of tags is required, the direct approach is cheaper; otherwise, for instance for smartphone applications is easier to attach an RFID tag (Gikas et al., 2015). Apart from cell-based solutions, lateration and fingerprinting are applicable for RFID positioning if the RSSI are measured in addition. The positioning accuracies obtained using RFIDs depend heavily on the propagation of RSSI in a given environment and the range between tag and its interrogator (Gikas et al., 2016a, b).

4.2 MEMS-Based Inertial Navigation

Recently, the development of low-cost, low-weight, rugged built Micro-Electro-Mechanical Systems (MEMS) navigation sensors facilitates the introduction of guidance, navigation, and control into applications previously considered out of reach. MEMS inertial sensors (i.e., accelerometers and gyroscopes) when integrated with GNSS can increase tremendously the system performance capabilities, especially in GNSS-denied environments where the satellite signal is either totally blocked or attenuated. However, despite their many advantages, MEMS Inertial Measurement Units (IMUs) sensors, because of their small size and low cost, are relatively inaccurate and their data include considerable measurement noise. Especially, the drift biases commonly found in MEMS inertial sensors and the lack of GNSS measurements still render vehicle navigation a challenging problem indoors. In general, the performance of MEMS IMUs is constrained mainly by the gyro performance (Weinberg and Kourepenis, 2006), which ranges between 10°/h and 30°/h, and to a lesser extent by accelerometer performance, which has demonstrated tens of micro-g or better (Barbour, 2010). Today, the use of MEMS inertial sensors has been verified in many transportation applications ranging from prevailing ITS applications (Gikas and Perakis, 2016; Clausen et al., 2017) to driver behavior characterization (Antoniou et al., 2016; Antoniou et al., 2017). However, given the limitations of any system type advanced sensor fusion algorithms (see Section 6.2) are needed as no single sensor or technique is able to meet the positioning requirements for the increasing number of safety and liability critical mass market applications.

4.3 Optical Technologies

Image-based navigation or visual odometry technologies rely on camera (vision) data (Kealy et al., 2015). They aim at navigating objects by processing series of image data which may be recorded with passive sensors such as digital cameras or active instruments like laser scanners. The analysis of image sequences forms the backbone of optical technologies where 3D motions between subsequent scenes may be deduced (Hofman-Wellenhof et al., 2003). Especially for autonomous and driverless vehicles, these techniques play an important role as they serve a critical component of a multisensor navigation system being responsible for specialized tasks such as collision avoidance. A detailed description is out of the scope of this book chapter. Thus, only selected techniques for the use case of smartphone positioning are briefly reviewed in the following.

The built-in cameras in contemporary mobile devices can be used for localization so that significant patterns are detected for extracting the user's location. The employed localization technique relies on scene analysis. Another technique involves the matching of perspective images of the environment captured by a smartphone camera to prerecorded images or videos which have been collected to build up 3D models stored in an image/video database (Retscher, 2016). Images are captured at known positions during an initial 'mapping' survey and added to a database. This database can then be queried to search for images that appear to be of the same place, hence providing occasional position updates when a location with an earlier position estimate is observed. The information contained in images can then be used to recognize when the camera is pointing at a known object. Visual features in a close surrounding environment may be also detected and relative positioning information could be obtained by detecting the motion of the features in consecutive images (Hide et al., 2009; Ruotsalainen, 2013). These schemes are robust to changes in scale, illumination, camera position, and small changes in the scene. Moreover, databases of hundreds of thousands of images can be queried in real time with error rates of just a few percent, depending on the update frequency and the nature of the environment (Cummins and Newman, 2008). The variation of the recorded features in images enables extracting the instant translation and heading of the camera. This information may be further integrated with GNSS or other sensor measurements to obtain complementary information for positioning as the images contain accurate motion information. This is of great importance particularly because image information is unaffected by accumulating measurement errors like inertial measurements or signal obstruction for GNSS.

