Sensors and Data in Mobile Robotics for Localisation

Victoria J. Hodge
https://orcid.org/0000-0002-2469-0224
University of York, UK

INTRODUCTION

Robot navigation is challenging. Leonard and Durrant-Whyte (2012) define it by three questions:

- ”where am I?”,
- ”where am I going?”, and
- ”how should I get there?”

The first question is localisation: establishing the exact position and orientation of the robot within the frame of reference in its environment, and is the focus here. The robot may be navigating in static or dynamic environments, in indoor or outdoor environments and using static (pre-defined) path determination or dynamic path determination. Each of these variants requires different considerations. Gul, Rahiman, & Nazli Alhady (2019) provide a survey of the algorithms used for robot navigation. Effective navigation requires success in the four building blocks of navigation (Siegwart, Nourbakhsh, & Scaramuzza, 2011):

1. perception - the robot must be able to analyse its sensors data to extract meaningful knowledge;
2. localization - the robot must be able to calculate its position in the environment;
3. cognition - the robot must be able to determine how to navigate to its goals using the information from 1 and 2;
4. motion control - the robot must be able to modulate its movement to achieve the desired trajectory.

This survey focuses on 1 and 2 but also considers 3. It focuses on the sensor data used, how and where they are used and their respective advantages and disadvantages. The **Background** section outlines the different types of mobile robots and identifies the focus for this survey, and **Sensors for Robotics** describes robotics sensors, their use in robot navigation and where the main challenges lie for localisation, **Solutions and Recommendations** examines the literature on localisation for local and global localisation and indoor and outdoor robotics. **Future Research Directions** considers the most likely developments in localisation and the **Conclusion** provides an overview of the article.

DOI: 10.4018/978-1-7998-9220-5.ch133

BACKGROUND

A key task for any autonomous system is acquiring knowledge about its environment. For mobile robot navigation, this is done by taking measurements using various sensors and then eliciting meaningful information from those measurements. Jones, Seiger, & Flynn, (1998) surveyed mobile robotics sensors. Many of these sensors are still used today (in enhanced forms) but new sensors and data have been introduced. The aim of this survey is not to merely catalogue all publications on robot localisation. Rather, it surveys a broad cross-section of contributions that provide the reader with good coverage and insight into the subject. It focuses on interesting and varied contributions from the last decade that use affordable, consumer-grade sensors which have progressed significantly.

Mobile robots can be classified into five different types according to their mode of operation: autonomous ground vehicles (AGVs), autonomous aerial vehicles (AAVs), autonomous surface vehicles, autonomous underwater vehicles, and autonomous spacecraft. This survey considers the first two types. AGVs are used in a broad range of applications for sensing, monitoring, data collection and surveillance, from agriculture to manufacturing logistics, surveillance to transportation, last-mile delivery to mining, defence to construction, environmental (ecological) monitoring to wildlife monitoring, warehouses to distribution centres, search and rescue to disaster analysis and utilities (oil, electricity and gas) and other environments (particularly in logistics, in hospitals or retail). There are also developmental robots and prototypes for domestic use. AAVs can be used in many applications due to their ease of deployment, low maintenance cost, high-mobility and ability to hover. They are used for remote sensing, real-time monitoring and management of road traffic, providing wireless coverage, heat source location, damage assessment, search and rescue operations, delivery of goods, security and surveillance, agriculture, construction and civil infrastructure inspection, environment monitoring, hazard monitoring and weather monitoring, specifically atmospheric forecast and wind.

SENSORS FOR ROBOTICS

Sensors used in robot navigation subdivide into proprioceptive and exteroceptive sensors. Proprioceptive sensors measure the robot itself using data from accelerometers, gyroscopes, magnetometers and compasses, wheel encoders and temperature sensors. Some of these are useful for robot localisation, for example pose estimations or establishing distance travelled during navigation. Exteroceptive sensors measure the external world and acquire information about the robot's environment. Localisation algorithms often need to combine measurements from proprioceptive sensors with information collected by exteroceptive sensors to obtain an overall view of the position, motion and surroundings of the robot within its environment. The various sensors have different operating characteristics and Kelly and Sukhatme (2014) investigate a framework to harmonise the measurement data generation from a cross-section of these sensors to allow a robot to generate information about its environment.

Navigation systems

A typical robot navigation system comprises the five layer architecture shown in Figure 1.

Sensor data are transmitted either as a time-series where data are produced continuously / periodically or, a sequence of readings where data is generated ad hoc, for example generated every time the robot moves. The various data analytics for robot navigation can be performed continuously, periodically or ad hoc. Continuous data transmission is most accurate for localisation and navigation but it is computationally expensive; energy hungry which is a problem for on-board systems as they need power; and the sensor data are very noisy which requires careful processing to ensure accuracy. Periodic data processing is cheaper, uses less energy and allows time for data cleaning and filtering. However, localisation and navigation will be less accurate due to the time gaps. Ad hoc data transmission which only transmits given specific criteria is a trade-off providing the accuracy of continuous transmission with more energy saving of periodic transmission.

