RADAR-BASED INDOOR NAVIGATION SYSTEM FOR VISUALLY IMPAIRED

Abdullah Akaydin**, Oluwakayode Onireti, Wasim Ahmad, Julien Le Kernec

James Watt School of Engineering, University of Glasgow, Glasgow, UK

**a.akaydin.1@research.gla.ac.uk*

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Abstract

The absence of the Global Positioning System (GPS) inside buildings makes indoor navigation more difficult compared to outdoor environments. This paper provides a summary of visually impaired indoor navigation technologies to identify the needs of the visually impaired to safely navigate indoors. Radar as a sensor is preferred because it works in conditions where other systems cannot work properly and has unique features. In particular, this paper reviews different radar SLAM and ego-motion estimation approaches that can aid indoor navigation. This paper concludes with a brief insight into the future direction for a novel radar-based wearable indoor navigation system.

1 Introduction

According to the 2019 report of the World Health Organization [1], 2.2 billion people have a vision impairment or blindness. The same report states that the number of people with eye conditions, vision impairment, and blindness is expected to increase dramatically with population growth and ageing in the coming decades. The sense of sight has a crucial role in life. Therefore, visual impairment negatively affects daily activities such as navigating in unfamiliar environments and reduces mobility. Moreover, visual impairment increases the risk of injury when navigating unfamiliar environments. For these reasons, navigation assistance is needed.

A navigation assistance system designed according to the needs of the visually impaired should include three important factors for safe navigation. First, the device should know where the visually impaired is located for accurate guidance, which is a localisation problem. Second, the device needs to know the destination to help the visually impaired reach the destination. Third, the device should know how the visually impaired can reach the destination. This includes pathfinding, path-following, and obstacle detection [2].

The outdoor navigation systems mostly exploit GPS and Global Navigation Satellite System (GLONASS) to guide the visually impaired. However, the GPS cannot provide accurate position information for indoor environments because the signals will be blocked or reflected by walls [3]. Since indoor navigation is not effective with GPS signals, alternative methods, which are based on Computer Vision, Pedestrian Dead Reckoning (PDR), Radio Frequency (RF), Visible Light (VL) and hybrid, are proposed [4]. As the GPS technology provides accurate positioning information for outdoor and the studies with GPS and the complementary technologies to GPS are well established, this paper will focus on indoor navigation of the visually impaired.

The vision and laser sensors are the most researched sensor types for indoor navigation. However, they are ineffective in visually degraded environments such as smoke or dust, causing failure in both localization and mapping. In addition, since both cameras and lidars operate in or near the visible spectrum, their measurements can be affected by lighting conditions. While using these sensors, optical reflective surfaces such as glass and mirrors, which are abundant indoors, may also cause incorrect measurements. Radar is a good alternative for situations where the lidar and camera do not perform properly and can compete with these sensors in other situations. A framework for a radar-based indoor navigation system will be proposed within this paper, which is aimed to be comparable to systems developed with other sensors in terms of accuracy and will perform in conditions they fail to operate.

The remainder of this paper is structured as follows: Section 2 introduces related works for visually impaired navigation, section 3 presents radar-based navigation technologies, and section 4 discusses the navigation system aimed to be developed and gives future directions.

2 Visually Impaired Indoor Navigation

A human indoor navigation system mainly consists of the following three modules: an indoor positioning module, a navigation module, and a human-machine interaction (HMI) module. The user's position is estimated by the positioning module, the navigation module determines routes to the destination from the current location of the user, and the HMI module provides instructions to the user for navigation [3]. There are technologies developed considering those modules: computer vision-based systems, RF-based systems, light/laser-based systems, PDR-based systems, hybrid systems, etc. A brief explanation and discussion of the technologies existing in the literature are presented in this section.

2.1 Computer Vision-Based Navigation Technologies for the Visually Impaired

Computer vision-based indoor navigation systems use the information collected by cameras and a set of image processing techniques to identify, track, and navigate the visually impaired in indoor environments [5]. Computer vision-based navigation for the visually impaired is well researched in literature [3], [2], [6]-[8], and some works achieve high accuracy in terms of localisation and navigation [2]. Some computer vision-based navigation systems use a mobile device's camera and processing power [6]-[8]. Modern mobile devices come with inbuilt inertial sensors, such as accelerometers, gyroscopes and magnetometers. There is a reduction in infrastructure installation, and this reduces cost significantly. On the other hand, a map of the surrounding environment is required to describe the surroundings and travel between the current location and the destination. For this purpose, the Simultaneous Localisation and Mapping (SLAM) technique is frequently used [2], [7]. Vision-based SLAM (V-SLAM) approaches are very well researched in the literature, and many V-SLAM approaches have high accuracy in both localisation and mapping. Moreover, computer vision-based navigation systems can provide better mindfulness about encompassing environments compared with other technologies [3].

