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Infrastructure-Independent Indoor Localization and Navigation

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In the absence of any global positioning infrastructure for indoor environments, research on supporting human indoor localization and navigation trails decades behind research on outdoor localization and navigation. The major barrier to broader progress has been the dependency of indoor positioning on environment-specific infrastructure and resulting tailored technical solutions. Combined with the fragmentation and compartmentalization of indoor environments, this poses significant challenges to widespread adoption of indoor location-based services. This article puts aside all approaches of infrastructure-based support for human indoor localization and navigation and instead reviews technical concepts that are *independent* of sensors embedded in the environment. The reviewed concepts rely on a mobile computing platform with sensing capability and a human interaction interface ("smartphone"). This platform may or may not carry a stored map of the environment, but does not require *in situ* internet access. In this regard, the presented approaches are more challenging than any localization and navigation solutions specific to a particular, infrastructure-equipped indoor space, since they are not adapted to local context, and they may lack some of the accuracy achievable with those tailored solutions. However, only these approaches have the potential to be universally applicable.

CCS Concepts: • **Information systems → Location based services**; **Mobile information processing systems**; • **Human-centered computing → Ambient intelligence**;

Additional Key Words and Phrases: spatial information, indoor localization, human navigation, infrastructure-independent positioning

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1 INTRODUCTION

This article reviews technical concepts and techniques supporting human indoor localization and navigation *independent* of sensors embedded in the environment. The scope covered centers on a user and their off-the-shelf mobile sensing and computing device (“smartphone”), and it explicitly excludes *in situ* internet access or reliance on any positioning technology in the environment, because these technologies simply may not be universally available or may be prone to outages and disruptions. Such a radical self-restriction poses a challenge that is different from similar localization and navigation tasks:

- This scope is distinct from the tasks of a *robot* capable of simultaneous localization and mapping (Durrant-Whyte and Bailey 2006) for navigation purposes. On one hand, this is due to distinct perceptual, cognitive, and communication abilities of both the smartphones and the human decision-makers. For example, a human does not need technology for self-localization within the vista space such as a room or hall. On the other hand, this is due to the character of at least some of the reviewed approaches that build on some form of human knowledge about the structure of indoor environments, and thus mapping may not even be required.
- The task is also distinct from *outdoor* localization and navigation in a multitude of ways, including the lack of a global positioning and global spatial reference system for indoor environments, but also the different cognitive scales and dimensions of indoor and outdoor environments, and the presence of a vertical dimension and movements between levels.
- Finally, the challenge is different from any *indoor* localization and navigation solution relying on specific—and in lieu of global solutions necessarily *local*—infrastructure for positioning (Avariento et al. 2015; Correa et al. 2017; Potorti et al. 2017) and communication: Abstaining from deploying infrastructure may appear at first sight more cumbersome or less accurate (two of the assumptions that still need to be investigated).

Self-localization and navigation methods that are *infrastructure-independent*, i.e., that are limited to reliance on sensors in the hands of people, impose further challenges. These challenges are interesting for highly relevant reasons:

- First, infrastructure-independent methods are applicable in any indoor environment, independent from any sensor-based infrastructure. Thus, they are a step forward towards global indoor localization and navigation solutions.
- Second, abstinence from *in situ* internet access is mission-critical for example in emergency evacuations, where communication infrastructure may be damaged or destroyed, or communication networks may be congested or blocked by the authorities.
- Third, these methods are more closely integrated with ways people perceive and interact with their environments, and thus are already closer to cognitive concepts of human-computer interaction.

Some of the methods discussed also allow for infrastructure-free connectivity between positioned mobile devices, such as through near-field peer-to-peer communication between smartphones. Other methods discussed still rely on prior access to the Internet—but never *in situ*. Prior internet access may be required to, for example, download a particular application or map data for a specific building.

Universally applicable support for people in their indoor localization and navigation is needed. Reports state that people spend on average above 80% of their time indoors (Jensen et al. 2011; Klepeis et al. 2001). More importantly, Klepeis et al. observed that US employees on average spend 18.4% of their time in indoor environments *other than home*—more than twice as outdoors. These figures may vary with culture and lifestyle, but they are significant. Notwithstanding, people's needs for support in localization and navigation are limited to:

- environments they are unfamiliar with: A visit at the first time poses the regular *wayfinding* challenge;
- environments they are coarsely familiar with but look for a fine-grained destination (e.g., a particular gate at an airport or a particular shop in a mall): Here, people require support for *hierarchical wayfinding*;
- environments that are subject to change (e.g., environments that are impacted by congestion, accidents, or disasters): Here, people require support for *dynamic wayfinding*.

The classification is actually environment-independent, and thus applicable equally to outdoor localization and navigation (e.g., Richter et al. 2008).

This article will review infrastructure-independent, smartphone-based indoor localization and navigation methods. We first provide a synopsis of the common ground for all human indoor localization and navigation systems (Section 2) before reviewing recent, complementary infrastructure-independent positioning and localisation methods (a) from a sensing and vision perspective (Section 3.1), (b) from a reasoning with partial knowledge perspective (Section 3.2), and (c) from a cognitive perspective (Section 3.3). The article concludes with open challenges for this field of enquiry.

2 COMMON GROUND FOR HUMAN INDOOR LOCALIZATION AND NAVIGATION

Localization and *navigation* in indoor environments address two fundamental human information needs: the answers to *Where am I* and *Where do I need to go*, at a scale, granularity and selectivity relevant to their decision-making in indoor environments or outdoors. Indoor environments have certain characteristic properties reviewed in this section to lay the common ground for the approaches of *infrastructure-free* localization and navigation discussed later in the article.

2.1 Indoor Environments

A shared definition and understanding of *indoor environments* is necessary to be able to discuss indoor localization and navigation. Many of the following characteristics are gradual distinctions from *outdoor environments*, but sufficient to identify particular challenges for indoor localization and navigation. These challenges are linked to the design of indoor environments and to human perception and cognition (Hirtle and Bahm 2015). Popular science (Ellard 2009) has phrased it in the catchy subtitle "Why we can find our way to the moon, but get lost in the mall." A significant amount of literature is also looking into how people learn indoor environments (e.g., Münzer and Stahl 2011; Srinivas and Hirtle 2015).

