# SMART HOME AND INDOOR POSITIONING SYSTEMS FOR AGING IN PLACE

# A SMART HOME PLATFORM AND HYBRID INDOOR POSITIONING SYSTEMS FOR ENABLING AGING IN PLACE

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# Lay Abstract

By 2031, the number of people aged 65 and over is expected to nearly double. This population shift is concerning for healthcare providers as limited resources become increasingly constrained. Resultantly, older adults, the largest consumers of healthcare, face longer wait times and reduced quality of care.

Remote health monitoring is an emerging field aimed at utilizing technology for monitoring older adults within their homes. In this thesis, we report a Smart Home platform and two indoor positioning systems (IPSs) for tracking resident mobility, the primary predictor of falls among older adults.

For the Smart Home platform, the design methodology and technological features were explained. As for the IPSs', position accuracy of multiple occupants within multiple rooms of a residential apartment was evaluated. Upon reviewing literature system cost, implementation ease, and scalability, were identified as key metrics for developing an IPS for enabling aging in place. Both IPSs performed well, achieving high localization accuracy for multiple occupants.

# Abstract

Activities of daily living (ADLs) are everyday routine tasks which provide insight into the physical and cognitive wellbeing of older adults. ADLs are commonly self-reported to clinicians, which can lead to overestimation and underestimation of a patients' functional abilities. Remote health monitoring is an emerging field aimed at utilizing technology for monitoring ADLs remotely, improving clinical accuracy and enabling older adults to age safely within their homes.

In this dissertation, we report a Smart Home platform and two indoor positioning systems (IPSs) – (i) a hybrid Bluetooth Low Energy (BLE) and radar motion sensor system and (ii) a hybrid radio-frequency identification (RFID) and infrared (IR) range-finding system for tracking occupant mobility, the primary predictor of falls among older adults.

For the Smart Home platform, the design methodology and technological features were explained. As for the IPSs', position accuracy of multiple occupants within multiple rooms of a residential apartment was evaluated. The systems were also evaluated for cost, implementation ease, and scalability, which, upon reviewing literature, were identified as key metrics for developing an IPS for enabling aging in place. Both IPSs enforced a decentralized localization architecture and performed well, achieving high localization accuracy for multiple occupants.

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# List of Abbreviations

| | |
|---|---|
| ADL | Activity of daily living |
| AoA | Angle of arrival |
| BLE | Bluetooth Low Energy |
| EM | Electromagnetic |
| FoV | Field of view |
| GDP | Gross domestic product |
| GPS | Global positioning system |
| HF | High frequency |
| IADL | Instrumental activity of daily living |
| IMU | Inertial measurement unit |
| INS | Inertial navigation system |
| IPS | Indoor positioning system |
| IR | Infrared |
| kNN | K-nearest neighbour |
| LAN | Local area network |
| LF | Low frequency |
| MEMS | Micro-Electro-Mechanical System |
| NLOS | Non-line-of-sight |
| PAN | Personal area network |
| PDR | Pedestrian dead reckoning |
| PIR | Passive infrared |
| PoE | Power over ethernet |
| RF | Radio frequency |
| RFID | Radio frequency identification |
| RPi | Raspberry Pi |
| RSSI | Received signal strength indicator |
| SHS | Step-and-heading system |
| TDoA | Time difference of arrival |
| ToA | Time of arrival |
| ToF | Time of flight |
| UHF | Ultra high frequency |
| US | Ultrasonic |
| UTI | Urinary tract infection |

# List of Symbols

| | |
|---|---|
| $d$ | Distance between signal receiver and reference node |
| $d_0$ | Distance between signal transmitter and reference node |
| $f_d$ | Doppler frequency |
| $n_p$ | Path loss factor |
| $\Delta\phi$ | Phase difference of arrival |
| $P_0$ | Power of initial signal |
| $P$ | Power of received signal |
| $c$ | Velocity of electromagnetic wave |
| $V$ | Velocity of moving body |
| $\lambda$ | Wavelength |

# Declaration of Academic Achievement

I hereby certify that I am the sole author of this thesis and that no part of this thesis has been published or submitted for publication. I certify that, to the best of my knowledge, my thesis does not infringe upon anyone's copyright nor violate any proprietary rights and that any ideas, techniques, quotations, or any other material from the work of other people included in my thesis, published or otherwise, are fully acknowledged in accordance with the standard referencing practices. Furthermore, to the extent that I have included copyrighted material that surpasses the bounds of fair dealing within the meaning of the Canadian Copyright Act, I certify that I have obtained written permission from the copyright owner(s) to include such material(s) in my thesis and have included copies of such copyright clearances to my appendix.

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# Chapter 1

# Introduction

As the demographics of the global population shifts, health care providers worldwide are facing new challenges. With hospitals increasingly reaching maximum capacity, the struggle to maintain high quality of care persists at an alarming rate[1]. As of 2014, global healthcare costs are increasing at an annual rate of 5.3%[2] and in North America, 17.4% of the Gross Domestic Product (GDP) is spent on healthcare.[2] As illustrated in **Figure 1.1**, healthcare costs in Canada begin to increase exponentially with age for adults aged 65 and above.[3]

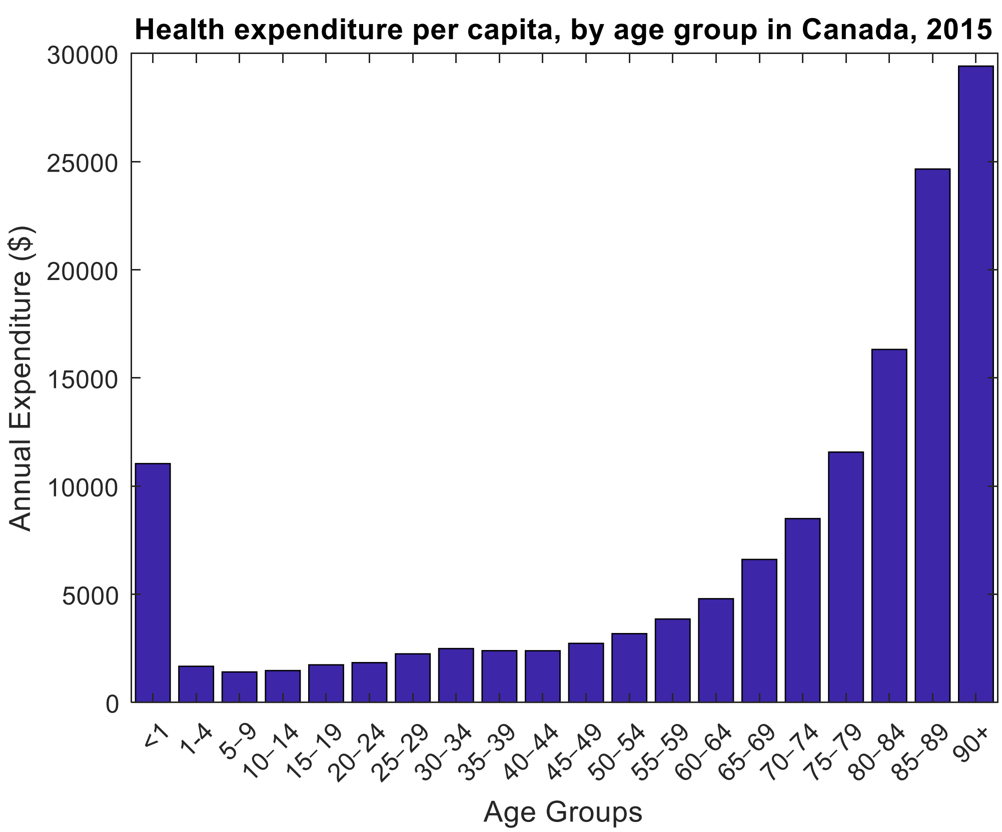


**Figure 1.1** Government health expenditure per capita, by age group, Canada 2015*[3]*

Between 2010 and 2031, the entire baby boomer population, North America's largest demographic, will reach the age of 65.[4] During this period, the number of Canadians aged 65 and above is expected to nearly double, leading to soaring healthcare costs and increased strain on governments, health care providers, insurance companies and healthcare consumers.[2] These increased social and financial challenges underscore a need for stakeholders to leverage technology and innovative solutions to improve quality of care while reducing burden on caregivers and cost to the healthcare system.

As strain increasingly weighs down on traditional healthcare institutions, innovative methods of monitoring and diagnosing patient health will continue to arise. Priorities will include monitoring patient health outside of hospital and clinic walls, and a shift in will o understanding patient health within their place of living. For older adults, community dwellings such as assisted living and long-term care residences will continue to serve as platforms for monitoring and maintaining health of its residents.

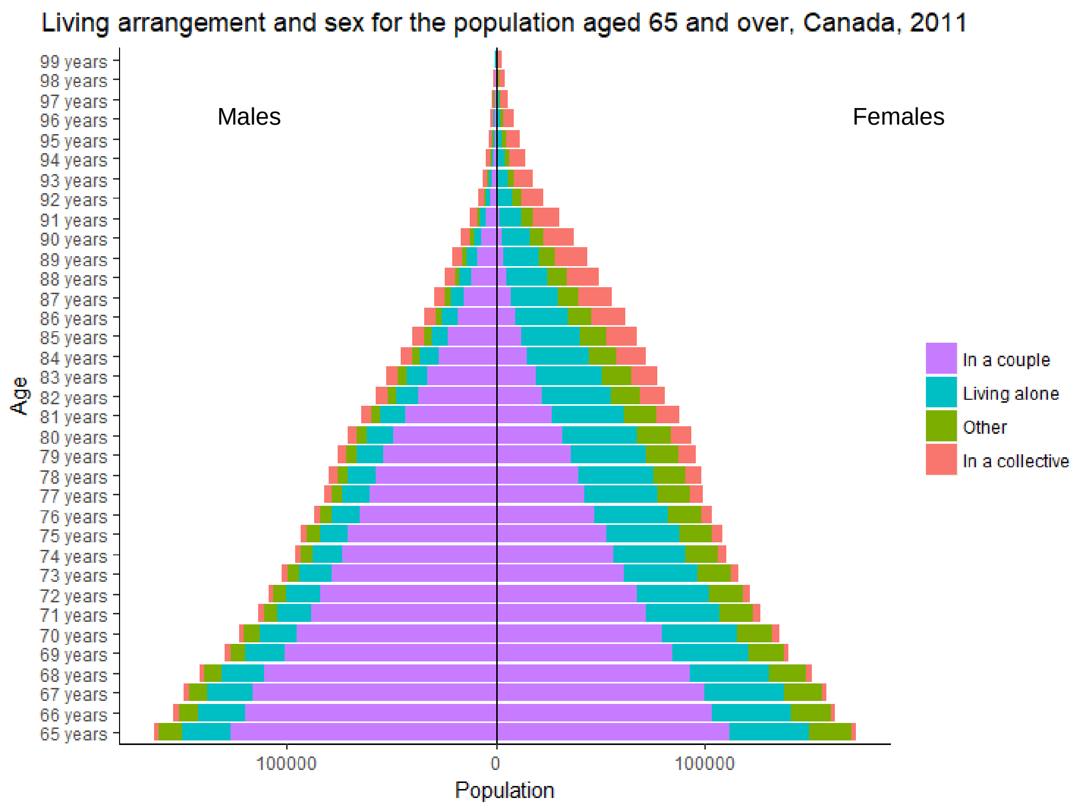


**Figure 1.2** Living arrangement and sex for the population aged 65 and over, Canada, 2011[5]

As depicted in **Figure 1.2**, the majority of older adults continue to reside in their homes as they age. Older adults seeking to maintain independence and safety within their homes as they experience aging will require new models of care, supported by technological solutions within the existing living arrangements.

## 1.2 Activities of Daily Living

Performance of activities of daily living (ADLs) and instrumental activities of daily living (IADLs) are useful metrics in determining physical well-being, cognitive state, and independence.[6] ADLs include functional routine tasks such as mobility, dressing, washing, and sleeping.[6] IADLs are less fundamental than ADLs, and evaluate clients' abilities to complete complex tasks, such as financial management, communication, and health management.[6] Traditionally, performance of ADLs and IADLs are evaluated by clinicians such as OTs through visual observation or interviews.[6], [7] Although interviews are fast and low-cost to administer, they can suffer from inaccuracies if clients over or underestimate their abilities.[6] Visual observation provides clinicians with greater insight, however, can take a long time to administer and may be inaccurate if not conducted in the clients' native setting and at the appropriate time.[6]

## 1.3 Remote Health Monitoring

Many older adults prefer to continue living in their homes as they age, citing high level of independence, improved personal social networks, greater performance of personal habits, and greater confidence as reasons.[8] Health-monitoring technologies embedded in the home and worn by residents can enable older adults to extend their length of stay in the home, while providing relief to formal caregivers as well as informal caregivers such as family members and friends.

Likewise, there are number of additional benefits in implementing remote health monitoring devices in assisted living communities as well. Although living communities for older adults vary in staff and resource availability, it is quite common for these facilities to experience staff shortages, making it challenging to provide care for a large number of residents.[9] In order to mitigate risk for patients that are prone to falls, physical restraints such as a bed rails, vests, and straps may be implemented. Restraints have potentially negative consequences such as physical harm, psychological harm, and loss of dignity, and are consequently minimized.[10] Alternatively, increasing human observation results in improved resident safety, but places greater stress on staff and reduces residents' privacy.[9] In more recent years, bed-side alarms such as pressure-sensitive mattresses and floor-mats have been adopted by living communities to alert staff if fall-prone residents are ambulating or have fallen from their bed. Despite enhancing resident safety, frequent false alarms can be burdensome to staff and result in alarm fatigue and complacency.[9] However, highly accurate and specific monitoring systems can benefit residents and staff by enhancing clinical knowledge, mitigating resident risk, promoting mobility, and improving staff efficiency.[9]

Sensor technology worn by occupants and embedded innocuously within their residences has been shown to effectively monitor health-related ADLs such as mobility, bathing, preparing meals, and filling medication dispensers.[11]–[14]

## 1.4 Functional Mobility Tracking

Functional mobility declines with age and is a predictor of cognitive status, psychosocial status, and likelihood of slips and falls among older adults.[15] Step count, elevation, distance travelled, stride length, gait analysis, sit-to-stand transfer duration, frequency of rooms visited, and use of assistive devices such as canes and walkers, are among the metrics used for quantifying mobility. As will be discussed in **Chapter 2,** IPSs can provide insight into many of these metrics.

## 1.5 Research Focus

Smart Home technology, which embeds ubiquitous sensors innocuously throughout the home and aims to enable older adults to age independently in their homes while maintaining safety, reducing stress on caregivers, predicting injuries, and reducing healthcare costs. As will be discussed in **Chapter 3,** remote health monitoring platforms and devices for enabling aging in place are being actively developed and evaluated. Among the measured conditions is functional mobility, which can be determined from a variety of sensor modalities, as will be discussed in **Chapter 2.**

The primary goal of our research was the development and subsequent implementation of an IPS for a residential setting. We seek to evaluate the strength of our system by the following criteria:

*Location Accuracy.* In order to provide valuable health-related information to caregivers and clinicians, the IPS must accurately determine and store the location of residents.

*Ease of implementation*. In order to develop an IPS that will be adopted for consumer use, the system must be easily installed within the home. Plug-and-play solutions that function directly out-of-the-box are considered ideal while systems that require a complex knowledge of RF distribution and a long configuration time should be avoided.

*Multiple rooms.* Fusing residents' location and temporal information provides insight into their activities. Occupancy of adjacent rooms can imply very different activities. For instance, an older adult who has resided in the restroom for several hours during the night-time could indicate an emergency event such as a fall, while the same action within the adjacent bedroom would indicate4 normal behaviour. Consequently, the IPS must accurately determine the occupants' location for multiple rooms.

*Multiple residents.* As depicted in **Figure 1.2**, most older adults do not live alone. Therefore, the IPS must accurately maintain a high positioning accuracy for multiple residents occupying the home.

*Scalability.* The size of residential homes and apartments varies. The ideal system would not increase in complexity for large homes or community dwellings.

*Cost.* In order to reduce overall healthcare costs, the ideal system would implement low-cost sensor technology.

Furthermore, we developed a smart home platform for enabling the development, subsequent integration and validation of health monitoring devices within the home. The smart home platform and features are detailed in **Chapter 3.**

## 1.6 Overview

*Chapter 2.* This chapter provides an overview of the different sensor modalities and techniques that have been implemented for indoor positioning, as well as their strengths and limitations.

*Chapter 3*. Activities of daily living are used by clinicians to gain insight into older adults' physical and cognitive status. In this chapter, an overview of techniques for remotely monitoring ADLs is provided. In order to support our own research in developing remote monitoring technology, a Smart Home platform was designed and implemented. The motivation and novel aspects of the home are discussed.

*Chapter 4.* In this chapter, the development and subsequent implementation of an IPS for monitoring mobility within the home is described. The system integrates Bluetooth Low Energy (BLE), ultrasonic (US) range finders, and radar motion sensors to determine the direction and identification of multiple occupants in a residential home.

*Chapter 5.* A second IPS was developed and implemented. The system integrates Radio Frequency Identification (RFID), US range finders, and infrared (IR) range finders to determine the direction and identification of people crossing through doorways. The strengths and limitations of the hybrid-RFID and hybrid BLE systems are then summarized.

*Chapter 6* provides a reflection of the indoor positioning systems developed in this thesis as well the future steps that will be taken.

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# Chapter 2

# Indoor Positioning Systems

## 2.1 Introduction to Indoor Positioning Systems

Global Positioning Systems (GPS) have become ubiquitous within mobile phones and other personal electronic devices, leading to the development of healthcare driven location-based services such as activity tracking and emergency response systems.[1] Unfortunately, GPS services do not function well indoors due to their coarse lateral resolution. Indoor positioning systems (IPSs) seek to address this problem. IPSs can be designed in numerous ways, implementing a wide range of sensor modalities and computational techniques to determine the location and identity of indoor occupants. This chapter reviews common indoor positioning techniques that have been developed by research and industry groups.

## 2.2 Pedestrian Dead Reckoning

The term *dead reckoning* originated from ship navigation and refers to the calculation of one's relative position using known terms such as initial location, speed and heading information.[2] Inertial navigation automates dead reckoning through the implementation of inertial measurement units (IMUs) such as gyroscopes, accelerometers and magnetometers.[2] A subset of inertial navigation is pedestrian dead reckoning (PDR), which combines IMUs with algorithms for describing human gait patterns to track the relative position of a person. In PDR, one or more IMUs are worn by the user. Once an initial reference point is set, direction, orientation and acceleration data is used to track subsequent positions of the user. Benefits of this technique is that PDR does not require additional physical infrastructure within a building, reducing implementation complexity and installation costs. Also, due to advancements in Micro-Electro-Mechanical System (MEMS) technology, these sensors are low cost, have a low footprint, and are ubiquitous within modern mobile phones.

Harle [3] makes the distinction between two subsets of PDR, called Inertial Navigation Systems (INSs), and Step-and-Heading Systems (SHSs). The latter tracks the distance and heading of the user by implementing algorithms that are specific to human gait patterns, while the former uses IMU data to recreate a full 3D trajectory of the sensors.

The primary human gait patterns in question for SHS are *stance* and *swing*. When a person is in the stance phase, their foot is planted firmly on the ground. When the swing phase occurs, the foot lifts off the ground to step in a desired direction.[3] There are also transition steps such as *push-off* and *foot-down* that occur between *stance* and *swing*. IMUs collect this gait information while attached to the user's foot or waist, and can alternatively be worn on a helmet, or carried by the user in their hand or pocket.[3]–[5] Accelerometers are responsible for determining gait patterns, while magnetometers determine the direction of the step. The gyroscope data can be fused with the magnetometer signal to assist in determining direction by reducing unwanted noise from magnetic interference from nearby infrastructure.[6]

Reviews of PDR algorithms can be in literature. [3], [7]–[9] To select the optimal algorithm for a PDR solution one must consider the IMU placement on the person's body, the number of sensors available on the IMU, walking speeds and versatility of the user and computational availability.[9] Filtering and machine learning techniques are also implemented to improve accuracy, reduce drift and remove outliers.[3], [7]

Kang et al developed a middleware for mobile phones, utilizing the device's on-board IMUs.[6] The authors adopted an approach from Weinberg [10] which estimated that step length and vertical impact were proportional to one another, allowing for calculation and tracking of dynamic step length. The novel algorithm, SmartPDR, was evaluated against magnetometer-based PDR and gyroscope-based PDR. The authors demonstrated that their algorithm matched with the reference path with an error of less than two metres, for both real-time and reconstructed data, and was superior to the other two algorithms, which suffered from errors of 10 metres or more.

