Beacon and beacon-less indoor assisted navigation

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Abstract - In this comparative paper, we review the technologies for indoor navigation for persons with disabilities and persons that require monitoring in Ambient Assisted Living (AAL) environments. We focus on the distinction between beacon-based and beacon-less technologies. We present the categorization of indoor navigation technologies based on the approach taken to determine the location. We identify features of localization technologies that provide classification based on constraints for deployment. We also propose using floor plans to generate a navigation graph, and we give the algorithm for graph creation.

I. Introduction

Indoor assisted navigation could improve accessibility and mobility and provide independence for persons with visual impairment. This technology could also be used in smart living environments, especially in ambient assisted living (AAL) care facilities and homes to provide localization of the person that requires monitoring. In this paper, we focus on less invasive technologies that preserve user privacy; thus, we don't consider solutions such as video monitoring and facial recognition.

Indoor navigation presents a challenge that researchers have addressed using emerging technologies. It is a new field of research that is continually improving. The indoor navigation has two fundamental problems it needs to solve: localization in the environment and mapping of the next steps. There exist several technologies for the localization of visually impaired persons [1]. For this paper, we separate them in beacon-based and beacon-less.

To complete indoor navigation, once the location is determined, we need to guide the person to the desired destination using path planning. When the person taking advantage of the indoor navigation system has mobility or visual impairments, the system should provide not merely the shortest path but a personalized preferred path.

In the next section, we list approaches to the indoor navigation problem. Section III gives an overview of the beacon-based technologies. In section IV, we discuss beacon-less techniques and describe and classify beacon-less technologies. Section V provides a methodology and algorithm for generating navigation graphs. Section VI concludes the paper.

II. Indoor Navigation Approaches

Various approaches can determine indoor localization. The indoor navigation technologies, according to Adler et al. [2], fall under the following categories:

- **Inertial** Systems use pedestrian dead reckoning (PDR) or other IMU tracking techniques. The basic premise of this approach is to estimate relative movements and determine the current position as the sum of individual vectors.
- **Map Matching** Systems that use any previously generated or recorded maps, including patterns of environmental characteristics for the position estimation, such as received signal strength indicator (RSSI).
- **RSS** Systems that use RSS for range estimation.
- **Time of Flight (ToF)** category contains all approaches that use some form of TOF estimation to calculate the distance to another network member.
- **Sound** systems, including ultrasound beacons or other sound sources with known position to estimate their distance to known anchor beacons.
- **Other** Systems that use different spatial depended on environmental properties than described above, including light, magnetic fields, visual object recognition.
- **Multiple** Systems using multi-modal sensing.

For each approach, there can be multiple technical implementations and algorithms to calculate the location. Some implementations can fall under more than one approach. For example, a system can use both sound and ToF to triangulate the location of a device using sound beacons.

The Bluetooth low energy BLE beacons fall under the RSS category. In this category also fall the Wi-Fi signal based and other radio signal based. All such technologies use triangulation algorithms to determine the location of the person.

III. BEACON TECHNOLOGIES

The beacon technologies rely on permanently places beacons with well-known spatial coordinates. These beacons emit a signal that is used in triangulation. Depending on the type of signal, such as with audio signal, a Doppler effect may also be used to measure velocity. When discussing beacon technologies, we usually assume that the beacons are based on BLE. The BLE radio protocol provides new opportunities for the indoor location. It supports portable battery-powered beacons that can be easily distributed at low cost, giving it distinct advantages over Wi-Fi [3]. BLE beacons have omnidirectional radiation, and due to the laws of electromagnetic spreading, the strength of the signal always decreases with the inverse square of the distance from the source, also known as the inverse-square law. The Received Signal Strength Indicator (RSSI) provides information on the distance from the beacon. A minimum of three beacons are required for spatial localization of the receiver (usually a mobile device like a smartphone [4]). There are two main commercial standards for BLE beacon technologies; one is iBeacon, developed by Apple Inc., and the other is Eddystone, developed by Google Inc. The most crucial advantage of iBeacon is that it is very energy efficient, which translates to possible quick deployment of small size beacons that only need to be powered by a battery and eliminates the necessity to rely on any existing infrastructure as Wi-Fi networks [5]. Beacons have a logarithmic proportional correlation between the number of beacons in an area and precision. Adding more beacons gives better results, but after a certain number, a level of saturation is achieved [6]. The optimal layout of beacons in an indoor positioning system was presented in [7].