5 MEASURING TYPES AND POSITIONING TECHNIQUES

5.1 Absolute Positioning Techniques

5.1.1 Proximity

Proximity, known also as CoO, is the simplest and most broadly available positioning technique. It is based on the cell identity and the location associated to it (Chen, 2012; Trevisiani and Vitaleti, 2004). Despite its simplicity, the CoO provides only discrete positions whereas the final accuracy depends on cell size. In the case of a cellular phone network, the mobile unit (vehicle or pedestrian) is located in the signal coverage area (i.e., cell) of a Base Transeiver Station (BTS) which is located in its center. The output position of the cellular phone is then the location of the BTS. Thus, a cell-based approach can be employed if a mobile user's appearance in the transmitters' coverage areas is detected (Retscher et al., 2012; Retscher, 2016). For applications in which a compromise between a relatively low-position quality and cost is required, the CoO technique is generally used.

5.1.2 Lateration

(Tri)lateration is a localization technique which is used to determine the position of the intersection of at least three spherical surfaces given their centers and radii. To obtain a unique position fix in 2D space ranges to three different transmitters or receivers from the user location have to be measured (Retscher, 2016). Either one-way or two-way range measurements can be distinguished. The former is also referred to as TOA which requires precise time synchronization between transmitters and receivers or mobile device. In the latter, the round trip time of flight (RTOF) is measured which requires a more moderate relative clock synchronization than TOA. Positioning fixing could also be performed using received signal strength (RSS) measurements, for instance, Wi-Fi. RSS theoretically decreases with the transmitted energy propagating into space to estimate the path loss, and thus, the propagation distance between a mobile receiver and a transponder. However, in complex and dynamic environments, signal obstructions and reflections may result in ambiguous distance computations and thus position fixes (Retscher et al., 2012). To overcome the main drawbacks of RSS-based lateration, differential approaches have been proposed for Wi-Fi positioning that make use of reference stations deployed in the area of interest to perform continuous RSSI scans of the surrounding APs as it is done in DGNSS (Retscher and Tatschl, 2016a, b). The applicability of the method for C-ITS, however, is limited in areas occupied by APs, such as in car parks. An alternative to range lateration is the hyperbolic lateration. This technique computes the difference in timing between the reception of the signal emitted from two stations, without reference to a common clock. Plotting the potential locations of the receiver for the measured delay produces a series of hyperbolic lines, the intersections of which reveals the receiver's location. In the case of cellular networks hyperbolic lateration is referred to as TDoA. Finally, using the angle of arrival (AoA) approach positions can be determined by measuring the angle of the incoming signals at a receiver or transmitter. Given two or more directions from fixed locations to the same mobile device, the location of the target device can be estimated. A major problem in the AoA technique is the multipath effect which can cause interference of the signals or even false observations of the angle to a reflected instead to the LoS signals (Retscher, 2016) (Fig. 4).

5.1.3 Fingerprinting

An approach for vehicle localization based on RSS values is the fingerprinting technique. This technique mainly consists of two basic phases (Kim et al., 2012; Wu et al., 2013). Firstly, the establishment of the location-fingerprint database offline and, secondly the online positioning part at a decision phase. At the stage of database configuration and radio mapping, all locations in the area of interest are sampled, while their signal intensity is recorded to formulate a position fingerprint. At the stage of online positioning, fingerprint information is collected around the position to be localized. These estimates are compared with fingerprints in the offline database via a matching strategy. This leads to the estimation of the final position which is the candidate for which fingerprinting attains

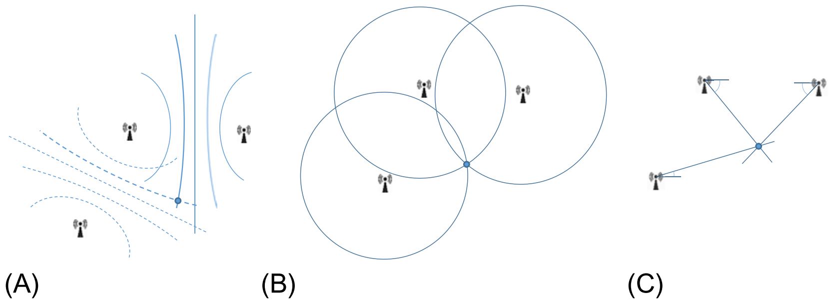

FIG. 4 Geometric principles of most commonly used position estimation methods (ToA, AoA, TDoA).

the best match. Fingerprinting requires a dense, well-balanced spatial distribution of APs and thus is a promising technique for indoor and hybrid area Wi-Fi positioning. Its applicability for C-ITS is then restricted in confined areas such as in parking lots and depots.