Despite accurate readings, PDR algorithms have limitations. The algorithms perform well under controlled environments; however, longer temporal experiments with many subtle turns increase drift in the position due to cumulative error in the low-cost sensors.[11] Furthermore, the algorithms are optimized for sensor hardware, which varies among different phone models as well as users' walking signature. For older adults, this gait signature is likely to change over time, which reduces the reliability of the tracking algorithm.[7] Another challenge is that PDR systems require the user to wear an IMU at all times, which can be undesirable and inconvenient. Lastly, PDR algorithms require an initial position, which is not trivial to implement in real applications.

## 2.3 Infrared, Ultrasonic, and Motion Sensor Modalities

Infrared (IR) and Ultrasonic (US) range-finding and motion sensors are a well-documented technique for IPS.[12]–[16] Range-finding sensors record time-of-flight (ToF), the time that is required for an emitted pulse to reflect off a nearby object and return back to the sensor. The distance is then measured as

$$d = c * \frac{ToF}{2} \qquad 2.1$$

where $c$ is the velocity of the wave.[17] US and RADAR motion sensors use the Doppler Effect to detect an observed change in frequency (or wavelength) from a signal reflected off of a moving body.[18] For a sound wave emitted at frequency, $f_0$, travelling at velocity, $c$, the Doppler frequency, $f_d$, reflected off a body moving at velocity, $v$, can be calculated as

$$f_d = \frac{2vf_0 cos\theta}{c} \qquad 2.2$$

where $\theta$ is the angle between the moving body and the transit beam.[18]

Passive infrared (PIR) sensors are another common modality for detecting motion. PIR sensors detect the IR radiation emitted from heat-generating bodies. The sensors record a profile of the IR spectrum in their field-of-view (FoV), and then emit an electric pulse when that profile is disrupted by a sudden change in heat (and IR radiation), as emitted from a person or animal in the FoV.[19]

For motion-tracking based IPSs, sensors are strategically placed within an indoor setting and track movement occurring within a pre-determined region. There are a number of benefits to these sensors: (i) they do not interfere with communication protocols such as Wi-Fi and Bluetooth, (ii) they do not require the users to wear any devices, (iii) they are low cost, (iv) compared with camera-based techniques they are able to maintain the privacy of the user, and (v) they require less computation power. Not having a wearable device is a favourable feature for tracking older adults in their homes since there is no required interaction with a device.[20]

A challenge with these types of systems is that in order to achieve location accuracy with high-resolution, a network of distributed motion sensors is required throughout the infrastructure. This can accrue high installation and maintenance time and cost. The distribution of sensors is also dependent on the layout of the building, so custom planning with knowledge of the sensors is required.[12] Another challenge is that motion sensor IPSs depend on biometric data, such as height or weight to distinguish between multiple occupants within the home.[21], [22] These modalities alone can prove to be unreliable if there are multiple residents with similar biometric profiles.[15]

Hnat et al [15] achieved room-level tracking by monitoring signals from US and PIR sensors mounted in doorways. The direction of travel through doorways was inferred from extrapolating the change in height, and maximum height was used to identify targets. The authors used future observations to weigh and remove ambiguities. The authors detected direction with 81% accuracy, and achieved room-level tracking with 90% accuracy.

Yang et al [23]  divided a mock apartment into a grid-based accessibility map. The floor plan was weighted to determine location of occupants. Walls and furniture were applied a weight of 0, and all areas in free space were applied a weight of 0.5. Additional weights were added to areas where occupants most often frequent, such as the living room couch, beds, and a dining room chair. 10 PIR sensors were used to compare two walking trajectories of a single person within an apartment using OptiTrack as the ground proof measurements. A heuristic algorithm was used to predict the user's next step from their current position achieving an average distance error of 0.21m.

## 2.4 Bluetooth Low Energy

Bluetooth Low Energy (BLE) is a wireless communication protocol designed for personal area networks (PANs) to extend the functionality of modern mobile devices and PCs. Unlike its predecessor, Bluetooth, which was designed for high-throughput data transfer for applications such as audio streaming, BLE was designed for low duty-cycle applications, making it a suitable choice for wearable devices such as activity trackers.[24] BLE's low cost, low energy consumption, and ubiquity in mobile phones and activity trackers has made the modality popular for developing research and commercial IPSs.[8], [16], [25]–[28]

A feature of the BLE specification is the received signal strength indicator (RSSI), where modules process the power level of a received signal, typically in dBm. The propagation loss of radio signals, derived from empirical measurements by Hata [29], has been applied to modelling the relationship between distance and received power from BLE transceivers.[27], [30] In **Equation 2.3**, if an initial signal strength, $P_0$, was recorded at a distance, $d_0$, away from a reference node, then the received signal strength, $P$, at distance, $d$, is obtained from

$$P(d) = P_0 - 10n_p \log\left(\frac{d}{d_0}\right) \qquad 2.3$$

where $n_p$, the path loss factor, varies depending on the environment.[11]
There are a number of different methods for locating position using BLE including fingerprinting from received signal strength (RSS), triangulation, and proximity analysis through hot-spotting.

### *2.4.1. Fingerprinting*

Fingerprinting is a localization technique in which a network of stationary BLE reference nodes are dispersed across a building's infrastructure and an *offline* radio map is created by recording the RSS of mobile BLE nodes at known positions.[8] User position is identified in the *online* phase, where real-time RSS values are collected, converted to distances using **Equation 2.3**, and fit to the reference dataset using algorithms such as least-square, k-nearest-neighbour (kNN), support vector machines, and neural networks.[8], [31] Jianyong et al. used this technique along with Gaussian filtering in a single rectangular room and achieved a spatial localization error of 2.5 m or less with a cumulative probability of 1.[27]

One of the challenges in implementing fingerprinting is the random fluctuations in RSS values caused by the orientation of the radios, reflections from obstacles, and interference with radio signals.[31] Furthermore, training datasets can become obsolete when the *online* and *offline* conditions vary significantly, such as when furniture is moved, or many occupants are present at once.

### *2.4.2 Trilateration*

Trilateration is a trigonometric technique where signals emitted from three or more reference nodes, termed *beacons*, at known locations intersect to identify the unknown location of a mobile node.[32] **Figure 2.1** depicts this geometric technique, where reference nodes $P_1$, $P_2$, and $P_3$, assumed to be located on the same vertical plane, are located at coordinates ($x_1$,$y_1$), ($x_2$,$y_2$), and ($x_3$,$y_3$), respectively, and the target mobile node, *A*, is located at coordinate ($x_A$, $y_A$). The distance between $P_1$, $P_2$, and $P_3$ and the mobile node, *A*, are $r_1$, $r_2$, and $r_3$, respectively.

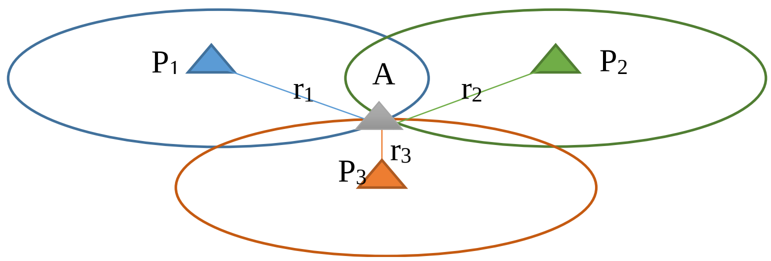


**Figure 2.1** 2-dimensional trilateration technique implemented for indoor localization. The relative position of mobile node A is calculated from a minimum of three reference nodes, $P_1$, $P_2$, and $P_3$.

The radius, $r_i$, between *A* and reference node, $P_i$, can be calculated from the RSS values and **Equation 2.3.** It can be shown that the coordinates ($x_A$, $y_A$) can be found from the following equation

$$r_i^2 = (x_A - x_i)^2 + (y_A - y_i)^2 \qquad 2.4$$

where the number of reference points, 3 ≤i<n-1. [32]

For three reference nodes, Cotera et al [33] show that if $P_1$ is set as reference coordinate (0,0), $P_2$ is set as coordinate $(x_2,0)$, and $P_3$ is then coordinate $(x_3, y_3)$, then the coordinates, $(x_A, y_A)$, of mobile node A can be calculated as

$$x_A = \frac{r_1^2 - r_2^2 + x_2^2}{2x_2} \tag{2.5}$$

$$y_A = \frac{r_1^2 - r_3^2 + x_3^2 + y_3^2 - 2x_3x_A}{2y_3} \tag{2.6}$$

with respect to node $P_1$. When there are more than three mobile nodes present, multilateration can be applied through least squares fits.[11]

To evaluate a trilateration algorithm, Röbesaat et al mounted eight BLE beacons in a single corridor.[11] A user carrying a mobile phone walked a predetermined path, collecting RSS values from nearby beacons. The path was then reconstructed and a mean accuracy of 0.73 ± 0.22 m was achieved.

In wide rooms, where users are not in close proximity to walls, there is a challenge in ensuring that an entire area is covered by at least three beacons at all times. This would require a large quantity of beacons and long installation time to ensure that proper coverage requirements are met. For such a system, positions are not calculated in real-time, which would be required for identifying potentially health-risk events or fusing with other sensor activity.

In general, despite accurate measurement in single-room environments, upon reviewing the literature, a case of multi-room localization could not be found. The reflection, attenuation and transmission of the 2.4 GHz radio signal through walls can create false position readings.[34] Furthermore, a case of trilateration for multiple people in a single space could not be found.

### *2.4.3 Proximity*

Proximity systems are the simplest implementation of BLE for indoor positioning. A mobile BLE transceiver is worn by the occupant and used to locate nearby BLE beacons. Although its resolution is coarse, its ease of implementation and low cost increases its adoptability. In [35], Han et al installed two BLE beacons in two adjacent rooms. Threshold RSS values were used to distinguish between the locations of two users wearing mobile BLE modules. After three days of collecting data, the system achieved a mean room-level accuracy of 59 ± 6% for reading correct messages and 96 ± 1% for time spent in accurate rooms.

## 2.5 RFID

In the electromagnetic (EM) spectrum, the radio-frequency (RF) band, extending from 20 kHZ to 300 GHz, is largely responsible for wireless communication. One subset of this is radio-frequency identification (RFID), which uses RF readers to detect the presence of RF tags. There are three types of RFID tags: passive, active, and semi-passive. Passive tags are one of the most common implementations of RFID since they do not require a power source and are inexpensive to manufacture. For passive systems, a RF pulse is emitted by the reader. If a tag exists within the scanning radius, then the tag's ID and data is collected and processed by the reader. For active systems, the tags are battery powered and periodically emit a signal.[36] Although they are more costly than passive systems, active tags have a number of advantages such as increased range, ability to scan multiple tags at once, and lower power requirements from the reader.[36] Semi-passive tags behave similarly to passive tags, but include a built-in battery to increase range and signal strength.

The primary frequency bands used for RFID are low-frequency (LF), high-frequency (HF), and ultrahigh-frequency (UHF). [36] Each band and their respective frequency range and application is shown in **Table 2.1** below.[36], [37]

**Table 2.1** Radio frequencies and applications of common RFID transceivers.

| Band | LF | HF | UHF |
|---|---|---|---|
| **Frequency** | 121-131 kHz | 13.56 MHz | 300 MHz-3GHz |
| **Application** | Animal tagging | Low-range, retail | Fast data transfer, warehouses, races |

The most common RFID positioning techniques are based on temporal measurements,[36] such as time-of-arrival (ToA), time-difference-of-arrival (TDoA), and angle-of-arrival (AoA).

### *2.5.1 Time-of-Arrival*

ToA algorithms are a form of trilateration. RSSI-trilateration, discussed in **Section 2.4.2**, differs from ToA-trilateration in its method for calculating distance. Rather than calculating distance from RSS measurements, the detection radius, shown in Figure 2.1, is calculated from the recorded absolute travel time of a message transmitted from a tag to a reader, as described in **Equation 2.7**.

$$r_i = c * t_{travel_i} \tag{2.7}$$

Because measuring the ToA requires synchronization between the tags and readers, active systems are most commonly implemented.[38] This synchronization requirement increases the sophistication of the algorithms and the computation complexity. Alternatively, roundtrip ToA can be implemented for passive tags, which does not require synchronization between tags and readers.[36] Synchronized readers record the time that a

RF pulse is emitted and a tag ID is received**. Equation 2.8** is then used to measure the radius of detection.

$$r_i = c * (t_{arrival_i} - t_{emission}) \tag{2.8}$$

Lee et al[39] validated a ToA RFID system in a construction site. With the target tag mounted to their helmet, a participant completed a predefined path with no obstacles between themselves and three RFID antennas, accomplishing an average localization error of 86.50 ± 63.62 cm. The test was then repeated in a more complex environment, with a greater number of obstacles between the target and the antennas. To overcome errors, an assistant tag, a virtual reader of known location and in line-of-sight of the target, was implemented. Despite greater obstacle interference, the system's performance improved, accomplishing a localization error of 44.97 cm ± 34.44 cm.

### *2.5.2 Time-Difference-of-Arrival*

TDoA algorithms employ multiple RFID readers to record the difference in received detection times. Detection synchronization is required between readers, but is not required between tags and readers. Unlike ToA, the time of travel does not need to be known, instead, only the received signal times at the readers are required. Fang et al described how to estimate position from an intersection of hyperbolic curves.[40] The hyperbolas, achieved from TDoA measurements are described in **Equation 2.9** where $t_i$ and $t_j$ are arrival times for reader *i* and *j*, respectively, located at positions ($x_i$, $y_i$) and ($x_j$,$y_j$), respectively. A diagram of the hyperbolic curves are shown in **Figure 2.2.**[41]

$$r_{ij} = \sqrt{(x_i - x)^2 + (y_i - y)^2} - \sqrt{\left(x_j - x\right)^2 + \left(y_j - y\right)^2} = c(t_i - t_j) \tag{2.9}$$

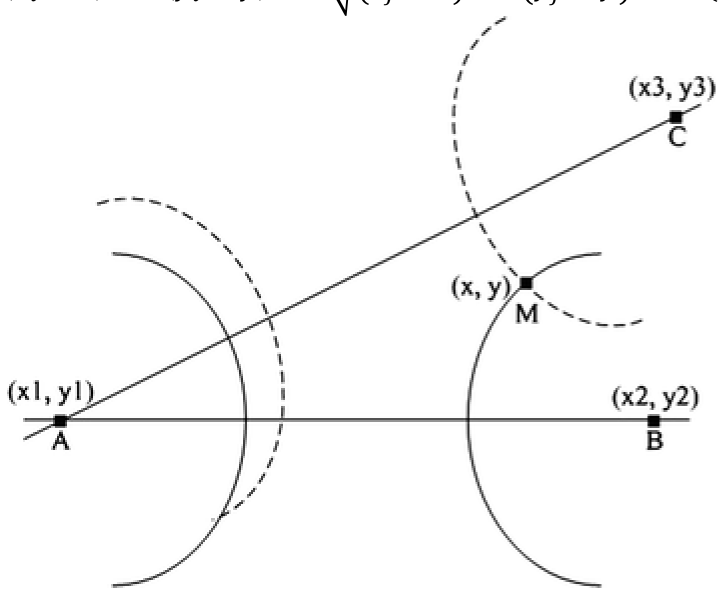


**Figure 2.2** Hyperbolic curves employed to estimate position in TDoA localization algorithms.

### *2.5.3 Angle-of-Arrival*

The AoA is defined as the angle between the propagation direction of the tag and the direction of the reader. The simplest approach to AoA measurements is derived from measuring the phase difference of a received signal from two or more reference antennas, as described in **Equation 2.10**, where $\theta$ is the AoA, $\Delta\phi$ is the phase difference of the incident wave, $\lambda$ is the wavelength of the signal, and d is the distance between antennas.[42] These antennas may be two or more different readers, or a single reader with an antenna array.

$$\theta = \arcsin\left(\frac{\Delta\phi \cdot \lambda}{-2\pi d}\right) \tag{2.10}$$

ToA, TDoA, and AoA measurements are prone to non-line-of-sight (NLOS) error. This error occurs because the above equations assume that measurements are captured from the shortest distances between the tags and reader. In reality, the signal may reflect off of nearby objects and reduce the reliability of distance measurements.

## *2.6 Wi-Fi*

The techniques used for Wi-Fi IPSs are identical to the techniques used for BLE and RFID systems. Residents wear a Wi-Fi module, or more commonly, a mobile phone, and their location is determined using one of the aforementioned techniques. One advantage for choosing Wi-Fi as a positioning modality is its ubiquity in homes. However, homes commonly have only one wireless router, whereas these techniques require two or more. Furthermore, knowledge of the RF transmission must be known to determine the location of the routers.

## *2.7 Hybrid Systems*

Despite achieving low localization error, the indoor positioning systems described in this chapter have varying limitations. For instance, the deployment complexity of non-inertial indoor positioning systems has been summarized by Shi et al[41] and shown in **Figure 2.3.**

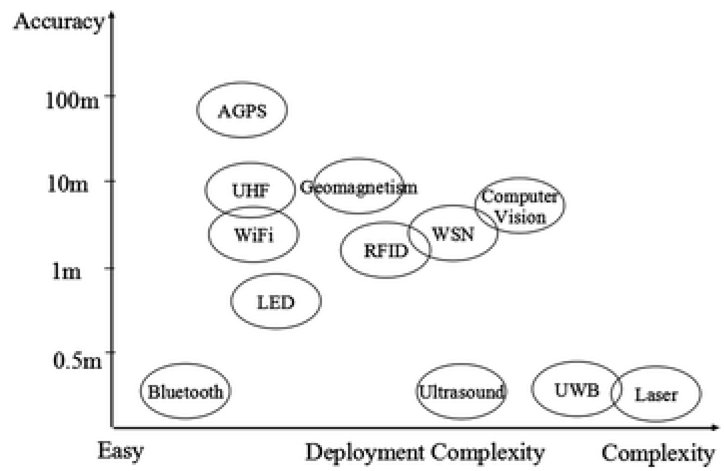


**Figure 2.3** Deployment complexity and accuracy of non-inertial based IPSs, summarized by Shi*[41]*.

Wang et al[7] summarize a number of key factors related to the performance and adoptability of indoor positioning systems, as summarized in **Table 2.2**.

To overcome some of these limitations, researchers have developed hybrid IPSs by combining different sensor modalities. For instance, Röbesaat et al[11] developed an IPS based on Bluetooth trilateration fused with PDR. The group developed a mobile phone application which analyzed IMU data and Bluetooth RSS data from eight nearby beacons. Fusing the trilateration and PDR paths with a Kalman filter, the authors achieved a measuring accuracy of 0.82 m. The group showed that by fusing PDR with trilateration, the sensor drift, inherent in low-cost PDR systems, was reduced. Furthermore, this technique no longer required PDR systems to include the user's initial position. In another study, Azghandi et al[43] combined low-cost PIR sensors with costly RFID readers. The group investigated cases when two or more people were present in an apartment. Using ceiling-mounted PIR sensors, the participants' trajectories were estimated, and crossed-paths were disambiguated using RFID proximity. Based on their results, the group developed a tree-based architecture for optimizing the position of RFID readers, thus reducing the cost of the system.