Computer vision-based navigation systems have shortcomings as well as advantages. First, the performance of computer vision-based navigation systems is highly dependent on lighting conditions. The presence of bright/low lightning conditions and motion blur can significantly degrade navigation performance. Furthermore, transparent objects may not be recognised. Dedicated infrastructures such as RGB beacons, barcodes, colour codes and QR codes are required for some computer vision-based techniques. These dedicated infrastructures bring a range of limitations to the systems. Moreover, if indoor spaces are not equipped with these infrastructures, the related navigation systems become useless [4]. Another shortcoming is that different cameras may be needed for different purposes in computer vision-based systems, such as localisation on the map and obstacle avoidance.

2.2 RF-Based Navigation Technologies for the Visually Impaired

RF-based indoor navigation technologies for the visually impaired includes RFID, Wi-Fi, Bluetooth, Ultra-Wide Band (UWB) and radar. RF-based technologies use RF signals and infrastructures to determine the position of a visually impaired and sense the environment for obstacle avoidance and navigation purposes.

RFID technologies consist of an RFID reader and RFID tags attached to the objects in the surrounding environment. RFID technology has been used for visually impaired navigation [9], [10] as they have low costs and can be easily attached to objects. However, RFID technology is unsuitable for high-precision indoor localization due to the range limitations.

Wi-Fi technology uses high-frequency radio waves to connect and communicate between routers and devices in a coverage area. Wi-Fi-based approaches are suitable for indoor environments, which mostly contain enough Wi-Fi access points, and dedicated infrastructures are not required since these approaches can utilise existing infrastructures [3]. Despite this advantage of Wi-Fi technology, existing Wi-Fi networks are used for communication, not for localisation and navigation purposes. Therefore, localisation accuracy is not sufficient (3 to 30m) for visually impaired navigation. Moreover, the proposed systems for visually impaired navigation need to be supported by Inertial Measurement Units (IMUs) and Near Field Communication (NFC) tags [11], [12].

Bluetooth is a short-range wireless technology for exchanging data between devices over short distances. Bluetooth-based navigation systems track users' locations using proximity sensing approaches or Received Signal Strength Indicator (RSSI) fingerprinting. These approaches require Bluetooth low energy (BLE) beacons as the source of the RF signals, and users must be equipped with a mobile Bluetooth-enabled device. The proposed Bluetooth-based indoor navigation systems for the visually impaired [13], [14] have similar accuracy to Wi-Fi-based systems in localisation.

UWB is a wireless radio communication technology and has a resistance to non-line of sight (NLOS) and multipath effects [4]. UWB can provide centimetre level localisation accuracy [15]. UWB-based navigation technology can be classified as passive and active systems. Passive UWB-based navigation systems operate as radar systems that use signal reflections and do not require an attached tag to determine the position of a user or an object [16]. Active UWB systems consist of UWB sensors (fixed), active UWB tags (mobile), a central software controller and WLAN [4]. The sensors used in these systems are expensive, and their power requirements are very high. Moreover, slow progress in UWB standards development has limited the use of UWB in consumer products and portable user devices [2].

Radar has not been extensively researched for visually impaired navigation, although it has great potential. There are studies on object detection and human recognition in the literature to aid the visually impaired by using only radar [17], [18]. These works cannot be classified as navigation systems since they don't contain localisation information and destination, but rather travel aid systems for the visually impaired.

In summary, all RF-based navigation systems have their shortcomings. They all experience the indoor environment propagation effects such as absorption, reflection, scattering, refraction, interference, multipath and attenuation [4]. Signal transmission in the indoor environment may deteriorate significantly due to these effects, which may lead to the deterioration of the vitally important localisation accuracy.

