Technology-supported Aging in Place

By

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Abstract

Aging in place is a priority for many older adults, but challenges such as reduced mobility, cognitive decline, and increased risk of injury can compromise their independence and well-being. Early detection of changes in health and behavior is critical to preventing emergencies, yet current monitoring methods often raise privacy concerns or are too intrusive.

This research is part of a bigger project to identify activities of daily living and track those changes over time. This study explores a non-invasive approach to monitor activities of daily living (ADLs) using relative signal strength indicator (RSSI) data from an Apple AirTag worn on the wrist, tracked through strategically placed smartphones within the home. The system estimates the location of the wearer and infers patterns of movement to approximate ADLs. By establishing a behavioral baseline, deviations may indicate emerging health concerns.

Preliminary results show that room-level positioning using RSSI data can effectively identify key daily routines such as sleep, kitchen use, and bathroom visits. This foundational work sets the stage for training AI models to detect significant deviations that could trigger healthcare provider alerts. Future work will focus on improving localization accuracy, expanding the dataset, and integrating machine learning models to support timely interventions in care for older adults.

Technology-supported Aging in Place

A Thesis

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Master of Science in Biomedical Engineering

By

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Dedication

This thesis is dedicated to the loving memory of my father, M A Baten. It was from him that I first learned the wonder of Mathematics and Science. His guidance, encouragement, and unwavering belief in me continue to inspire every step of my academic journey. Though he is no longer with me, his memory remains a constant source of strength and motivation.

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Table of Contents

List of Tables

List of Figures

Chapter 1 - Introduction

Older people face some difficulties, like reduced eyesight and mobility, and they are more prone to falling because of some health-related issues (Arthritis, Parkinson's disease, etc.) [1]. Therefore, they need physical and mental support from their families and surroundings [1]. In previous studies, researchers suggested that devices like smoke alarms, small sensors, hidden cameras, and sometimes voice-controlled speakers have the potential to make their lives comparatively safer and more convenient [1].

Apart from some physical issues, research by Austin et al. (2016) [2] also pointed out loneliness as one of the significant circumstances in older adults, which is accompanied by morbidity [2] and mortality [3], reduced sleep quality, memory loss [2], and so on. Loneliness was estimated using phone logs, computer logs, etc., but was challenging for the researchers because of older people's unwillingness to invade their privacy [2,4] so they suggested finding possible better scientific ways to measure and evaluate their physical and mental issues [5]. Initially, this study focuses on older people's health related to loneliness and will attempt to understand their in-home behaviors of interests through computer software-enhanced algorithms, phone monitors, and wireless motion sensors [6] and will suggest necessary instrumentations [2,6]. A significant percentage of older adults are living with chronic illnesses or disabilities [7], and an in-home healthcare system [5] can be initiated through current engineering technologies. Another study on smart home environmental control system by Zhang et al. (2019) [8] demonstrated the potential use of an asynchronous electrooculography (EOG)-supported human-machine interface (HMI) system [8,9] to provide daily aid for intense spinal cord injury (SCI) patients [8]. They proposed that the HMI methods can be implemented in a smart home that can interact with older people (study of the interests) through eye and eyebrow movements [8,9].

1.1 *Cost of care*

As individuals age, the decision to remain at home or transition into a care facility comes with significant financial considerations. The cost of care varies widely based on location, with home health aide (HHA) services costing approximately $4,004 per month in Greenville, NC, compared to $6,473 per month in San Diego, CA. Similarly, skilled nursing facility private room (SNF-PR) costs range from $6,540 monthly in Greenville to $12,167 monthly in San Diego.

Table 1.1: Cost of long-term care by accommodation type

Care Type	Monthly Cost	Annual Cost
Home health aide	$5,148	$61,776
Assisted living facility	$4,500	$54,000
Skilled nursing facility (semi-private room)	$7,908	$94,896
Skilled nursing facility (private room)	$9,034	$108,408

These expenses often exclude additional costs for essential needs such as medication, incontinence supplies, and personal items, making long-term care a substantial financial burden. Without long-term care insurance or substantial savings, many individuals find that selling their homes is the only viable option to afford care. While Medicaid can provide financial assistance, eligibility is highly restrictive, requiring individuals to have very low income and assets. This financial strain underscores the importance of planning for long-term care to ensure stability and quality of life in later years.