**Table 2.2** Comparison of parameters, advantages, and disadvantages of IPSs by Wang[7].

| Technology | Measurement Methods | Suitable Environment | Accuracy | Extra Device | Power | Cost | Advantages | Disadvantages | Examples |
|---|---|---|---|---|---|---|---|---|---|
| RFID | RSS, Proximity | Indoor | 1-3 m | Tag | Low | Moderate | Moderate cost; high accuracy | Positioning coverage is limited; extra devices | Cricket[44]; SpotON[45]; RADAR[46] |
| UWB | TOA; TDOA | Indoor | 6-10 cm | Tag | Low | High | Excellent accuracy; effectively passing through obstacles | High cost; short range; NLOS problems | Ubisense [47] Dart[48] |
| WiFi | RSS | Indoor | 1-5 m | Mobile Phone | High | Low | Reuse existing infrastructure ; low cost | Fingerprinting requires recalculation | Nibble[49] Wayes[50] |
| PDR | IMUs | Indoor or outdoor | 1-5 m | Mobile Phone | High | Low | No additional hardware such as beacons | Sensor drift | SensorTile[51] |
| BLE | Proximity; RSS | Indoor and Semi-outdoor | 1-5 m | Mobile Phone | Low | Low | Low infrastructure cost; low power consumption | Limitation in user mobility; low accuracy | Estimote[28] |
| Acoustic | ToA; TDOA | Indoor | 0.03-0.8m | No Device | Low | Moderate | No requirement for LOS; does not interfere with EM waves | Cannot penetrate solid walls; loss of signal due to obstruction; false signals because of reflections | Active Bat[52] Sonitor[53] |

## 2.8 Conclusion

A literature review of the methods for performing indoor localization was conducted. Although not an exhaustive summary, this review provided insight into important characteristics of an IPS, including accuracy, cost, complexity, ease of implementations, and adoptability. The radio and IMU-based systems discussed demonstrated their strengths and limitations. Most recently, development of hybrid IPSs seek to improve location accuracy at the cost of increasing system complexity. In order to develop IPSs to enable aging in place, the optimal trade-off of these functional and hardware requirements must be further investigated.

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# Chapter 3

# Smart Home Technology for Enabling Aging in Place

## 3.1 Introduction to ADLs and Their Clinical Use

Activities of daily living (ADLs) are the everyday routine tasks that are instrumental to people's lives. They include fundamental independent activities such as bladder management, sleeping, transferring, mobility, self-care activities such as maintaining hygiene, washing, cleaning, and getting dressed, as well as other integral human activities such as preparing meals, eating, and sexual activity.[1] From *Pedretti's Occupational Therapy,* a list of ADLs and Instrumental Activities of Daily Living (IADLs) is shown in **Table 3.1**.[1] IADLs are more complex than ADLs and are a good measure of one's ability to execute cognitively challenging tasks in less predictable environments, such as communicating with others.

**Table 3.1** List of ADLs and IADLs used by clinicians to identify older adults' cognitive and physical abilities.*[1]*

| ADLs | IADLs |
|---|---|
| Functional mobility | Care of others/pets/child rearing |
| Self-Feeding | Communication management |
| Eating | Community mobility |
| Dressing | Financial management |
| Personal hygiene and grooming | Health management and maintenance |
| Bathing and showering | Religious observance |
| Bowel and bladder management/toilet hygiene | Safety and emergency management |
| Sexual activity | Meal preparation and cleanup |
| Sleep | |

Patients' performance of ADLs are measured by clinicians, such as occupational therapists (OTs), and are used for evaluating physical abilities and independent function. These evaluations are used to prescribe interventions such as therapeutic exercises, caregiver assistance, or assistive equipment. Performance of ADLs also indicate a clients' mental well-being and contribute to patients' sense of independence and self-esteem.[1]

One method for determining patients' performance of ADLs is through clinician interviews. However, this method is often found to be insufficient since patient bias, confusion, self-efficacy, or memory loss may lead to inaccurate reporting.[1] It is therefore important for clinicians to additionally observe patients' ADLs and grade their abilities accordingly. This is not trivial since the optimal method for performing an ADL assessment is in the patients' natural setting at the usual time of occurrence.[1] For instance, a patient's morning routine should be observed within their home upon waking up. Simulating these tasks in an artificial environment, such as a clinician's office, many hours later, is sub-optimal as some patients will not be able to transfer their abilities over.[1] Furthermore, ADL evaluations determine patients' performance at one specific time. For many patients, performance may vary over time, depending on the patient's mood or other health factors. Longitudinal observance of ADLs gathers information from many temporal nodes, providing a richer understanding of patients' abilities.

## 3.2 Sensor Technology for Detecting ADLs

Installing sensors within a patient's residence resolves some of the challenges associated with OT evaluations. Sensors embedded in the home or worn by residents provide a continuous measure of ADL performance longitudinally. In order to evaluate patients, The Canadian Assessment of Daily Living[2] requires physicians to observe patients' mobility and locomotion abilities. In this assessment, patients demonstrate ADLs such as bed transfers, toilet transfers, walking indoors, climbing stairs, walking outdoors, and using assistive devices. By implementing sensors within the home, these tasks can be conducted remotely by patients, allowing for the assessment to occur within the person's natural setting, reducing travel time for clinicians, improving reliability, tracking progression of physical rehabilitation or degradation, providing fine-grained data, removing observation bias, and understanding long-term behaviour and abilities.

### *3.2.1 Mobility*

Walking ability is a very important feature to evaluate, as it has been shown to be the primary predictor of falls among older adults.[3] Besides causing painful acute injuries, such as fractures, falls can lead to increased life-changing consequences for older adults, as their likelihood to repeat a fall increases after their first incidence, significantly reducing their independence. Approximately one-third of older adults experience a fall every year, and for community-dwellers, 50-60% of these falls will occur within their homes.[4] In one study with 1465 respondents, 32.5% of participants fell while undergoing physical tasks such as bending, carrying objects, or completing chores.[3]

In order to detect changes in walking ability, research groups developed and evaluated sensors and electronic devices aimed at tracking gait characteristics remotely. [4]–[6]

Accelerometer measurements have shown to accurately determine walking characteristics such as stride frequency, walking speed, stride length, and symmetry, which have been strongly correlated with predicting falls of older adults.[4]

Increasing the number of inertial measurement sensors worn by residents can increase measurement sensitivity for tracking changes in walking ability. One study evaluated a body-suit with 17 mounted inertial measurement sensors and collected data from participants conducting a 6-minute walking test.[6] Clinically validating the suit with a group of cancer patients undergoing chemotherapy, the sensors quantitatively reported fatigue from the patients' postures.

Similarly, pressure sensors embedded within sneaker insoles have been demonstrated for remotely determining walking ability.[5] Clinically validating the technology with stroke survivors, the sensor readings were compared with the traditional Rivermead Mobility Index (RMI). Linear regression identified the *heel duration standard deviation* and *forefoot vs. heel maximum pressure standard deviation* as statistically significant features in predicting the RMI score.

### *3.2.2 Self-Care*

The Rivermead ADL Scale[7], [8] considers independent management of self-care activities as the most important indicator of a patient's recovery. The assessment suggests that washing, brushing teeth, dressing/undressing, and lavatory use are among some of the top predictors for determining functional ability. Among older adults, self-care and self-efficacy have been shown to be closely correlated, and are closely linked with overall well-being.[9] Cognitive impairment has also shown to be closely linked to performance of ADLs and IADLs such as showering and completing housework.[10]

Different sensor modalities have shown to detect self-care activities. For instance, Yin et al[11] retrospectively analyzed data from a wireless network of sensors tracking resident behaviour in a Smart Home. By analyzing the time series data of temperature and humidity readings in the bathroom and kitchen, researchers identified that natural background fluctuations correlated to activities such as bathing and cooking, respectively. Fusing different sensor data was also found to be useful. For identifying cooking activities, the humidity/temperature readings were combined with temporal data and measurements from a power meter connected to the stove.

Motion sensors fused with temporal data estimated activities such as making meals.[12] Fortin-Simard et al[13] explored the recognition of ADLs in the kitchen based on the Naturalistic Action Test (NAT), a clinical assessment of everyday cognitive activities. Implementing RFID antennas throughout the kitchen and tagging objects such as cups and plates, the researchers simulated 5 kitchen activities: making coffee, preparing a sandwich, making tea, making spaghetti, and preparing a bowl of cereal. Using a Bayesian network, the group achieved an activity recognition rate of 92.8%. Similarly, Jérémy Lapalu et al[14] implemented a variety of sensors such as RFID tags, pressure mats, localization systems, and audio devices. A participant conducted scenarios such as cooking, toileting, reading a book, and sleeping in the bedroom. An unsupervised clustering algorithm called the Flocking model was used and achieved a cluster purity of 92%.

### *3.2.3 Transfers*

Transfers, the phase in which a person transitions between sitting, standing, or lying positions, are ADLs that are performed dozens of times in a single day.[15, p.] Parameters associated to transfers are important to track as they can be linked to fall risk, mobility, physical decline and other age-related pathologies.[15], [16] These events occur frequently every day and are a promising variable to record and track longitudinally.

A number of different assessments have been evaluated to quantify transfers. Among them is the Timed Up and Go (TUG) test which measures the time it takes to stand up from a chair, walk 3 metres, turn around, return to the chair, and sit back down. The test was designed to assess fall risk but has also been used to monitor the progression of diseases including Parkinson's disease, Alzheimer's, and multiple sclerosis. Patients are asked to complete the test at a comfortable pace, measuring the time taken to complete the entire test with a standard stop watch. Research has been conducted on using IMUs to effectively monitor the TUG test and capture the duration of all phases, providing more fine-grained precision and insight than the traditional method. Research on sensor-based TUG tests have shown to identify frailty, correctly classify at-risk fallers, and predict symptoms of Parkinson's disease.[17]–[20]

The sit-to-stand (SiSt) duration has been identified as *"a representative measure of a person's status of physical mobility"*.[21] Wearable IMU sensors successfully determined the vertical acceleration and power associated with transferring from a sitting to standing position.[16] Less intrusive floor-mounted force plate sensors have also been used to determine the SiSt duration.[16, p.], [21] Other non-intrusive anonymous sensors such as PIR motion sensors and magnetic door contacts have been fused with temporal data to measure transfer durations indirectly.[12]

### *3.2.4 IADLs*

IADLs are tasks that are less predictable than traditional ADLs and require greater cognitive processing. These include the ability to use a telephone, shop, prepare food, maintain housekeeping, use transportation, adhere to medication, and handle finances.[22]

For instance, maintaining household tasks such as cleaning and preparing meals requires many different physical and cognitive abilities. As adults age, a reduction in strength, memory, and vision increases the difficulty to perform household tasks. The cognitive and physical state of older adults has been linked to their ability to maintain the demands of their environment[23]–[25]. Poor maintenance of an environment can also place a greater risk on older adults, as misplacing objects can lead to a less predictable environment and potentially introduce hazards that lead to falls.[26] Further study into older adults' ability to maintain their environment can inform us on how to develop environments that are optimized for aging and allow older adults to manage their environment independently.[26]

The Lawton IADL Scale is a questionnaire that measures the ability to perform IADLs. Although the Lawton Scale is simple to administer, it is determined through self-reports. Patient bias can skew the results to either under or overestimate ability. Therefore, remotely monitoring these tasks can greatly improve the accuracy of determining adults' performance.

In one study, IADLs such as telephone usage, food preparation, eating, filling a medication dispenser, writing a birthday card, writing a cheque, selecting an outfit and cleaning were detected in a smart apartment featuring an array of different sensor technologies.[27] Among these were motion sensors, temperature sensors, water usage sensors, stove usage sensors, and telephone usage tracking. It was found that an unsupervised method was able to correctly match 87.5% of sensor events to their correct clusters.

Another important IADL is adherence to medication. In the United States, approximately 87.7% of older adults are prescribed medication.[28] Drug noncompliance among older adults reportedly ranges between 40%-75% and can lead to adverse health effects such as worsening disease, increased hospitalization and increased therapy dosages leading to more severe side effects.[29], [30] Adherence to medication can provide insight into a patient's cognitive ability and development of age-related diseases such as Alzheimers.[31] Traditional methods of measuring adherence, such as pill-counting or patient testimonials, have shown to be inaccurate.[32] Alternatively, electronic pill management solutions such as the Medication Event Monitoring System (MEMS ®) by Aardex Group[33], MedTracker[34], and others[27], [30] have shown to be more robust than the current clinical gold-standard. Electronic solutions provide fine-grained insight into the date and time that pills are administered, specify days when pills are not adhered, and prompt patients to improve adherence. Providing a low-adhering patient with feedback about their pill usage was shown to improve compliance.[35] One study showed that a context-aware pill monitor combined with wearable and home sensors improved adherence from 68.1% to 92.3%.[27]

## 3.3 Smart Homes for Detecting ADLs

Research groups have recognized that the home is an advantageous setting to measure older adults' cognitive and physical abilities. Smart Home projects aimed at monitoring health are summarized in **Table 3.2.**

**Table 3.2** Researchers found in literature developing Smart Homes for remotely monitoring the health of older adults.

| Project | Activities | Sensors | Method | Reference |
|---|---|---|---|---|
| LIARA | Mobility | Passive RFID | Trilateration and Bayesian Network | [13] |
| | Preparing meals, reading a book, toileting, sleeping in the bedroom | Passive RFID, pressure mats, audio/video devices | Trilateration and Bayesian Network. Flocking model | [13], [14] |
| Smarter Safer Homes | Mobility | Motion | Binary sensors | [36] |
| | Bathing | Motion, temperature, humidity sensors | Markov chains, clustering | [11],[36] |
| | Device Usage | Circuit Monitoring | Markov chains, clustering | [36] |
| | Preparing and eating meals | Circuit Monitoring, reed switches, acoustic sensors | Markov chains, clustering | [36] |
| | Bed transfer and sleep quality | Accelerometer, motion | Markov chains, clustering | [36] |
| Smart Condo | Location | BLE, motion, RFID | Confidence maps | [37], [38] |
| Tiger Place | Mobility | Motion, Stove-monitoring, pressure, | Activity density map | [39], [40] |
| | Gait | Optical fiber | Low-pass Filter | [41] |
| AILISA | Mobility, eating, washing, grooming, sleeping | Motion sensor, magnetic door sensors | Activity sequence | [12] |
| CASAS Smart Home | Filling medication dispenser, watching DVD, watering plants, conversing on phone, writing birthday card, preparing meal, cleaning, and selecting outfit | Motion, temperature, water use, stove use, phone use, switch sensors on doors and cabinets, pressure sensors on items | Clustering | [27] |
| dwellSense | Medication adherence | Snap action switches, accelerometers | Temporal visualization of sensor events | [35], [42] |
| | Coffee making | Contact sensors | Temporal visualization of sensor events | [35] |
| | Phone use | Phone decoding circuit | Temporal visualization of sensor events | [35] |

**Table 3.2** is not an exhaustive list of all smart home research projects, but provides good insight into the technologies and platforms that have been used for monitoring many health related ADLs.

## 3.4 Our Smart Home Platform

Our research group constructed a smart home laboratory in a residential house to develop and evaluate devices aimed at improving the well-being of older adults, providing relief for caregivers and generating valuable information for clinicians.

The smart home laboratory was developed to facilitate short-term and long-term research. As technologies improve and new standards are introduced, it is important that the home can be modified with ease to incorporate future innovation and replace obsolete technology. Thus, the home platform was designed to be modular, in order to embed various devices and technologies, both foreseen and unforeseen.

The primary objective of this project was to create a collaborative environment for a range of research faculties at McMaster University, external researcher, industry partners, healthcare professionals, policy makers, and healthcare utilizers, dedicated to improving the quality of life for older adults. This objective involves developing innovative technology and gaining an understanding of the behaviour of users, caregivers, and clinicians utilizing a smart home.

### *3.4.1 Smart Home Features*

The smart home platform is represented in **Figure 3.1**. An electrical raceway was installed along the perimeter of the walls in order to mount, power, provide a communication channel for sensors through a Cat6 and an AC power line. As IoT devices continue to populate the marketplace, this raceway will provide the communication and power required for enabling such devices, particularly power-over-Ethernet (PoE) devices. The modularity of the raceway allows for implementation of other wireline standards such as fibre optic cables. Another foreseen wireline technology is low-voltage DC power and communication, which has become increasingly popular in controlling lighting and devices in commercial buildings. This also enables DC microgrids which use DC power sources such as solar panels or batteries to power DC devices such as LEDs, improving energy efficiency.

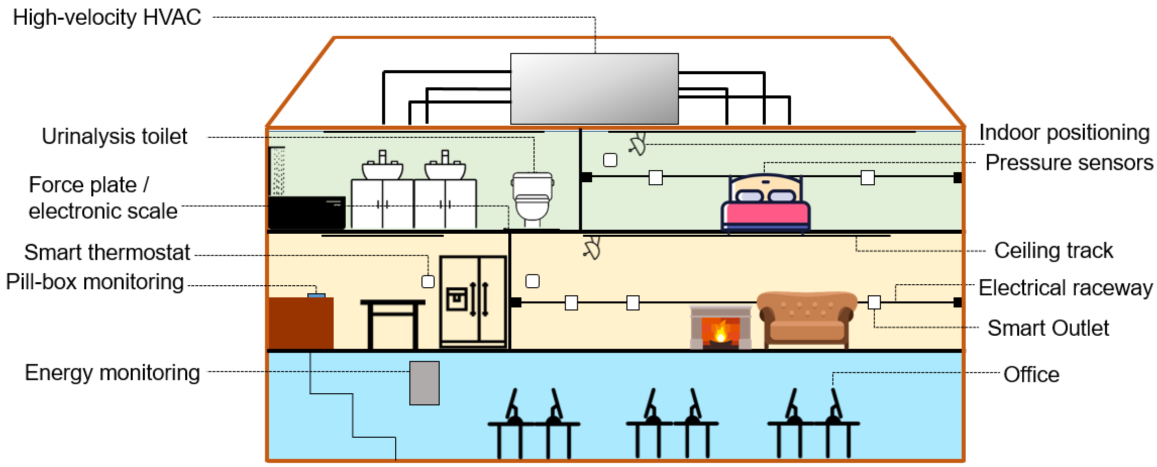


**Figure 3.1** A representation of our Smart Home platform for developing and evaluating remote sensing technology for enabling aging in place.

Electrical tracks were installed along the ceilings to provide power for lighting and sensors. Ceiling mounted sensors included RFID antennas, Bluetooth transceivers, motion sensors, and cameras.

The washroom is an important area to monitor since ADLs such as washing, grooming and toileting occur there. A custom toilet with an accessible drain was implemented in order to develop a smart toilet monitoring system. The system is intended for monitoring toileting frequency and evaluating remote point-of-care devices for monitoring urinary tract infections (UTIs) and kidney function automatically. A force plate at the base of the toilet is used to automatically monitor adult's sit-to-stand time, which has been linked with walking ability, and monitor changes in weight.

A smart thermostat system along with a high velocity HVAC system was used to accurately and quickly set precise temperature zones within the house. This is intended to determine the effects of temperature and humidity environment on aging, in order to establish the optimal setting for aging within the home.

The indoor positioning systems (IPSs) discussed in **Chapters 4** and **5** were installed in rooms throughout the home. Although IPSs did not feature the use of invasive sensors such as cameras, these would be installed along the ceiling track to determine the accuracy and reliability of the IPSs, as they provide accurate ground-truth measurements. To supplement the IPSs, a commercial smart-lock was implemented within the home in order to identify when residents enter and leave the home, as well as to know if they are receiving caregiver assistance.

An energy monitoring system was installed in the electrical panel of the home. The system, along with individual smart outlets, are used to identify ADLs. For instance, stove use and laundry machine use can be indicative of cooking and completing housework, respectively.

The basement of the house has been retrofitted into an office setting to allow researchers to monitor participants simulating various ADLs throughout the day and night, without interfering in the studies.

## 3.5 Conclusion

As the population continues to age, many older adults seek to stay in their homes where they have a high level of independence, a social network, performance of personal habits, and confidence. Health-monitoring technologies embedded in the home and worn by residents can enable older adults to extend their length of stay in the home, while providing relief to formal caregivers as well as informal caregivers such as family members and friends. A "smart home" can monitor residents and collect, store, analyze, and share health-related information by means of utilizing innocuous cost-efficient sensors while residents perform ADLs. A smart home can also provide feedback for the resident through automatic control of appliances and living conditions, such as temperature and lighting, to enhance quality of life.

In this chapter, sensors for monitoring health-related ADLs and IADLs were reviewed. The Chapter also provided a description and analysis of a smart home laboratory in a residential home, which was constructed to develop, validate, and improve devices aimed at improving the well-being of older adults, providing relief for caregivers, and generating valuable information for clinicians.