Image schemata. The word *indoor* is a composite of *in* and *door*, which indicates a place with certain limits, or bounded space (in a mathematical sense, these limits do not need to be crisp). The peculiar boundedness of indoor space, however, is the ceiling, not the walls; outdoor spaces are at least open in z-direction. If indoor environments are distinct from outdoor environments at all, it is then by this conceptualization of a bounded space. Image schemata (Johnson 1987) distinguish *surfaces* (outdoor, unlimited) and *containers* (bounded). Containers, however, are not the only image schemata applied to indoor environments. When Raubal and Egenhofer investigate the complexity of wayfinding in indoor environments they also identify schemata such as paths and links (Raubal and Egenhofer 1998). For example, a corridor may be a container in one context ("in the corridor"), but a path in another one ("go through this corridor"). While image schemata illuminate some of the meaning of indoor environments, the identified schemata are not exclusive for indoor environments. Containers, paths, and links can be found in conceptualizing outdoor environments as well (Winter 2012), e.g., "in the street"—container, and "rain on the street"—surface, or "traveling on the street"—path. Furthermore, the existence of gradual differences between outdoor and indoor environments does imply that there are spaces in-between, typically facilitating the transition between indoor and outdoor (Kray et al. 2013). This transition space can be as crisp (with regard to describing human movement) as a door or its sill, or as vaguely bounded as open portals, train platforms, stadiums, or roofed shopping streets. Finer distinctions can be made in reference to indoor environments as bounded spaces: While the roofed platforms of a train station may count as indoor because they are conceptually part of the train station building, the space under a bridge is not considered indoor because the feature under the bridge is generally not bounded space.—Rüetschi and Timpf (2005) subsume such spaces of transition between spaces *scene spaces*. Scene spaces have a granularity and salience that are relevant for navigation. Thus, navigation must be able to deal with the contrasting properties and conceptualizations of outdoor and indoor environments, and with the spaces in between.

Vistas. In addition, the physical bounds of indoor spaces restrict the perception of the surroundings; views are blocked off and sound and smell are absorbed by the walls, floors, and ceilings. It is typically impossible to get an overview of the larger indoor environment from a single viewpoint, and it is equally impossible to get vistas to distant landmarks, in contrast to outdoor spaces. This is reflected in the complex ways professionals design indoor spaces: *Wayfinding performance* is rarely approached with computer-aided, quantitative approaches at the design stage (Kuliga et al. 2014), and is known to be limited by rigidly limited vistas (Peponis et al. 2004). Furthermore, the rigidly limited vistas, or high degree of compartmentalization, requires localization and navigation support at a granularity unprecedented by outdoor environments.

Uniform design. Indoor environments are built environments. The builder typically applies a uniform design to an indoor environment as a matter of economy. Outdoor environments are less constrained in their design, and the different owners can compete for individuality and recognisability in a neighborhood. With respect to wayfinding and navigation, this means in particular that indoor environments are typically poor in salient landmarks (Richter and Winter 2014), or less intelligible (Carlson et al. 2010). Wayfinding information must reflect on this property. In addition, the homogeneous design of each indoor environment has an impact on wayfinding strategies and wayfinding success that varies largely between types of buildings and design intentions. For example, hotels, offices, and transport interchanges (e.g., train stations, airports) rely more on numbering and invoke corresponding wayfinding strategies, while museums and shopping malls rely more on names and vistas, and invoke different wayfinding strategies. Some buildings are designed for high throughput (such as train stations), and others are seemingly designed to keep people inside (such as shopping malls or certain shops). For this article, we do not favor or exclude any building type or any design choice.

Levels. In outdoor environments, most activities are limited to the Earth's surface, which, although it has a height component, remains two-dimensional for the purpose of positioning and navigation under open sky. In indoor environments with discrete levels, two-dimensional positioning remains ambiguous. The different levels are linked by lifts, escalators, or staircases. This characteristic poses other distinct challenges for indoor navigation (Hölscher et al. 2006, 2012; Li and Klippel 2012). Among these challenges is the difference of cognitive scales for horizontal and vertical movement. For example, with lifts and escalators, the vertical distance is travelled with no locomotion at all, but with varying speeds and also with varying waiting times. Thus, usually a vertical distance is considered a barrier in indoor spaces (Hanyu and Itsukushima 1995; Kraut et al. 1988; Soeda et al. 1997), since the different levels are visually inaccessible from each other. A physical transfer between them does not offer an experience that would cognitively connect the two spaces (for the reasons stated above) and in addition often results in disorientation. Also, broadly accepted topological reasoning models such as RCC8 (Randell et al. 1992; Renz 2002) are not applicable in environments where *above*/*below* is a significant distinction and are also connected by the lifts and staircases.

Conventions and patterns. Indoor environments have particular structures that are different from outdoor structures. Built environments are more regularly structured within each level and even across levels, down to grammars (Khoshelham and Díaz-Vilariño 2014). Universally, levels tend to be sequentially numbered, in contrast to outdoor space where streets are usually—but not always—named. The strict order of numbers provides a sense of distance from ground level or exits. The structured nature of indoor environments also suggests further conventions on addressing patterns, such as the systematic labeling of rooms, gates, or platforms. Typical are *floor-room number* patterns (e.g., the room numbers on the first floor all starting with "1"), and *sequential room numbering* along a corridor (e.g., Room "100' followed by "101"). Similarly, gates at airports and platforms in train stations are numbered sequentially. Such numbering combined with appropriate signage on which direction to head for; for example, "100–116 to the left" or "Gates B1–B11" allows for finding a specific room or gate with ease. These systems also allow for hierarchical navigation strategies (Timpf et al. 1992). For example, "Level 1" (or "Terminal B") indicates that all rooms starting with "1" (or all gates starting with "B") can be found in the indicated directions (Raubal and Worboys 1999). Thus, such combination of intuitive numbering and signage provides already a sensor-independent navigation system: if a person receives at check-in the information on the gate, this person is able to develop a procedural plan such as "go through customs [conventional knowledge], look out for signs to terminal, then look out for any gate number and the order of the numbers and decide on a direction—take the difference of the local gate number and the assigned one as an indication of distance." These heuristics, however, can be violated by counter-intuitive numbering systems, such as a missing 13th floor in a building (Tomko and Richter 2015). In addition, since the mode of movement in indoor environments is mostly walking, which is less restricted compared to road or rail traffic, there are challenges for modeling routes, especially in large, open indoor spaces such as halls. Exceptions are lifts, escalators, and moving walkways that suddenly restrict movement, thus adding to the complexity of indoor navigable mobility networks. The high degree of fragmentation means that usually qualitative localization and navigation is sufficient (Winter and Kealy 2012), an important distinction from indoor localization and navigation for robots.