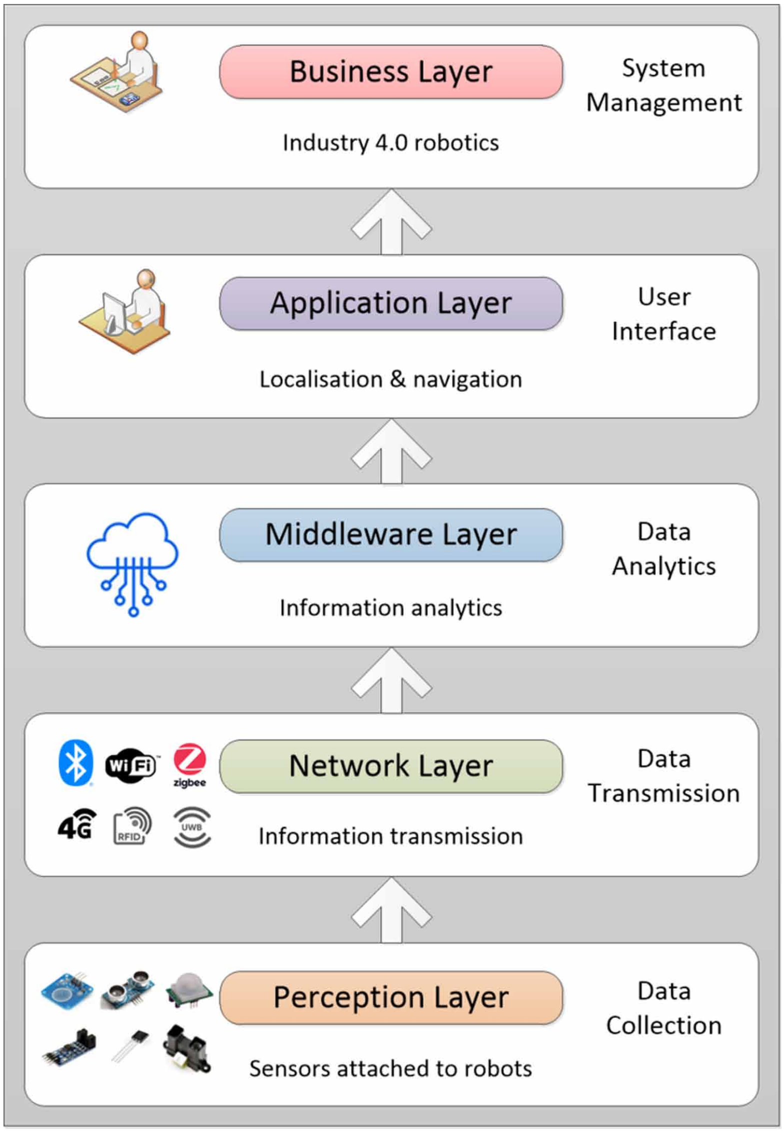
Leonard and Durrant-Whyte's (2012) first question of robot navigation is "where am I?". Precise localisation is the first step of navigation for both indoor and outdoor environments.

- Indoor navigation has gained increased attention as Industry 4.0 develops. Robots must be able to navigate dynamic environments safely to assure Industry 4.0 safety (Jaradat, Sljivo, Habli, & Hawkins, 2017). GNSS (Global Navigation Satellite System) is frequently unavailable indoors as there is no line of sight of the satellites (Siegwart et al., 2011). Indoor environments differ from outdoors: indoor spaces are smaller, there are many structural objects such as walls, doors, and furniture or machinery, there may be people moving around and the illumination conditions will change (including artificial lights which can affect sensor data quality from vision-based sensors). However, the variety of obstacles and structures tends to be lower and more regular which can help with object recognition and indoor environments are largely static as their general layouts change infrequently.

Localising indoor AAVs is particularly challenging and needs higher fidelity and faster data processing, position calculation and collision avoidance compared to outdoors as indoor environments are more constricted and compact. AAVs can use autonomous navigation (Hodge, Hawkins, & Alexander, 2021) but autonomous capabilities are often restricted due to state regulation.

- Outdoor spaces vary hugely according to the domain of application, and the type and capabilities of the robot. All robots have to contend with varying weather conditions and varying light conditions, shadows, seasonal changes and temperature changes which adversely affect sensor data accuracy. They also have to contend with wind currents which can displace the robot. All of these aspects make sensor data analysis for localisation and navigation very difficult.

Figure 1. Five-layer system architecture for (IoT) robot navigation



For robot localisation, the information extracted from the sensor data provides global or local estimates of the robot position.

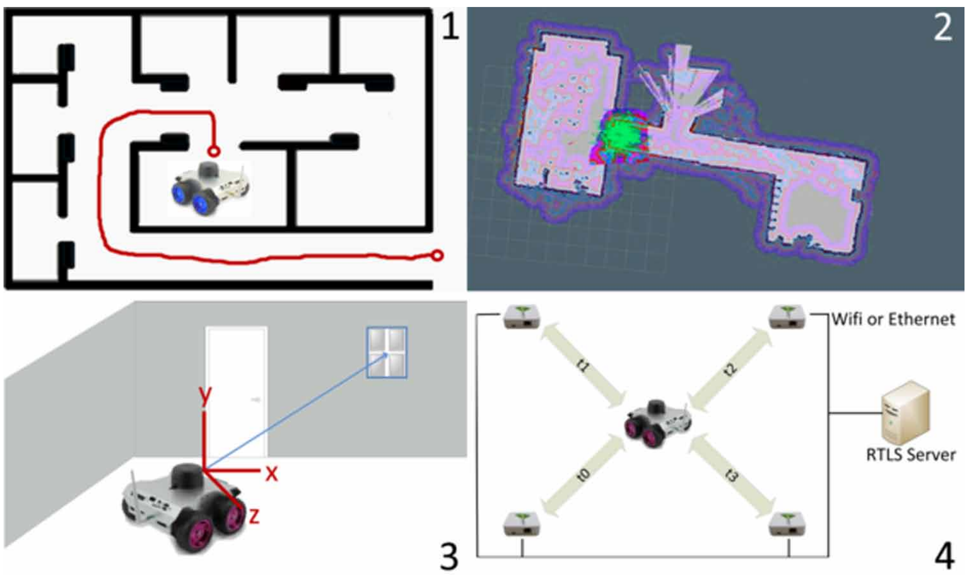
- Local estimation has a known starting location as an input. The sensors provide information regarding the immediate vicinity of the robot so its pose, and distance and direction moved can be estimated. The position estimation is cumulative (an offset from the start). The sensor data describe the immediate locality. Local estimates enable local navigation as they can accurately determine if the robot has rotated, moved a small distance or its distance to nearby objects. They provide high accuracy local data (mm accuracy) but lower confidence in the overall position than global estimates.
- Global estimates are provided by external sensors or on-board cameras among others. They provide a global approximation of the robot's position when it has no knowledge about its initial

position. The estimates tend to have higher confidence of the overall position than local estimates but lower granularity (lower degree of accuracy).