Furthermore, research into understanding the interaction between older adults and their environment can inform us on how to develop environments that are optimized for aging and allow older adults to manage their environment independently.[26]

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# Chapter 4

# Hybrid Bluetooth Low Energy Indoor Positioning System

## 4.1 Introduction

As the baby-boomer population, North America's largest demographic, continues to enter late adulthood, strain on healthcare systems and governments will continue to increase. As discussed in **Chapter 1**, healthcare costs significantly increase as adults reach older age. New models of care are leveraging wearable health monitoring technology to diagnose stages of aging outside of traditional healthcare institutions. Places of living serve as promising platforms to host technology for monitoring health related activities of daily living (ADLs) such as mobility, which provides insight into cognitive and psychosocial status, as well as predicts falls, which can significantly reduce quality of life of older adults.

Mobility can be categorized as community mobility and functional mobility. Community mobility, which includes outdoor activities such as walking, bicycling, driving and other modes of transportation[1], has been well documented for monitoring with commercial GPS-enabled devices such as smart phones and wearable activity trackers.[2] Functional mobility describes the motions required to complete ADLs such as standing, bending, walking, and climbing movements and is a strong predictor of falls, most of which occur within homes.[3], [4] Due to short travelling distances, GPS-enabled devices do not provide the required resolution for monitoring functional mobility within the home.

In this chapter, the development and subsequent implementation of an indoor positioning system (IPS) for monitoring mobility within the home is described. The system integrates Bluetooth Low Energy (BLE), ultrasonic (US) range finders, and radar motion sensors to determine the direction and identification of people crossing through doorways.

## 4.2 Doorway Monitoring Systems

Doorway monitoring systems, which are a subset of IPSs, identify two characteristics of a person travelling through a doorway – their identification and direction of travel.[5] System implementation is limited to the doorway of a home, achieving room-level accuracy and providing insight into ADLs such as sleeping patterns, social interactions, grooming, toileting, and eating, among others. Doorway systems benefit from deployment ease and short installation time since sensor placement and distribution does not require planning or expertise to attain optimal coverage. This can reduce the number of sensors and the overall system cost.

## 4.3 Materials and Methods

As discussed in **Section 2.3**, motion sensor based IPSs depend on biometric data to identify residents. This becomes increasingly challenging to track when multiple residents have similar biometric characteristics. To address this issue, we implemented a hybrid doorway monitoring system consisting of anonymous motion sensors fused with eponymous BLE transceivers. Deployment ease is further improved as the doorway system does not implement machine learning techniques required by traditional BLE IPS systems. For instance, IPS techniques such as trilateration require offline radio maps. Producing radio maps requires multiple users to complete trajectories throughout a building. This is a time consuming process which must be repeated when objects, such as furniture, are relocated or removed. This is not required in our system, enabling it to be quickly installed and setup as plug-and-play. Furthermore, the system computes location locally at each doorway node. This decentralized approach improves scalability since computation time and complexity is independent of the number of sensors deployed and a server application is not required to store the relative position of each doorway. The resolution of doorway system can be further improved by creating “virtual doorways” to monitor ambulation in corridors.

Motion sensors (radar and PIR) and range-finders (IR and US) were characterized to determine the optimal modality for identifying direction of travel through the doorway. BLE transceivers were attached to doorframes and worn by volunteers to identify people crossing the doorway. The optimal transmission power and thresholds for the BLE transmitters were determined to discriminate between multiple people residing in the same room. The sensor system was then combined to identify multiple residents within multiple rooms in the home.

### *4.3.1 Direction Sensor Selection*

A resident’s direction of travel was determined through the implementation of anonymous motion sensors. By supplementing numerous costly eponymous radio transceivers with inexpensive anonymous motion sensors, the overall system cost is reduced. In order to determine the optimal sensor modality for detecting the direction of travel, four different sensor modalities were evaluated. Key metrics for the radar, PIR, ultrasonic range-finding, and IR range-finding sensors were characterized.

#### *4.3.1.1 Ultrasonic Range Finders*

The detection angle of a digital US sensor (DFRobot URM37 V4.0, 40 kHz) was evaluated by placing a white box (dim 9.4*10.4*5.2 cm) at varying discrete angles (0-30$^o$, with 15$^o$ intervals) and distances (5-400 cm, with 5 cm intervals) from the sensor in a laboratory environment as shown in **Figure 4.1**. An Arduino Uno microcontroller was used for data acquisition**.** The experiment was repeated five times at each angle. The actual distance, average measured distance, and standard deviation are shown in **Table 4.1** and **Figure 4.2.**

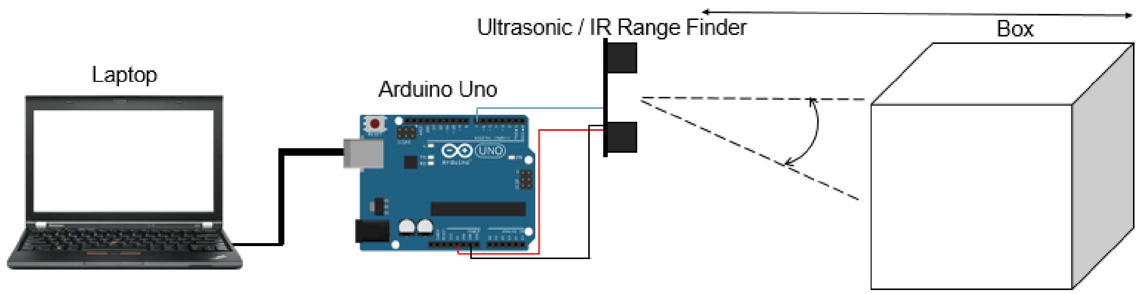



**Figure 4.1** Experimental setup for determining the detection angle and range of the US and IR rangefinder.

The results in **Table 4.1** and **Figure 4.2** illustrate that for the entire 400 cm length, the US sensor achieved mostly accurate distance measurements when the object appeared directly in front of the sensor, with some significant errors occurring between 290 cm and 395 cm. When the object appeared 15$^o$ from the centre of the sensor, the measurements remained accurate for a range of 155 cm. For a 30$^o$ angle, the system was accurate up to 90 cm. These results show that the US sensors evaluated are highly predictable and accurate, and have a detection angle of 30$^o$ within a 90 cm range.

**Table 4.1** Average distances and corresponding standard deviations between measured from an ultrasonic range finder.

| Actual distance ± 0.05 (cm) | 0 deg Average Distance (cm) | SD (cm) | 15 deg Average Distance (cm) | SD (cm) | 30 deg Average Distance (cm) | SD (cm) |
|---|---|---|---|---|---|---|
| 5.0 | 5 | 0 | 5 | 0 | 5 | 0 |
| 10.0 | 9 | 0 | 10 | 0 | 10 | 0 |
| 15.0 | 14.4 | 0.5 | 15 | 0 | 15 | 0 |
| 20.0 | 19 | 0 | 20 | 0 | 20 | 0 |
| 25.0 | 25 | 0 | 25 | 0 | 25 | 0 |
| 30.0 | 29 | 0 | 30 | 0 | 30 | 0 |
| 35.0 | 35 | 0 | 35 | 0 | 35 | 0 |
| 40.0 | 39 | 0 | 40 | 0 | 40 | 0 |
| 45.0 | 45 | 0 | 45 | 0 | 45 | 0 |
| 50.0 | 49 | 0 | 50 | 0 | 50 | 0 |
| 55.0 | 55 | 0 | 55 | 0 | 55.4 | 0.5 |
| 60.0 | 60 | 0 | 60 | 0 | 61 | 0 |
| 65.0 | 66 | 0 | 65 | 0 | 67 | 0 |
| 70.0 | 70 | 0 | 70 | 0 | 70 | 0 |

| | | | | | | |
|---|---|---|---|---|---|---|
| 75.0 | 75 | 0 | 75 | 0 | 75 | 0 |
| 80.0 | 80 | 0 | 80.8 | 0.4 | 82 | 0 |
| 85.0 | 85 | 0 | 86 | 0 | 86.6 | 0.5 |
| 90.0 | 90 | 0 | 90 | 0 | 92 | 0 |
| 95.0 | 95 | 0 | 95 | 0 | N.A. | N.A. |
| 100.0 | 100 | 0 | 100 | 0 | N.A. | N.A. |
| 105.0 | 106 | 0 | N.A. | N.A. | N.A. | N.A. |
| 110.0 | 111 | 0 | 109 | 0 | N.A. | N.A. |
| 115.0 | 116 | 0 | 114 | 0 | N.A. | N.A. |
| 120.0 | 122 | 0 | 119 | 0 | N.A. | N.A. |
| 125.0 | 127 | 0 | 124.6 | 0.8 | N.A. | N.A. |
| 130.0 | 131 | 0 | 128 | 0 | N.A. | N.A. |
| 135.0 | 134 | 0 | 133.8 | 0.9 | N.A. | N.A. |
| 140.0 | 139.4 | 0.5 | 138 | 0 | N.A. | N.A. |
| 145.0 | 145 | 0 | 143 | 0 | N.A. | N.A. |
| 150.0 | 150 | 0 | 152 | 4 | N.A. | N.A. |
| 155.0 | 155.4 | 0.5 | 155 | 0 | N.A. | N.A. |
| 160.0 | 160 | 0 | N.A. | 0 | N.A. | N.A. |
| 165.0 | 165.8 | 0.4 | N.A. | N.A. | N.A. | N.A. |
| 170.0 | 170 | 0 | N.A. | N.A. | N.A. | N.A. |
| 175.0 | 175 | 0 | N.A. | N.A. | N.A. | N.A. |
| 180.0 | 180 | 0 | 180 | 0 | N.A. | N.A. |
| 185.0 | 184.6 | 0.5 | N.A. | 0 | N.A. | N.A. |
| 190.0 | 189.4 | 0.5 | N.A. | N.A. | N.A. | N.A. |
| 195.0 | 195.2 | 0.4 | 221 | 1 | N.A. | N.A. |
| 200.0 | 199.8 | 0.4 | N.A. | N.A. | N.A. | N.A. |
| 205.0 | 204 | 0 | N.A. | N.A. | N.A. | N.A. |
| 210.0 | 208.6 | 0.5 | N.A. | N.A. | N.A. | N.A. |
| 215.0 | 214.4 | 0.5 | N.A. | N.A. | N.A. | N.A. |
| 220.0 | 219 | 0 | N.A. | N.A. | N.A. | N.A. |
| 225.0 | 224.4 | 0.5 | N.A. | N.A. | N.A. | N.A. |
| 230.0 | 230 | 0.6 | N.A. | N.A. | N.A. | N.A. |
| 235.0 | 234.8 | 0.4 | N.A. | N.A. | N.A. | N.A. |
| 240.0 | 239.8 | 0.4 | N.A. | N.A. | N.A. | N.A. |
| 245.0 | 245.4 | 0.5 | N.A. | N.A. | N.A. | N.A. |
| 250.0 | 249 | 1 | N.A. | N.A. | N.A. | N.A. |
| 255.0 | 255.2 | 0.4 | N.A. | N.A. | N.A. | N.A. |
| 260.0 | 258.8 | 0.4 | N.A. | N.A. | N.A. | N.A. |
| 265.0 | 264.8 | 0.4 | N.A. | N.A. | N.A. | N.A. |
| 270.0 | 270.8 | 0.7 | N.A. | N.A. | N.A. | N.A. |
| 275.0 | 276.0 | 0.6 | N.A. | N.A. | N.A. | N.A. |
| 280.0 | 283 | 2 | N.A. | N.A. | N.A. | N.A. |
| 285.0 | 286 | 1 | N.A. | N.A. | N.A. | N.A. |
| 290.0 | 4 | 0 | N.A. | N.A. | N.A. | N.A. |
| 295.0 | 295.6 | 0.8 | N.A. | N.A. | N.A. | N.A. |
| 300.0 | 303 | 2 | N.A. | N.A. | N.A. | N.A. |
| 305.0 | 305.6 | 0.8 | N.A. | N.A. | N.A. | N.A. |
| 310.0 | 310.8 | 0.4 | N.A. | N.A. | N.A. | N.A. |
| 315.0 | 316 | 0 | N.A. | N.A. | N.A. | N.A. |
| 320.0 | 320 | 0 | N.A. | N.A. | N.A. | N.A. |
| 325.0 | 325.8 | 0.4 | N.A. | N.A. | N.A. | N.A. |
| 330.0 | 330.6 | 0.5 | N.A. | N.A. | N.A. | N.A. |
| 335.0 | **224** | **156** | N.A. | N.A. | N.A. | N.A. |
| 340.0 | **273** | **135** | N.A. | N.A. | N.A. | N.A. |
| 345.0 | 347 | 1 | N.A. | N.A. | N.A. | N.A. |
| 350.0 | 350.6 | 0.5 | N.A. | N.A. | N.A. | N.A. |
| 355.0 | 355.8 | 0.4 | N.A. | N.A. | N.A. | N.A. |
| 360.0 | 361.2 | 0.7 | N.A. | N.A. | N.A. | N.A. |
| 365.0 | 365.4 | 0.5 | N.A. | N.A. | N.A. | N.A. |
| 370.0 | **77** | **148** | N.A. | N.A. | N.A. | N.A. |
| 375.0 | 4 | 0 | N.A. | N.A. | N.A. | N.A. |
| 380.0 | 4 | 0 | N.A. | N.A. | N.A. | N.A. |

| | | | | | | |
|---|---|---|---|---|---|---|
| 385.0 | 4 | 0 | N.A. | N.A. | N.A. | N.A. |
| 390.0 | 392 | 0 | N.A. | N.A. | N.A. | N.A. |
| 395.0 | 4 | 0 | N.A. | N.A. | N.A. | N.A. |
| 400.0 | 399.0 | 0.6 | N.A. | N.A. | N.A. | N.A. |

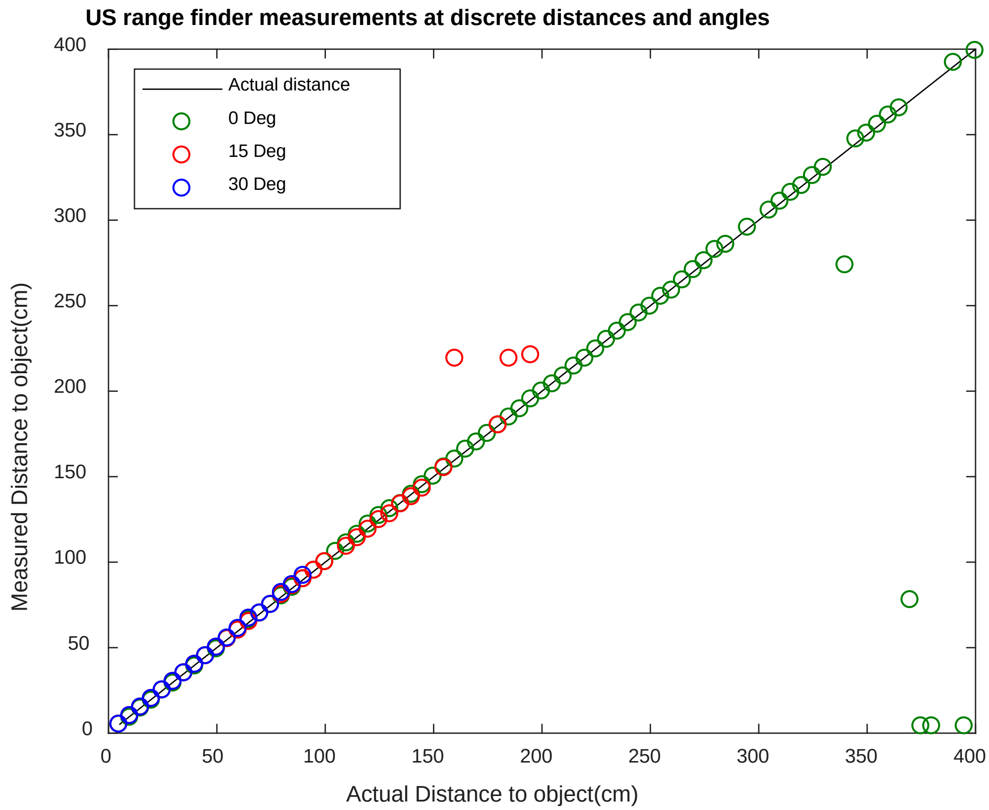



**Figure 4.2** Average measurements of objects from US range finder at discrete angles of $0^o$, $15^o$ and $30^o$. Distances between the object and sensor ranged from 0-400 cm, with 5 cm intervals. Distance measurements were repeated 3 times.

### *4.3.1.2 Infrared Range Finders*

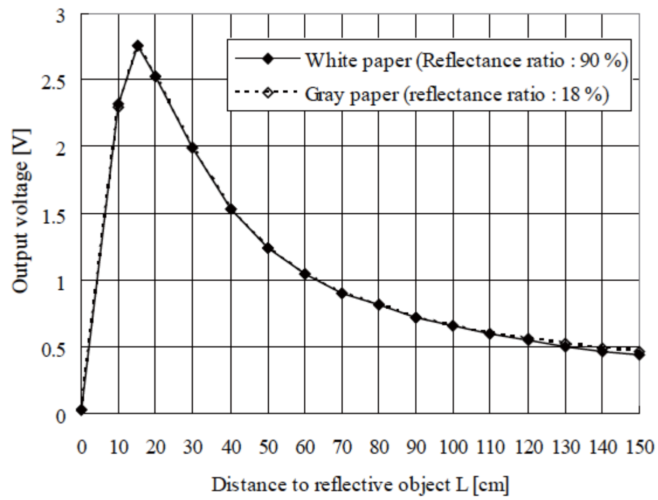
The infrared (IR) range finding sensors (SHARP GP2Y0A21YK0F) output an analog signal that is related to the distance (shown in **Figure 4.3 (A)**). The distance and angle measurements depicted in **Figure 4.1** were repeated for a white surface and a black surface to determine how light absorption affected the distance measurements. The measurements were conducted at discrete angles (0-30$^o$) and distances (0-150 cm). The measurements were repeated five times, with the results shown in **Table 4.2, Figure 4.3 (B)** and **Figure 4.4.**

The results show that measuring the white surface at $0^o$ closely matched the expected results in **Figure 4.3 (A)** for the entire length measured. The measurements of the black surface matched closely with the white surface between 0-35 cm but then diverged and plateaued at 1.4 V. Because of this plateau, the measuring distance of the sensor was limited to 15-45 cm, with ambiguity due to colour dependence. The angled measurements were significantly more volatile than the measurements directly in front of the sensor and were deemed inappropriate for determining distance.

