

Editorial

Editorial for Special Issue Indoor Navigation in Smart Cities

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The lifecycle of indoor navigation includes various phases.

- The first one is mapping, i.e., creating a map of the indoor environment, where points of interest (e.g., elevators, offices etc.) are to be displayed. Indoor positioning theoretically is by XYZ (e.g., a building with floors), whilst outdoor typically is by XY. The map may be pre-stored or acquired in real-time.
- Secondly, positioning phase addresses the question “Where am I?”, thus identifying the location of the navigator on the map.
- Thirdly, path planning manages the process of plotting the course from the current position to a given destination through the floors.
- Fourth, in-route assistance addresses a twofold issue, namely (a) avoiding moving obstacles and detecting near objects, a sort of proximity sensing, and (b) informing the navigator the actual progress versus the planned course.
- Finally, the analysis of navigation flows analyzes the way people (or objects) move within a given space, e.g., a supermarket.

Ideally, a complete navigation system should support the whole lifecycle. In fact, research papers addressed a subset of these phases, from different points of view, depending on their respective target that could be a robot, a disabled person, a data collection tool, an analysis of indoor flows.

Indoor navigation relies on a twofold technology approach. On one side, sensors, installed in the building, can provide an infrastructure, by infrared signals, audible sounds, ultrasounds, RFID, Wi-Fi, visible light, etc. In this case, the navigator uses a wearable device (e.g., a smart phone) that interacts with the infrastructure. Hence, navigation is limited to the infrastructure area. On the other side, other technologies, as computer vision and magnetic fields, do not need an infrastructure. Of course, a navigation system can integrate these two approaches.

Navigation data are processed by a variety of models that include dead reckoning, trilateration, etc. Processing logic relies on various models (e.g., path planning can rely on Dijkstra or the ant colony model) and on AI-related paradigms to filter and organize data.

In short, the scope of indoor navigation can be imagined as an intersection of four elements, namely the navigator (pedestrian, disabled, robot/machine), the navigation phases, the technologies, and the processing models. Let us position on that frame the papers of this special issue.

“Towards a predictive bio-inspired navigation model” [1] intends to integrate the phases of navigation lifecycle, from mapping to in-route assistance. The model, as it happens with other papers of the authors, stems from biology and it is essentially cognitive; as such, it covers both indoor and outdoor spaces. As a theoretical research paper, it introduces a new research direction rather than discussing or applying navigation technologies.

The other papers address, in an innovative way, specific issues the indoor navigation should deal with. A first point is estimating distance, an issue of in-route assistance. “Deep Learning-Based Indoor Distance Estimation” [2] bases distance estimation on frequency difference between generated and received signals. Deep learning model classifies distance



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data, thus improving accuracy. The related system is wearable and independent from building infrastructure.

In “Successive Collaborative SLAM” [3], the navigator develops his/her map from signals coming from other navigators (hence, by collaboration) or from multiple sensors. Again, the innovation is in integrating and structuring data, i.e., the numerous partial maps coming from collaborators, and in assuring accuracy. In this case too, navigation is independent from the infrastructure and focuses on the phase of in-route assistance.

“Discovering Influential positions in RFID-based indoor tracking data” [4] addresses an application issue typical to shopping malls, i.e., which are the most influential spots in terms of count, density, and duration. Data, which are collected by Wi-Fi and RFID (a common technology in public buildings), are processed by the H-index, an algorithm used to measure the influence of an author in academia. The paper is a good example of the flow analysis phase.

“Classroom attendance systems” [5] is another example of position analysis, which uses a low-cost technology—i.e., Bluetooth—to collect position data of students in a classroom, which are filtered by trilateration of the received signal and compared against previously recorded values.

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