Localisation methods

There are four ways robots can pinpoint their position to allow them to navigate (illustrated in Figure 2).

Figure 2. The four approaches to localisation



1. using a map (see Rubio, Valero, & Llopis-Albert (2019) for a survey) which is ideal for navigation around immovable objects and fixed structures. It calculates the current location of the robot within the map to determine the robot's position in the environment. The current position can be obtained from a variety of sensors. The data can incorporate range-finding sensor data to identify the distance to obstacles to prevent collisions. Maps are static and navigation using maps requires prior knowledge of the layout to generate the map.
2. using vision-based sensor data to build a map of the environment (topological mapping). This can cope with dynamic environments but vision-based mapping is slow and computationally intensive due to the large data size required for high-fidelity mapping.
3. using object recognition or landmark recognition (this may be mapless or in conjunction with a map). It uses external elements (landmarks) in known locations. These can be either artificially placed landmarks, or natural landmarks. Artificial landmarks may be fiducial markers recognised by computer vision or beacons which transmit signals to receivers on-board the robot.
4. using GNSS or Real-Time Location System (RTLS) (mapless or in conjunction with a map). RTLS uses global estimation with Internet of Things (IoT) receivers in known locations, and ubiquitous connectivity to localize and position IoT tags on-board robots. GNSS and RTLS work indoors and outdoors and are suitable for positioning in dynamic environments. However, they cannot locate dynamic obstructions or humans unless they are also tagged.

Challenges

Industry 4.0 robots need to model their environments, estimate their position and orientation within this model, and navigate to the target. Finding a robust solution to these tasks is crucial to increase the autonomy, adaptability and safety of mobile robots. The main challenges are:

- Sensor data accuracy – sensor data are susceptible to faults such as calibration errors, reflections, shadows, aliasing, illumination variations, insufficient features in open spaces to allow navigation, movement (of robots and objects) and interference. This reduces the accuracy and utility of sensor data and increases computational complexity. Many authors use multi-sensor fusion to mitigate issues with the individual sensors, frequently mixing the high definition accuracy of local estimation with the overview generation of global estimation. To mitigate noisy data, authors use algorithms such as (Extended) Kalman filters, extended unbiased finite impulse response filters, particle filters and Markov or Monte-Carlo localisation to detect and correct noisy data. Panigrahi and Bisoy (2021) provide a review.
- Sensor data need to be transmitted for processing and analysis (Hodge, O'Keefe, Weeks & Moulds, 2015). Indoor robots have readily available networks, usually Wi-Fi networks. Sensor nodes consume energy during data communication yet on-board power is constrained and there is often a lack of bandwidth outdoors. Thus, outdoor transmission is more difficult so the transmission technology (Wi-Fi, Bluetooth, cellular, ZigBee, or satellite) used and design of the network needs to be carefully considered.
- Data processing - the robot needs to provide: access control, data storage, fault tolerance, privacy and security, and data transmission. These severely limit on-board data processing capabilities so data are transmitted for processing. This can introduce latency so transmission must be carefully designed and optimised. Real-time analytics for localisation needs to process huge volumes of data so scalable cloud-based computing architectures are used to enable Industry 4.0 capabilities.
- Standardisation – data need to be integrated for robotics but heterogeneous sensors and heterogeneous transmission protocols produce data in different formats and at different rates leading to compatibility issues. This is exacerbated by a lack of sensor and data standards. Standardisation ensures different systems can share data using a consistent interface.
- Security and privacy - the level of security will be dictated by the value of the asset, the type of asset and the consequences of a failure. The sensor data needs to be secure against intrusion, eavesdropping, data tampering and unauthorized control. IoT devices often have default passwords left unchanged, unpatched software and other major security vulnerabilities.
- If we are truly to realise Industry 4.0 then robotic sensors, data analytics and processing networks need to self-organise to allow new devices to join and devices to leave to make the network proactive rather than reactive. This includes identity management.

The following sections analyse localisation; subdividing it into global or local estimates. Sensors providing global estimates can generate an approximate localisation and ensure that the robot is not lost, while the local sensors provide the higher accuracy information of the robot's vicinity so it can be geo-located precisely and navigate accurately while avoiding collisions. Combining both local and global can provide the best (most accurate and most confident) overall localisation and navigation view.

SOLUTIONS AND RECOMMENDATIONS

Localisation technologies are discussed in the following sections. Many are suitable for both indoor and outdoor localisation.

Local Estimation

Range Sensors: Infrared, Laser and Ultrasound

Both IR and ultrasonic sensors (Leonard and Durrant-Whyte, 2012) can be used for range finding in local estimation indoors or outdoors. The speed of sound and light are almost constant in air so calculating the time between sending a pulse of data and receiving its reflection gives the distance to the reflected object. IR, ultrasonic and laser pulses are not affected by ambient lighting conditions unlike vision cameras where data quality degrades as light levels reduce or in very high light levels (glare). Laser range finders (Biswas and Veloso, 2012) transmit laser pulses and detect their reflections to map the environment's contours. Laser range finders are highly accurate, and detect moving objects such as humans or novel objects such as temporary obstructions. However, all three sensors require line-of-sight between the robot and receiver as the signals cannot penetrate materials (Aqel, Marhaban, Saripan, & Ismail, 2016). Also, the data are noisy, the signal reflections are dependent on the orientation of the object and its material (for example, lasers do not reflect in corridors with glass walls) plus there are no reflections in open areas. Data analysis for these sensors is complex often requiring powerful processing hardware, for example Biswas and Veloso (2012) use particle filters to process laser data.