**Table 4.2** Results from discretely varying angle and distance of measured object from IR Range Finder.

| | 0 Deg White | | 15 Deg White | | 30 Deg White | | 0 Deg Black | | 15 Deg Black | | 30 Deg Black | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Distance (cm)** | **Average Distance (cm)** | **SD (cm)** | **Average Distance (cm)** | **SD (cm)** | **Average Distance (cm)** | **SD (cm)** | **Average Distance (cm)** | **SD (cm)** | **Average Distance (cm)** | **SD (cm)** | **Average Distance (cm)** | **SD (cm)** |
| 5 | 1.7949 | 0.003 | 1.8389 | 0.061 | 2.073 | 0.010 | 2.035 | 0.072 | 1.690 | 0.061 | 1.418 | 0.020 |
| 10 | 2.6094 | 0.020 | 2.7324 | 0.003 | 1.149 | 0.003 | 2.613 | 0.002 | 2.683 | 0.004 | 1.242 | 0.007 |
| 15 | 2.7783 | 0.009 | 0.96582 | 0.013 | 1.381 | 0.009 | 2.792 | 0.013 | 2.074 | 0.013 | 1.235 | 0.009 |
| 20 | 2.5986 | 0.066 | 0.90625 | 0.007 | 1.407 | 0.082 | 2.008 | 0.002 | 1.376 | 0.083 | 1.252 | 0.043 |
| 25 | 2.1992 | 0.003 | 1.123 | 0.017 | 1.353 | 0.020 | 2.235 | 0.004 | 1.201 | 0.003 | 1.210 | 0.008 |
| 30 | 1.9551 | 0.003 | 1.1855 | 0.070 | 1.381 | 0.086 | 2.003 | 0.009 | 1.194 | 0.008 | 1.255 | 0.076 |
| 35 | 1.6895 | 0.012 | 1.1875 | 0.082 | | | 1.754 | 0.002 | 1.248 | 0.081 | | |
| 40 | 1.5264 | 0.003 | 1.1348 | 0.023 | | | 1.645 | 0.045 | 1.185 | 0.015 | | |
| 45 | 1.3516 | 0.002 | 1.1758 | 0.072 | | | 1.472 | 0.003 | 1.201 | 0.084 | | |
| 50 | 1.249 | 0.027 | | | | | 1.399 | 0.011 | | | | |
| 55 | 1.1641 | 0.003 | | | | | 1.353 | 0.000 | | | | |
| 60 | 1.0811 | 0.006 | | | | | 1.315 | 0.002 | | | | |
| 65 | 1.0107 | 0.027 | | | | | 1.319 | 0.011 | | | | |
| 70 | 1.0049 | 0.002 | | | | | 1.317 | 0.009 | | | | |
| 75 | 0.95508 | 0.016 | | | | | 1.331 | 0.003 | | | | |
| 80 | 0.9502 | 0.003 | | | | | 1.346 | 0.010 | | | | |
| 85 | 0.93262 | 0.008 | | | | | 1.370 | 0.003 | | | | |
| 90 | 0.9834 | 0.122 | | | | | 1.421 | 0.013 | | | | |
| 95 | 0.9248 | 0.034 | | | | | 1.460 | 0.009 | | | | |
| 100 | 0.72852 | 0.002 | | | | | 1.282 | 0.067 | | | | |
| 105 | 0.74805 | 0.036 | | | | | 1.240 | 0.050 | | | | |
| 110 | 0.71191 | 0.002 | | | | | 1.233 | 0.012 | | | | |
| 115 | 0.69336 | 0.000 | | | | | 1.269 | 0.014 | | | | |
| 120 | 0.66602 | 0.009 | | | | | 1.285 | 0.020 | | | | |
| 125 | 1.0674 | 0.046 | | | | | 1.376 | 0.061 | | | | |
| 130 | 0.69629 | 0.007 | | | | | 1.391 | 0.014 | | | | |
| 135 | 0.69238 | 0.002 | | | | | 1.451 | 0.009 | | | | |
| 140 | 0.70117 | 0.011 | | | | | 1.507 | 0.089 | | | | |
| 145 | 0.74609 | 0.074 | | | | | 1.483 | 0.078 | | | | |
| 150 | 0.70313 | 0.045 | | | | | 1.525 | 0.075 | | | | |

(A)




(B)

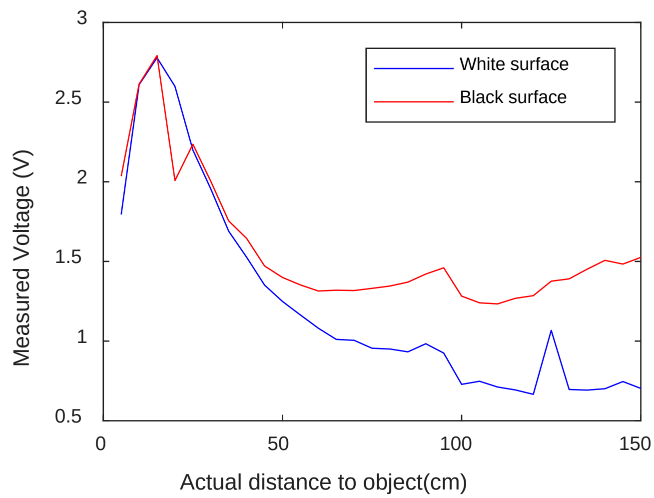



**Figure 4.3** (A) Expected voltage measurements from IR range-finding sensors for white and gray surfaces at distances between 0 cm and 150 cm away. **Figure reproduced from datasheet**. (B) Actual voltage measurements from IR range-finding sensor for white and black surface objects at distances between 0 cm and 150 cm away.

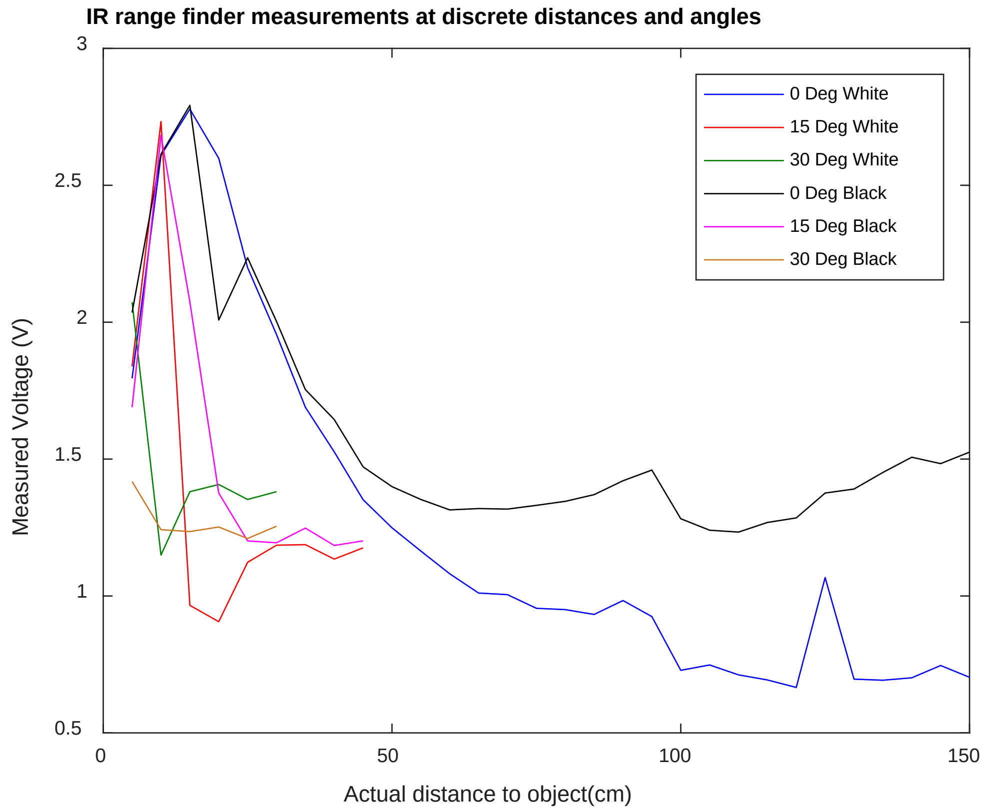



**Figure 4.4** Voltage measurements from IR range-finding sensor for white and black objects at discrete angles, ranging between $0^o$ and $30^o$, and distances, ranging between $0^o$ and $150^o$.

#### *4.3.1.3 Doppler Radar Motion Sensors*

The motion sensor (DF Robot SEN0192 10.525 GHz) is a binary sensor that transmits a microwave signal and uses the Doppler Effect to detect a shift in frequency caused by relative movement. Since the sensor detects binary movement and not absolute distance, the previous experimental setup was deemed inapplicable and a different experimental procedure was used. For the following experiments, a person stood in front of the sensors at discrete angles and distances, and moved slightly side-to-side, triggering the motion sensor.

A potentiometer on the sensor was used for adjusting the maximum detection distance, which was documented to range between 2-16 m.[6] All of the measurements were conducted with the potentiometer tuned to its lowest value, as a decreased specificity was observed at higher sensitivities.

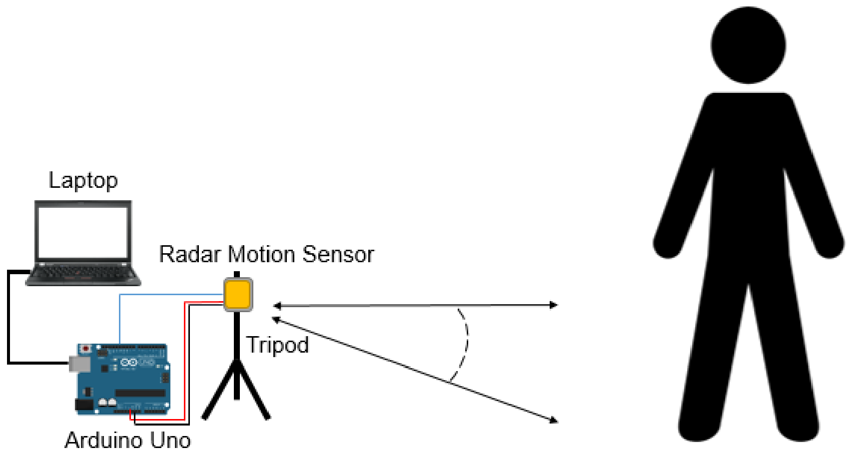



**Figure 4.5** Experimental setup for determining the detection angle and range of radar motion sensors. A person swayed from side-to-side while remaining in the same position at discrete distances and angles. The experimental setup was repeated for PIR motion sensors in Section 5.6.1.4.

The results depicted in **Figure 4.6** agreed with the specification in the datasheet, as the sensor consistently measured movement in the range of 0 – 200 cm when the person stood directly in front. Movement was inconsistently detected between 220 – 300 cm. Beyond 310 cm, no movement was detected. The sensor documentation specifies a 3 dB beam width of 72°. In our experiment, consistent motion tracking reduced to 0 – 40 cm at a 15° orientation, but did not reduce significantly further at greater angles. At a 60° angle, the sensor consistently detected motion in a range of 0 – 30 cm, and inconsistently measured motion between 40 and 90 cm.

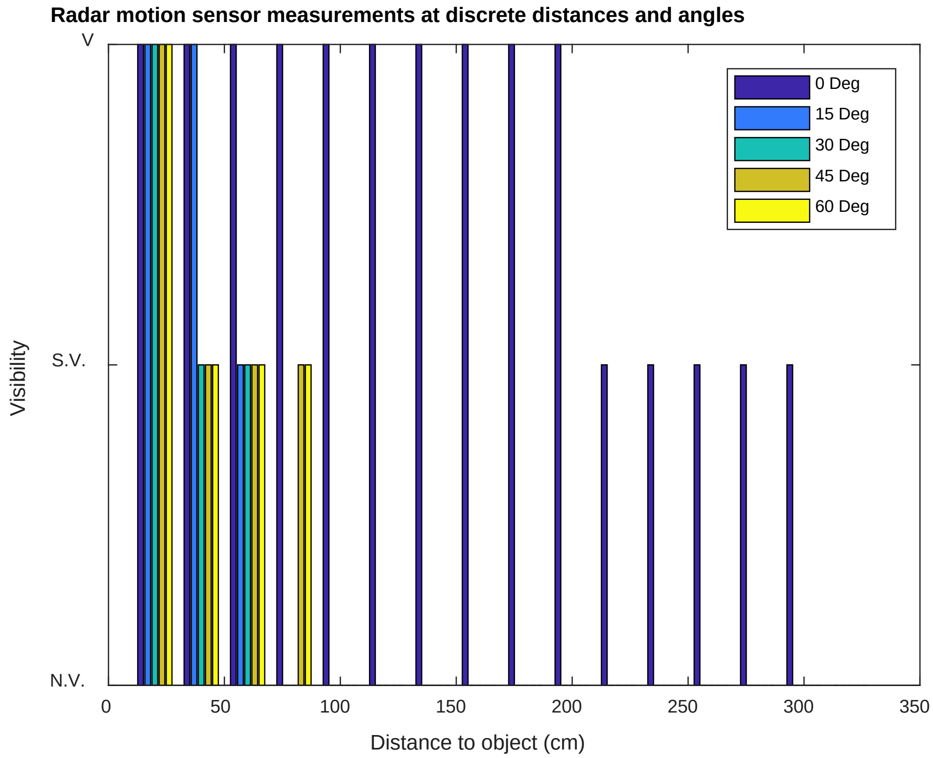



**Figure 4.6** Radar motion sensor results for detecting movement at discrete angles (0-60$^{o}$) and distances (0-350 cm). The experiments identified whether a person was Visible (V), Sometimes Visible (S.V.) or Not Visible (N.V.) to the sensor.

#### *4.3.1.4 PIR Motion Sensors*

PIR motion sensors detect movement when the IR radiation in the detection area, emitted from warm-bodies like humans, differs from ambient IR radiation. The wide angle PIR sensor (Phi Robotics PIR motion sensor) is a binary sensor with a maximum detection distance of 7 m and a maximum detection angle of 110$^{o}$. Two potentiometers on the sensor module modify the sensitivity and delay time. Since increased sensitivity can lead to reduced specificity for the sensor, the potentiometer was reduced to the lowest sensitivity and delay time for the evaluation. The experimental setup depicted in **Figure 4.5** was reused, and the radar motion sensor was swapped for a PIR motion sensor. The results for evaluating the sensor's detection range at discrete angles and distances are shown in **Figure 4.7.**

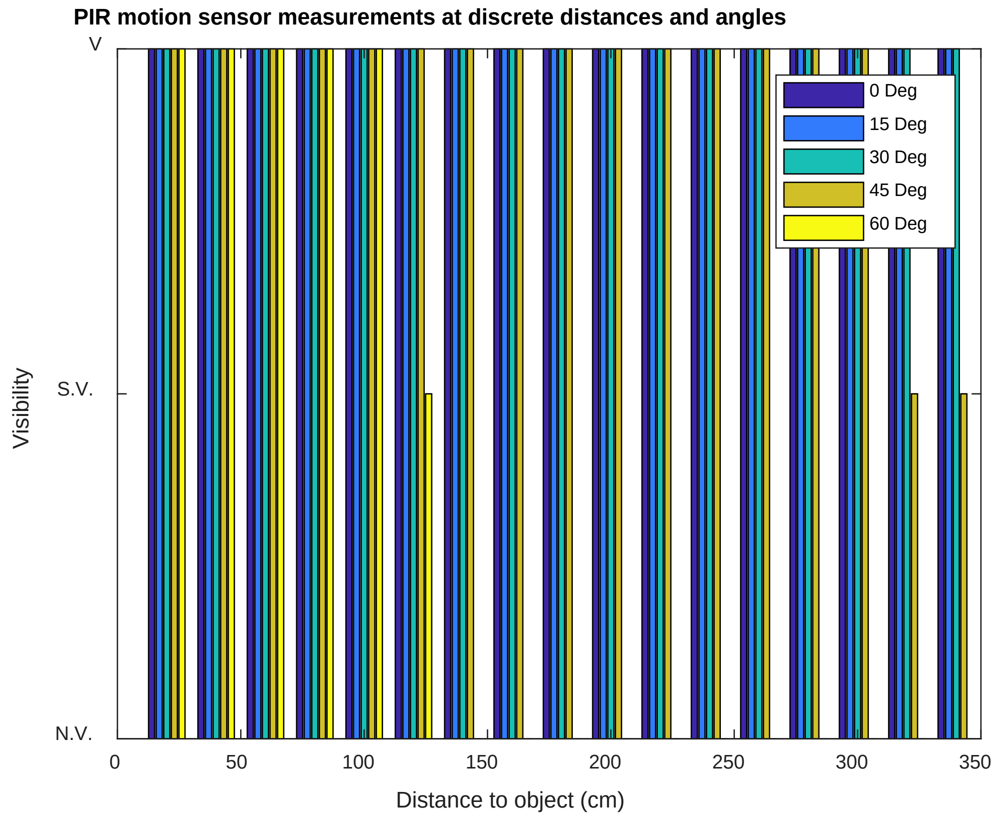



**Figure 4.7** PIR motion sensor results for detecting movement at discrete angles (0-60$^{o}$) and distances (0-350 cm). The experiments identified whether a person was Visible (V), Sometimes Visible (S.V.) or Not Visible (N.V.) to the sensor.

The sensor exceeded its documented expectations for low angle measurements which specified a maximum detection range of 300 cm. In our measurements, the sensor accurately detected motion at 350 cm for low angle tests. At 45$^{o}$, the sensor accurately observed motion within 300 cm. The sensor's sensitivity reduced at 60$^{o}$ for measurements beyond 100 cm.

### *4.3.2 Summary of Sensor Evaluations*

Low-cost motion and range-finding sensors were evaluated to identify the optimal modality for detecting direction of travel through the doorway. The experiments are summarized in **Table 4.3**. Due to the dynamic nature of home environments where objects, such as furniture or people, do not always remain in a static location, Doppler and pyroelectric sensors (or radar and PIR, respectively) were identified as the most suitable candidates, since they detect changes in motion, not distance alone. These sensors also demonstrated the widest detection angles. As such, the PIR and radar sensors were identified as the most promising sensors.

In **Table 4.3**, the time delay for resetting motion sensors is shown. For PIR sensors, a 0.5 s delay is necessary for calibrating background infrared radiation. It is inherent in most low-cost commercial PIR sensors and cannot be reduced. This delay limits the detection rate of the doorway monitoring system and omits people walking through the doorway. Consequently, the PIR sensors were abandoned and the radar sensors, which had a significantly shorter delay period, were chosen for further evaluation.

**Table 4.3** Summary of low-cost motion and range finding sensors evaluated for detecting the direction of a person crossing through a doorway.

| Modality | Trigger | Detection angle | Max Detection range (m) | Delay | Description | Output |
|---|---|---|---|---|---|---|
| Radar[6] | Change in microwave frequency | 60° | 2-16 | 5us | DF ROBOT SEN1092 10.525 GHz | Binary |
| Ultrasonic[7] | Sound wave ToF | 15° | 2-4 | 100 ms | DF ROBOT URM37 V4.0 | Distance |
| IR[8] | EM wave ToF | < 15° | 0.45 | 40 ms | SHARP GP2Y0A21YK0F | Analog Voltage |
| PIR[9] | Change in IR radiation | 60°-110° | 3-7 | 0.5 – 18.2 s | Phi Robotics PIR motion sensor | Binary |

### *4.3.3 Detecting Direction of Travel through Doorway*

An outward facing motion sensor was installed on each side of the doorway. A Raspberry Pi 3 Model B (RPi) acquired the sensor signal, computed the direction, and stored the result in a local SQL database. A flowchart for the algorithm used to determine direction is shown in **Figure 4.8** below.

To evaluate direction accuracy, a person crossed through a doorway 30 times. This experiment was repeated 3 times. The results of this experiment are shown in **Table 4.4** below.

**Table 4.4** Detected direction of a single person crossing through a doorway using radar Doppler sensors. A person crossed through the doorway 30 times, and the experiment was repeated 3 times.

| Trial | Correct Direction Detected | Incorrect Direction Detected | Total Detections |
|---|---|---|---|
| 1 | 29 | 1 | 30 |
| 2 | 29 | 1 | 30 |
| 3 | 28 | 2 | 30 |

The system observed successful direction identification with an accuracy of 96% and probability of correct detection of 85% with 85% confidence.

### *4.3.4 Selecting Bluetooth Technology*

As discussed in **Chapter 2**, Bluetooth Low Energy (BLE) is a wireless communication protocol. The protocol was originally designed for personal area networks (PANs) to extend the functionality of phones and PCs, but has also shown to be a promising technology for indoor positioning. The benefits of implementing BLE for indoor positioning are its low cost, low energy consumption, ubiquity in mobile phones and activity trackers, and low foot-print.

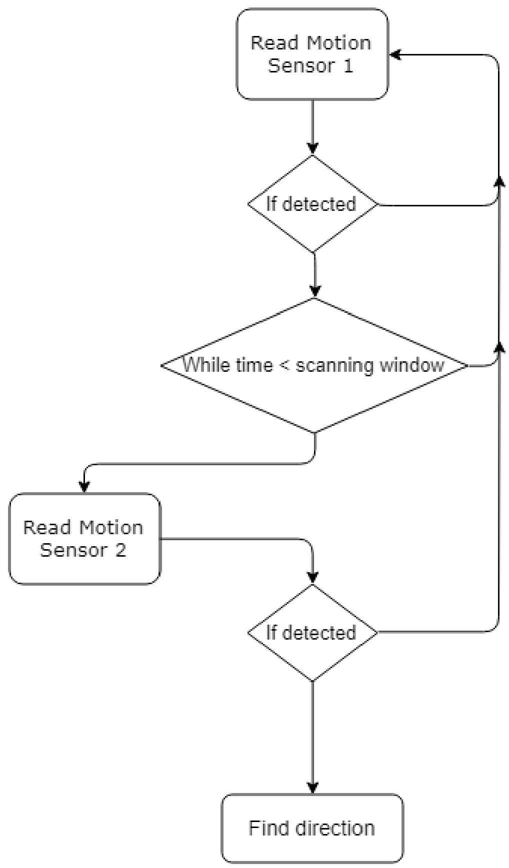



**Figure 4.8** Flowchart of algorithm for detecting the direction of a person crossing through a doorway using a motion sensor on each side of the door.