Cost-effective instrumentation and convenient telehealth methods will be proposed in this research with the aim of benefiting individuals with disability and older adults in our social community [5]. With advanced biomedical instrumentation, responsible caregivers and doctors will provide suggestions and assistance for essential instant care of older people via continuous telecommunication. This study will focus on the use of sensors technology to track activities of daily living in order to determine a baseline of daily activities. This will set the foundation for a smart homecare system to identify significant changes in activities of daily living over time which may indicate the onset of health conditions that should prompt a discussion with a care provider.

Chapter 2 - Literature Review

2.1 Loneliness estimation

Irfan et al. (2021) [6] focused on older people's health related to loneliness and tried to understand their in-home behaviors of interests through computer software-enhanced algorithms, phone monitors, and wireless motion sensors [6] and proposed necessary instrumentations [2,6]. At first, they presented the outcomes demonstrating the precision of the approach in measuring loneliness within 16 older adults who consented to having the detector installed in their houses for almost eight months. They also showed that loneliness is significantly associated with both times out-of-home and the number of computer sessions. Then, they demonstrated the model's ability to predict out-of-sample loneliness and the correlation between true loneliness and predicted out-of-sample loneliness [2]. By allocating the sensors in the house, they could measure people's behaviors from the system. The sensor shared data to a computer via Wi-Fi, and the USB transmits mobile phone monitoring data. After that, all the data are transferred through a protected wireless connection and encrypted and then saved in the servers. So, they could analyze the data from there and utilize that for research.

This study had some limitations since they generated their data within a short time frame; so, the sample sizes were small. In my future research, we can study user's (or sample's) behavior for an extended period and should have more average observation per participant.

2.2 Electrooculography (EOG)-based Human Machine Interface (HMI)

Another research on smart home environmental control system by Zhang et al. (2019) [8] demonstrated the potential use of an asynchronous electrooculography (EOG)-supported human-machine interface (HMI) system [8,9] to provide daily aid for intense spinal cord injury (SCI) patients [8]. They proposed that the HMI methods can be implemented in a smart home that can interact with older people (study of the interests) through eye blinking and eyebrow movements [8,9]. They had multiple buttons that could respond to a control command. Therefore, users could control their home environment with just a blink of an eye. In this research, 7 spinal cord injury patients participated, and they could maintain the smart home environment (for example, the wheelchair or nursing bed) [8].

They used a multi-layered Graphical User Interface (GUI) format to control the smart home environment system. Level 1 is for selecting the main menu. Level 2 has 4 interfaces: one for regulating the TV, one for maintaining the AC, one for the nursing bed, and the fourth one for directing the wheelchair. People can also select the room and destination from the fourth interface. The author designed the interfaces with C++ programming language. People can command by blinking their eyes synchronously and can choose a specific switch [8].

From the data, they found that their system was very satisfactory and dependable as well. However, they found two problems in their approach. One is to compare unforced eye movements with automatic eye movements. They measured the voluntary blinks as they synchronized with the sparkles of the switch and also estimated the reaction time. Another problem was to exclude false functions in the inactive form. For example, the wheelchair or nursing bed can move when the person does not intend to because of the faulty operation. These conditions should be optimized in the future [8]. So, we can find other methods or procedures that can differentiate between unforced and reflexive eye movement's reaction time.

2.3 Smart home for older adults and people with bodily impairment

Stefanov et al. (2004) [10] developed a smart home for people who cannot move independently and for older adults. They installed appliances to aid their movement for those who have physical dysfunction such as lower eyesight, hearing problems, etc. These appliances help them perform their daily activities correctly [10]. They categorized the established appliances according to their operations into five groups: (1) Machines for automation and control of the home environment, (2) Aiding instruments, (3) Machines for health monitoring of critical variables, (4) Appliances for data swap, and (5) Recreational appliances [10]. Also, much research has been done on the "survival function" features, and I can see a great possibility of researching the “entertainment features” of the smart home system.

Previous techniques were hardware-based, but recent strategies are mainly software-oriented. We can use nanotechnology, which will help minimize the device size and look equivalent to an ordinary house without making significant changes. The goal is to create a system that will remain invisible to others and not hinder the users' everyday activities. Also, there might be some possibilities to use the smart home system for detecting illnesses early, not only for disabled persons but also for non-disabled people [10]. For instance, we can use wearable or portable devices like watches, cell phones, etc. to make their lives longer.