Dead-reckoning (odometry)

Dead-reckoning for indoor or outdoor AGVs locally estimates the robot's position using data from proprioceptive sensors such as wheel encoders which transmit a tick for each rotation of the wheel and/or inertial measurement units (IMU) such as accelerometers, gyroscopes and magnetometers which provide acceleration, angular velocity and magnetic field measurement data respectively. Odometry calculates the robot's current position from a combination of the last known position plus an estimate of the distance and direction moved. Modern smartphones contain all of the sensors required making this technique easily accessible and cheap. However, over long periods of time, the position estimate can drift and accuracy is also affected by wheel slippage. Accuracy can be improved using techniques such as (Extended) Kalman Filters and Markov Localisation (Panigrahi and Bisoy, 2021). Duan, Cai, & Min (2014) detect sensor faults and wheel slippage using particle filters (probabilistic modelling), and incorporate a laser range-finder to correct the errors.

Visual odometry (VO) for indoor or outdoor localisation estimates the distance moved and the robot's rotation with respect to a reference frame using real-time frame-to-frame image analysis. It works with consumer-grade cameras and in GPS-denied environments. VO can use monocular or stereo cameras for 2-D or 3-D analyses (Yousif, Bab-Hadiashar, & Hoseinnezhad, 2015). VO algorithms use either appearance (intensity values) or feature detection (key-points) and track their optical flow through frames providing a cumulative estimate of the robot's position. VO outperforms dead reckoning odometry with respect to accuracy (Yousif et al., 2015) but similarly to dead reckoning, VO can suffer from drift. It has been implemented successfully indoors. However, outdoors remains challenging as mitigating varying light and imaging conditions causes high computational cost and the environment (reference frame) must be static and identifiable to allow the robot's movement to be detected by the algorithm. Zhan, Weerasekera, Bian, & Reid (2020) integrated deep learning with monocular VO for indoor and outdoor localisation to overcome scaling and drift issues, and provide more accurate localisation but deep learning is computationally intensive. The Mars Rover and AAVs use VO (Aqel et al., 2016).

Global estimation

GNSS

The most commonly used global estimation for outdoor localisation of all aerial, ground and surface robots is GNSS. This includes the GPS (Global Positioning System) and its data describing the robot's location by longitude, latitude, altitude, and a timestamp. Siegwart et al. (2011) note that:

If one could attach an accurate GPS (Global Position System) sensor to a mobile robot, much of the localisation problem would be obviated.

GNSS is passive; a receiver on the robot receives signals from earth-orbit satellites and processes these data to calculate its location and velocity. However, the position estimate is not free of deviations, and these increase with signal occlusions so, GPS is often used with other localisation mechanisms. Many commercial AAVs fuse GPS data with dead-reckoning IMU data to improve the localisation accuracy.

Magnetic compass

Digital magnetic compasses can provide directional measurements relative to the earth's surface using the earth's magnetic field. They are cheap compared to GPS modules, are readily available in smartphones and are suitable for both indoor and outdoor localisation (Ashraf, Hur, & Park, 2018). Magnetic compasses are most frequently used in conjunction with other sensors, such as cameras and range finders to provide accurate direction estimation. The earth's magnetic field is not affected by weather conditions and is pervasive. However, the earth's magnetic field is often distorted near power lines or steel structures.

Real-Time Location System (RTLS)

Radio-Frequency RTLS measures the distance between transmitter (on-board the robot) and RF receivers (mounted in known locations), see Zafari, Gkelias, & Leung (2019) for a survey of techniques. It is most frequently used indoors but can be used outdoors. The most common methods are based on triangulation which calculates the robot location by measuring signal arrival times or, the radial distance or direction of the received signal from two or three different points. RTLS uses a broad range of positioning technologies including: Wi-Fi, Bluetooth, RFID, UWB, visible light, infrared, ultrasonic, GPS, cellular, ZigBee, and RFID. Deak, Curran, & Condell (2012) provide a survey splitting positioning methods into active and passive. The majority of the localisation techniques are active as they estimate the robot's position using data transmitted from tags mounted on the robot or other objects. Passive systems use readers, often placed in the floor, which power the tags to detect and locate robots locally. Passive systems are cheaper but can only locate robots passing within a short-range of the reader. Active systems can locate robots anywhere inside their range. Martinkovič, Mičieta, & Binasova (2019) investigate a real-time location system for hybrid assembly factories in Industry 4.0. They analyse how UWB tracking can be incorporated in manufacturing where humans and robots cooperate closely and, in the future, collaborate seamlessly and safely. Černohorskỳ, Jandura, & Rydlo (2018) investigate the issues with indoor UWB tracking in confined spaces such as corridors and provide suggestions for overcoming issues with interference and accuracy variability. Outdoor RTLS for both AGVs and AAVs uses transmission technologies such as RF, Laser or UWB. It is often used where GPS fails due to line-of-sight issues. Guo et al. (2016) use UWB RTLS for AAV navigation in spatially restricted areas or dense environments, such as woods or urban canyons where other techniques such as GPS, range sensors or vision-based techniques produce poor quality or no data due to line-of-sight issues.

Visual navigation

The latest visual navigation techniques work indoors or outdoors. They can detect moving objects and handle dynamic environments using Simultaneous Localisation and Mapping (SLAM). SLAM simultaneously maps the robot's location and estimates its pose using probabilistic concepts. SLAM is a global visual mapping of the robot and its environment compared to the local estimation of VO. SLAM can use relatively cheap yet powerful depth sensors such as the Microsoft Kinect RGB-D sensor that was originally designed for the Microsoft Xbox (Biswas and Veloso, 2012) or the Google Tango (Winterhalter, Fleckenstein, Steder, Spinello, & Burgard, 2015). Lu, Xue, Xia, & Zhang (2018) survey visual AAV navigation focusing on approaches that use cheaper and more flexible cameras for pose estimation. AAVs can use regular image processing techniques to reconstruct a 3D map of the environment by estimating the depth value and can then use the depth to estimate the AAV's position. The depth measurement accuracy from these cameras is sufficient for AGV and AAV navigation but requires heavy pre-processing to remove noise, smooth it and to fill gaps where no depth data are produced. Winterhalter et al. (2015) generate proximity measurements from the environment to allow AGV navigation, combine this with RGB-D data and compare it to a 2D outline of the environment, such as a floor plan or map. Kundu, Mazumder, Dhar, & Bhaumik (2016) use 3D-point clouds to generate 2D (binary) occupancy grids with 0 for unmapped or occupied grid cells and 1 for empty cells. The robot uses this grid information to navigate the environment.