## 4.4 Single Person Monitoring

In **Section 4.3.3** it was suspected that the falsely identified crossing events were caused by movement occurring simultaneously on opposite sides of the doorway. This occurred because the system could not accurately differentiate between a person passing through the doorway, and movement occurring on opposite sides, with no crossing event. To reconcile this error, an ultrasonic range finder directed across the doorway path was integrated into the system. Additionally, a BLE receiver (Bluegiga BLE 113), connected to the RPi UART through an Arduino Uno microcontroller, was implemented to identify the person crossing through the doorway. A BLE transmitter was worn on a bracelet by the user to transmit a unique identification number to the receiver.

The hybrid doorway monitoring system is depicted in **Figure 4.9.** The system diagram and algorithm for the updated doorway monitor are shown in **Figure 4.10** and **Figure 4.11**, respectively. In order to scale the system for multiple doorways, the data was sent over TCP/IP to a remote RPi server on the local area network (LAN). The organization of the data packet was: *<room id, person id, RSSI, direction, date&time>*.

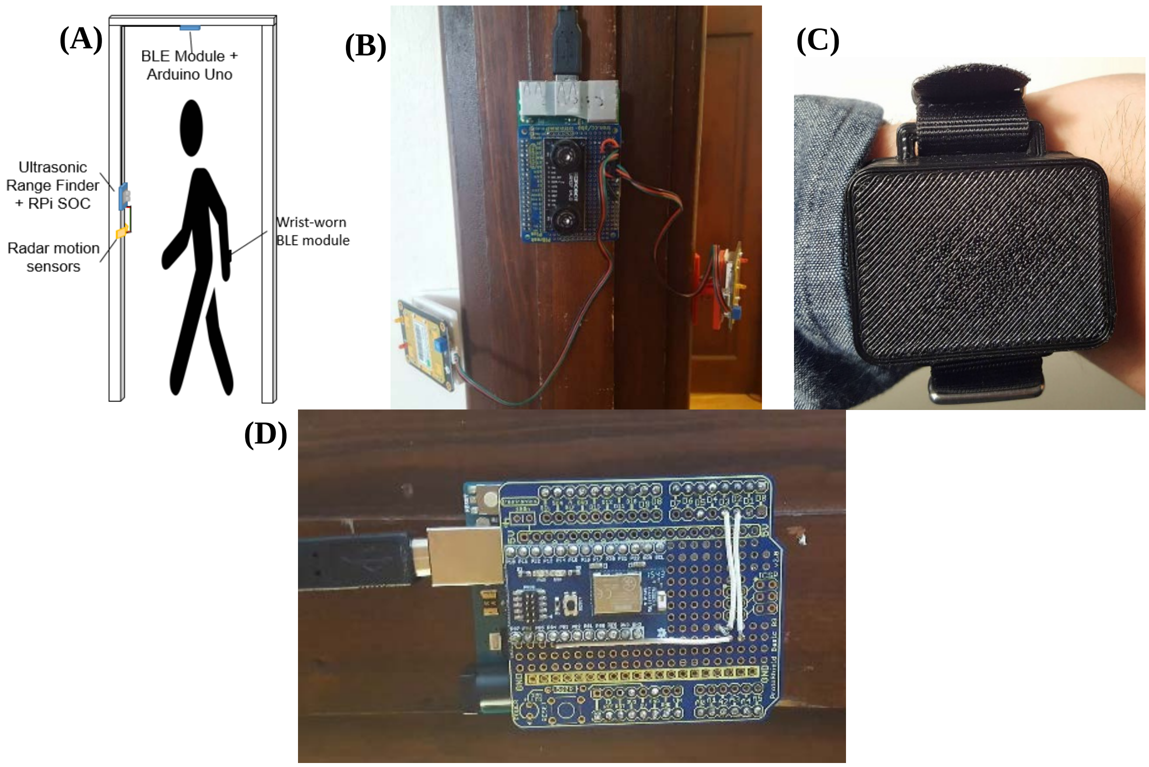



**Figure 4.9 (A)** Doorway indoor positioning system utilizing radar motion sensors, ultrasonic range finder, and Bluetooth Low Energy transceiver. **(B)** Radar motion sensors with adjustable angle stages connected to a Raspberry Pi SoC via a protoboard shield. Ultrasonic sensor is connected to the shield for detecting crossing events through the doorway. **(C)** Wrist-worn 3D-printed case containing BLE module and 3.7V LiPo battery. **(D)** Bluegiga BLE 113 module connected to an Arduino Uno microcontroller through a protoboard shield. Messages from the BLE module are serially transmitted to the nearby Raspberry Pi SoC over USB.

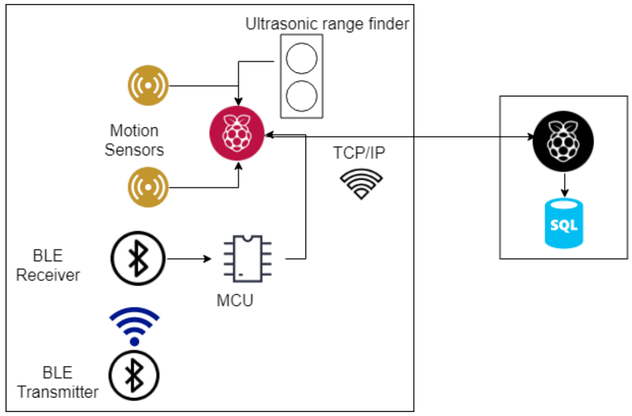



**Figure 4.10** System diagram of the hybrid BLE doorway monitor for determining the direction and identity of occupants crossing through a single doorway. The system implements two radar motion sensors, an ultrasonic range finder, and a BLE transceiver.

Repeating the direction experiment from **Section 4.3.3** with the updated hardware yielded the following results, summarized in **Table 4.5**.

**Table 4.5** Detected direction of a single person crossing through a doorway using radar Doppler sensors, BLE transceiver, and ultrasonic rangefinder. A person crossed through the doorway 30 times, and the experiment was repeated 3 times.

| Trial | Correct Detections | Incorrect Detections | Total Detections |
|---|---|---|---|
| 1 | 30 | 0 | 30 |
| 2 | 28 | 2 | 30 |
| 3 | 30 | 0 | 30 |

Subsequently, this improved system achieved a 95% probability of correctly determining the direction, with 95% confidence.

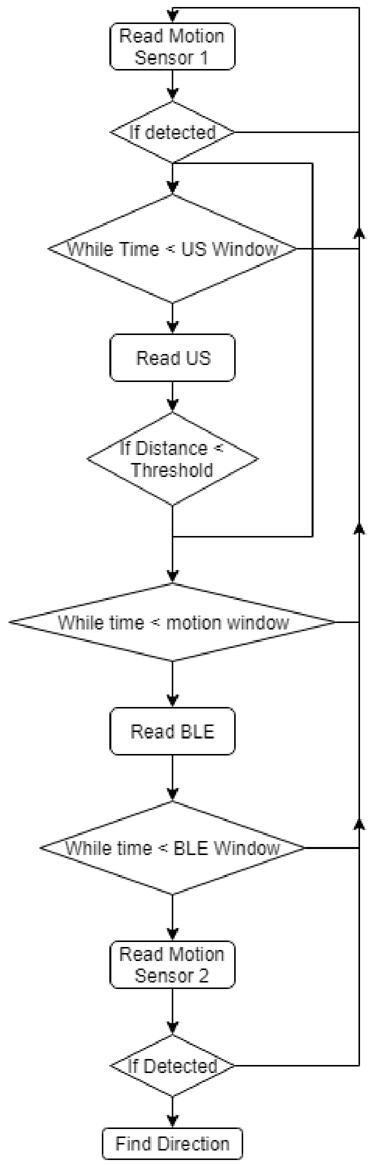



**Figure 4.11** Flowchart of algorithm for hybrid BLE doorway monitor. System identifies a crossing event, computes direction and identifies person for a single doorway.

The architecture described in **Figure 4.10** and **Figure 4.11** was expanded to multiple doorways, as depicted in **Figure 4.12**. The doorway system was installed in three doorways in a residential apartment. Each doorway client transmitted a data packet to the RPi server's SQL database. The effectiveness for tracking a single resident in an apartment with multiple rooms was evaluated. The layout of the apartment and trajectory followed is shown in **Figure 4.13**.

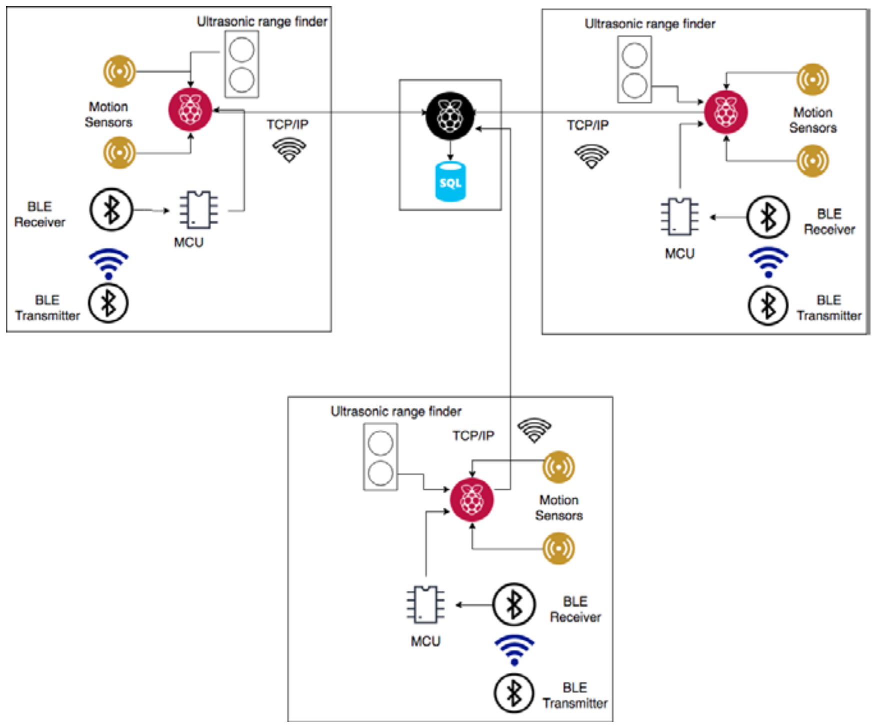



**Figure 4.12** System diagram of the hybrid BLE doorway monitor for determining the direction and identity of occupants crossing through multiple doorways. The system implements two radar motion sensors, an ultrasonic range finder, and a BLE transceiver for each doorway.

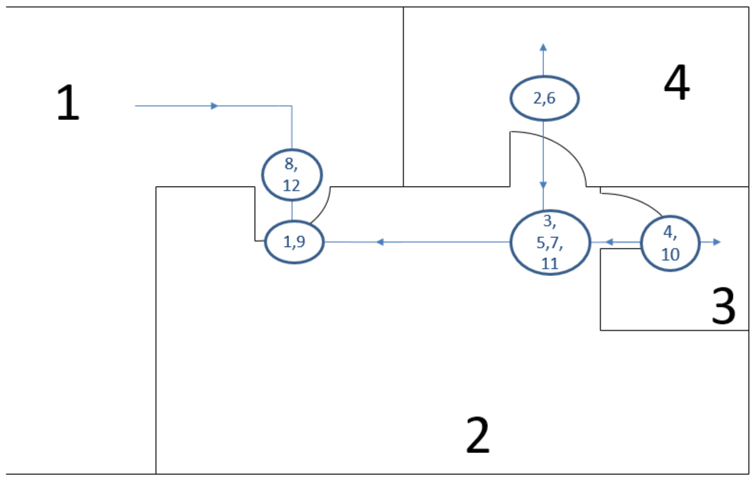



**Figure 4.13** The trajectory of a single participant walking through a residential apartment equipped with three hybrid BLE doorway monitoring systems. The trajectory was used to evaluate the IPS's accuracy for monitoring the position of the occupant within multiple rooms.

A participant completed the trajectory three times and the results are summarized in **Table 4.6.**

**Table 4.6** Recorded path of single occupant completing the trajectory depicted in **Figure 4.13** three times. The hybrid-BLE positioning system stored the room number, direction and RSSI for each detected crossing event.

| Step | Expected Path | | Actual Path | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Trial 1 | | | Trial 2 | | | Trial 3 | | |
| | Room | Dir | Room | RSSI | Dir | Room | RSSI | Dir | Room | RSSI | Dir |
| 1 | 2 | IN | 2 | 48 | IN | 2 | 55 | IN | 2 | 53 | IN |
| 2 | 4 | IN | 4 | 63 | IN | 4 | 52 | IN | 4 | 64 | IN |
| 3 | 4 | OUT | 4 | 63 | OUT | 4 | 60 | OUT | 4 | 66 | OUT |
| 4 | 3 | IN | 3 | 66 | IN | 3 | 58 | IN | 3 | 66 | IN |
| 5 | 3 | OUT | 3 | 65 | OUT | 3 | 60 | OUT | 3 | 65 | OUT |
| 6 | 4 | IN | 4 | 65 | IN | 4 | 64 | IN | 4 | 65 | IN |
| 7 | 4 | OUT | 4 | 65 | OUT | 4 | 64 | OUT | 4 | 66 | OUT |
| 8 | 2 | OUT | 2 | 52 | OUT | 2 | 63 | OUT | 2 | 51 | OUT |
| 9 | 2 | IN | 2 | 63 | IN | 2 | 66 | IN | 2 | 62 | IN |
| 10 | 3 | IN | 3 | 63 | IN | 3 | 62 | IN | 3 | 64 | IN |
| 11 | 3 | OUT | 3 | 66 | OUT | 3 | 61 | OUT | 3 | 66 | OUT |
| 12 | 2 | OUT | 2 | 66 | OUT | 2 | 62 | OUT | 2 | 64 | OUT |

As depicted above, the system identified the direction of travel with an accuracy of 100% and a specificity and sensitivity of 100%. An 'N-1' Chi squared of 71 was achieved with a P-value < 0.0001.

## 4.5 Multiple Person Monitoring

IPSs for single users have been addressed by many different research groups, however, indoor positioning for multi-person tracking remains a relatively undeveloped field in literature.[10] Multi-person tracking is particularly important for older adults, as systems can provide insight into social interaction, assistance from caregivers, or individual tracking of older adults living in a community dwelling.

Indoors, BLE radios have a transmission radius of 10 m. This creates a challenge when multiple people are present in a room, as the system is responsible for correctly identifying the person crossing through the doorway and not misclassify them as a person already present within the room. As discussed in **Section 2.4**, BLE RSS can be directly linked to distance. A RSS threshold value was implemented to classify a person crossing through the doorway and a person within the room.

The transmission power of the BLE transceivers could be set between 1 and 14 (arbitrary units). In order to determine the optimal transmission power, a signal was transmitted from a wearable BLE bracelet to a BLE receiver installed within the doorway at various power levels and distances from the doorway. A 2-minute scanning window was used to collect RSS signals and the experiment was conducted three times. The resulting RSS values for each power level and distance are displayed in **Figure 4.13**. Fitting a linear regression model to each power level identified level 14 as having the largest slope, thus allowing for the best possible discrimination between distances. Non-line-of-sight effects were observed for all transmissions at 0 Ft from the doorway, resulting in RSS values that did not fit within a linear model.

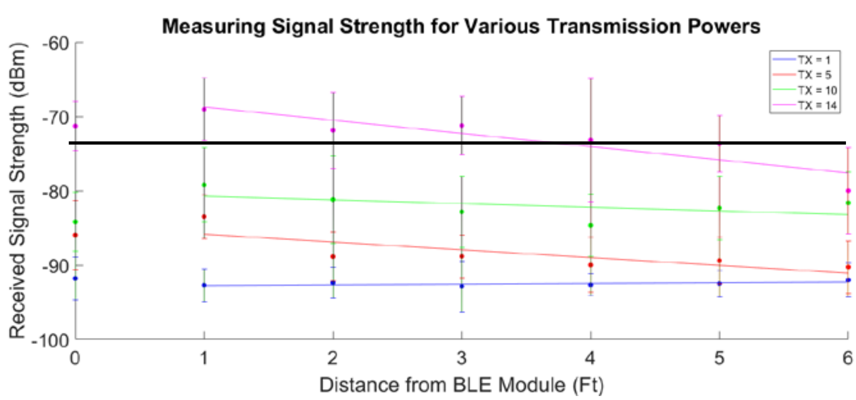



**Figure 4.14** Strength of signal transmitted from a wrist-worn BLE module to a BLE transceiver mounted on a doorway frame. Signal scan was repeated for 2-minutes. Discrete distances (0-6 ft) and transmission powers (1-14 AU) were evaluated. The dark horizontal line depicts the identified optimal threshold value to discriminate between a person crossing through a doorway and a second person standing 6 ft away.

A threshold of -74 dBm, depicted as a black horizontal line in **Figure 4.14**, was chosen to distinguish between two people present within the same room. To validate the effectiveness of the threshold, one person remained standing 6 Ft away from the doorway, while a second person walked through the doorway, 30 times. The system recorded the identification of the first available BLE ID when a crossing event occurred and the experiment was repeated 3 times. **Figure 4.15** summarizes the results and demonstrates the effectiveness of the threshold. Consequently, a threshold value of -74 dBm improved the identification accuracy from 42% to 72%, when compared with no threshold. The experiment was then repeated with a threshold of -69 dBm which improved the identification accuracy to 90%.

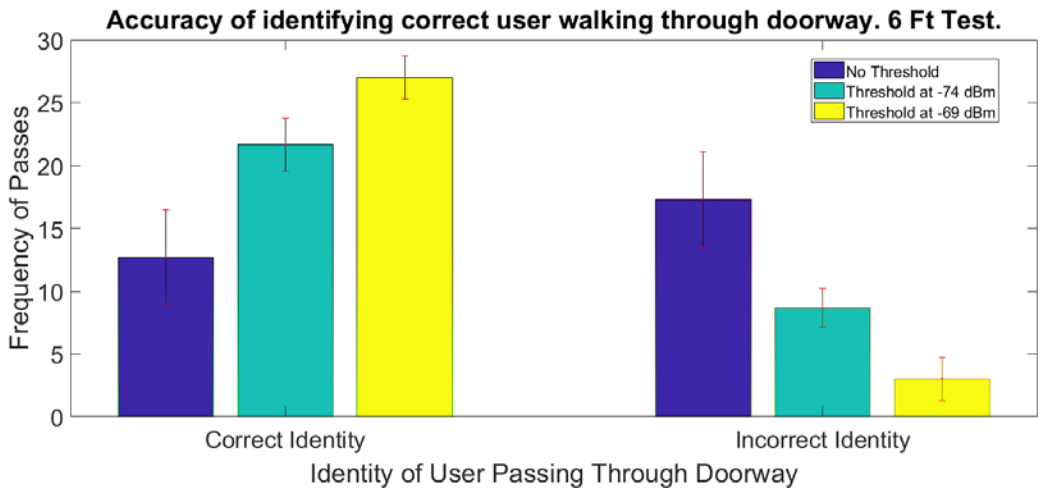
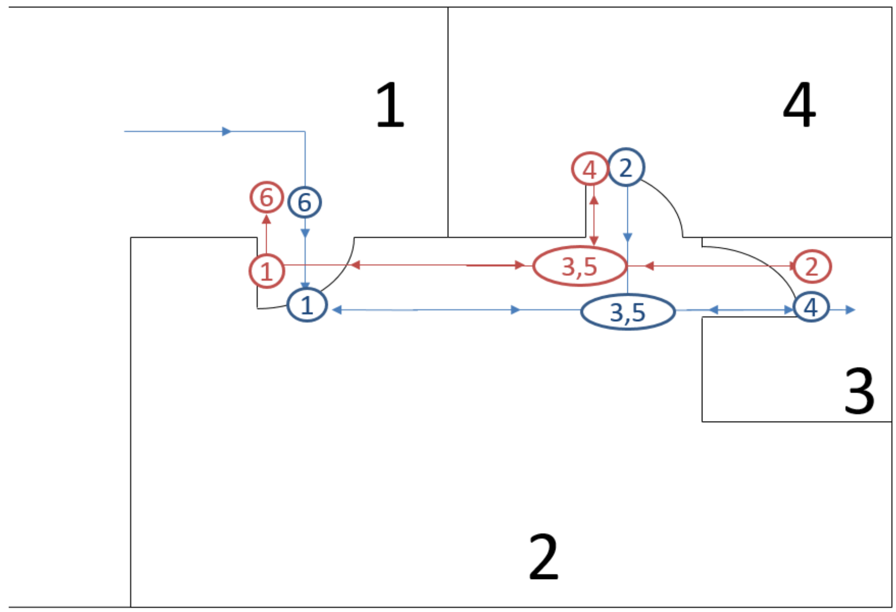



**Figure 4.15** The identification accuracy of the hybrid BLE doorway monitoring system when two people are present within a single room for different thresholds of BLE transmission power. Error calculated from the standard deviation of three trials. 30 crossing events occurred for each trial.