5.2 Relative and Hybrid Positioning Techniques

5.2.1 Dead Reckoning

Dead Reckoning (DR) is usually associated with inertial positioning. In this case, the accelerometers integrated in a mobile device can be used to estimate the distance travelled from measured accelerations, while the gyroscopes and magnetometers provide the current heading of the user. Starting from a known position (e.g., determined by GNSS or Wi-Fi), the current position of the user can then be "*dead reckoned*" using observations of the inertial sensors (Antoniou et al., 2016). Thus, it is possible to predict positions of the user by projecting an ordered course and speed from a known present position. A major disadvantage is that DR is subject to significant cumulative errors due to many factors as both velocity and direction must be accurately known at all instants for position to be determined accurately. New positions are calculated solely from previous values, so the error and uncertainty in the position grow with time. Thus, an update with an absolute positioning technique is required from time to time part way through the journey. Apart from GNSS, other RF-based localization methods can be applied for this purpose. Suitable techniques are included in Table 3.

5.2.2 Map Matching

Map matching (MM) usually refers to the technique that combines electronic maps with location information to obtain the actual position of vehicles. The common MM techniques traditionally use spatial information in an attempt to improve navigation accuracy (Ochieng et al., 2003). A feature-based MM approach is thereby most descriptive and originates from the field of pattern recognition. In this case, the search area is limited by the current location determined by the absolute positioning sensors. The current vehicle position can then be derived from this matching process. Other MM procedures derive the position from a curvature pattern of the road elements and mutual allocation by cross correlation. Apart from using simple searching techniques, more complex MM algorithms enable fuzzy logic models, Kalman filtering (KF), particle filters, and belief theory. Quddus et al. (2007) has categorized them into four groups: (i) geometric, (ii) topological, (iii) probabilistic, and (iv) advanced MM algorithms. With the advancement of ICT technologies and optical sensors, together with the improvement of road infrastructure (e.g., road marking), the usage of MM techniques in ITS technologies is continuously increases.

5.2.3 Other Techniques

In addition to the main localization techniques discussed in previous sections, other techniques of lesser importance can be used for urban road C-ITS. For instance, the traffic management of large parking facilities and depots can benefit from the virtual "gate configuration" provided that a dense network of RFID readers and tags is deployed in the area of interest. At critical transit passages RFID tags are installed at fixed, known positions defining these virtual gates. If the reader in the vehicle detects these tags, a vehicle passage through the virtual gate is detected, which defines the location and direction of movement of the vehicle (Niedermayr et al., 2013; Gikas et al., 2015; Gikas and Retscher, 2015). Moreover, in the car garage scenario, the determination of the altitude of a vehicle can be of high importance when locating the floor in a multistorey car park. Such a task can be accomplished with the barometric pressure sensor (altimeter). Thereby, from the changes observed in the air pressure, altitude differences can be calculated using a simple relationship between the pressure changes and height differences (Gikas et al., 2016a, b).

6 CP FOR C-ITS

6.1 From Single Sensor Positioning to CP

While Section 5 introduced the main positioning techniques that individual technologies adopt depending on their operating principle, contemporary positioning systems used in C-ITS, feature rather complex data acquisition setups and sophisticated computational processes.

As shown in Fig. 5, a paradigm shift in the navigation solution has been observed in recent years. This has been manifested by an evolution from a conventional single-sensor, single-platform solution to a multisensor, single-platform approach, and now to multisensor, multi-platform collaborative navigation. Typically, traditional single-sensor systems enabled by GNSS,