Early vision-based approaches for robots relied on artificially placed landmarks such as barcodes. The advent of deep neural networks in 2000s provided a leap forward in vision processing capabilities. Modern vision-based approaches can operate in unmodified environments. Hence, indoor and outdoor localisation can use landmarks, external elements that are either artificially placed or natural occurring but are distinctive, recognisable and fixed position. Natural landmarks can be doors, trees or walls. This visual recognition requires line-of-sight of the landmarks and vision accuracy degrades under obscurants such as fog and smoke, so practitioners fuse multiple sensor data, particularly for AAV navigation, often incorporating IMU data. Alternatively, Khattak, Papachristos, & Alexis (2018) design fiducial markers for the pose estimation of aerial robots. The markers work with (long wave infrared) thermal cameras which are not affected by obscurants. LiDAR has rapid data collection, is highly accurate and recent developments in autonomous vehicles has dramatically reduced the cost of LiDAR so Wang et al. (2021) use 2-D LiDAR SLAM for centimetre-level precision localisation of AAVs in warehouses using artificial landmarks (reflective geometric objects that reflect the laser). LiDAR is susceptible to obscurants so the reflective objects assist recognition but LiDAR has high energy usage.

Even today, visual navigation can be difficult for AGVs and AAVs both indoors and outdoors, see Lowry et al. (2015) for a survey. It is computationally demanding due to the large data size. It faces other challenges including; multiple locations in the environment can appear very similar and difficult to distinguish (known as perceptual aliasing), the appearance of a location can change dramatically under different lighting conditions, shadows or occlusion, obscurants such as fog or smoke can degrade image quality and thus data quality, and locations may be viewed from differing viewpoints if the robot is in a slightly different position from previously. These all impact recognition accuracy. It also needs to factor in the motion of the robot itself.

Localisation with beacons

The robot's on-board receiver captures the beacon data to determine the robot's location from analysing the strength and direction of the data received and identifying the location of the transmitting beacon. Localisation can be achieved using beacons which generate Wi-Fi, Bluetooth, ultrasound, infrared, radio transmissions, visible light, or any similar signal data. Sheinker et al. (2016) perform indoor AGV localisation by analysing magnetic field data. They place magnetic beacons in known locations that can be detected by robot-mounted receivers, such as smartphones or tablets that contain a magnetometer. The robot's position is calculated by software running on the phone that determines which beacon produces the strongest signal. However, magnetic variations can cause signal fluctuations and require compensating mechanisms. Ogiso, Kawagishi, Mizutani, Wakatsuki, & Zempo (2015) combine wheel odometry data with acoustic data collected by on-board microphones for indoor localisation of AGVs. The sound sources (beacons) have known locations and frequency bands and the localisation algorithm estimates the direction-of-arrival (DOA) of the sound sources using 4 microphones in a square array to calculate the location and pose of the AGV. Similar to range-sensor localisation, acoustic localisation is susceptible to occlusion and reflections and requires a clear audio signal between transmitter and receiver.

Sensor data fusion

As mentioned in the previous section of this survey, many authors have turned to sensor data fusion approaches to overcome the limitations of individual sensors and their data. Sensor fusion merges data from multiple sensors (including proprioceptive and exteroceptive sensors) and can fuse local and global estimates. Data fusion aims to obtain a precise position for the robot, generate a richer overview of the robot's environment and reduce uncertainty through increased accuracy, reliability, and fault tolerance of sensor data. Data fusion increases the sensor data coverage (including spatial and temporal coverage); improves the data resolution and increases the data variety. This richer data allows data processing algorithms to generate a richer overview of the robot and its environment. This richer data, however, may cause compute intensive algorithms to be unable to process the data fast enough so the data processing and algorithm used to processed fused data has to be carefully considered. Data from each sensor may be processed first by separate algorithms and the results analysed for localisation or the data may be fused and then analysed by a single algorithm or multiple algorithms. The algorithms need to handle data outages from individual sensors, the data granularity and data transmission rates of the different sensors will vary and need to be accommodated and synchronised, and data are often noisy which needs to be mitigated. Authors often use filter algorithms to mitigate data noise (see Panigrahi and Bisoy, 2021).

Dobrev, Flores & Vossiek (2016) fuse global radar data with local ultrasonic (pose estimation) and odometry (precise location) data for indoor localisation of AGVs where GNSS data are unavailable. The radar data places the robot in its environment and, in conjunction with the local ultrasonic and odometry estimates, places it on a grid map of the environment. The authors claim that fusing data from the three sensors provides an absolute location so the robot can relocate even if it is picked up and moved.

Quigley, Stavens, Coates, & Thrun (2010) consider indoor localisation using smartphones. They use the smartphone's Wi-Fi signal power measurements for fast global convergence with circa 4 metre accuracy and combine this with computer vision from the phone's built-in camera which offers greater tracking accuracy over long periods. The combined approach aims to ensure fast convergence and high precision. Li, Queralta, Gia, Zou, & Westerlund (2020) combine local motion estimation (odometry) data with real-time visual data and a detailed pre-built map for localising delivery AGVs in urban (outdoor) environments. They fuse 3D LiDAR data, inertial (IMU) data, GNSS data and wheel encoder readings. Their analyses identify that using combinations of sensor data allows them to mitigate deficiencies with the individual sensors. For example adding IMU data to a combination of LiDAR and GNSS data increases the accuracy and stability of localisation.