To validate the system further, the multiple room test was modified for two participants. The trajectory of the two participants within the apartment is described in **Figure 4.16.**

**(A)**




**(B)**


**Figure 4.16 (A)** The trajectory of two participants walking through a residential apartment equipped with three hybrid BLE doorway monitoring systems. The trajectory was used to evaluate the IPS's accuracy for monitoring the position of multiple occupants within multiple rooms. **(B)** The order in which each participant crossed through a doorway.

To improve classification between multiple residents even further, an array of the last 5 RSS readings following a crossing event was recorded. When multiple user IDs were recorded within the array, the ID with the largest mean RSS was identified as the correct person crossing through the doorway. The trajectory was repeated 5 times and the results are summarized in **Table 4.7.** The system performed well in correctly identifying the user crossing through the doorway, achieving an identification accuracy of 90.6%. The largest error appeared from missed crossing events, but performed well regardless, with an identification sensitivity of 88.3%. The source of this error was likely caused by an improper algorithm reset caused from movement occurring on both sides of the motion sensors. Likewise, this was also the reason for a slight decrease in direction accuracy, to 96.2%. No false positive events were recorded. False positive events were defined by the system falsely recording crossing events, when no events occurred in reality. As a result, the specificity of the system was 100%. An 'N-1' Chi squared of 94.13 was achieved with a P-value < 0.0001

**Table 4.7** Recorded path of two occupants completing the trajectory depicted in **Figure 4.16**. An array of 5 RSS values is recorded after each crossing event. The greatest mean RSS is used to classify the person crossing through the doorway.

| Step | Expected Path | | | Actual Path | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | Trial 1 | | | | Trial 2 | | | | Trial 3 | | | | Trial 4 | | | | Trial 5 | | | |
| | Room | ID | Dir | Room | ID | RSSI | Dir | Room | ID | RSSI | Dir | Room | ID | RSSI | Dir | Room | ID | RSSI | Dir | Room | ID | RSSI | Dir |
| 1 | 2 | 1 | IN | 2 | 1 | 65 | IN | 2 | 1 | 65 | IN | 2 | 1 | 64 | IN | 2 | 1 | 62 | IN | 2 | 1 | 72 | IN |
| 2 | 4 | 1 | IN | 4 | 1 | 67 | IN | 4 | 1 | 62 | IN | 4 | 1 | 63 | IN | 4 | 1 | 66 | IN | 4 | 1 | 77 | IN |
| 3 | 2 | 2 | IN | - | - | - | - | 2 | 2 | 70 | IN | - | - | - | - | 2 | 2 | 68 | IN | 2 | 2 | 76 | IN |
| 4 | 3 | 2 | IN | 3 | 2 | 60 | IN | 3 | 2 | 62 | IN | 3 | 2 | 62 | IN | 3 | 2 | 70 | IN | 3 | 2 | 65 | IN |
| 5 | 3 | 2 | OUT | 3 | 2 | 61 | OUT | 3 | 2 | 64 | OUT | 3 | 2 | 62 | OUT | 3 | 2 | 64 | OUT | 3 | 2 | 66 | OUT |
| 6 | 4 | 2 | IN | 4 | 2 | 69 | IN | 4 | 2 | 75 | IN | 4 | 1 | 71 | IN | 4 | 2 | 64 | IN | - | - | - | - |
| 7 | 4 | 1 | OUT | 4 | 1 | 64 | OUT | 4 | 1 | 65 | OUT | 4 | 1 | 65 | OUT | 4 | 2 | 72 | OUT | 4 | 1 | 65 | OUT |
| 8 | 3 | 1 | IN | 3 | 2 | 83 | OUT | 3 | 1 | 71 | IN | 3 | 1 | 72 | IN | - | - | - | - | 3 | 2 | 67 | IN |
| 9 | 4 | 2 | OUT | 4 | 2 | 72 | OUT | 4 | 2 | 61 | OUT | 4 | 1 | 67 | OUT | 4 | 1 | 66 | IN | - | - | - | - |
| 10 | 2 | 2 | OUT | 2 | 2 | 67 | OUT | 2 | 2 | 57 | OUT | 2 | 2 | 68 | OUT | 2 | 2 | 66 | OUT | 2 | 2 | 65 | OUT |
| 11 | 3 | 1 | OUT | - | - | - | - | 3 | 1 | 73 | OUT | 3 | 1 | 74 | OUT | 3 | 2 | 75 | OUT | 3 | 1 | 76 | OUT |
| 12 | 2 | 1 | OUT | 2 | 1 | 61 | OUT | 2 | 1 | 67 | OUT | - | - | - | - | 2 | 1 | 71 | OUT | 2 | 1 | 74 | OUT |

## 4.6 Effects of Closed Doorway

The single person experiment in **Section 4.4** was repeated to determine the effect that closed doors had on the system. A person repeated the trajectory depicted in **Figure 4.13**. The door was closed upon arrival at each doorway and was again closed after crossing. The most significant feature to be affected by the closed door was the direction accuracy, which reduced by 22% to 78%. When the resident walked through the door, they would be required to reach again through the doorway to close the door. Reaching through the doorway was most likely the reason for the increase in false-positive results – crossings that were identified but did not actually occur. Consequently, specificity was reduced to 89%. The number of missed events also increased, reducing the sensitivity by 8% to 92%. This could have been caused from more time being spent at each doorway, leading the algorithm to reset before a crossing event occurred. Nevertheless, an 'N-1' Chi squared of 46.11 as achieved with a P-value < 0.0001.

**Table 4.8** Recorded path of single occupant completing the trajectory depicted in **Figure 4.13** when the doorways were closed.

| Step | Expected Path | | Actual Path | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Trial 1 | | | Trial 2 | | | Trial 3 | | |
| | Room | Dir | Room | RSSI | Dir | Room | RSSI | Dir | Room | RSSI | Dir |
| 1 | 2 | IN | 2 | 82 | OUT | 2 | 81 | IN | 2 | 86 | IN |
| 2 | 4 | IN | 4 | 76 | IN | 4 | 70 | IN | - | - | - |
| 3 | 4 | OUT | 4 | 75 | OUT | 4 | 71 | OUT | - | - | - |
| 4 | 3 | IN | 4 | 76 | OUT | 4 | 67 | OUT | 3 | 74 | IN |
| 5 | 3 | OUT | 3 | 77 | IN | 3 | 76 | IN | 3 | 79 | IN |
| 6 | 4 | IN | 3 | 73 | IN | 3 | 76 | OUT | 4 | 66 | IN |
| 7 | 4 | OUT | 4 | 81 | IN | 4 | 78 | IN | 4 | 72 | OUT |
| 8 | 2 | OUT | 4 | 73 | IN | 4 | 71 | OUT | 2 | 81 | OUT |
| 9 | 2 | IN | 4 | 73 | OUT | 4 | 76 | OUT | 2 | 82 | IN |
| 10 | 3 | IN | 2 | 73 | OUT | 2 | 82 | IN | 3 | 74 | IN |
| 11 | 3 | OUT | 2 | 76 | IN | 2 | 71 | OUT | 3 | 74 | IN |
| 12 | 2 | OUT | 3 | 79 | IN | 3 | 76 | IN | 2 | 84 | IN |
| | | | - | - | - | 3 | 72 | OUT | | | |
| | | | 2 | 81 | OUT | 2 | 81 | IN | | | |

## 4.10 Visualization

### *4.10.1 Real-time visualization*

A web application was developed to visualize the residents' position in real-time. The application displays the identity and location of residents over a floor map of the home. The intended application of the visual interface is to assist in validating undefined trajectories for many occupants within the home and monitor the location of residents in real-time.

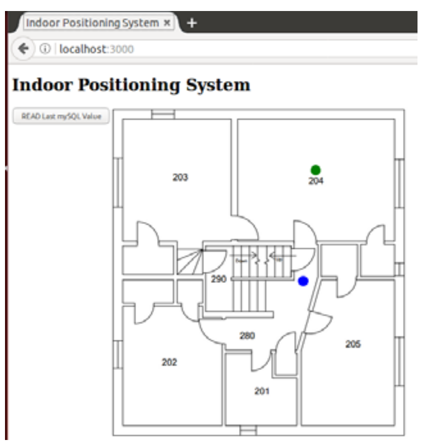



**Figure 4.17** Web application created for visualizing the identity and location of occupants in the home in real-time.

### *4.10.2 Descriptive Dashboard*

One of the motivations for location monitoring is to understand long-term resident behaviour and track habitual change. As discussed in **Chapter 3**, room utilization fused with temporal context can provide information on health-related ADLs such as sleeping patterns, toileting, and eating. Descriptive information on ADLs has shown to be clinically useful, and can provide additional support for caregivers, family, as well as the residents themselves.[13] These changes can be linked to residents' physical, cognitive, and mental health state.  Although the current tracking method identifies the present location of residents in real-time, it does not provide insightful trends. A descriptive dashboard, show in **Figure 4.18** was developed. Moving forward, this dashboard will utilize stored location history to describe resident behaviour and provide useful information to family members, caregivers, and healthcare professionals.

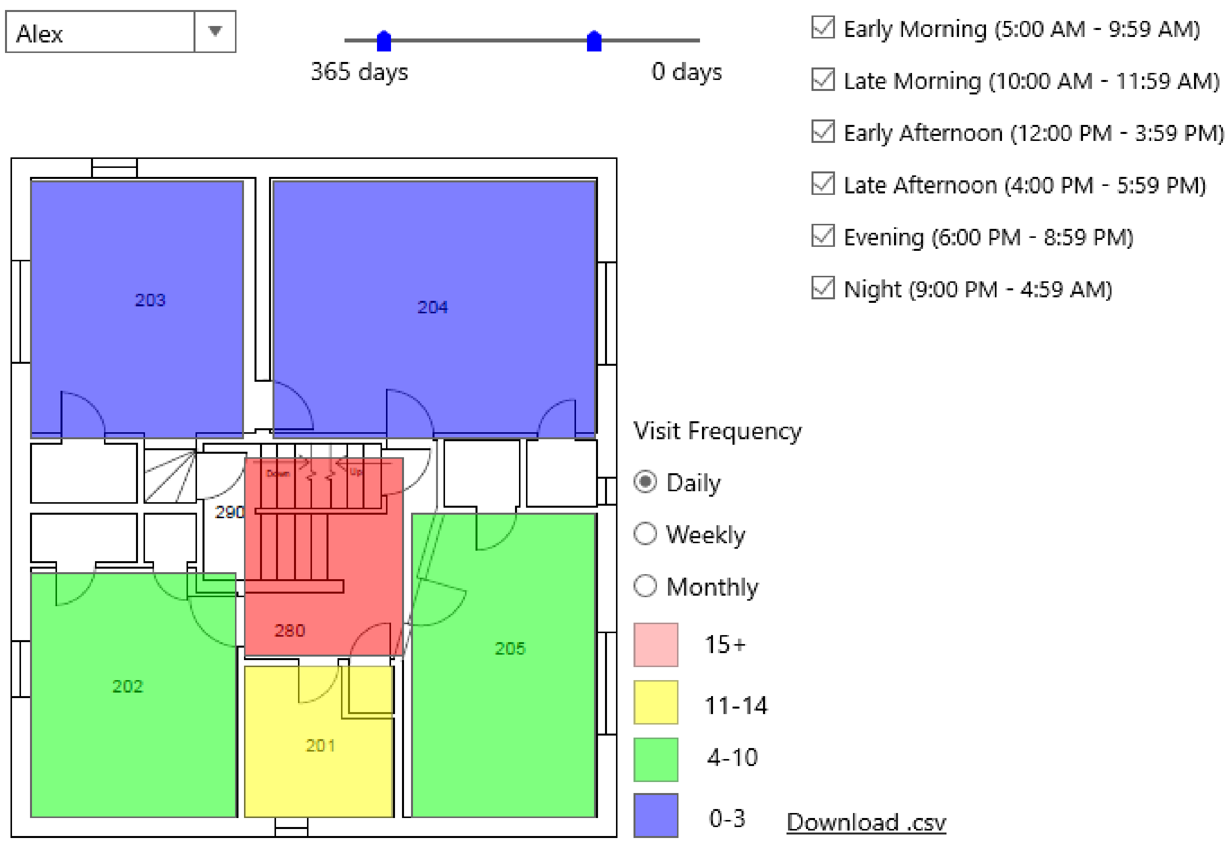



**Figure 4.18** Descriptive interface for visualizing room utilization trends of occupants within the home. The interface displays the visit frequency and time spent in each room for various occupants, times, and date ranges.

## 4.11 Conclusion

A hybrid BLE doorway monitoring IPS was developed in order to track the identification and position of residents within the rooms of a home. The system was evaluated for single and multiple residents. The monitoring system demonstrated promising results in monitoring two people within an apartment, achieving an identification accuracy of 90.6% and a crossing sensitivity and specificity of 88.3% and 100%, respectively. Closing doors after entering a room reduced direction accuracy, identification sensitivity, and identification specificity. In order to validate the system's accuracy in real-home environments with unspecified trajectories and multiple occupants, invasive monitoring sensors, such as cameras, will need to be deployed. Future work includes utilizing a descriptive dashboard for visualizing residents' mobility and ADLs, and creating *virtual doorways* to monitor the position of residents with greater resolution.

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# Chapter 5

# Hybrid RFID Indoor Positioning System

## 5.1 Introduction

In **Chapter 4**, an indoor positioning system utilizing BLE transceivers was described. As discussed in **Chapter 2,** RFID technology has also been utilized for indoor positioning. Since RFID and BLE share many of the same methods and algorithms for localization, the IPS described in **Chapter 4** was modified, replacing the BLE transceivers with RFID readers and tags. The strengths and limitations of each system were then evaluated.

## 5.2 Materials and Methods

### *5.2.1 RFID Reader and Tags*

RFID has shown to be a promising modality for indoor positioning. RFID tags can be developed in many flexible forms, such as key fobs, flexible paper tags, pins, bracelets, or surgical implants. This flexibility allows for tags to be integrated in different forms, such as embedded into the occupant's clothing, which does not require interaction between the user and the system.

One major challenge in utilizing UHF band RFID for indoor localization of humans is that the radio waves are strongly attenuated by water. In order to ensure that the system would effectively identify people at short ranges, an RFID reader with a transmission power of 27 dBm was selected (OBID ISC.MRMU102-A 860-960 MHz). Although linearly polarized antennas have a longer read range than circularly polarized antennas, a circularly polarized antenna (RFMAX S9028PCR/S8658PCR RHCP) was implemented as it would allow for unpredictable tag orientations.

Battery assisted semi-passive RFID tags were discussed in **Chapter 2**. These tags are an ideal choice for monitoring people indoors since they provide sufficient power, are low-cost and have a battery life of 2 years. GAO RFID Battery Assisted UHF Gen 2 RFID Tags were used.

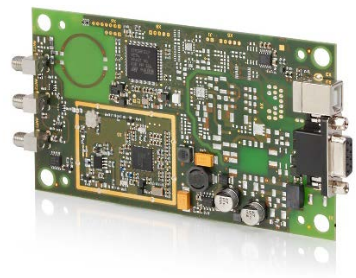

**Figure 5.1** RFID reader implemented in hybrid RFID doorway IPS.*[1]*

### *5.2.2 Direction Sensor Selection*

Upon initial evaluation of the RFID system, it was observed that the RFID reader emitted unintended second harmonic frequencies. These signals interfered with the radar motion sensors that were responsible for determining the direction of the occupants, as described in **Chapter 4**. This interference was confirmed with a spectrum analyzer (Keysight N9917A Fieldfox) and resulted in false direction measurements when the RFID reader triggered a pulse. To avoid false direction measurements, the microwave sensors were replaced with IR distance measuring sensors (SHARP GP2Y0D02YK0F), which did not interfere RFID reader. These binary sensors output an electric signal when an object appeared within a range of 80 cm.

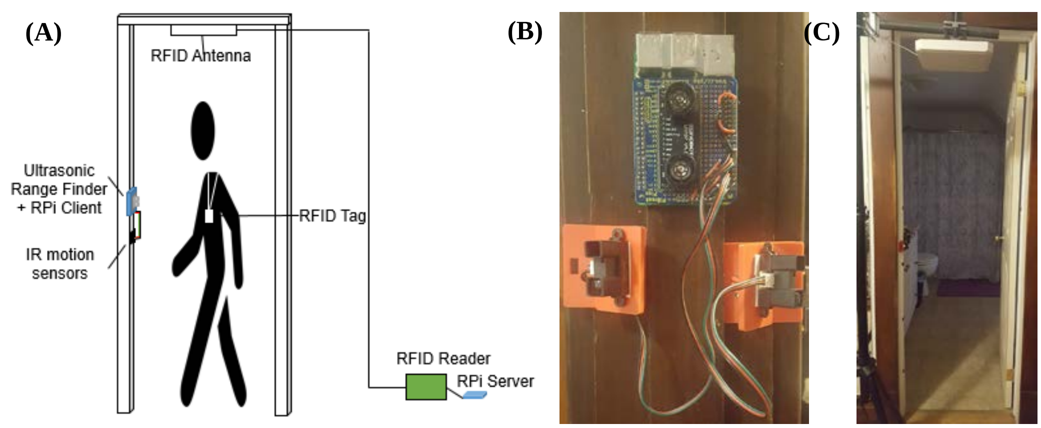


**Figure 5.2 (A)** Doorway indoor positioning system utilizing IR distance sensors, ultrasonic range finder, and RFID. **(A)** Direction detecting unit. IR distance sensors with adjustable angle stages connected to a Raspberry Pi SoC via a protoboard shield. Ultrasonic sensor is also connected to the shield for detecting crossing events. **(B)** RFID antenna attached to tripod to detect identification of resident crossing through doorway.

## 5.3 Single Person Monitoring

The RFID reader depicted in **Figure 5.1** incorporated and internal multiplexer for reading from three onboard antenna connections. One of the reasons for choosing this reader was to reduce capital cost, avoiding the purchase of three separate readers. This, however, required a change in architecture from the BLE system in **Chapter 4**, as depicted in **Figure 5.3**.

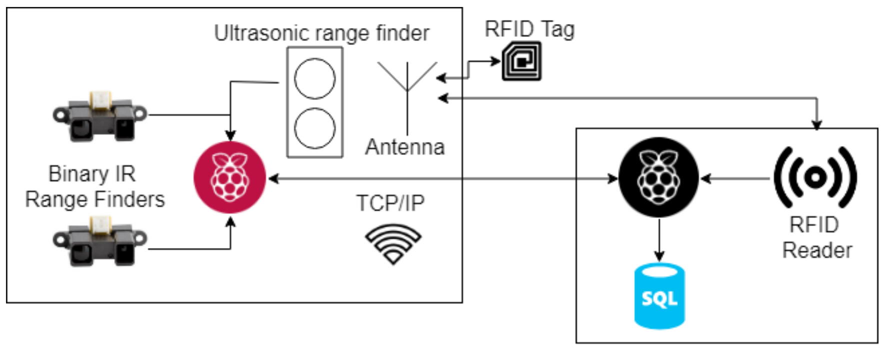


**Figure 5.3** System diagram of single doorway monitoring system utilizing RFID, IR distance, and ultrasonic range finder.