2.3 Light/Laser-Based Navigation Technologies for the Visually Impaired

Light/Laser-based indoor navigation technologies for the visually impaired include VL and lidar. VL-based systems require a light source as a transmitter, a mobile terminal or image sensor as a receiver and a Line-Of-Sight (LOS) communication channel [4]. The proposed navigation systems in [19]-[20] have the advantage of electromagnetic interference immunity, licence-free operation and availability of light sources in every indoor space. However, the receiver needs a LOS signal from the light source. Moreover, VL navigation systems may also require complex designs, especially when considering a wide coverage area. On the other hand, lidar has been used in visually impaired navigation for providing a map of the environment and localisation within the map by using the SLAM algorithm [21], and solely for obstacle detection purposes [22]. Although lidar provides highly accurate results in range detection, localisation and mapping, lidar is bulky and expensive for indoor spaces. Moreover, it may not operate accurately in long corridors [23] or low visibility environments [24].

2.4 PDR-Based Navigation Technologies for the Visually Impaired

PDR is the process of calculating the current position of a moving pedestrian by using a previously determined position in navigation. PDR is widely used with other technologies instead of alone in visually impaired navigation since PDR is prone to drift errors over long periods. PDR is a low-cost system, and position estimations are accurate in real-time. In addition, PDR does not require external reference measurements or sensors to determine the user's position, orientation, or velocity once it has been initialised [4]. There are numerous PDR-based multimodal visually impaired navigation systems with other technologies.

2.5 Discussion on Navigation Technologies for the Visually Impaired

Table 1 presents a comparison of indoor navigation technologies.

Visually impaired navigation can be classified into two categories as infrastructure-based and infrastructure-free. For infrastructure-based systems, the environments in which the visually impaired will navigate must be set according to the systems. These systems may not be suitable for every indoor environment because of the special structures of the buildings, and some infrastructures require a special placement to operate, such as VL-based navigation. Moreover, equipping the indoor environment with infrastructures like UWB sensors can be very expensive [15]. In addition, infrastructure-based systems limit visually impaired navigation to specific places, and localisation accuracy is not sufficient for safe navigation of the visually impaired, excluding the UWB-based systems.

To navigate the visually impaired without infrastructures, a sensor system, a map of the environment, localisation of the user on this map and pathfinding/path-following algorithms are needed. The two most researched sensor types for navigation are vision-based sensors (cameras) and lidar sensors. These two sensors perform well under certain conditions, but there are conditions where the operation accuracy of these two sensors drops significantly. Lidars and cameras both are prone to fail under visually degraded conditions such as smoke or dust, causing failures in both localization and mapping. In addition, since both cameras and lidars operate in or near the visible spectrum, their measurements can be affected by lighting conditions. While using these sensors, optical reflective surfaces such as glasses, mirrors, etc., which are abundant indoors, may also cause incorrect measurements.

Table 1 Comparison of indoor navigation technologies

Technology	Advantages	Limitations
Computer Vision-Based	+ High accuracy	- Lighting conditions - Transparent objects - Visually degraded environments
RF-Based	+ Robust + Low cost	- Multipath effect - Interference
Light/Laser-Based	+ High accuracy + Licence-free	- Lighting conditions - Reflective surfaces - Visually degraded environments
PDR-based	+ Low cost	- High drift errors

Radar is a good alternative for situations where the lidar and camera do not perform properly and can compete with these sensors in other situations. Radar performs well in any lighting conditions and weather. In addition, radar has a longer wavelength than lidar, which ensures that it is not affected by particles such as dust and smoke. Another advantage of the radar is that it can return multiple readings from the same transmission. Furthermore, radar sensors are much cheaper than lidar and cameras. Finally, radar sensors are lightweight and can be placed on the visually impaired. For these reasons, in the rest of this paper, radar-based navigation systems will be investigated.

3 Radar-based Navigation Technologies

There are two different directions for radar-based navigation: SLAM and ego-motion estimation. Moreover, two different types of radar are used for these methods, namely automotive and scanning radar. Automotive and scanning radars have different characteristics, and different methods are applied for both SLAM and ego-motion estimation. Automotive radars offer radial velocity measurements since they can acquire Doppler information. However, measurements from automotive radars are of relatively low accuracy and sparse. On the other hand, scanning radars provide raw power-range images with relatively high angular and range resolution. However, radar images from scanning radars include noise and do not provide velocity information.