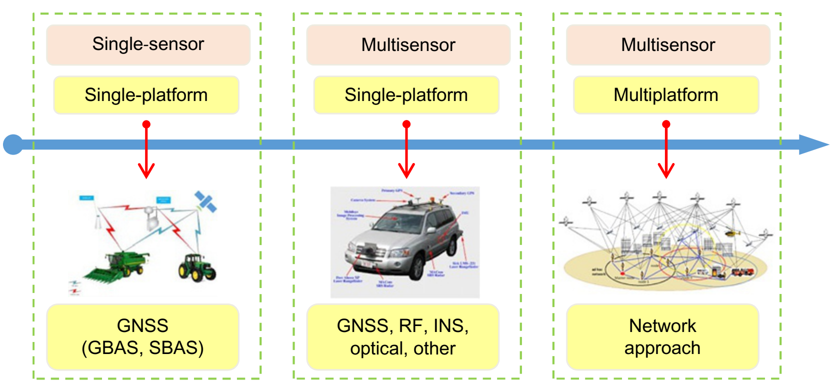

FIG. 5 Evolution of positioning from single-sensor approach to CP.

and enhanced by Ground-based Augmentation systems (GBAS) or SBAS, which provide position, velocity and timing information to an unlimited number of users provided there is satisfactory reception of the satellite signal. The development of multisensor, single-platform systems date back in the early 1990s. These systems evolved as driver for mobile mapping of collecting geospatial data using mapping sensors (e.g., GPS, inertial devises, digital compasses, cameras) that are mounted on a mobile platform (e.g., land vehicles, aircrafts, and water-based vessels) (Tao and Li, 2007).

To overcome the shortcomings of GNSS positioning and further improve the navigation capability of a group of users the concept of CP has been developed. CP techniques leverage the availability of a communications infrastructure to share information and data between objects within a neighborhood using a multisensor, multi-platform configuration. Therefore, the concept of CP implements a dynamic network environment of variant complexity depending on individual problem characteristics (Fig. 5). The key components of CP networks as defined in Kealy et al. (2015) are (i) the inter-nodal ranging subsystem in which each user can be considered as a node of a dynamic network, (ii) the optimization of dynamic network configuration, (iii) time synchronization, (iv) the optimum distributed GNSS aperture size for a given number of nodes, (v) the communication subsystem, (vi) the selection of master or anchor nodes, and (vii) network topology.

In the context of C-ITS, the CP approach relies on information being shared between vehicles within a vehicular ad-hoc network (VANET) and the infrastructure, to overcome the limitations for positioning in the GNSS navigation gap. In this case, the information shared can be in the form of inter-vehicle ranges, relative speed, orientation, satellite related data, and other type of contextual information. Sharing information could help the vehicles within a network to obtain positioning solutions even when the requirement of GNSS positioning cannot be met (Kealy et al., 2013).

6.2 Fusion Algorithms and Techniques for CP

Any CP system implements an algorithm to provide an optimum positioning solution for all networked users. Perhaps the most widely used algorithm in CP for C-ITS, the KF is a recursive algorithm that uses a series of prediction and measurement update steps to obtain an optimal, in a minimum variance sense, estimate of the state vector. The algorithm works in a two-step process. In the prediction step, the KF produces estimates of the current state variables, along with their uncertainties using knowledge of the system kinematics. Once the outcome of the next measurement is observed, these estimates are updated using a weighted average, with more weight being given to estimates with higher certainty. Extensions to the method have been developed, such as the Extended KF (EKF) and the Unscented KF (UKF) which work on nonlinear systems (Grewal and Andrews, 2001). The underlying model is similar to a hidden

Markov model except that the state space of the latent variables is continuous and all latent and observed variables have Gaussian distributions.

A different algorithmic approach used for dynamic network positioning is the Monte Carlo Localization (MLC) (Thrun et al., 2005). Given a map of the environment, MCL estimates the position and orientation of a moving node as it moves and senses the environment. The algorithm implements a particle filter to represent the distribution of likely states, with each particle representing a possible state. As the user moves, the filter shifts the particles to predict its new state. At a filtering phase, the particles are resampled to assess how well the actual sensed data correlate with the predicted state. A variant of MLC is the SPAWN algorithm that makes use of Factor Graphs (FG) and Sum Product Algorithm (SPA) (Wymeersch et al., 2009). However, it is noted that both MLC and SPAWN algorithms are suited best for indoor environments and particularly for wireless networks, which can directly be applied in VANET.