Cognitive scale. From a perspective of cognitive scales (Montello 1993), relating the size of the human body to the size of the environment, indoor space lacks the *geographic scale*—environments of such a size that they cannot be explored by locomotion any longer and can only be learned from pictorial representations. This is in stark contrast to outdoor environments, where the existence and importance of geographic scale for outdoor localization and navigation is a major case for maps. Indoor environments, in contrast, can be explored by locomotion, and hence, the role of maps is diminished or changed, since vistas and path integration become more prominent parts of the localization and navigation strategies (Münzer and Stahl 2011). This difference should impact on the requirements specifications for information needs and human-computer interaction. For example, indoor navigation needs can be down to manipulable table-top scale, such as finding certain items on a supermarket shelf (e.g., Krüger et al. 2007).

Temporal scale. Indoor localization and navigation is also linked to temporal scales (which are not addressed by Montello) such as locating a meeting at a particular time in a particular room, or navigating an escape route if a fire blocks usual egress paths. Actually, a significant portion of the research on indoor localization and navigation is motivated by safety considerations (such as not getting lost) rather than by economic considerations (such as finding the least cost path). Safety considerations, however, add to the challenge: Accidents and other disasters have an immediate and often rapidly changing effect on accessibility in an indoor environment, and thus methods and systems are required that provide localization and navigation in a dynamically changing indoor environment, even in environments people are familiar with. Regardless, since sensing and locomotion are highly automated in people, aspects of localization and navigation such as obstacle avoidance, or updating internal (cognitive) maps, happen without further technical support.

Private space. Indoor space is an enclosed environment also because it is a private space. In contrast to outdoor traffic, most movements indoors occur with particular access restrictions and regulations. Different groups of people have access to different parts of the environment, and thus require highly tailored information supporting their particular navigation requirements. As access to buildings is also often regulated by times of the day, the navigable mobility network has a dynamic component as well.

Maps. Another example of a navigation system based on "knowledge in the world" is the traditional You-Are-Here map put up on walls (or sometimes in information kiosks) to help people orient themselves and navigate in emergency situations. These maps are notorious for their difficult reading, requiring advanced mental rotation and orientation skills to align map content with the environment (Klippel et al. 2006; Levine 1982; Montello 2010), and often also advanced map-reading skills due to their non-standard designs. Putting these maps on smartphones can overcome rotation and orientation challenges by centering and orienting the maps according to the current location and movement direction—if the smartphone can localize itself without relying on sensors in the environment; we will present such solutions below.

Affordance. Affordance (Gibson 1979), or the perception of an offered action by an object, is not only a heuristic of our cognitive system that enables to make sense of an environment (e.g., a child will perceive different affordances of a room than an adult), but can also be used to design an object that communicates well its intended use (Norman 1988). A trivial example of the importance of affordance in navigation is a sign with the word "Exit" on it, exuding the affordance to find a way out in the indicated direction, or an arrow on a sign ("→ B1–B7" exuding the action of turning right for the gates B1–B7). More subtle forms of how affordances may influence our wayfinding decisions are wide corridors for paths the unfamiliar visitor should consider and narrow (or dark) corridors designed only for special use (e.g., cleaning, maintenance). Experienced designers can make spaces more legible (Hölscher and Brösamle 2007; Hölscher et al. 2012; Zacharias 2001).

Positioning. Outdoor positioning has been revolutionized by global navigation satellite systems (GNSS). But satellite radio signals rarely penetrate buildings, thus indoor environments are GNSS-deprived environments. In consequence, indoor environments do not share a single spatial reference frame for navigation. Indoor localization methods, however, are plenty—those based on WiFi, UWB, RFID, CCTV, wireless telecommunication networks, QR, and many more (Maghdid et al. 2016; Retscher and Kealy 2006; Xiao et al. 2016; Yang et al. 2015)—which all require a building to be equipped with a particular, tailored infrastructure, to which the visitor of the building has to connect for navigation. Thus, none of these systems provide a once-installed global coverage (like GNSS provides), and since indoor environments are private spaces, there is no force to establish compatible systems. Also, the significant costs for installing new hardware and/or for maintaining mappings of some sensor characteristics to building locations have to be carried by private owners, which makes it unlikely that every space will be equipped. In contrast, infrastructure-less positioning and navigation is then rather comparable to indoor wayfinding before technical localization methods were developed, except that smartphone devices are providing some autonomous support in addition to the information, patterns, and affordance in the environment.

Thus, the wealth of knowledge about the provision of localization and navigation information that was created for outdoor space must be scrutinized, extended, or revised to be applicable in indoor environments (Karimi 2015; Winter 2012). It also has become clear that people enter an unknown indoor environment with certain expectations on its design, scale, and conventions. These expectations—let us call them world knowledge—enable people to apply wayfinding heuristics, i.e., strategies to approach their wayfinding tasks. Any system to support indoor localization and navigation has to fit in and complement and support these heuristics.

2.2 Spatial Models of Indoor Environments

Spatial data modelling aims to formally describe the real world in a way such that decisions derived in the digital representation are matching those that have to be made in the real world. In spatial data modelling, the real world and the human perception of it are decomposed into entities, and then the way the entities are spatially related to each other is described. There are endless phenomena (human-made and natural) in the real world, as well as several understandings of the phenomena by humans. It is not practical to have a single, universal spatial data model describing the real world in terms of scale, the level of detail, and types of entities. As such, data models are developed with a particular scope and application in mind (e.g., navigation (Li and Lee 2013), urban planning (Sabri et al. 2015), emergency management (Tashakkori et al. 2015), or security of land tenure (Kalantari et al. 2008)).

Indoor environments can be modelled in several levels of detail, including physical and cognitive details. Physical details comprise both spatial (e.g., surface) and semantic aspects of indoor entities (e.g., doors, walls). Cognitive details refer to phenomena that cannot be physically seen but are subjectively perceived by humans (e.g., navigation route; the spatial extent of rights, restriction, and responsibilities of occupants of apartments). As such, several spatial models have been developed, both open and proprietary. In this article, we focus on prominent standards for spatial models.

CityGML is a 3D spatial modelling approach for human-made urban environments (Kolbe et al. 2005). It is an open standard that describes entities, attributes, and spatial relationships required in urban settings. It allows for specifying (a) semantics of entities (e.g., surface x is a wall); (b) geometries of entities using spatial coordinates; (c) topological relationships (e.g., a window can only exist in another surface such as a wall); and (d) appearance properties of entities (e.g., assigning the photo of a roof to its corresponding surface geometry). In CityGML, urban settings are divided into several themes including buildings, bridges, vegetation, land use, water bodies, transportation, and facilities using the concept of Levels-of-Detail, or LoD (Biljecki et al. 2014). The finest LoD in the building theme caters for entities of indoor environments. This LoD includes objects that model rooms, walls, doors, windows, floors, ceilings, installations (e.g., staircases), and furniture. Application domains such as emergency response often require extending the entities in CityGML. As such, a mechanism called Application Domain Extension exists for augmenting the current capacity of CityGML (Kolbe 2009).