3.1 Radar SLAM

The SLAM techniques provide information to the user to be placed at an unknown location in an unknown environment and to build a consistent map of this environment while simultaneously determining its location within this map. The SLAM algorithm comprises a joint estimation of the user state and a map of the environment. The user's state is described by its pose. On the other hand, the map is a representation of the environment in which the user operates [25].

In [26], a landmark-based radar SLAM was developed by using automotive radar sensors. A 360° radar image of the environment was obtained by using multiple automotive radars. The mean error of the proposed system for mapping was reported mostly around 1m. The localisation accuracy is constantly better than 1m in lateral and longitudinal errors. In [27], an automotive radar-based SLAM algorithm is proposed, which builds a 2D occupancy grid map, and a particle filter-based approach for the localisation of a vehicle in a parking lot and driveway. RMS positioning errors are between 0.29 and 1.7 m, and the last position errors are approximately between 0.16 and 1 m. A pose graph SLAM system using the Iterative Closest Point (ICP) method for scan matching based on point cloud-like measurements obtained from a single front-facing automotive radar is proposed in [28]. The proposed system exploits the vehicle's odometry measurements that are fused with the velocity information obtained by the radar to determine relative transformation estimation between consecutive radar scans. Moreover, a loop closure component is proposed to reduce localisation errors. Root Mean Square (RMS) rotational absolute trajectory errors (ATEs) were reported approximately between 0.4 and 0.75 m, and RMS translational ATEs are between 0.6 and 10.5 m. In [29], the proposed radar SLAM approach builds on the truncated signed distance function (TSDF)-based lidar SLAM. The TSDF approach is modified with a forward sensor model that enables the usage of radar data and introduces their scan matching technique to handle noisy, sparse and outlier-rich radar measurements. In experiments, translational mean absolute errors are between 0.018 and 0.056 m, and rotational mean absolute errors are between 26.5 and 33.02 mrad. To effectively solve the problems of poor azimuth resolution and multipath reflection of the automotive radar in [30], the authors employ angular super-resolution radar imaging through compressed sensing (CS). Moreover, the ICP algorithm is used for scan matching. The mean translational ATEs in experiments are between 0.218 and 1.084 m, and the mean rotational ATEs are between 0.766 and 2.677 °.

A scanning radar-based SLAM system for indoor is proposed [31]. An ICP algorithm is used to determine the radar location and movement, whereas a particle filter optimises measurement performance. In a single radar frequency sweep, they only consider the range with maximum reflected power as the detected range, although the radar might receive the reflected power of multiple objects in a single sweep. Authors claim that their system shows a good ability to map walls and other relevant structures. A novel indoor scanning radar SLAM system is proposed for the automated removal of asbestos [32]. In radar pre-processing, the Otsu thresholding is used for discarding the noisy scan points and object penetration and angle of detection related low-intensity values from the scan set. Furthermore, detecting thick objects is done by segmenting scans into clusters, and only the detections from the front layer of objects are considered.

3.2 Radar Ego-Motion Estimation

Ego-motion estimation is the process of determining the position and orientation of a user/robot by analysing the associated sensor readings. The main difference between ego-motion estimation and SLAM is that ego-motion estimation focuses on local consistency and aims to incrementally estimate the path of the user/robot pose after pose. On the other hand, SLAM aims to obtain a globally consistent estimate of the user/robot trajectory and map [33].