7 APPLICATION CASES OF INTEGRATED URBAN C-ITS

7.1 Case 1: Smart-Bike Systems as a Component of Urban C-ITS

The ongoing trend toward global urbanization and the fast growth of smart cities has led to the development and adoption of new, environmental friendly urban mobility plans and transport sharing systems. Particularly, bicycle mobility initiatives and bike-sharing programs have received considerable attention at first in Europe and more recently in other continents. At the early days of public bicycle programs, a user could simply ride a bike to the nearest station of his destination and leave it for the next user. Today, more than 1000 public bike-sharing systems exist worldwide counting more than 1.2 million bicycles (en. wikipidea.org). In recent years, the rapid expansion of sensor and communication technologies and the continuously increasing complexity of megacities structure and living style have totally changed the picture of bike-sharing and cyclists needs in general.

In response to this situation, numerous studies proposed various bike monitoring and management tools that in many cases have been adopted and implemented commercially. For instance, Flüchter and Wortmann (2014) proposed a user trajectory tracking tool for route optimization and for transport studies. Other studies (Razzaque and Siobhan, 2015) focus on developing an Internet of things (IoT)-based management framework for user safety, while other researchers concentrate in monitoring air pollution (Vagnoli et al., 2014) or theft prevention (Pias et al., 2009). However, despite the various initiatives in the field, a self-contained, automated bicycle system having the potential to be integrated to an urban C-ITS system is still missing. Such a bicycle system, named "smart-bike", would have the ability to sense and monitor the environment and opportunistically communicate information to a control system and other users (Fig. 6).

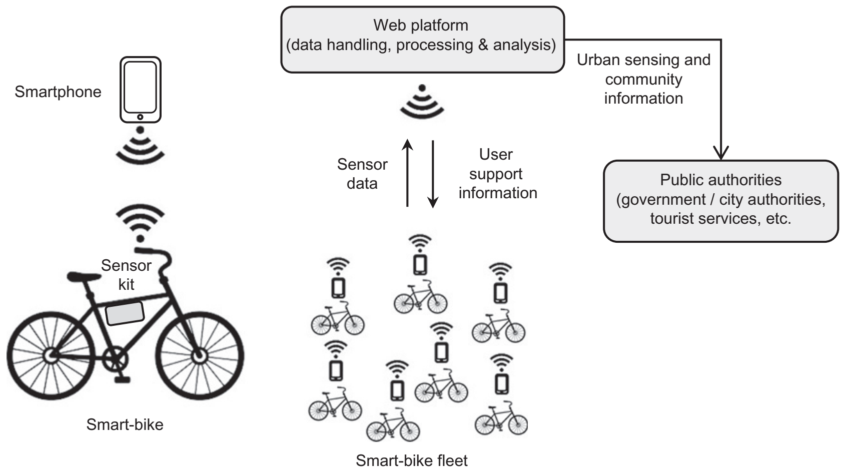

FIG. 6 Operational concept of "Smart-bike".

To this purpose, three major areas of information gathering are envisioned for a smart-bike system; namely, (a) user support, (b) urban-sensing and, and (c) community-oriented information. Data collected to support user needs include route and navigation information, effort, rhythm, as well as other biometric data. Such information should be private and exclusively to the rider's interest. Urban-sensing information includes air quality, noise pollution, weather, etc. Such data would help public authorities to continuously monitoring the city environment and improve relevant services. Finally, community-oriented information may refer to road infrastructure conditions, transport conditions, lighting, pedestrian and bike density, illegal parking, etc. This type of information will be collected anonymously for use by the city authorities for monitoring and controlling the transport network as well as for statistical analyses leading to strategic planning of city functioning.

Irrespective of the type of data collected, a smart-bike system in order to be capable to be integrated in a city C-ITS, a number of points should be taken in to account at a design stage. Firstly, it should accommodate advanced data transfer and communication means to allow information exchange in real time. This is particularly important for cyclist and pedestrian safety-critical applications in a fully operational C-ITS scenario. Furthermore, in this case, a thorough pre-analysis of the needs concerned with the navigation sensor technologies and data fusion techniques are required. Other technical issues to consider relate to the sensor platform architecture (i.e., smartphone-based or external), energy consumption issues and ease of installation. Table 4 summarizes the type of sensors and data concerned with a modern smart-bike system.