Beacon technologies can include various methods to determine the location, including:

- Direct RSSI measurement and triangulation.
- Fingerprinting/Scene Analysis which includes: probabilistic methods that rely on the likelihood of the user being in position 'x' provided the RSSI values; Artificial Neural networks (ANN) used in many classification and forecasting scenarios; k-Nearest Neighbor (kNN) algorithms relies on the online RSSI to obtain the k-nearest matches; and Support Vector Machine SVM, primarily used for machine learning (ML) and statistical analysis that has high accuracy [8,9]

IV. BEACON-LESS TECHNOLOGIES

A detailed survey of indoor localization systems and technologies is provided by Zafari et al. in [9]. In summary, the following beacon-less techniques are identified:

- Channel State Information (CSI) – This technology has higher granularity than the RSS as it can capture both the amplitude and phase responses of the channel in different frequencies and between separate transmitter-receiver antennae pairs. Potentially it can have more stable measurements and higher localization accuracy.
- Angle of Arrival estimates the angle at which the transmitted signal impinges on the receiver by exploiting and calculating the time difference of arrival at individual elements of the antennae array. As this requires having multiple antennas, it has limited use with smartphone localization as the measurement is done by the external system and the data then needs to be sent to the smartphone.
- Time of Flight (ToF), Time Difference of Arrival (TDoA) - the principle used by GPS, and Return Time of Flight (RToF) have limited use in indoor navigation because the time precision required would be expensive to deploy. However, in theory, it can be used with ultrasound as the sound speed is slow. One such android based application is presented in [10].

From the same survey, we select the following technologies, whose characteristics are shown in Table I:

- Wi-Fi-based systems usually use or extend existing Wi-Fi infrastructure for indoor navigation. Various techniques, including RSSI measuring, are used to determine indoor location. Although it is possible to build a practical Wi-Fi-based indoor localization system, developing such a system for a large indoor area is not an easy task [11]. The positioning experiment for a pedestrian shows that the reported position is shifted from the actual position before arrival to the vicinity of structures with steel such as elevators. Those factors cause instability of electric waves [12]. Such errors can be corrected using dead reckoning or probabilistic methods. This technology should be considered for indoor assisted navigation as it reuses existing investment in Wi-Fi access points.
- Ultra-Wideband (UWB) has been a particularly attractive technology for indoor localization because it is immune to interference from other signals (due to its drastically different signal type and radio spectrum). UWB can be used to locate people with high precision, but it cannot identify the target individual, so it has limited use for assisted indoor navigation in crowded areas.
- Visible light communication (VLC) uses AoA for localization. As this requires receivers not usually found on smartphones, any implementation would require an additional module that could connect to the smartphone. Due to this limitation, it has limited use for assisted indoor navigation.
- Passive Infrared sensors require sensors to be installed in the environment and are used to detect human motion against the background. These sensors could be used when a small number of people are present. In our previous research, we have shown that these sensors could be used not only to identify the presence of a person but also to detect activities in daily living [13,14].