Localising indoor micro-AAVs is particularly challenging due to their mobility and low payload but carefully selected sensors coupled with data fusion can assist. Sensor data fusion can combine camera data with range finding data to implement SLAM algorithms. Li et al. (2018) use a separate (off-robot) wireless network comprising two types of 3-D range finder: a spinning 2-D range finder, which provides omnidirectional measurements and a Time-of-Flight camera that measures the distance in a fixed field of view (like a normal camera). The localisation algorithm fuses these data to build a 3-D map of the area. The AAVs carry low-level path tracking sensors to monitor their motion in the 3-D map. Paredes, Álvarez, Aguilera, & Villadangos (2018) developed a hybrid acoustic and optical positioning system for the accurate 3D positioning of indoor AAVs. It uses ultrasonic data to compute the horizontal position combined with optical data that provides an initial estimation for the AAV's altitude. A recursive algorithm refines the estimated position. This combination requires line of sight for the ultrasonic data, and varying light conditions and visual obscurants will affect the optical data. Azhari et al. (2017) overcome visual obscurants during outdoor AAV navigation by fusing visual SLAM, IMU and ultrasonic (sonar) data generated by sensors on-board the AAV. The SLAM camera is a monochromatic charge-coupled device (CCD) that localises by identifying fiducial markers (waypoints). By processing the sonar data, the localisation algorithm estimates the distance of an object from the AAV using the pulse width of the sound waves. These sound data produce a 3D model approximation of the environment (mines).

Similar to Li et al. (2018), Canedo-Rodríguez et al. (2016) use a multi-sensor fusion approach that combines on-board and external (off-robot) sensors. The authors fuse data from a 2D laser range-finder, a Wi-Fi card, a magnetic compass, and an external multi-camera network of USB webcams for mobile AGV localisation in crowded indoor environments. Their localisation algorithm is based on particle filters. The Wi-Fi positioning system and the cameras provide rough estimate of the robot's position while the laser and the compass refine these estimates and provide location accuracy. The system aims to degrade gracefully if any sensors are unavailable.

There are issues for RTLS such as network contention and network slowdown during heavy traffic, data reception fluctuations due to variations in signal strength, and for active systems the anchors need to be synchronized very precisely as a small timing error translates into a large distance error. Hence, Mirowski, Ho, Yi, & MacDonald (2013) combine an ensemble of RF signals to build multi-modal signal maps for indoor or outdoor localisation of AGVs. They harness off-the-shelf smartphone sensor data collecting time-stamped Wi-Fi, Bluetooth, cellular, magnetic field magnitude, GPS (outdoors) plus near-field communication readings at specific landmarks to create a signal map in buildings and determine the location of the smartphone.

FUTURE RESEARCH DIRECTIONS

Industry 4.0 requires innovation in data, analytics and physical technology. Robotics, IoT and its networks of sensors are crucial for Industry 4.0 realisation. The latest robots, sensor devices, AI, and cloud solutions will underpin this innovation producing smart, integrated and trustworthy systems. Future Industry 4.0 applications will exploit fog and mobile edge computing architectures. As industrial automation advances, sensor technology will be the foundation for data collection and data analytics that will transform industry into the connected, cost-effective, and reliable factories of the future. A key element of this future is autonomous robots which are capable of autonomous and safe navigation. A key element of autonomous and safe navigation is robot localisation, answering the question "Where am I?" precisely. Current sensor technology is developing rapidly but there is still some way to go to bridge the gap between the physical and digital (data-driven) world and precise localisation. This will require development of:

- device interoperability so that sensors become plug-and-play into any robot where they will function seamlessly and allow data collection for localisation,
- multi-purpose sensors,
- standardization of sensor data and data collection architectures,
- standard sensor data processing pipelines (sensorOps),
- multi-channel communications to enable collection of high volume sensor data and a wide variety of data types from different sensors,
- multi-stage data fusion – combining data from a variety of sources (sensors and contextual data) and over a range of time epochs to generate a consolidated state history for advanced localisation,
- privacy and end-to-end security of sensor data as data are collected and transmitted by robots,
- well-defined policies and regulations of data, its collection and processing,
- reductions in costs of sensors, data collection architectures and processing frameworks,
- reduction in power consumption of sensors and on-board processing to allow data to be processed on-board the robots, plus efficient power supply mechanisms (such as self-power or energy-harvesting),
- extending existing localisation algorithms or developing new algorithms to process this enhanced data. The algorithms need to handle high volume, high variety and highly granular data to generate precise localisation for the robots,
- localisation algorithms running on-board the robots must process the full range of data, generate precise localisations while remaining within the limits of energy consumption available from the on-board power sources.

If Industry 4.0 robots are to become fully autonomous then they need to rely on on-board sensors and their data to make navigation decisions including localising.

CONCLUSION

Industry 4.0 and IoT are rapidly innovating sectors with potential to change and automate industrial processes. Robotics, sensors, data and machine learning are central to this innovation. In particular using sensor data for robot navigation to ensure safety and enable autonomy. However, issues of performance, security and standardisation need to be addressed to ensure robot navigation is safe and effective. A crucial aspect of robot navigation is localisation: determining the robot's exact location. The chapter aims to provide readers with a clear understanding of robotic localisation and the different solutions for Industry 4.0. It identifies the advantages and disadvantages of the approaches and will help practitioners find solutions to particular tasks.

ACKNOWLEDGMENT

The research was supported by the Assuring Autonomy International Programme (www.york.ac.uk/assuring-autonomy).