While CityGML has capabilities for describing the physical properties of indoors, another spatial standard called IndoorGML can model a cognitive aspect of indoors: the ability to model entities that help with navigating inside buildings (Li and Lee 2013). IndoorGML is used for defining abstract spaces and their topological relationships. Using IndoorGML, one can specify the spatial layout of the indoors independent from their physical characteristics. One may create spaces that do not correspond to any physical feature. These cognitive spaces are topologically linked, and there may be layers of them (e.g., rooms, WiFi, and RFID service areas). From these spaces, for each layer, graphs are extracted that can be used for navigation purposes.

Table 1. Analogue and Digital Information Supporting Indoor Orientation and Wayfinding

	analogue	**digital**
dynamic	concierge	location-aware map centering and orientation, location-aware routing
static	signs, wall (YAH) maps, numbering systems, affordance by design	digital floor plan, information kiosk

Developed for the architecture, engineering, and construction industries, Industry Foundation Classes (IFC) is a standard data model that caters for entities for the whole life-cycle of buildings and infrastructure (Howard and Björk 2008). IFC provides capabilities for modelling various building elements based on the geometric primitives: points, curves, and surfaces. These geometric primitives are combined using approaches such as Constructive Solid Geometry (Requicha and Voelcker 1977), Boundary Representation (Lienhardt 1991), bounding boxes, surface models, or tessellated models. In IFC, topology is defined using vertices, edges, or faces, and their associations with the geometry of a point, curve, or surface, respectively. IFC caters for several disciplines, including architecture, building controls, plumbing and fire protection, structural elements, heating, ventilation, and air conditioning (HVAC), and electrical and construction management. Regarding indoor entities, IFC can model both physical and cognitive aspects. IFC models buildings, building floors, arbitrary spaces, windows, doors, walls, slabs, stairs, and utility networks of interiors (e.g., pipes, cables, and ducts). IFC can be customized for indoor applications such as emergency response (Tashakkori et al. 2015) and property management (Atazadeh et al. 2017).

Besides CityGML, IndoorGML, and IFC, there are other methods that potentially can be used for spatially modelling indoor environments. These models primarily provide the geometric definition of objects and have limited capacity to cater for the semantics of the objects. These other models include VRML (ISO 2004), X3D (Daly and Brutzman 2007), COLLADA (Arnaud and Barnes 2006), and KML (Wilson 2008). These methods of 3D representation can be used in modelling indoor environments such that the physical reality of indoor environments can be stored and visualised. However, these methods fall short in indoor navigation where concepts such as space, navigation path, emergency exit, and so on have a significant function, and data models behind these methods are not designed for such concepts.

2.3 Indoor Localization and Navigation Support

Indoor localization and navigation aims to produce spatial information in support of particular human decision-making processes, here especially the processes of human orientation and wayfinding in indoor environments. The value of the produced information depends on its capacity to improve these decisions (Shapiro and Varian 1998). Typically, the decisions can be improved in three ways: (i) coming to a better decision in terms of some set criteria such as uncertainty or length of routes, (ii) coming faster to a decision than without the information, or (iii) coming cheaper to a decision, compared to other channels such as calling somebody for help. With this understanding of *information*, clearly indoor localization and navigation support cannot only cover the required sensing and data analytics, but must include the human interaction with the provided information as well.

The information supporting human indoor orientation and wayfinding can be static or dynamic and analogue or digital (Table 1). For the wayfinder seeking the information for decision support, the information is embedded in the environment (tangible on a sign, on a screen, on a smartphone display) and perceived and interpreted together with the remainder of the physical environment.

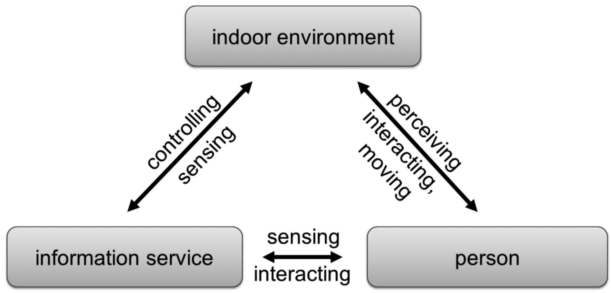

Fig. 1. The semiotic triangle between environment, person, and information system.

The traditional analogue form of indoor orientation and wayfinding information is the you-are-here map (YAH). You-are-here maps are well known for their challenges to be read, aligned, and used in decision-making (Ellard 2009; Levine 1982; Montello 2010). Digital replications of you-are-here maps overcome one challenge: Being ubiquitous, they are available when and where needed (Levine et al. 1984).

The process of reading supportive wayfinding information includes the alignment of perceived information with the environment—a major cognitive challenge. In indoor navigation, any digital information, verbal or graphical, is perceived together with the available analogue information in the environment; for example, static signs in the environment or designs of the indoor environment that afford a particular behavior and thus suggest a particular decision (Gibson 1979; Norman 1988). Digital indoor localization and navigation support is only a portion of the evidence taken into account in a human decision-making process and has to be produced to align with other perceived evidence.

Design for affordance covers not only spatial layout, but also the encoding of the layout in labelling, such as consecutive floor or room numbering. Such encoding is justifiable with the expectation that the layout of the environment does not change. However, if people know their destination not by a room number but instead by, e.g., its function or role, or if their destination is not recognized as a proper room (i.e., it is a location outside of sequential numbering, such as infrastructure control rooms), then this static system will likely fail people. The same holds for environments where allocations of functions to spaces are dynamic. For example, at airports, gates *in principle* follow the systematic structure described above, but most people hardly ever want to get to gate "A17" or "B03" specifically, but rather to their flight (i.e., "flight to Melbourne"), which might be allocated to these gates only during a certain time interval. Thus, digital support of orientation and wayfinding should address challenges of semantic information, such as functions of spaces ("the cafeteria") or roles ("Tom's office"), and it should address dynamics in the environment ("the gate of your flight") (cf. Richter 2015).

