Indoor Localization and Navigation Independent of Sensor Based Technologies

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Abstract

In this short article we present concepts of indoor localization and navigation that are independent of sensors embedded in the environment, and thus, standing against the tide of technology-based indoor localization. The motivation for doing so is clear: We seek solutions that are independent of particular environments, and thus globally applicable.

1 Introduction

Indoor localization and indoor navigation are frequent topics of SIGSPATIAL papers. The Special Interest Group's annual conference has even workshops specifically dedicated to this topic, and beyond this conference there are other working groups and conferences established just on this domain. Why is indoor localization and navigation taking so much attention and effort, and why should sensor-less methods be considered in this context? There are several reasons for this.

First, in contrast to outdoor positioning and navigation there is no global system available (or even possible) for indoor localization, and thus no single frame of reference for navigation. Satellite radio signals rarely penetrate buildings, thus indoor environments are GNSS deprived environments. Indoor localization methods, however, are plenty – those based on WiFi, UWB, RFID, CCTV, wireless telecommunication networks, and many more [13] – which all require a building to be equipped with a particular, tailored infrastructure, to which the tracked visitor of the building has to connect.

Second, in contrast to outdoor traffic, most movements indoors occur in private spaces, with particular access restrictions. 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 often regulated by times of the day, adding a dynamic component to the navigable mobility network is critical.

Third, indoor environments have particular structures that are different from outdoor structures. Most prominently, indoor environments are multi-level environments, but then they are also more regularly structured within each level and even across levels, down to grammars [4]. Since the mode of movement is mostly walking, which is less restricted compared to road or rail traffic, there are challenges for modelling routes, especially in large, open indoor spaces such as halls. However, for indoor localization and navigation the qualitative aspects of information (level, room) are often more important than a quantitative position [19].

Fourth, people spend on average above 80% of their time indoors[1], which would emphasize a case for indoor localization and navigation. The navigation needs are more subtle, more oriented towards activities and

[1]A figure varying with culture and lifestyle, but [6] found that an average US employee spends 86.9% indoors, and 18.4% in indoor environments other than home – more than twice as outdoors.

events, such as finding certain items in a supermarket or locating a meeting at a particular time in a particular room, or an escape route if fire blocks usual egress paths. This is in contrast to routes that are to a large extent pre-computable or predictable, as we know them from outdoor vehicular routing.

Fifth, a significant portion of the research on indoor localization and navigation is motivated by safety considerations 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.

Last, the highly structured nature of indoor environments and the familiarity with the indoor addressing patterns (e.g., a floor-room number pattern, and the clockwise order of room numbers on a floor) offer heuristics that can be used in indoor route directions and wayfinding. This, however, also poses challenges where common-sense assumptions have to be overridden, for example, when conditions change or the heuristics are not valid. Examples of non-valid heuristics are counter-intuitive (room or level) numbering systems, such as a missing 13^{th} floor in a building [17].

While all of the above reasons motivate research in indoor localization and navigation in general, this article will concentrate on methods that are independent of sensor based technologies in the environment. The methods discussed in this article allow only for sensors in the hands of people, and to varying degrees of connectivity to a communication network, in short: smartphones, both for their sensors and their apps[2]. These smartphone-based localization and navigation methods, even if they may appear in the first instance more cumbersome, or less accurate (two assumptions that still need to be investigated), are interesting for two reasons:

- Firstly, they will be applicable in any indoor environment, independent from any sensor-based infrastructure. Thus, they are a step forward towards global solutions.
- Secondly, they are, as it will turn out, more closely integrated with ways how people perceive and interact with their environments, and thus already close to cognitive concepts of human-computer interaction.

From a computational perspective these approaches provide unique challenges, which will be discussed in the following.

2 Preliminaries

Our understanding of *indoor environments* is a broad one, referring generally to *roofed* and usually but not necessarily *walled* spaces. Prototypical examples are the inside of a house ('between doors'), but included are also subway stations, malls, train stations, high-rising buildings, or stadiums. Indoor environments are at least conceptually *closed* spaces [15], in contrast to outdoor environments, which are typically open at least in z-direction. Thus, while the roofed platforms of a train station may count as indoor because they are conceptually part of the train station, the space under a bridge is not considered indoor because it is conceptually not a closed space: it is neither part of the road above the bridge nor part of the feature below the bridge.