TABLE I. LOCALIZATION TECHNOLOGIES

Technology	*Range*	*Line of sight*	*Requires infrastructure*	*Required network connection*	*Precision*
Wi-Fi-based	Long	No	Yes	No	Low to medium
Ultra-wideband	Medium	Usually	Yes	Yes	High
Visible light communication	Medium	Yes	Yes	Yes	Medium
Passive infrared (PIR) sensors	Medium	Yes	Yes	Yes	Low to medium
Acoustic signal-based	Medium	Usually	Yes	No	Medium to high
RFID	Short	Yes	Yes	No	High
Computer vision	Medium	Yes	No	No	Medium
Visual/depth	Short/medium	Tes	No	No	Low to high
Magnetic localization	Long	No	No	No	Low
Inertial navigation systems	N/A	N/A	No	No	Low

- Acoustic Signal-based localization technology leverages the ubiquitous microphone sensors in smartphones to capture acoustic signals emitted by sound sources and estimate the user location with respect to the sound source. Although acoustic-based systems have been shown to achieve high localization accuracy, due to the smartphone microphone limitations of receiving only audible band acoustic signals, the transmission power should be low enough not to cause sound pollution. Techniques for signal modulation can help improve localization in a noisy environment. This technology has plausible use for assisted indoor navigation. This approach can also be used in reverse where the phone speaker could emit a sound that, in turn, will be received by connected microphones to triangulate the person receiving assisted navigation. Such systems include the Active Bat system, where a network of wires link the receivers fixed on the ceiling with the network of receivers connected to the server [15].

- RFID is a generic term used to describe a system that transmits the identity of an object or person wirelessly using radio waves. RFID technology is most used to automatically identify objects in large systems [16]. This technology has a very short range, and although cannot be used to locate a person in an indoor area, it can be used to identify objects such as entrances to rooms and can be used in a feedback look for opening automatic doors or requesting a floor in elevators from the smartphone.

- Computer vision systems could use known images and 3D models of the building to determine the location based on the structural objects and landmarks registered by the smartphone camera and calculate the distance based on perspective and field of view. Some types of camera systems are based on AOA. Other techniques use pattern recognition with image processing [17]. This technology requires intensive computation, which can be offloaded to the edge nodes or gradually moved to the phone once the algorithms and processing power become sufficient. This approach has great potential for assisted in indoor navigation. An alternative approach would be to use facial recognition of the person using assisted navigation. This approach has privacy implications and cannot be used in all areas.

- Visual/Depth sensors are used in many research fields due to many available resources, making their implementation easy and fast. This technology can be subdivided into structured light technology, pulse light technology, and stereo camera [17]. Some phones use structured light technology for face unlocking of the phones. As most modern smartphones have multiple cameras, the stereo camera approach can be used. Still, the implementation would vary for each device, and as the cameras are not separated enough, the precision would be hard to achieve.

- Magnetic localization uses magnetic sensors to estimate localization or orientation. Compasses and inclinometers can be fused to estimate the 3 DOF orientation of an object [17]. Most smartphones are equipped with magnetic sensors, and this technique could be used in the sensor fusion approach.

- Inertial Navigation Systems (INSs), aka Dead Reckoning, is a device that approximately determines the current position by knowing the past position and the velocity in which it moves. The dead reckoning is a navigation technology that requires to begin with a known position, and then it will add and track changes. These changes can be in the form of Cartesian coordinates or velocity [16]. Usually, IMUs consist of three main sensors: the accelerometer used for acceleration calculation and linear motion sensing, the gyroscope for angular motion sensing, and the magnetometer. This technique is used primarily for counting steps that a person takes. However, the accumulative increasing error in addition to the need for initial position specification makes IMU not reliable, especially in indoor environments where no GPS can be added [17]. Inevitably, measurement errors are present within the sensor data, and the triple integration of them results in a potentially cubic growth in time (drift). INSs for aviation, marine, and the military use highly accurate sensors that keep the error sources very small and permit tracking for many hours. These are too bulky and expensive for pedestrian navigation [18].

We did not consider techniques such as floor tiles and other more "exotic" technologies that require expensive installations and have only been tested in laboratories in extremely controlled environments or need dedicated hardware other than a smartphone.