The classical semiotic triangle (Ogden and Richards 1923) can be adapted for this discussion (Figure 1). While a person interacts with both the indoor environment and representations of this environment in the form of information, the information system can sense the environment (and update its representation of the environment) as well as sense the person and update its awareness of the person's location or intentions. In general, an information service can also interact with an indoor environment (e.g., by interacting with dynamic signage or by controlling access), but this article in particular focuses on information services that do not rely on infrastructure in the environment.

The information is produced in support of human *orientation* and *wayfinding* in indoor environments. *Spatial orientation* is the ability of humans and animals to relate the position and movement of their bodies, body parts, or foreign objects to spatial cues (Schöne 1984). This ability to relate includes the establishment and maintenance of spatial relationships and requires managing spatial reference frames. Technical localization supports the human process of maintaining spatial orientation. *Wayfinding* is, according to Montello (2005), the part of navigation concerned with the planning and decision-making aspect with respect to the distal environment. The other part of navigation is locomotion, the body movement coordinated to the local environment. Indoor localization and navigation information supports only wayfinding and leaves the locomotion to individuals.

The remaining challenge of indoor navigation systems is therefore the production of instructions of *relevant* content for navigation: aligned, up-to-date, on people's terms, and of minimal amount of information provided (Meilinger et al. 2007), thus, maintaining low cognitive load on the user (Schmid 2009; Schmid et al. 2010).

2.4 Relevant Granularities in Applications

Indoor localization and navigation presents an inverse version of the "through walls" collaborative work introduced by Piekarski and Thomas (2009). In the "through wall" collaboration of Piekarski and Thomas, a worker in the office is able to guide a co-worker out in the field, perceiving the outdoor location in a virtual reality environment. In indoor localization and navigation, the "field worker" is in an indoor environment, and the colleague in the remote office can be a centralized system if communication infrastructure is available to the wayfinder. However, in infrastructure-independent localization and navigation, the wayfinder is not directly connected to a dispatcher, as there is no Internet or other telecommunication infrastructure available (or relied upon) that would provide for data transfer. Thus, the support by a remote person or service is limited to the asynchronous provision of an application software and some pre-loaded data on the wayfinder's hand-held device. Orientation and navigation instructions are then generated locally by this device based on integration of stored map data and sensed spatial data. As a corollary, even if the wayfinder *had* some other means to communicate with the outside world, the most up-to-date information would be only available in the environment itself.

Navigation in this built environment covers a range of scales. Richter et al. (2013b) proposed a hierarchical classification of navigation scales reflected in human location descriptions consisting of seven granularities, from the coarsest (*country*) to finest (*furniture*). Indoor navigation would encompass three of these scales: *building*, *room,* and *furniture* (from coarse to fine granularity, respectively). For some specialized applications, a finer-grained scale is necessary—one that is of relevance when locating small but potentially critical parts of infrastructure, such as duct valves, electrical installation, and switches (see Table 2). We therefore introduce a finer granularity, *component*, and note that this is mapped by, for example, IFC classes. In indoor navigation, such components may often be hidden from sight (e.g., finding studs or electrical cables in a wall) or be parts of a larger assembly (e.g., a breaker in a switchboard). Infrastructure-free localization is of importance here, as the location of some of these parts may be critical for restoring the function of infrastructure itself, as is the case with electric switches. Note that the granularity `building` includes floors (vertical partitions) and wings (horizontal partitions), as well as other, functional partitions (e.g., staff-only areas or contained laboratory spaces). With this system of granularities, which is grounded in indoor wayfinding needs, we go beyond the current standardized levels of detail, but also abstract from more differentiated systems that are based on geometric thresholds (Biljecki et al. 2014).

Building-scale positioning (identification of the floor and wing of the building a wayfinder is in) is now perceived to be technically unproblematic, with the bulk of the attention on infrastructure-based as well as infrastructure free positioning localization and navigation focused on room-scale

Table 2. Enriched System of Granularities (Richter et al. 2013b) (Coarse to Fine, Italics for Expanded Classification) of Indoor Navigation, with Applications and the Natural Language (NL) Equivalent of the Instruction at the Given Level of Granularity

Scale	**P**$[10^x \text{m}]$	**Application**	**Example—NL equivalent**
Building	2	locate/navigate to floor/wing	"You are on the 5th floor," "Continue to Radiology."
Room	1	locate/navigate to room	"Take the corridor to room R120," "You reached Theater 2."
Furniture	−1	locate/manipulate equipment within a room	"Fire extinguisher is in the corner under the window," "Remove the cupboard on the West wall," "Spaghetti are in the top shelf of Section 3 or Aisle 10." (Dong et al. 2015)
Component	−2	instructions for location/manipulation of parts of assemblies and infrastructure	"In the top row, turn of the first switch from the left," "Do not drill within 20cm from the bottom of this section of the wall." (Bane and Hollerer 2004)

References indicate prior work addressing similar use-cases, not necessarily exclusively with infrastructure-free solutions.

problems. The combination of techniques (e.g., for smartphone sensor-based IMU positioning and dead-reckoning) is focused on positioning a wayfinder within a room, along a path in a building. It could be argued that the main challenges of building-scale and room-scale indoor navigation remain in the human-user interface; in particular, in contextualized, natural communication of the location of the spaces, events, or objects to be located.

The next frontier now arguably lies in furniture-scale localization and navigation to furniture-scale objects, such as specific sections of an aisle in a supermarket or even specific product sections on a shelf (Dong et al. 2015). This scale of positioning and navigation has been traditionally the domain of Augmented Reality researchers in indoor contexts. Problems pertaining to spatial navigation and localization in augmented reality have been reviewed by Grasset et al. (2011). Applications of fine-grained localization and navigation in indoor environments of furniture and component scale discussed include detailed localization and visualization of hidden objects in, e.g., laparoscopic surgery. Peculiarities of fine-grained spatial instructions, in particular if they are linked to actions (assembly of components of an object), have been discussed by Heiser et al. (2004).

3 INFRASTRUCTURE-INDEPENDENT ORIENTATION AND NAVIGATION

In the following, three approaches will be discussed of how infrastructure-independent indoor localization and navigation may be realized. The first approach (Section 3.1) relies on devices carried by a user that are able to sense the environment and from the sensing data infer a position. The second approach (Section 3.2) has people's devices exchange knowledge about the layout of an indoor space and the accessibility of different areas. The third approach (Section 3.3) involves the user in the localization process by asking targeted questions about their current whereabouts and desired destination. All three approaches have in common that they can be implemented on smartphone devices: Devices carried around by people independent of their environment. The approaches are complementary to each other; they can be combined to make the navigation process more reliable.