Raad & Yang [5] designed a cost-efficient, easy-to-use telehealth scheme to aid the community's older and physically impaired individuals. With the help of advanced biomedical devices, responsible caregivers and doctors can provide the elderly with the immediate care advice and services they need through continuous remote communication. So, the user can transmit an emergency ring in the case of a crisis since he is continuously being monitored while moving around the intelligent house environment [5].

Irfan et al. [6] developed a system to analyze people's behavior in the smart house. They accumulated multimodal information from an IoT-based SABOS (Smart Environment Behavior Observation System) sensors. This system can observe their daily behavior without causing any inconvenience as it's obscure. Sensors are installed throughout the house and can send signals to doctors or family members in the event of an emergency [6].

2.4 Preliminary Sensor Technology Research and Evaluation

We have conducted extensive research on products designed for tracking the daily activities of individuals within smart home environments. One notable company in this field is 'Inpixon,' offering BLE Beacons that utilize Bluetooth Low Energy for precise location tracking, detectable by wireless and BLE-enabled devices. Additionally, 'Dusun' provides two highly programmable products capable of securely storing data on a server. 'INGICS Technology' introduces the iGS01S Wi-Fi Gateway, powered by micro-USB, facilitating seamless data forwarding to servers. Lastly, 'Estimote' offers a compact and colorful UWB Development Kit, boasting data storage capabilities and programmability. These products collectively represent a comprehensive suite for effective and efficient tracking solutions in smart home settings. More details regarding this technology and how it will be used in this study are discussed in Chapter 3.

Recent work has examined the anti-stalking safeguards of **Apple AirTags**, showing that safety alerts can be delayed (over eight hours during daytime) and that cloned AirTags can bypass alerts while still providing real-time tracking [16]. The study highlights both the privacy risks and the need for stronger protections in Bluetooth-based trackers [16]. A comparative study of **AirTag, SmartTag, and Tile** found that AirTag demonstrated improved location reporting frequency and accuracy, largely influenced by the density of nearby companion devices [17]. The results show that device density, rather than technology differences, is the key factor in performance, while Tile lagged in accuracy due to limited global adoption [17].

2.5 Sensor Integration

The first step of building a smart home system will be setting up different arrays of sensors in study participant's (older adult resident) rooms to track their daily activities. We selected the sensors in this project as they can capture daily activities non-intrusively while maintaining their privacy. The sensors we will use in this project and how to integrate the data from the sensors will be discussed in the following sections.

2.5.1 Motion Detectors

With motion detectors, we can track people's movement non-invasively throughout their home environment. The proposed system will determine the specific location of people through a multisensory network of motion detectors. As the structure of the living room environment hinders motion detectors from tracking the motion (because of interference with furniture obstructing views, multiple people, walls, doors, etc.), integrating data from multiple sensors is required to specify locations [11]. So, we can place motion detectors over the door and in other out-of-the-way places to trace movement via common walkways in the home. We can also measure the frequency of daily activities like using the washroom or kitchen, spending time in the living room or dining room, etc. If anybody passes through a motion sensor’s range, that will start a timestamped recording in a cloud-based spreadsheet. Thus, we can collect data for an extended period and predict if there is any significant change in their daily behavior.

2.5.2 Contact Sensors

Frequencies of daily activities will be tracked by placing contact sensors on doors, microwaves, and washing machines. So, if anyone enters or exits the home environment, we can count the times they cook, do laundry, etc. We can also put contact sensors on closet doors and drawers to track the usage of distinct items, like changing clothes.

2.5.3 Pressure sensors

Pressure sensors will be set under couch cushions and beds to count the time spent sitting and sleeping. The sleep-sensing mat [12] can measure not only the sleep hours but also evaluate sleep quality and resting heart rate.

2.5.4 Activity Trackers

Participants' number of daily taken steps and different critical signals like resting heart rate, skin temperature, and SpO2 levels will be measured from their Fitbit Sense watch. A resting heart rate is a suitable indicator of overall fitness. Low SpO2 levels may imply respiratory diseases, such as sleep apnea [13] or pneumonia. Based on skin temperature data, we can predict if someone has a fever or an infection, or any circulatory problem that could reduce their body temperature. Variations in skin temperature are also linked to diabetic complications [14].

Accumulating all this data, we can understand their patterns of activities of daily living and do some predictive analysis after enough days of observation. Our goal is to train an AI (Artificial intelligence) system via machine learning algorithm to detect significant changes in their daily behavior so that we can compare data from different sensors and predict their breakfast time or the time they wake up in the morning, and so on. If there are any major deviations in their daily behavior, the system will send a message to their family or medical team to help them immediately.