V. PATH PLANNING

In addition to localizing users, a navigation system can provide directions from the user's current location to a user-specified destination, which involves planning a path and turning it into easy-to-follow directions. As the user follows directions, the system will dynamically update its estimation of its location and generate a new direction once the previous has been completed. Path following algorithm tries to limit the inaccuracy and latency, which is inherited from the positioning system and to consider human factors [19]. Path-planning algorithms use graphs to represent the environment [20]. The graph is usually generated from the 2D grids and could also be based on 3D shapes [21]. When planning a path using graph-based approaches, the environment is divided into sets of nodes and edges connecting these nodes. The nodes are generated from the grid, where each empty cell yields one node. Depending on the path planning algorithm and constraints, these nodes might be any object type, such as hallway intersections, doors, or obstacles. Most of the current navigation systems use either Dijkstra or A* algorithm [19,22].

While optimizing path and avoiding obstacles has been extensively studied, much of the research was done to navigate robots [23]. While some of the models could be applied to assist the navigation of a person, we identify two constraints in such a scenario: bandwidth and precision. The bandwidth constraint is the limit of feedback data a person could receive and process. For example, in audio feedback, this is the amount of verbal information that could be obtained and be beneficial without overwhelming the person; in tactile feedback, the limiting factor is the variety and duration for acknowledging the feedback. The precision constraint refers to the ability to estimate distances and angles for people and the variation in standard measures such as length of a person's step. Considering these constraints, the navigation system should work with a large margin of error and have a limited guidance set of instructions. Algorithms used for navigating robots will have to be adjusted. For example, the algorithm for navigating a robot could safely use a path through a narrow distance between two obstacles, but such a route should be avoided for a person.

An additional consideration of path planning is given based on impairments or persons. Obstacles differ based on the type of impairment and severity. For example, escalators introduce difficulty to persons with visual impairment, and persons with a specific type of mobility impairment, escalators are an insurmountable obstacle. They should be removed from the path graph. Elevators, on the other hand, provide an accessible alternative for persons with mobility impairments. However, options for avoiding elevators should be provided to accommodate persons with claustrophobia. In certain premises, some areas might be off-limits to visitors or require visitors to be escorted, adding additional complexity to the path planning. These considerations on the application level translate to distances between the graph nodes, resulting in different graphs for different people.

Floor plan maps can be used to acquire a semantic plan [24]. When building the graph from the floor plan, we propose a two-step process. The first step identifies the points of interest that should be precisely defined; these include doors, starting points of stairs and escalators, and furniture. The second step is the partition of the transit area, such as hallways, and define some points based on the available area. These nodes should not be too far apart that a small change of direction could prevent the person from reaching the next point. A sample floor plan is shown in Fig. 1. Here we see several points of interest with graph nodes such as the nodes D, H, I, J, K, Q. The remaining space contains nodes in a grid-like pattern. To minimize the number of nodes after the initial graph from the grid is generated, we do a pre-processing to find a cluster of closely adjacent nodes that are fully connected and replace them with one node located in the geometrical mean of the 2D space. The points of particular interest, such as doors and elevators, can either be extracted from the floor plan by locating such objects. If we don't have the original plan, we can do vertical and horizontal pass to find narrow openings in the walls.

The graph is then connected so that any two nodes have a path clear of obstacles, and the distance between them is less than a given threshold. For this floor plan, we generate the bidirectional graph shown in Fig. 2. Here nodes G and E are not connected to avoid the sofa chair, and nodes F and I are not connected as the distance is too great, and it would be difficult for a visually impaired person to move precisely at the given angle. The weights are then calculated with consideration for distance, possible obstacle, preference for the forward direction, and difficulty to follow instructions. For example, "turn 90 degrees left" should have a lower weight than turn "45 degrees left". In [19], six possible instructions are identified: go forward; turn left a bit; turn left; turn right a bit; turn right; turn around. Multi-path is allowed as the person might pass the node, and another path should be available instead of instructing them to go back. Figure 3 presents the flow diagram for this algorithm.