The RFID reader was controlled by the RPi server in the right side of the figure, rather than by the RPi client on the left, as previously demonstrated by the hybrid BLE system in **Figure 4.9**. This updated architecture required synchronized communication between the RPi client controlling the sensors and the RPi server controlling the RFID. As such, the algorithm was written as a finite-state-machine (FSM) to ensure that the two systems remained synchronized throughout all primary and edge cases. The system was then scaled up to three RPi clients, as shown in **Figure 5.4**.

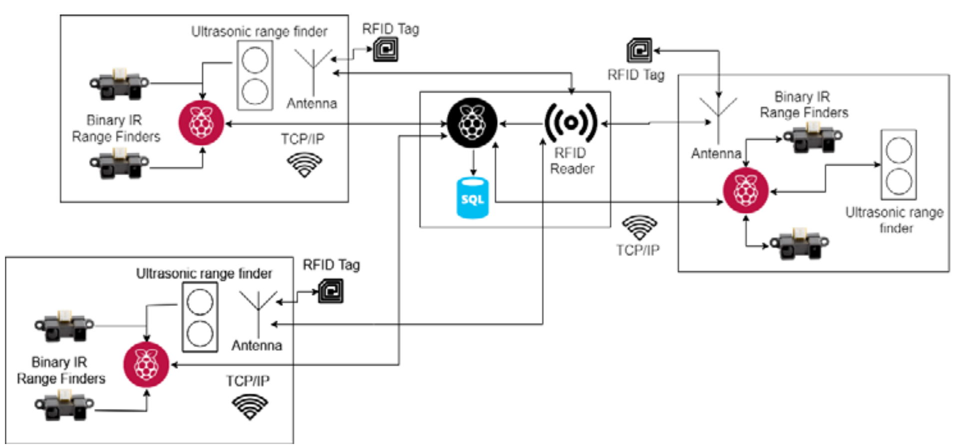


**Figure 5.4** System architecture of RFID indoor positioning system for three doorways.

The participant’s trajectory, depicted in **Figure 5.5** was repeated three times and the results are summarized in **Table 5.1**.

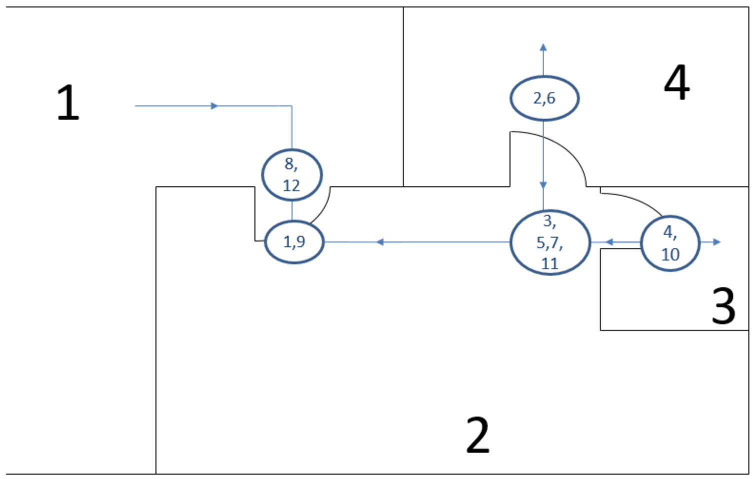


**Figure 5.5** The trajectory of a single participant walking through a residential apartment equipped with three hybrid RFID doorway monitoring systems. The trajectory was used to evaluate the IPS's accuracy for monitoring the position of the occupant within multiple rooms.

**Table 5.1** Results from single person completing the trajectory depicted in Figure 5.12. Table cells shaded in red do not match the expected path.

| Step | Expected Path | | Actual Path | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | | Trial 1 | | Trial 2 | | Trial 3 | |
| | Room | Dir | Room | Dir | Room | Dir | Room | Dir |
| 1 | 2 | IN | 2 | IN | 2 | IN | 2 | IN |
| 2 | 4 | IN | 4 | IN | 4 | IN | 4 | IN |
| 3 | 4 | OUT | 4 | OUT | 4 | OUT | 4 | OUT |
| 4 | 3 | IN | 3 | IN | 3 | IN | 3 | IN |
| 5 | 3 | OUT | 3 | OUT | 3 | OUT | 3 | OUT |
| 6 | 4 | IN | 4 | IN | 4 | IN | 4 | IN |
| 7 | 4 | OUT | 4 | OUT | 4 | OUT | 4 | OUT |
| 8 | 2 | OUT | 2 | OUT | 2 | OUT | 2 | OUT |
| 9 | 2 | IN | 2 | IN | 2 | IN | 2 | IN |
| 10 | 3 | IN | 3 | IN | 3 | IN | 4 | IN |
| 11 | 3 | OUT | 3 | OUT | 3 | OUT | - | - |
| 12 | 2 | OUT | 2 | OUT | 2 | OUT | 2 | OUT |

As depicted above, the system was able to identify the direction of travel with an accuracy, sensitivity, and specificity of 94%, 97%, and 100%, respectively. An 'N-1' Chi squared of 67.16 was achieved with a P-value < 0.0001.

## 5.4 Multiple Person Monitoring

In order to validate the system for multiple occupants in an apartment, the trajectory in **Figure 5.6** was repeated 5 times, with the results shown in **Table 5.2**.

**(A)**

**(B)**

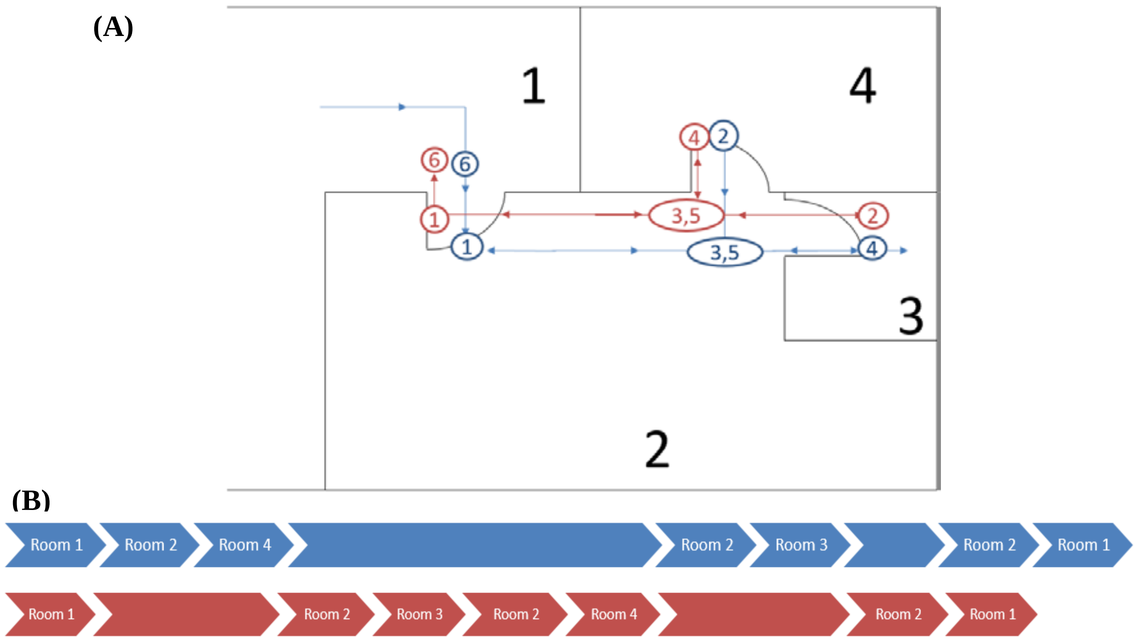


**Figure 5.6 (A)** The trajectory of two participants walking through a residential apartment equipped with three hybrid RFID doorway monitoring systems. The trajectory was used to evaluate the IPS's accuracy for monitoring the position of multiple occupants within multiple rooms. **(B)** The order in which each participant crossed through a doorway.

**Table 5.2** Recorded path of two people completing trajectory depicted in **Figure 5.6**.

| Step | Expected Path | | | Actual Path | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | Trial 1 | | | Trial 2 | | | Trial 3 | | | Trial 4 | | | Trial 5 | | |
| | Room | ID | Dir | Room | ID | Dir | Room | ID | Dir | Room | ID | Dir | Room | ID | Dir | Room | ID | Dir |
| 1 | 2 | 1 | IN | 2 | 1 | IN | 2 | 1 | IN | 2 | 1 | IN | 2 | 1 | IN | 2 | 1 | IN |
| 2 | 4 | 1 | IN | 4 | 1 | IN | 4 | 1 | IN | 4 | 1 | IN | 4 | 1 | IN | 4 | 1 | IN |
| 3 | 2 | 2 | IN | 2 | 2 | OUT | 2 | 2 | IN | 2 | 2 | IN | 2 | 2 | IN | 2 | 2 | IN |
| 4 | 3 | 2 | IN | 3 | 2 | IN | 3 | 2 | IN | 3 | 2 | IN | 3 | 2 | IN | 3 | 2 | IN |
| 5 | 3 | 2 | OUT | 3 | 2 | OUT | 3 | 2 | OUT | 3 | 2 | OUT | 3 | 2 | OUT | - | - | - |
| 6 | 4 | 2 | IN | 4 | 2 | IN | 4 | 2 | IN | 4 | 2 | IN | 4 | 2 | IN | 4 | 2 | IN |
| 7 | 4 | 1 | OUT | 4 | 1 | OUT | 4 | 1 | OUT | 4 | 1 | OUT | 4 | 1 | OUT | 4 | 1 | OUT |
| 8 | 3 | 1 | IN | 3 | 1 | OUT | 3 | 1 | IN | 3 | 1 | OUT | 3 | 1 | IN | 3 | 2 | IN |
| 9 | 4 | 2 | OUT | 4 | 2 | OUT | 4 | 2 | OUT | 4 | 2 | OUT | 4 | 2 | OUT | 4 | 2 | OUT |
| 10 | 2 | 2 | OUT | 2 | 2 | OUT | 2 | 2 | OUT | 2 | 2 | OUT | 2 | 2 | OUT | 2 | 2 | OUT |
| 11 | 3 | 1 | OUT | 3 | 1 | OUT | 3 | 1 | OUT | 3 | 1 | OUT | 3 | 1 | OUT | 3 | 1 | OUT |
| 12 | 2 | 1 | OUT | 2 | 1 | OUT | 2 | 1 | OUT | 2 | 1 | OUT | 2 | 1 | OUT | 2 | 1 | OUT |

The system correctly identified the user crossing through the doorway, achieving a direction accuracy of 98%, an identification accuracy of 97%, identification sensitivity of 98%, and identification specificity of 100%. A 'N-1' Chi squared of 115.1 with a P-value < 0.0001 was achieved.

## 5.5 Comparison of Hybrid RFID and BLE Systems

### *5.5.1 Indoor Monitoring Performance*

The hybrid RFID IPS in this chapter and the hybrid BLE IPS in **Chapter 4** demonstrated strong performance for monitoring the location and identification of single and multiple occupants in a residential apartment. The BLE system performed slightly better than the RFID system for the single-person test, improving identification sensitivity of the system by 3%. The RFID system performed significantly better than the BLE system for the two-person test, improving identification sensitivity by 10%.

### *5.5.2 Battery Performance*

The battery performance of the wrist-worn BLE transmitter was evaluated. The active tag repeatedly transmitted its unique identification number at a set frequency. The battery life for a BLE transmitter with an output power of 14 AU is shown in **Figure 5.5**.

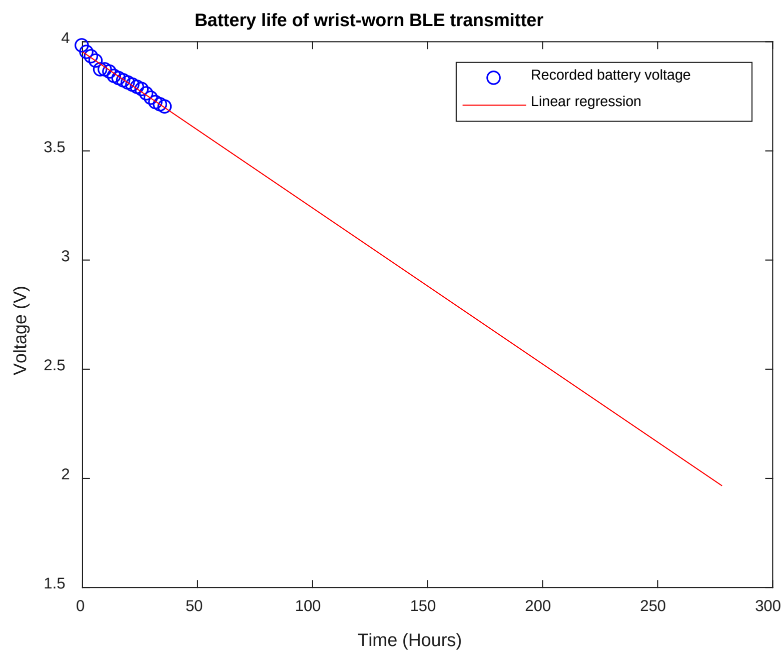


**Figure 5.7** Recorded battery performance of the Bluegiga BLE113 transmitter after 36 hours. The recorded data was fit to a linear regression model to predict when the battery would discharge to 2V, the BLE module’s minimum input voltage.

In the above figure, the voltage of a battery powering a wrist-worn BLE transmitter was recorded for 36 hours with 2 hour intervals. Assuming a linear regression model, the battery charge will reduce to 2 V, the module's minimum input voltage, within 270 hours, or approximately 11 days. However, all of the experiments in **Chapter 4** were conducted with a battery voltage of approximately 3.7 V, so it cannot be guaranteed that performance of the system will not be affected at a lower voltage. This should be further investigated. The power consumption of the BLE transmitters is considerably lower than the semi-passive RFID tags, which claim to consume a battery every two years.

Similar commercial BLE transmitters claim to require battery replacements every two years.[2] A number of strategies could be implemented to improve battery performance. Although reducing transmission power of the BLE transmitter can help, it can reduce performance as discussed in **Section 4.8** and shown in **Figure 4.13**. Other strategies include reducing the transmission frequency and using batteries with a larger electric charge. For instance, the battery used to power the BLE transmitter in **Chapter 4** had an electric charge of only 300 mAh. The architecture of the system could also be modified to improve battery life. In previous tests, the wrist-worn BLE transceivers were responsible for transmitting their identification, while the wall-mounted BLE transmitters were responsible receiving messages. To preserve the battery life of the wrist-worn transceivers, architecture can be modified so that the wall mounted BLE modules transmit their ID while the wrist-worn BLE modules receive nearby messages. The location algorithm would then determine the location of nearby beacons.

### *5.5.3 Costs*

The overall costs of the hybrid IPSs for a single doorway and single user are shown below in **Table 5.3**. Although RFID readers are relatively expensive, the tags, which are commonly found in identification cards, running bibs, and asset management, are low-cost. Therefore, although a large initial investment is required for deploying an RFID IPS, maintenance costs are low for residents that are prone to losing their identification tags.

The hybrid BLE IPS costs approximately 20% of the price of the hybrid RFID system. This cost can be further reduced if occupants prefer to carry BLE-enabled devices such as mobile phones, smart watches, or activity trackers.

**Table 5.3** Overall costs of monitoring system for single doorway and single user.

| Sensor | Bluetooth | RFID |
|---|---|---|
| Receiver | $15 | $300 |
| Tag | $15 | $18 |
| Antenna | N.A | $135 |
| Motion sensors | $18 | $30 |
| Ultrasonic rangefinder | $14 | $14 |
| RPi Client | $45 | $45 |
| Total | $107 | $542 |

### *5.5.4 Footprint*

One of the challenges in developing remote monitoring devices is to design systems that blend in naturally with the home environment. A small footprint is desirable for improving installation ease and developing an innocuous system. The RFID system requires a large antenna (25.9 x 25.9 cm) to be attached to each doorway, as seen in **Figure 5.2 (B)**. The BLE footprint is significantly smaller (3.3 cm x 2.0 cm), which can increase adoptability. The wrist-worn BLE transceiver is the same size as the wall-mounted transceiver, but may reduce adoptability because it requires rechargeable batteries. The RFID system may be more convenient because it does not require any external batteries or charging.

## 5.6 Conclusion

A hybrid RFID IPS was developed to monitor the location and identity of occupants in a home. The system was evaluated for monitoring single and multiple occupants within a residential apartment. The monitoring system demonstrated promising results in monitoring two people within an apartment, achieving an identification accuracy of 97% and a crossing sensitivity and specificity of 98% and 100%, respectively. System strengths and limitations, such as performance, cost, and adoptability were compared with the hybrid BLE system discussed in **Chapter 4**. The hybrid RFID system performed better at monitoring the location of multiple residents, however, it is significantly more expensive and has a greater footprint than the hybrid BLE IPS.

## References

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[2] "Estimote." [Online]. Available: http://estimote.com/. [Accessed: 28-Feb-2018].

# Chapter 6

# Conclusions and Future Work

## 6.1 Summary

Performance of ADLs is an important indicator for determining the cognitive and physical health of older adults.[1] Research into the development of IPSs and wireless sensor networks demonstrated that sensor networks can identify aging-related ADLs.[2]–[5] In this dissertation, we developed and evaluated two IPSs – (i) a hybrid BLE and radar motion sensor system and (ii) a hybrid RFID and IR range-finding system for tracking the location of occupants in an apartment.

We first reviewed the literature describing various sensor modalities and localization techniques for performing indoor positioning. The purpose of this review was to highlight the strengths and limitations of the systems, including factors such as accuracy, cost, system complexity, and scalability. Literature showed that further research into the system requirements and technological performance must be conducted in order to identify the optimal IPS for enabling aging in place. Sensor technologies developed for remotely tracking age-related ADLs were also reviewed. Motivated by the diverse sensor technologies and health-related metrics that could be measured remotely, we developed a Smart Home platform for enabling and validating remote health sensing technologies for monitoring aging-related ADLs and biometrics. In order to promote short-term and longitudinal research studies on aging in place, the Smart Home platform was designed to be modular, enabling modern technological standards as well as unforeseen technologies. The first technology designed for the Smart Home was a decentralized hybrid BLE IPS. Experimental validation of the system determined its accuracy for tracking multiple occupants within multiple rooms of a residential apartment. Maintaining approximately the same architecture, a hybrid RFID system was also devised and implemented. The performance of the two IPSs was compared. Although the hybrid RFID system demonstrated better localization performance for multiple occupants, the BLE system demonstrated lower cost, greater implementation ease, and lower system complexity.

## 6.2 Discussion and Future Work

Opposed to distributing a traditional positioning sensor network within each room, as discussed in Section 2.4, the IPSs described in this dissertation were installed in doorways. The rationale behind this design was to (i) minimize system cost by reducing the number of required eponymous sensors, (ii) increase implementation ease by creating a plug-and-play system, and (iii) optimize scalability by implementing a decentralized localization technique. As a result, the location accuracy of the system is limited to room-level localization. Room-level localization answers important health-related questions such as “How often is the occupant ambulating?”, “Are they regularly performing ADLs such as bathroom use and cooking?”, “What time do they wake up and go to sleep?”. However, in order to broaden the system’s functional scope outside of residential homes and into community dwellings, such as long-term care, further development is required to support more precise intra-room localization so that occupants could be accurately located within rooms or in corridors. This improved location accuracy as a result of these *virtual doorways* would, however, result in increased system complexity and cost.

As for the experimental validation of the IPSs in this dissertation, the systems were evaluated in a controlled environment with pre-defined trajectories. It remains unknown whether the systems would perform equally well in real home environments with multiple residents and undefined paths. To validate the effectiveness of the system, long-term in-situ monitoring within real homes of older adults must be conducted. Although the current system does not implement invasive monitoring devices, such as cameras, these obtrusive devices are very precise in determining ground-truth locations. In another doorway monitoring study, Griffiths et al[6] installed cameras within doorways to record the ground-truth identity and direction of occupants crossing through a motion-sensor based IPS. Adopting this method would accurately validate our system’s accuracy for long-term in-situ monitoring.

## 6.3 Conclusion

In conclusion, this thesis provides a Smart Home platform and two hybrid indoor positioning systems for enabling multi-room and multi-occupant localization. Long-term in-situ monitoring should be further conducted to determine the system’s performance for multiple residents and undefined walking paths. Furthermore, implementing virtual doorways would increase location precision, enabling intra-room localization for monitoring location in corridors.

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