3.1 By Sensing Devices

With the widespread availability of smartphones and other smart devices such as smart watches and smart glasses, indoor localization and navigation using these devices has received a great deal

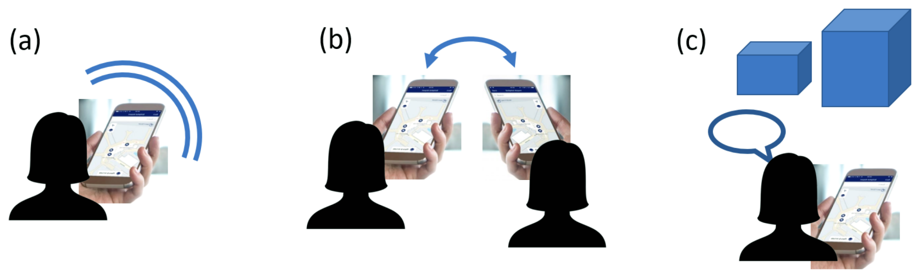

Fig. 2. Infrastructure-independent indoor localization and navigation approaches: (a) by sensing devices (Section 3.1), (b) by learning and sharing (3.2), and (c) by human map interaction (3.3).

of attention in recent years. These smart devices are typically equipped with a range of sensors, including inertial and magnetic sensors, barometer, microphone, light sensor, and cameras, which all can be used for location sensing and navigation independent of an infrastructure (Khoshelham and Zlatanova 2016). Accordingly, these approaches rely on the autonomy of the smart devices (Figure 2(a)).

Inertial and magnetic sensors are often used within a Pedestrian Dead Reckoning (PDR) approach to provide location estimates in indoor environments. The PDR method involves step detection, step length calculation, and heading estimation. Steps are usually detected in accelerometer data by detecting zero acceleration (Goyal et al. 2011; Ojeda and Borenstein 2007), sharp drops in acceleration (Link et al. 2011), or more commonly by detecting acceleration peaks (Chon et al. 2012; Loh et al. 2016; Susi et al. 2013; Zhang et al. 2015). Recent works incorporate additional constraints, such as periodicity, similarity, and continuity of the steps, to avoid over-counting caused by abrupt movements of the sensing device, especially when it is held in the user's hand or pocket (Gu et al. 2017).

The step length varies across users of different height, weight, and gender. Even for the same user, the step length varies with speed, environment, and health condition. Several step models have been proposed, which account for users' height (Weinberg 2002), step frequency (Shin et al. 2007), or both (Renaudin et al. 2012). More adaptive step models learn the model parameters for each individual user from sensor data (Gu et al. 2018b; Li et al. 2012) and incorporate knowledge of the device's pose in the step length estimation (Qian et al. 2015; Susi et al. 2013).

Heading estimation is a challenging task in PDR. Heading information obtained by the magnetometer is susceptible to ambient ferromagnetic interference (Harle 2013), and heading estimation using gyroscope readings (Deng et al. 2015) is influenced by the variable pose of the smart device (e.g., when in a pocket) and the inherent drift of the gyroscope measurements. Because of the complementary error characteristics of the two sensors, fusing their data generally results in more reliable estimates of the heading (Kang and Han 2015; Kim et al. 2004; Renaudin and Combettes 2014; Roy et al. 2014).

The main challenge in inertial navigation is the accumulation of errors, which results in the drift of the estimated trajectory. Foot-mounted systems detect the stance phase, during which the foot is in contact with the ground and apply a zero velocity update to reduce the drift (Foxlin 2005; Ojeda and Borenstein 2007). Such systems, however, have limited practical applications. In a more general setting, knowledge of the user's motion state can be used to constrain their location and eliminate the drift. For example, a straight vertical motion implies that the user is in an elevator. Various approaches to motion state recognition usually use machine-learning methods to classify the motion of the user into different categories such as still, walking, running, and moving up or down the stairs or in an elevator (Gu et al. 2015, 2018a; Gusenbauer et al. 2010; Hemminki et al.

2013; Lara et al. 2012; Lester et al. 2005; Liao et al. 2006; Martín et al. 2013; Pei et al. 2012; Ravi et al. 2005; Zhu and Sheng 2011).

Another common approach to overcome the drift issue is map matching (Lin et al. 2017; White et al. 2000), in which position estimates are constrained within navigable spaces derived from a map of the environment. Map matching is usually done via a particle filter (Bao and Wong 2014; Davidson et al. 2010; Qian et al. 2015; Tian et al. 2015; Widyawan et al. 2008; Woodman and Harle 2008), which is computationally expensive, considering the limited processing power of current smart devices.

A more efficient way of fusing spatial information with position estimation in PDR is to use indoor landmarks (Hile and Borriello 2007; Wang et al. 2012). Indoor landmarks are defined as location points in the indoor environment that are associated with a distinct and recognizable pattern in some sensor data (Gu et al. 2016b; Török et al. 2014). Examples of landmarks that have been used to improve the indoor localization accuracy include acceleration landmarks (e.g., doors), orientation landmarks (e.g., turns), pressure landmarks (e.g., elevators or stairs), visual landmarks, audio landmarks, and magnetic landmarks (Abdelnasser et al. 2016; Gu et al. 2016a; Shang et al. 2015).

Another sensor that is available on most smart devices and can be used for indoor localization is the camera. Various types of cameras have already been used for localizing robots and moving platforms in indoor environments. The two main approaches to image-based localization are visual odometry and simultaneous localization and mapping (SLAM). Visual odometry is essentially a local motion estimation method. It works based on extracting salient image features and matching them across pairs of images. These feature correspondences are then used to estimate the local motion of the camera (Nister et al. 2004). In visual SLAM, the feature correspondences are typically used to construct a map of the environment and estimate the pose of the camera with respect to the map (Davison 2003). Huang et al. (2018) introduce an alternative approach based on unique 3D signatures of specific anchors, such as doors and entrances.

Similar to PDR, visual odometry and SLAM suffer from the drift of position estimates. In these approaches the localization is incremental, i.e., the position of the camera is estimated relative to a previous position. Consequently, estimation errors accumulate, and the estimated position drifts from the true position (Khoshelham and Ramezani 2017). Fusion of visual features and inertial measurements has been shown to improve the localization accuracy (Ramezani et al. 2017), though it cannot completely eliminate the drift. State-of-the-art SLAM algorithms detect loop closures and improve the position estimates by applying a pose graph optimization (Kümmerle et al. 2011). However, in the context of navigation, accurate position estimates are needed in real time, and so loop closing is not always practical.