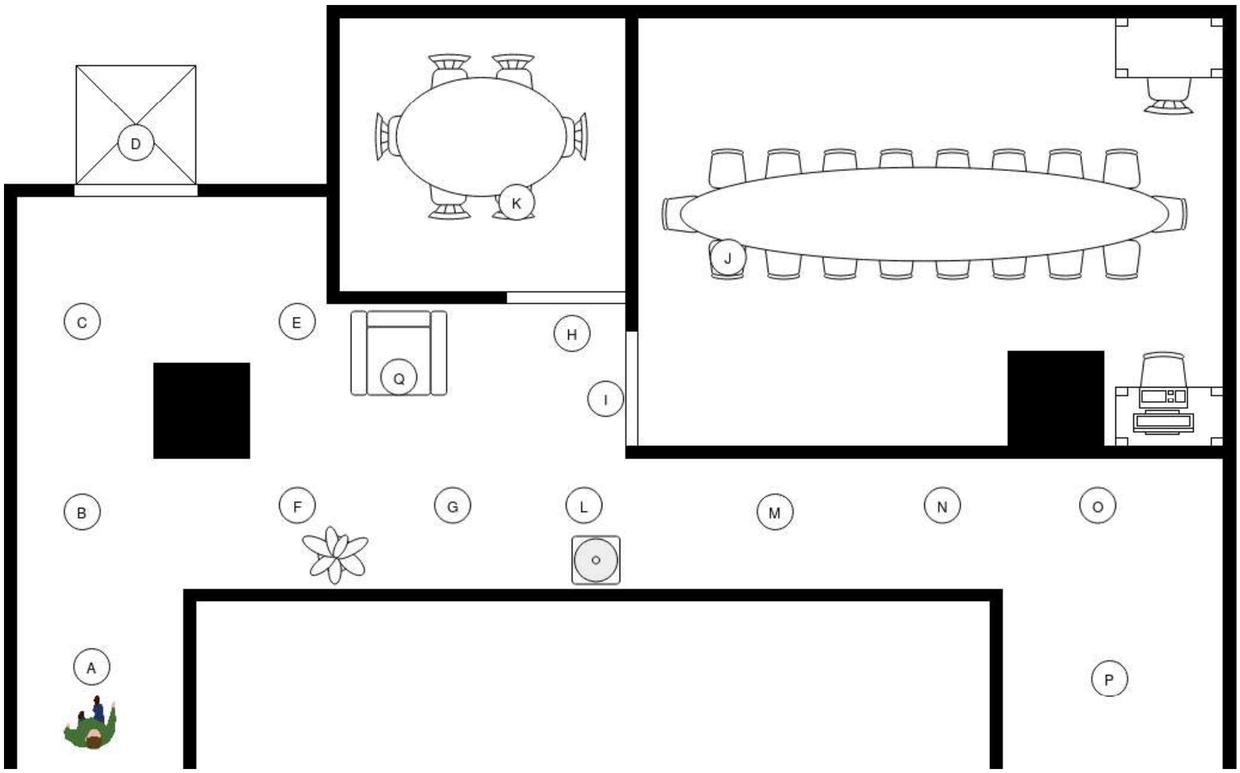

Figure 1. Example of floor plan for indoor navigation

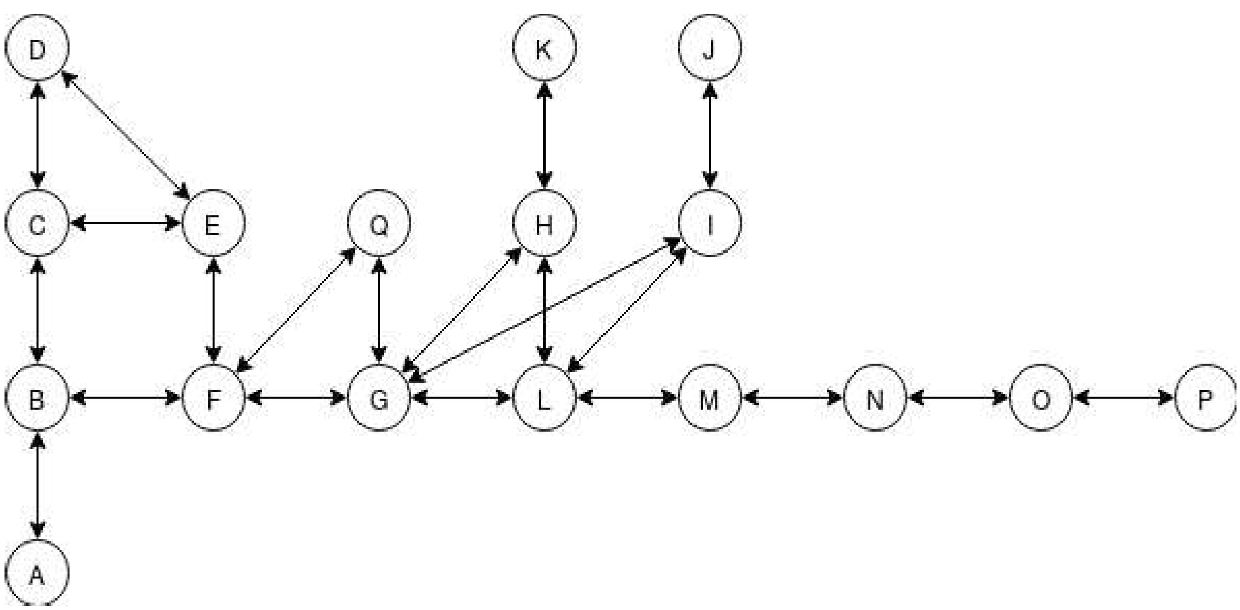

Figure 2. Example of a graph generated from the floor plan in Figure 1

VI. Conclusion

In this paper, we made a comparative study of indoor navigation technologies focusing on the difference between beacon-based and beacon-less techniques. We noted the multiple approaches for determining the location of a person. We described each technology and provided classification based on multiple environmental constraint parameters.

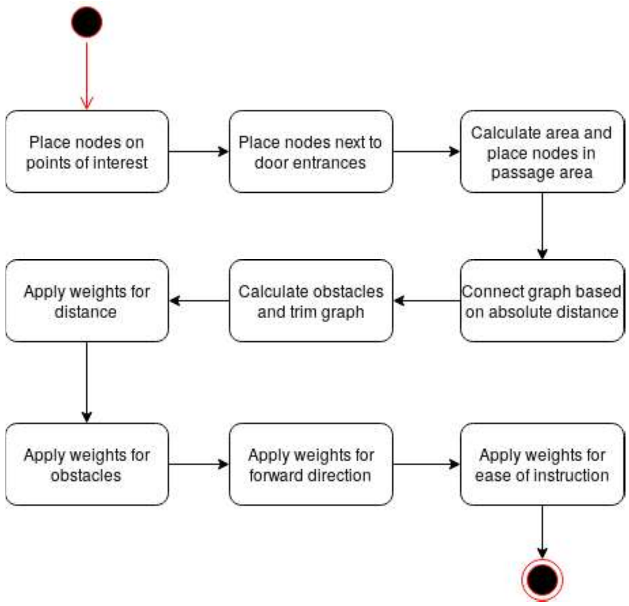

Figure 3. Flow chart diagram for graph generation algorithm

As we have shown, many approaches, technologies, and techniques exist for indoor localization and navigation, each presenting a set of advantages and challenges to overcome. Implementing a fusion of these technologies, new systems are designed, and existing systems improved.

In the previous section, we developed a methodology to use floor maps to generate a navigation graph, and we proposed an algorithm for graph creation with consideration of constraints. Having accurate data on the indoor environment, including obstacles, is essential for indoor navigation as the localization techniques. Our approach aims to reduce the complexity by pre-creating a navigation graph as an alternative to a real-time calculation that may face scaling challenges for larger areas.

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