REFERENCES

Aqel, M. O., Marhaban, M. H., Saripan, M. I., & Ismail, N. B. (2016). Review of visual odometry: Types, approaches, challenges, and applications. *SpringerPlus*, *5*(1), 1–26. doi:10.118640064-016-3573-7 PMID:27843754

Ashraf, I., Hur, S., & Park, Y. (2018). MagIO: Magnetic field strength based indoor-outdoor detection with a commercial smartphone. *Micromachines*, *9*(10), 534. doi:10.3390/mi9100534 PMID:30424467

Azhari, F., Kiely, S., Sennersten, C., Lindley, C., Matuszak, M., & Hogwood, S. (2017). A comparison of sensors for underground void mapping by unmanned aerial vehicles. In *Proceedings of the First International Conference on Underground Mining Technology* (pp. 419-430). Australian Centre for Geomechanics. 10.36487/ACG_rep/1710_33_Sennersten

Biswas, J., & Veloso, M. (2012). Depth camera based indoor mobile robot localization and navigation. In *IEEE International Conference on Robotics and Automation* (pp. 1697-1702). IEEE. 10.1109/ICRA.2012.6224766

Canedo-Rodríguez, A., Alvarez-Santos, V., Regueiro, C. V., Iglesias, R., Barro, S., & Presedo, J. (2016). Particle filter robot localisation through robust fusion of laser, WiFi, compass, and a network of external cameras. *Information Fusion*, *27*, 170–188. doi:10.1016/j.inffus.2015.03.006

Černohorský, J., Jandura, P., & Rydlo, P. (2018). Real time ultra-wideband localisation. In *19th International Carpathian Control Conference (ICCC)* (pp. 445-450). IEEE. 10.1109/CarpathianCC.2018.8399671

Deak, G., Curran, K., & Condell, J. (2012). A survey of active and passive indoor localisation systems. *Computer Communications*, *35*(16), 1939–1954. doi:10.1016/j.comcom.2012.06.004

Dobrev, Y., Flores, S., & Vossiek, M. (2016). Multi-modal sensor fusion for indoor mobile robot pose estimation. In *Proceedings of IEEE/ION Position, Location and Navigation Symposium (PLANS) 2016* (pp. 553-556). 10.1109/PLANS.2016.7479745

Duan, Z., Cai, Z., & Min, H. (2014). Robust dead reckoning system for mobile robots based on particle filter and raw range scan. *Sensors (Basel)*, *14*(9), 16532–16562. doi:10.3390140916532 PMID:25192318

Gul, F., Rahiman, W., & Nazli Alhady, S. S. (2019). A comprehensive study for robot navigation techniques. *Cogent Engineering*, *6*(1), 1632046. doi:10.1080/23311916.2019.1632046

Guo, K., Qiu, Z., Miao, C., Zaini, A. H., Chen, C. L., Meng, W., & Xie, L. (2016). Ultra-wideband-based localization for quadcopter navigation. *Unmanned Systems*, *4*(01), 23–34. doi:10.1142/S2301385016400033

Hodge, V. J., Hawkins, R., & Alexander, R. (2021). Deep reinforcement learning for drone navigation using sensor data. *Neural Computing & Applications*, *33*(6), 2015–2033. doi:10.100700521-020-05097-x

Hodge, V. J., O'Keefe, S., Weeks, M., & Moulds, A. (2015). Wireless sensor networks for condition monitoring in the railway industry: A survey. *IEEE Transactions on Intelligent Transportation Systems*, *16*(3), 1088–1106. doi:10.1109/TITS.2014.2366512

Jaradat, O., Sljivo, I., Habli, I., & Hawkins, R. (2017). Challenges of safety assurance for industry 4.0. In *13th European Dependable Computing Conference (EDCC)* (pp. 103-106). IEEE. 10.1109/EDCC.2017.21

Jones, J. L., Seiger, B. A., & Flynn, A. M. (1998). *Mobile robots: Inspiration to implementation*. CRC Press. doi:10.1201/9781439863985

Kelly, J., & Sukhatme, G. S. (2014). A general framework for temporal calibration of multiple proprioceptive and exteroceptive sensors. In *Experimental Robotics* (pp. 195–209). Springer. doi:10.1007/978-3-642-28572-1_14

Khattak, S., Papachristos, C., & Alexis, K. (2018). Marker based thermal-inertial localization for aerial robots in obscurant filled environments. In *International Symposium on Visual Computing*, (pp.565–575). Springer. 10.1007/978-3-030-03801-4_49

Kundu, A. S., Mazumder, O., Dhar, A., & Bhaumik, S. (2016). Occupancy grid map generation using 360∘ scanning xtion pro live for indoor mobile robot navigation. In *First International Conference on Control, Measurement and Instrumentation (CMI)* (pp. 464–468), IEEE. 10.1109/CMI.2016.7413791

Leonard, J. J., & Durrant-Whyte, H. F. (2012). *Directed sonar sensing for mobile robot navigation* (Vol. 175). Springer Science & Business Media.

Li, H., & Savkin, A. V. (2018). Wireless sensor network based navigation of micro flying robots in the industrial internet of things. *IEEE Transactions on Industrial Informatics*, *14*(8), 3524–3533. doi:10.1109/TII.2018.2825225

Li, Q., Queralta, J. P., Gia, T. N., Zou, Z., & Westerlund, T. (2020). Multi-sensor fusion for navigation and mapping in autonomous vehicles: Accurate localization in urban environments. *Unmanned Systems*, *8*(03), 229–237. doi:10.1142/S2301385020500168

Lowry, S., Sünderhauf, N., Newman, P., Leonard, J. J., Cox, D., Corke, P., & Milford, M. J. (2015). Visual place recognition: A survey. *IEEE Transactions on Robotics*, *32*(1), 1–19. doi:10.1109/TRO.2015.2496823 PMID:26512231

Lu, Y., Xue, Z., Xia, G. S., & Zhang, L. (2018). A survey on vision-based UAV navigation. *Geo-Spatial Information Science*, *21*(1), 21–32. doi:10.1080/10095020.2017.1420509