A probabilistic joint ego-motion estimation approach is proposed in [34], which includes two major components. The first component consists of the probabilistic spatial alignment of consecutive scans based on a Gaussian mixture model with NDT. The second component uses the Doppler velocity to estimate the motion of the vehicle. The proposed system shows competitive results in 2 Degree-of-freedom (DOF) cases at low computational complexity. In the 3 DOF case, the estimation of the longitudinal velocity shows the same accuracy as in the 2 DOF experiment. However, the lateral velocity and yaw rate estimation have a higher bias and standard deviation. A new point association technique to match the sparse measurements of automotive radar for indoors is presented in [35]. The sensor trajectory is estimated by iteratively applying the normal distributions transform (NDT) scan matching technique. In the proposed design, bi-directional LSTM (bi-LSTM) is used for the motion estimation model. The proposed system's mean translational ATEs change between 2.5 and 12.5 cm and the mean rotational ATEs are between 1.3 and 2.9 ° in the experiments. The point registration problem of the automotive radar, which is caused by sparse and noisy radar data, is solved by a data-driven learning approach [36]. Unlike conventional methods relying on explicit point matching, the proposed approach directly learns the motion transformation, making odometry feasible and reliable. The proposed system can surpass the state-of-the-art visual odometry method and IMU only in both 3D and 2D planes. It yields an average 3D ATE of 1.895 m, equivalent to a 1.8 % trajectory drift. In the 2D space, its error is further reduced to 1.252 m. The translational and rotational motions of a vehicle are estimated separately in [37] from a radar's Doppler and spatial data. The static targets are used to calculate the translational velocity estimation. Moreover, the measurement uncertainty of the target's azimuth angle is considered. On the other hand, the proposed system estimates rotational ego-motion from the spatial data captured in radar images. The proposed system's achieved median expected yaw rate uncertainty was 4.8 °/s which is the same as the radar's theoretical azimuthal angle uncertainty only. Moreover, the longitudinal velocity estimates have a median expected standard deviation of 0.02 m/s. A radar ego-motion estimation method that can operate on both scanning and automotive radar is proposed in [38]. The proposed system can provide dense information from automotive radars and remove noise from scanning radars by using the proposed probabilistic submap and thresholding. In the experiments, the translational error percentage and total rotational error are 3.85 % and 0.4430 °/m and 1.96 % and 0.0060 °/m for automotive and scanning radar, respectively.

A scanning radar-only ego-motion estimation with a landmark extraction method, which reliably identifies meaningful features while avoiding false detections, is proposed in [39]. The proposed method contains a novel scan matching algorithm for radar, which does not require a priori knowledge of the scans' orientations or displacements relative to one another, unlike ICP. Moreover, the proposed approach is to perform data association using not only individual landmark descriptors but also the relationships between landmarks, such as the set of distances from each point to its neighbours. Over a 10 km route, the median radar odometry error is about 0.106 m/s in translation and 0.321 deg/s in rotation. Importantly, even when visual odometry and GPS/INS are available, they are closely matched by radar odometry. In the dark and rain, visual odometry periodically fails while radar odometry gives a clean and smooth result. The same authors propose another landmark extraction method that requires only one input parameter in [40], which is highly robust to radar artefacts. Moreover, the authors claim that the extracted key points are interpretable and meaningful, and their design is adaptable to diverse settings without a priori knowledge.

4 Conclusion

In this paper, all visually impaired navigation system types in the literature are examined and the requirements for visually impaired navigation are determined. The radar has been selected as the sensor to be used to sense the environment. There is no radar-based indoor navigation system for the visually impaired in the literature. A few previously proposed radar-based systems are only on obstacle avoidance and human detection. The radar was chosen based on its strengths over other sensors. However, radar has its own shortcomings and design challenges, and these should be well addressed. For example, the uncertainty of radar detections is higher than other sensors. Furthermore, ghost targets can be observed indoors due to multipath effects.

The visually impaired navigation system must be robust and accurate for the safety of the user. Radar can ensure robustness since it can work in ambient conditions where other sensors do not operate. The proposed radar SLAM and radar ego-motion estimation techniques have been investigated considering accuracy and it has been observed that the proposed radar ego-motion estimation techniques can provide higher accuracy position tracking. Apart from that, the radar odometry provided by the radar ego-motion estimation is necessary to design a lightweight system without additional sensors since the system is planned to be placed on the user. The systems proposed with other sensors and radar SLAM systems benefit from other technologies such as IMU for odometry measurements. Moreover, the radar ego-motion system can be promoted to a SLAM system by adding mapping and a loop closure structure after achieving sufficient accuracy.

Using a low-cost automotive radar sensor is more effective for indoor navigation considering indoor conditions. Scanning radar is expensive and bulky, therefore it is not suitable for indoor environments or to be a wearable device. Radar ego-motion estimation techniques have been investigated for both scanning and automotive radar. It can be observed that the scanning radar gives better odometry results than automotive radar.

Future work considers the design of a highly accurate and robust radar-only indoor navigation system for the visually impaired considering the techniques proposed in automotive radar, and the advantages of the techniques proposed for scanning radar such as landmark extraction to enhance the performances of automotive radar techniques in the context of indoor navigation.

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6 References

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