Finally, as is the case for other ITS components, the deployment of a smart-bike system should take into account data privacy and ownership issues as well

TABLE 4 Type of Sensors and Raw Measurements Associated With a Smart-Bike System

Type of Sensor	Raw Measurement
GNSS	(φ, λ, h) WGS'84, (x, y, h) projection cords
	Pseudoranges
MEMS-based accelerometers	α_{tan}, α_{rad}, αz
MEMS-based gyroscopes	Heading, pitch, roll
Digital compass/ magnetometer	X, Y, Z
Barometric pressure sensor	Z
Cellular network, Wi-Fi, Bluetooth	X, Y, (Z)
Camera	Geo-referenced images, video
Ambient light sensor	lm
Sound detector	dB
Air pollution	CO, CO_2, O_2, O_3, NO, NO_2, SO_2, NH_3, CH_4, H_2, H_2S, HCl, HCN, PH_3, ETO, Cl_2, particles

as policy issues, such as mobility prioritization and alerts in respect to other modes of transport including vehicles and pedestrians.

7.2 Case 2: Smart Intersection for Traffic Control and Safety

Up to now, several intersection management models have been proposed, the complexity and functionality grade of which varies with the constraints adopted and the level of automation envisioned. These models rely on innovative ITS (e.g., adaptive cruise control) and communication (e.g., ITS-5G) technologies, which are expected to enable efficient and environmental friendly traffic operations at urban intersections serving road users with different requirements and priorities to coexist in the confined space that is typical in the urban environment.

The key idea behind the automated intersection management resides in the reservation paradigm, in which vehicles "call ahead" to reserve space-time in the intersection (Dresner and Stone, 2008; Sharon and Stones, 2017). The detailing of this idea depends on the level of automation encountered. As an

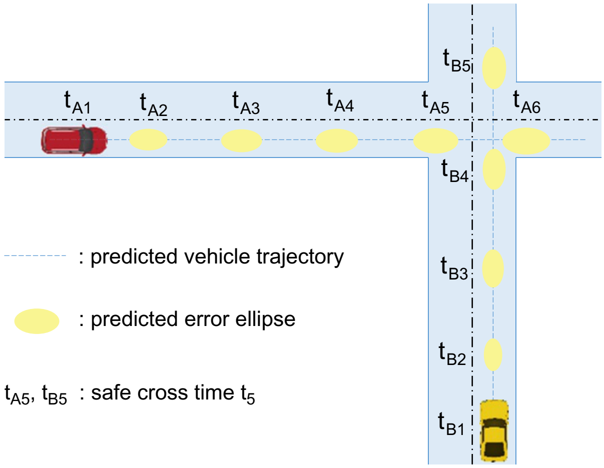

FIG. 7 The positioning problem of ICRW cooperative application.

example, following the model introduced by Au et al. (2015) which is applicable both for semi- and fully autonomous vehicles, the controlling of vehicles is performed by a driver agent, while an intersection manager (named arbiter agent) is fixed at each intersection. The driver agent attempts to reserve a block of space-time in the intersection, while the intersection manager decides whether to grand or reject requested reservations according to an intersection control policy. Simulation data have been used to test the feasibility of the method indicate decrease in the traffic delay compared to previous studies (Wuthishuwong and Traechtler, 2013; Tlig et al., 2014) that assume only fully autonomous vehicles.

Notwithstanding the promising results obtained from simulation studies so far, the implementation of the smart intersection concept in practice would face numerous technological challenges which are yet to be resolved. In this process, the need for robust, high-integrity position solution at road intersections is critical. As an example, Fig. 7 illustrates the navigation problem associated with the Intersection Collision Risk Warning (ICRW) cooperative application (Peyret et al., 2017). The trajectories of vehicles and their uncertainties are extrapolated from the current instant using the available navigation solution (position and direction). Based on this information, an estimation of the risk of collision is computed, and consequently the intersection manager decides whether to issue a warning to the drivers or not.

8 DISCUSSION, PERSPECTIVES, AND CONCLUSIONS

From the preceding analysis, it becomes evident that in order to support effectively urban traffic connectivity and automation, ICT and positioning technologies should advance and be integrated tightly together. However, the adverse operating conditions usually encountered in the urban environment, together with the stringent user requirements and the high complexity associated with most C-ITS applications introduce numerous technological challenges which are yet to be resolved.