Rather than relative localization, navigation requires absolute position estimation in a reference coordinate frame. In indoor environments, such a reference coordinate frame can be provided by a 2D map or a 3D spatial model (Kaiser et al. 2015). While 2D maps have been used in map-matching methods to constrain the localization error, the application of 3D spatial models for indoor localization has received little attention so far. Today, such 3D models are increasingly available for many large buildings and are an indispensable source for a variety of indoor location-based services (Khoshelham et al. 2017). The integration of visual sensing and 3D spatial models provides a promising approach to indoor localization. By matching an image of the indoor environment with a corresponding view of the 3D indoor model, the position of the camera in the coordinate frame of the model can be estimated. The challenge is to fuse the image and model information in an efficient way such that accurate position estimation can be done in real time on a resource-limited smart device.

Other sensors on smart devices such as the barometer, microphone, and light sensor have also been used for indoor localization. Indeed, barometers were seen as an important addition to smartphones especially for indoor positioning (Muralidharan et al. 2014). However, due to the lower localization accuracy of these sensors, usually at the floor or room level (e.g., Ye et al. 2016), they are often used in combination with other sensors. For example, Chen et al. (2015) use the barometer in a PDR approach to detect stairs as pressure landmarks and improve the localization accuracy. Fusion of light sensor, microphone, and magnetometer to perform room-level localization has also been proposed (Galván-Tejada et al. 2015).

3.2 By Learning and Sharing Knowledge

The second approach adds the capacity to collaborate to a smartphone's capacity to localize and track itself (Figure 2(b)). It uses the analogy of a person learning an environment. Learning any reasonably large and complex environment is a time-consuming process (Montello and Pick 1993; Thorndyke and Hayes-Roth 1982). Simply asking a person, who is unfamiliar with an environment, to go and figure it out by themselves is not a helpful, constructive approach to navigation assistance, especially if that person is not likely to visit the environment more than once or twice. But it would be perfectly conceivable that a person unfamiliar with an environment learns from other people about that environment. They can ask others for the location of specific features or for directions to some place. There are established, almost codified, procedures of how such an exchange of knowledge happens in human-human interaction (Allen 2000). The persons asked can be local experts, providing a full solution to the orientation and navigation task. They also can have only partial knowledge, in which case the recipient would learn incrementally—which would also address the challenge with environments subject to rapid changes.

Adopting similar concepts, such a knowledge exchange can also happen between devices (computer-computer interaction); for example, by employing NFC technology. And similar to asking people, such device-device interaction would provide knowledge about the layout of the environment or on how to reach a specific destination. But different to the approach outlined in Section 3.1, it would not allow for any straightforward continuous updating of a user's position.

Such sharing may happen on equal terms, i.e., by each device having some knowledge about parts of the environment. This knowledge may be acquired through mapping using a smartphone's built-in sensors, such as compass and accelerometers (Constandache et al. 2010). Sharing partial knowledge of previously traveled paths would then require merging parts into coherent larger maps, similar to multi-robot exploration scenarios (e.g., Burgard et al. 2000; Lakaemper et al. 2005). This way, over time users or their devices acquire knowledge about an environment's navigable space through a combination of *exploring* it themselves and *learning* from others they meet in the environment.

Sharing knowledge about the state of an environment is also useful in scenarios where users have complete knowledge about the (static) state of an environment in principle, but it may undergo dynamic changes that are difficult to foresee or predict and may happen rapidly. This holds particularly in cases of disaster and the need for evacuation. Here, even people with very good knowledge about the environment may get lost because passages may be blocked and some areas of the environment may be rendered inaccessible.

In such a scenario, anytime two users meet they might exchange knowledge about the state of the environment. This may include information about blocked and unblocked pathways, i.e., paths they managed to travel and those where they hit some obstacles. It may also include information about the location of the disaster, especially if it is a local or locally spreading disaster. Receiving updated information about the state of the environment allows agents to avoid using the (shortest) paths that are actually blocked or to accidentally move in the direction of a disaster.

Agent-based simulations (Richter et al. 2013a; Winter et al. 2011; Zhao et al. 2017) have shown that employing such a strategy of knowledge sharing is as successful in evacuation—in terms of number of agents leaving an affected area at one time—as having full global knowledge about the static and dynamic situation, which is often assumed in evacuation simulation and planning (e.g., Park et al. 2009; van Oosterom et al. 2005). This result is significant, because it explicitly included scenarios where the agents started with no knowledge at all about the environment (think of people switching on their app only when a disaster strikes), and where agents had route knowledge about traveled paths by tracing their way through the environment (think of an app that tracks in the background but has no global knowledge of the environment). It is also significant because it could deal with uncertain and changing environments effectively—which for a centralized, infrastructure-based system would require full functionality after the disaster and unblocked communication channels. For rapidly changing indoor environments, such as when a fire is spreading through a building, it has also been shown that older knowledge, since it is more likely to be outdated, should be less trusted by routing algorithms (Zhao and Winter 2016).

3.3 By User Interaction

The third approach to infrastructure-independent localization and navigation abstains completely from sensors. This approach is based on user interaction with a smartphone map application (Figure 2(c)). Accordingly, this approach is suited only for relatively stable environments such that the map is a sufficient representation for localization and navigation.

Realizing this approach, Wijewardena et al. (2016) have used the topology of an indoor space supplemented with qualitative user input to achieve localization and to support the navigation to other locations in the environment. This is consistent with observations about human self-localization, where also primarily local information is used (Meilinger et al. 2007).

Thus, the basis for user interaction is a topological data model (Sec. 2.2) that describes the connectivity properties between rooms and the corridors between them. For example, Worboys (2011) defines an adjacency graph such that its nodes and edges represent regions and their neighborhood (i.e., rooms sharing a boundary wall), respectively. Based on this adjacency graph, Yang and Worboys (2015) develop a navigation graph as a foundational data structure for indoor navigation, in which *connectivity* or *accessibility* relations between spatial entities, such as rooms, can be stored. Wijewardena et al. (2016) use a modified version of this navigation graph, implemented in a graph database management system (Neo4j[1]) to address both localization and navigation queries of a smartphone user. Nodes and edges in this extended graph also represent semantic properties, such as a unique room name for nodes and categorized affordances for corridors (e.g., enabling a path between rooms).

The localization logic follows interaction: The user is asked to select from a list of possible property values the one that corresponds to the location they are at—mostly, what she sees. For example, if a user is in a shopping mall, the user selects the name of the shop she is in or standing in front of. The user may also refer to multiple surrounding shops to resolve ambiguities. After the user's input, their location is displayed on a map. This map addresses the information needs for orientation (Meilinger et al. 2007). If the user further wants to navigate to a different location, they are asked to define the destination in the same manner (Richter et al. 2008). The application then computes the shortest path, or any other desirable path (cf. Golledge 1995; Richter and Duckham 2008), based on the navigation graph, and displays it.