In addition to the differences between indoor and outdoor spaces outlined in the introduction, indoor spaces are usually narrower and less open than outdoor spaces. They may be considered to be more immediate, in the sense that our ability to perceive the surroundings is more restricted; our view is blocked off by the walls, floors and ceilings immediately next to us. In other words, it is typically impossible to get an overview of the larger environment from a single viewpoint. This is reflected in the complex way even professionals (e.g., architects,

[2]In principle, the approaches discussed in the following work with only local processing directly on the smartphones, and local connectivity, e.g., NFC technology between smartphones. In practice, however, they would likely still rely on at least occasional access to the Internet, e.g., for downloading data on a specific building.

designers) design indoor spaces [8]. While wayfinding as an embodied experience is paramount for the users of an indoor space, *wayfinding performance* is rarely approached with computer-aided, quantitative approaches as is the case in outdoor environments.

It also seems that computational *modeling* of indoor spaces is more challenging than outdoor spaces. At least there is less agreement on how to model these spaces with regard to human navigation, even if international standards exist by now, for example, OGC's CityGML for modeling at city level of granularity[3] and IndoorGML at indoor level of granularity[4], or the Industry Foundation Classes[5] (IFC) that are used to set up building information models (BIM) with a special focus on facility management. Commonly, approaches to indoor modeling for navigation inherit aspects of outdoor modeling, in particular, many approaches create some kind of graph of indoor spaces in order to allowing for path planning and navigation support. Constructing such graphs brings up several challenges that relate to the segregated and immediate nature of indoor spaces, e.g., conceptualizations of rooms in more open indoor environments, or of rooms with concave corners or other visibility issues, representations of such rooms in the graph, and relating the location of an individual to the graph.

Tools supporting indoor navigation independent of sensor based technologies have been around for a long time; in fact we are so used to them that we most likely do not think about them as navigation support anymore. The tool we are talking about here is a systematic labeling of rooms, as they are commonly present in hotels and public buildings, such as universities (with exceptions of course). In such buildings there is usually a logical order to room labels, for example, all rooms on the first floor of a hotel starting with '1', all those on the second floor with '2', and so on. Further, room numbers would appear one after the other, i.e., Room '100' followed by '101', followed by '102', and so on. Such numbering combined with appropriate signage on which direction to head for, for example, '100-116 to the left', '117-135 to the right' then allows for finding specific rooms (room numbers) with relative ease. Thus, such combination of intuitive numbering and signage provides already a sensor independent navigation system.

While these systems for navigating are sensor independent, they do not work well for all indoor environments, and they are also only able to encode certain static information. If people know the room number they plan to go to, such a system is relatively easy to use. If their destination does not correspond to a proper room, or all the information they have is something like 'Stephan's office' or 'the coffee room', then this system will likely fail people. The same holds for environments where allocations of functions to spaces are (highly) 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 the flight to 'Melbourne' or 'Paris', which might be allocated to these gates for a (specified) time period, but before or after that period other flights will be assigned there.

Such dynamics, as well as the more semantic information often required to find a location in a building (e.g., 'Stephan's office') require more flexible, dynamic navigation support, such as potentially offered by those smartphone apps mentioned in the introduction.

Another example of a navigation system based on 'knowledge in the world' is the traditional You-Are-Here map put up at walls 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 [9, 7, 11]. Putting these maps on smartphones can overcome both 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.

The remaining challenges of sensor-less navigation systems are then producing maps of *relevant* content for navigation, in order to minimize the amount of information provided, thus maintaining low cognitive load on the user. This means, the systems should consider the discussed highly structured characteristics of indoor spaces.

[3]http://citygml.org
[4]http://indoorgml.net/
[5]http://www.ifcwiki.org

3 Learning and sharing knowledge

Assuming a person familiar with the environment: This person would not need any navigation support, i.e., this would constitute sensor independent navigation. Learning a complex environment, however, is a time-consuming process, even for robots. Obviously, if the environment is unknown to this person (and if she is not likely to visit it more than once or twice), simply being asked to figure it out by herself might not be a particularly helpful approach. But it would be conceivable that this person (or her smartphone) learns from others who are more knowledgeable about the environment.

Such an approach requires some form of knowledge transfer, which in direct human-human interaction might simply mean asking someone for directions. Between smartphones this knowledge transfer can be solved with NFC technology. This would provide general information about the layout of the environment and/or navigation instructions on how to reach a destination. However, it does not solve localization issues, i.e., such an approach will not allow for a continuous updating of a user's position. At best, such updates would only be possible when meeting the next interaction partner.

Still, such an approach may be powerful in specific situations, especially in such undesirable ones where an indoor environment may undergo rapid changes, i.e., 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 settings, we have shown in agent-based simulations that employing a communication strategy as outlined above is as successful in evacuation as having full global knowledge about the situation at least in some settings [14]. Any time two agents meet they exchange information about blocked and unblocked pathways, and the location of the disaster; information they have gathered in their attempts to evacuate the environment. Having this updating available allows agents avoiding to use (shortest) paths that are actually blocked or to move in direction of the disaster.