Martinkovič, M., Mičieta, B. & Binasova, V. (2019). The use of real - time location system in hybrid assembly. *Průmyslové inženýrství.* doi:10.24132/PI.2019.08948.101-108

Mirowski, P., Ho, T. K., Yi, S., & MacDonald, M. (2013). SignalSLAM: Simultaneous localization and mapping with mixed WiFi, Bluetooth, LTE and magnetic signals. In *International Conference on Indoor Positioning and Indoor Navigation* (pp. 1-10). IEEE. 10.1109/IPIN.2013.6817853

Ogiso, S., Kawagishi, T., Mizutani, K., Wakatsuki, N., & Zempo, K. (2015). Self-localization method for mobile robot using acoustic beacons. *ROBOMECH Journal*, *2*(1), 1–12. doi:10.118640648-015-0034-y

Panigrahi, P.K., & Bisoy, S.K. (2021). Localization strategies for autonomous mobile robots: a review. *Journal of King Saud University-Computer and Information Sciences*.

Paredes, J. A., Álvarez, F. J., Aguilera, T., & Villadangos, J. M. (2018). 3D indoor positioning of UAVs with spread spectrum ultrasound and time-of-flight cameras. *Sensors (Basel)*, *18*(1), 89. PMID:29301211

Quigley, M., Stavens, D., Coates, A., & Thrun, S. (2010). *Sub-meter indoor localization in unmodified environments with inexpensive sensors. In 2010 IEEE/RSJ international conference on intelligent robots and systems*. IEEE.

Rubio, F., Valero, F., & Llopis-Albert, C. (2019). A review of mobile robots: Concepts, methods, theoretical framework, and applications. *International Journal of Advanced Robotic Systems*, *16*(2), 1–22. doi:10.1177/1729881419839596

Sheinker, A., Ginzburg, B., Salomonski, N., Frumkis, L., Kaplan, B. Z., & Moldwin, M. B. (2016). A method for indoor navigation based on magnetic beacons using smartphones and tablets. *Measurement*, *81*, 197–209. doi:10.1016/j.measurement.2015.12.023

Siegwart, R., Nourbakhsh, I. R., & Scaramuzza, D. (2011). *Introduction to autonomous mobile robots*. MIT Press.

Wang, S., Chen, X., Ding, G., Li, Y., Xu, W., Zhao, Q., Gong, Y., & Song, Q. (2021). A lightweight localization strategy for LiDAR-guided autonomous robots with artificial landmarks. *Sensors (Basel)*, *21*(13), 4479. doi:10.339021134479 PMID:34208935

Winterhalter, W., Fleckenstein, F., Steder, B., Spinello, L., & Burgard, W. (2015). Accurate indoor localization for RGB-D smartphones and tablets given 2D floor plans. In *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)* (pp. 3138-3143). 10.1109/IROS.2015.7353811

Yousif, K., Bab-Hadiashar, A., & Hoseinnezhad, R. (2015). An overview to visual odometry and visual SLAM: Applications to mobile robotics. *Intelligent Industrial Systems*, *1*(4), 289–311. doi:10.100740903-015-0032-7

Zafari, F., Gkelias, A., & Leung, K. K. (2019). A survey of indoor localization systems and technologies. *IEEE Communications Surveys and Tutorials*, *21*(3), 2568–2599. doi:10.1109/COMST.2019.2911558

Zhan, H., Weerasekera, C. S., Bian, J. W., & Reid, I. (2020). Visual odometry revisited: What should be learnt? In *2020 IEEE International Conference on Robotics and Automation (ICRA)* (pp. 4203-4210). IEEE. 10.1109/ICRA40945.2020.9197374

ADDITIONAL READING

Al-Kaff, A., Martin, D., Garcia, F., de la Escalera, A., & Armingol, J. M. (2018). Survey of computer vision algorithms and applications for unmanned aerial vehicles. *Expert Systems with Applications*, *92*, 447–463. doi:10.1016/j.eswa.2017.09.033

Alatise, M. B., & Hancke, G. P. (2020). A review on challenges of autonomous mobile robot and sensor fusion methods. *IEEE Access: Practical Innovations, Open Solutions*, *8*, 39830–39846. doi:10.1109/ACCESS.2020.2975643

Kuutti, S., Fallah, S., Katsaros, K., Dianati, M., Mccullough, F., & Mouzakitis, A. (2018). A survey of the state-of-the-art localization techniques and their potentials for autonomous vehicle applications. *IEEE Internet of Things Journal*, *5*(2), 829–846. doi:10.1109/JIOT.2018.2812300

Peel, H., Luo, S., Cohn, A. G., & Fuentes, R. (2018). Localisation of a mobile robot for bridge bearing inspection. *Automation in Construction*, *94*, 244–256. doi:10.1016/j.autcon.2018.07.003

Rubio, F., Valero, F., & Llopis-Albert, C. (2019). A review of mobile robots: Concepts, methods, theoretical framework, and applications. *International Journal of Advanced Robotic Systems*, *16*(2). Advance online publication. doi:10.1177/1729881419839596

Siegwart, R., Nourbakhsh, I. R., & Scaramuzza, D. (2011). *Introduction to autonomous mobile robots*. MIT Press.

KEY TERMS AND DEFINITIONS

Global Localisation: The initial robot location is completely unknown, and the robot is localised externally to the robot.

Industry 4.0: Smart manufacturing and autonomous systems powered by interconnectivity, data, and machine learning.

Internet of Things (IoT): Connections between physical objects - people, sensors or machines and the internet.

Local Localisation: The initial location is known, and on-board sensors locate the robot within its environment.

Odometry: An estimation of a robot's location relative to where it started.

Sensor Data Fusion: Merging data from multiple sensors to reduce the uncertainty inherent in their data.

SLAM: Simultaneous localisation and mapping technology uses sensor data to create a map of the robot's environment and allows localisation of the robot to be performed simultaneously.