[1] https://neo4j.com/.

Such a lightweight concept, if implemented in a mobile platform using a smartphone-compatible graph database (e.g., Sparksee mobile[2]) to store the navigation graph, has the following benefits when compared with sensor-based technologies: (1) There are no sensor processing limitations; (2) The application is cost-effective and easy to maintain, with a periodic need for updating the navigation graph according to changes of the indoor layout; (3) It is energy-efficient in contrast to battery-depleting mobile sensors; (4) The graph database can efficiently store and be queried on large volumes of connectivity data; and (5) It provides consistent localization and navigation answers throughout the entire indoor space, independent of sensor-related measurement errors (see, for example, Section 3.1). Its shortcomings are the lack of real-time provision of localization (i.e., the user needs to ask for it) and the dependence on clear visibility of signs, names, or numbers for the user to identify the space they are in or in front of. In case visibility is hindered, users might need to move around to provide more reliable information on their whereabouts.

A similarly lightweight concept is presented by Löchtefeld et al. (2010). Here, using their smartphone, users take a photograph of a YAH map of the current floor and then calibrate the map scale by first marking their current location on the map and then walking a few meters in both x and y directions (sequentially), marking the respective new locations on the map as well. For the actual navigation, the system uses PDR mechanisms and additionally offers users to reset tracking by once again marking their current location on the map. While not relying on positioning infrastructure—PINwI stands for Pedestrian Indoor Navigation without Infrastructure—the system requires printed, photographable YAH maps (or similar) on each floor and easily identifiable locations for the users to calibrate the scale.

The same group also implemented infrastructure-independent navigation approaches on smart watches (Wenig et al. 2015, 2016). Here, users select their destination within a building with the help of a smartphone application, which then pushes (server-generated) route information to the smart watch. While moving towards their destination, users can scroll (pan) through a “StripeMap”—a linearized map display—or a sequence of video stills showing their (expected) current views (“ScrollingHome”). Thus, to successfully reach their destination, users need to “synchronize” the information currently seen on the watch display with what they see in the environment, i.e., concurrently “navigate” in the real world and on the display. Both approaches rely on server connectivity prior to the navigation task to compute and transfer the targeted route information, but can work offline once the navigation process has started.

4 CONCLUSIONS AND OPEN CHALLENGES

4.1 Summary

This article starts out from a discussion on why localization methods for indoor environments that are relying on sensors embedded in the environment may prove to be a roadblock for widespread dissemination of indoor location-based services due to the lack of a global infrastructure. In comparison, methods of localization and navigation *independent* of infrastructure-reliant technologies are immediately and ubiquitously applicable. Some of the reviewed approaches require only prior knowledge. For example, the vision-based localization approaches by smart devices (Section 3.1 and Figure 2(a)) are strengthened by a map or a Building Information Model (BIM) of the environment. The decentralized knowledge sharing approaches (Section 3.2 and Figure 2(b)) require only memory for the trajectories traveled in the environment. And the dialogue-based localization approaches (Section 3.3 and Figure 2(c)) require only a map of the environment. This prior knowledge—although usually in private and thus distributed ownership—exists and can be made

[2] http://www.sparsity-technologies.com/.

available cheaply, in comparison to any indoor positioning infrastructure. More and more countries demand a BIM for new developments, and standardization and integration with Geographic Information Systems is also underway (European Commission 2017).

Methods of indoor localization and navigation working independently of the physical infrastructure are particularly relevant in environments that (a) require navigation support for people—see our introduction for a broader discussion of this aspect—and (b):

- do not provide any external sensors for localization;
- do provide external sensors (such as WiFi) but lack their fingerprinting required for localization;
- do provide external sensors, but they are either blocked or damaged (such as in emergency situations).

While many, if not most, indoor navigation systems are designed for a specific environment, the case made here for sensor-independent solutions is a case for global indoor navigation support.

4.2 Open Challenges

This article deliberately discussed only methods for indoor localization and navigation that are independent of sensor and communication infrastructure. Although the approaches were discussed separately to highlight their individual characteristics, they can easily be combined to improve the accuracy of localization and navigation. For example, the vision-based approaches (Section 3.1) will improve the capabilities of the smart device in the approaches by user interaction and thus dramatically reduce the need for user interaction.

Similarly, the methods relying on infrastructure can support this task of localization and navigation. Since each of them is restricted to certain environments (i.e., environments providing the required positioning or communication infrastructure), the approaches presented here can form a fall-back technology for all the other indoor environments. It is also imaginable that the approaches here can locally improve the accuracy of infrastructure-reliant methods, and vice versa. What is then required is a platform that seamlessly integrates whatever technology is available. A seamless integration has been called for already for the infrastructure-dependent methods (e.g., Maghdid et al. 2016). Such integration could further extend to localization across a range of scales in which to position an object, potentially all the way to locations *within* the human body (Pahlavan et al. 2015).

A second challenge, motivated but not discussed in this article, is the human-computer interaction itself. Interface issues for indoor localization and navigation are an open field for research for many reasons mentioned above, among them a visually cluttered and constantly changing environment, a scale of an environment with larger autonomy of the person than outdoor, and the known difficulties with navigating with stairs or levels. This second challenge has not been addressed in this review, since it is orthogonal to the question of infrastructure-based or infrastructure-independent localization and navigation technologies and would justify another review article.

But in the narrow context of the three approaches described above (Sections 3.1–3.3) some of these challenges can be highlighted:

- The visual approaches (3.1) will be impacted by uniform design (e.g., not be able to distinguish between floors if they are designed similarly) and by the clutter in the environment that is not part of a BIM. In this case, user interaction for the resolution of ambiguities can be a way out.
- The collaborative approaches (3.2) do not have such challenges but have to guide based on trajectory data—their own or shared ones. Trajectory data is known to be semantically poor,

such that wayfinding information generated from trajectories must be short of references to semantically meaningful features in the environment. One way out is the integration of trajectories with map or BIM data of the environment, which would require some form of map matching. This integration will allow, for the purpose of meaningful guidance, a semantical enrichment of the trajectory data set.

- The third class of approaches, navigation by user interaction (3.3), is by its nature a human-computer interaction challenge. Interfaces such as language or stripe maps pose their individual challenges for the designer as well as for the wayfinder and need careful and extensive user testing.

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