In addition, evacuations from rapidly changing indoor environments, such as fire spreading in the building, show improved performance if the age of the local knowledge in the smartphone is considered [22]: Older knowledge is more likely to be outdated and should be less trusted by the routing algorithm, at the cost of accepting longer (but safer) routes.

4 User interaction

Even when such a knowledge transfer technology is not available, or direct human-human interaction is not the preferred option (i.e., when one just wanders around a shopping mall or an airport), there are still sensor-less techniques available to use smartphones for self-localization and navigation in indoor environments. They are based on smartphone map applications. Wijewardena *et al*. [18] use 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-localisation, where also primarily local information is used [10].

Topology describes the connectivity properties between entities in space – in case of indoor environments these entities might be separate rooms and the corridors between them. In order to represent the topology of indoor spaces, Worboys [20] defines the *adjacency* graph, the nodes and edges of which represent regions and their neighborhood (i.e., rooms sharing a boundary wall), respectively. Based on the adjacency graph, Yang and Worboys [21] develop the *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. In [18] a modified version of this navigation graph is used, implemented in a graph database management system (Neo4j[6]) to address both localization and navigation queries of a smartphone user. Nodes and edges in this extended graph

[6]https://neo4j.com/

get 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 is simple: 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 center, the user selects the name of the shop they were in or standing in front of. The user may refer to multiple shops around, in order to resolve ambiguities. After the user's input, her location is displayed on a map. If further the user wants to navigate to a different location, she is asked to define the destination in the same manner. The application can then compute the shortest path based on the navigation graph, and displays it.

Such a lightweight concept, if implemented in a mobile platform using a smartphone compatible graph database (e.g., Sparksee mobile[7]) to store the navigation graph, has the following benefits when compared with sensor based technologies: 1) There are no sensor signal transmission and processing time limitations, enabling the derivation of a user's location even in environments with no sensor infrastructure; 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 DB efficiently stores and can 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 5). 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 room they are in or in front of. In case visibility is hindered, users might need to move around in order to provide more reliable information on their whereabouts.

5 Vision

With the widespread availability of smartphone cameras there is a great potential for indoor localization using images. Cameras have been used already for localizing robots and moving platforms in indoor environments. 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 [12]. 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 [1]. The problem with both visual odometry and SLAM is that localization is incremental, i.e. the location of the camera is estimated relative to a previous location. Consequently, estimation errors accumulate and the estimated location drifts from the true location [5]. State of the art SLAM algorithms detect loop closures to apply a correction to the previously estimated camera locations. However, in the context of navigation, accurate location estimates are needed in real time, and so loop closing is not practical.

Rather than relative localization, navigation requires absolute location estimation in a reference coordinate frame. In indoor environments such a reference coordinate frame can be provided by a 2D map or a 3D building information model (BIM). While 2D maps have been used in map matching methods to constrain the localization error [16, 2], the application of BIMs for indoor localization has received little attention so far. Today, BIMs are increasingly available for many large buildings and are an indispensable source for a variety of indoor location-based services. The integration of visual sensing and BIM provides a promising approach to indoor localization. By matching an image of the indoor environment with a corresponding view of the BIM the location of the camera in the coordinate frame of the BIM can be estimated. The challenge is to automatically establish correspondence between image features and BIM elements (e.g., corner points, edges or polylines). Having an initial approximate estimate of the pose of the camera, e.g., by using the smartphone inertial sensors

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

[3], can assist in finding correspondences. In addition, the algorithm for correspondence establishment and location estimation should be computationally inexpensive to allow its implementation on smartphones.

This way, visual sensing in combination with BIMs has the potential to provide location information in indoor environments where a localization infrastructure is not available.

6 Conclusions

This article discusses why localization methods for indoor environments that are relying on sensors embedded in the environment may prove to be a roadblock for a widespread dissemination of indoor location-based services. In comparison, methods of localization and navigation *independent* of sensor-based technologies are immediately and ubiquituously applicable, at least to some degrees: decentralized knowledge sharing (Section 3) requires only memory for the trajectories traveled in the environment, dialog-based localization (Section 4) requires already a map of the environment, and vision-based localization (Section 5) then requires a BIM of the environment.

Methods of indoor localization and navigation working independently of the physical infrastructure are particularly relevant in environments that

- 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);

and require navigation support for people. While many, if not most of 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.

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