Despite the maturity and the underlay benefits that current data communication protocols (IEEE 802.11p, Long-Term Evolution, LTE) can offer, they have not been designed to support the forthcoming C-ITS requirements (Teixeiraa et al., 2014; Rappaport et al., 2013). Relevant issues concern with the limitations of current ICT technologies to support the increasing data volume and decreasing delays within the system. Also, message formatting and contextual information issues arise. Therefore, it is likely that new ontologies and semantics need to be defined to support effectively the evolving data volume communication requirements and the heterogeneity in the sensor data. Moreover, given the broad diversity of communication means (e.g., Bluetooth/ZigBee, cellular, WiFi, DECT) used in C-ITS, new frequency bands are required to support the exchange of data. This is particularly evident with technologies that operate in the Ultra High Frequency (UHF) band where additional frequencies are very limited.

In terms of data volume sharing, it is expected that the 5th generation mobile networks, known also as 5G (Rappaport et al., 2013; Zhang et al., 2017), will greatly benefit V2V and V2I communications. Moreover, the recent advances in cloud computing and big data processing would further support the demanding communication needs of connected vehicles over large areas. However, in order to facilitate sensor data and digital maps to be continuously updated and shared among vehicles the forthcoming network approaches should adopt new concepts, such as those based on predictive caching principles (Blaszczyszyn and Giovanidis, 2015; Dehghan et al., 2014; TalebiFard et al., 2015).

Regarding vehicle positioning the GNSS forms the primary source for deriving location information for road ITS. Nevertheless, the excessive error budgets accumulated in low-cost GNSS receivers and the low satellite availability encountered in the city environment bound its use, especially for safety-critical applications. Therefore, new cooperative positioning solutions need to be developed to maximize the benefits of GNSS in C-ITS, while a thorough assessment of GNSS performance capabilities should be undertaken that would lead to unified standardization procedures. In response to these issues, several working groups have recently launched in Europe and worldwide, either within standardization bodies such as ETSI or CEN/CENELEC (SSCC-CG, 2015), or through research networks such as the SaPPART EU Cost Action (Peyret et al., 2015). Moreover, it is expected that the combination of different GNSS (for instance, GPS and Galileo through EGNOS or EDAS) will further improve the accuracy and integrity of vehicle positioning.

As already pointed out in Section 4.1, radio-based measurements form a key technology for urban C-ITS. In fact, radio-based systems are used to support not only data exchange but also ranging tasks. However, regardless of the operating principle that a radio frequency system implements (T(D)oA, RSSI, etc.), propagation phenomena caused by NLoS conditions and severe multipath due to obstacles can lead to significant errors in ranging and position fixing computations (Karedal et al., 2011), giving rise for the development of new algorithmic approaches to tackle the problem. In next years, the development of ITS-5G ranging is anticipated to revolutionize the way localization is performed in deep urban environments. However, as ITS-5G is still not actually deployed there are no studies available to assess its potential and limitations for positioning applications.

Also, when it comes to data fusion from different sources a number of challenges also arise. For instance, source map data used in MM would need to be harmonized using different ontologies and semantic standards depending on specific application characteristics. Similar concerns also arise when fusing map data with heterogeneous types of information, such as LIDAR data, particularly regarding their sampling frequency and time stamping properties. Last but not least, the increasing penetration rates of modern technologies in urban societies (e.g., smartphones and PDAs) bring a new dimension of the localization problem for ITS applications attracting stakeholders from different areas. However, in order to maximize the benefits of every urban ITS deployment, care should be exercised in activity and regulation strategy coordination, so that, all relevant stakeholders are involved.

Recently, in response to the various challenges encountered in the development and operation of urban C-ITS and the role of positioning, a number of groups have been setup to study the problem. In the Northern America, among other players the US Dept. of Transportation plays a leading role (Hartman, 2016), while in Europe the driver of coordinated research in the field is undertaken mainly through EU supported projects; among others being the COMPANION (FP7), CoVeL (FP7), AutoNet 2030 (FP7), ECoMove (FP7), CODECS (H2020), HEIGHTS (H2020), and CIMEC (H2020). Among a number of technical findings pointed out in these studies, an obvious conclusion is the absolute requirement of bringing together ITS and positioning specialists to face the problem in an integral but viable way.

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