Chapter 3 - Methods

This research fits into a broader interdisciplinary project aimed at the comprehensive assessment of older adult health through passive, non-invasive activity tracking. As part of a larger smart home research project, this thesis builds upon and augments existing work by focusing specifically on using wearable wireless sensors to track individual locations within a lived environment. The goal is to develop a proof of concept demonstrating that such sensors can effectively localize individuals in real-time, enabling the non-intrusive monitoring of Activities of Daily Living. By processing the collected location data, this research aims to identify behavioral patterns and establish baseline activity profiles that may support early detection of health-related changes in older adults.

3.1 Location and Proximity Sensing

Extensive research was done on products which can track the location of a person in the home and can be analyzed to infer the current activity of the people in the smart home. Location and proximity tracking on an individual basis is an improvement upon the use of motion detectors because it allows the activities of daily living to be tracked individually and not to be interfered with by movements of other people or pets. The company named “Inpixon” has BLE Beacons which uses Bluetooth Low Energy to track the location and can be detected by wireless devices / BLE enabled devices. The brand “Dusun” has two workable products which have high programmability and can save the data on a server. The company “INGICS Technology” has iGS01S Wi-Fi Gateway which is powered via micro-usb and can forward the data to server. The company “Estimote” has an Ultrawideband (UWB) Development Kit which is small and colorful, can save the data on a server and can be programmed as well.

Among these products, we decided to use the UWB developer kit from the “Estimote” company since –

(1) It’s smart and configurable.

(2) Location data will be forwarded to a cloud-based server and that will help to analyze the data properly.

(3) The devices are vibrantly colored, making them an attractive addition to the home environment, so they will be non-invasive for the residents of the house.

A written summary of the comparison of alternative technologies is given in Table 3.1.

Table 3.1: Comparison of alternative technologies

Brand name	Product name	Bluetooth version	Size	Detected by	Power consumption	Programmable or not
Inpixon	BLE Beacons	5.1	small & versatile	wireless devices/ BLE enabled devices	very low	N/A
Dusun	DSGW-040 4G LTE IoT Router Gateway for Multi-in-one Network	5.2	Reasonable	LAN, Wi-Fi, & 4G LTE options to interact with IoT devices	4100 mAh Li Battery	High programmability
Dusun	Bluetooth 5.1 AOA Development Kit	5.1 / 5.2	Reasonable	contains an embedded application that transmits standard Constant Tone Extension (CTE) based on Bluetooth V5.1	USB type-C 5V/2A, Power over Ethernet (POE)	Smart and configurable
INGICS Technology	iGS01S Wi-Fi Gateway	N/A	55mmx40 mmx18mm (excluding dipole antenna)	The iGS01S listens for beacons	powered via micro-USB cable	The unix epoch timestamp requires an NTP server to be configured
Estimote	UWB Development Kit	N/A	small, colorful	Nearby devices that are UWB-enabled and have compatible apps connect to these beacons	2 x AA batteries	can be programmed
Apple	AirTag	N/A	Small	Nearby devices that are UWB enabled	CR032 button cell	can be programmed

3.1.1 Proximity Sensor Selection

This study initially explored the use of Estimote sensors for tracking movement within a home environment. However, due to limitations in achieving the desired outcomes, the methodology shifted to leveraging Apple AirTags for a similar purpose. Specifically, the Estimote only works with iPhones. It is desirable to track the movements of people using wearable devices and there was concern that older adults may not carry their phone with them throughout their home. The revised approach involves participants wearing an AirTag on their wrist, akin to a wristwatch while navigating a predefined home environment.

(a) (b)

Figure 3.1: (a) Picture of an AirTag & (b) the wristband where the AirTag is embedded in it

3.2 Correlation Between RSSI And Physical Distance

We are using the *"BLE Scanner 4.0"* app in a smartphone (Figure *3.2*), the smartphones continuously monitor the Received Signal Strength Indicator (RSSI) values from the AirTag, along with corresponding timestamps. The RSSI values indicate how close a person is to a wireless receiver because the received signal strength weakens as wireless devices are further away and strengthens when nearer in proximity. A smartphone is thus able to approximate the distance a person is from the phone by tracking the signal strength of a worn AirTag.

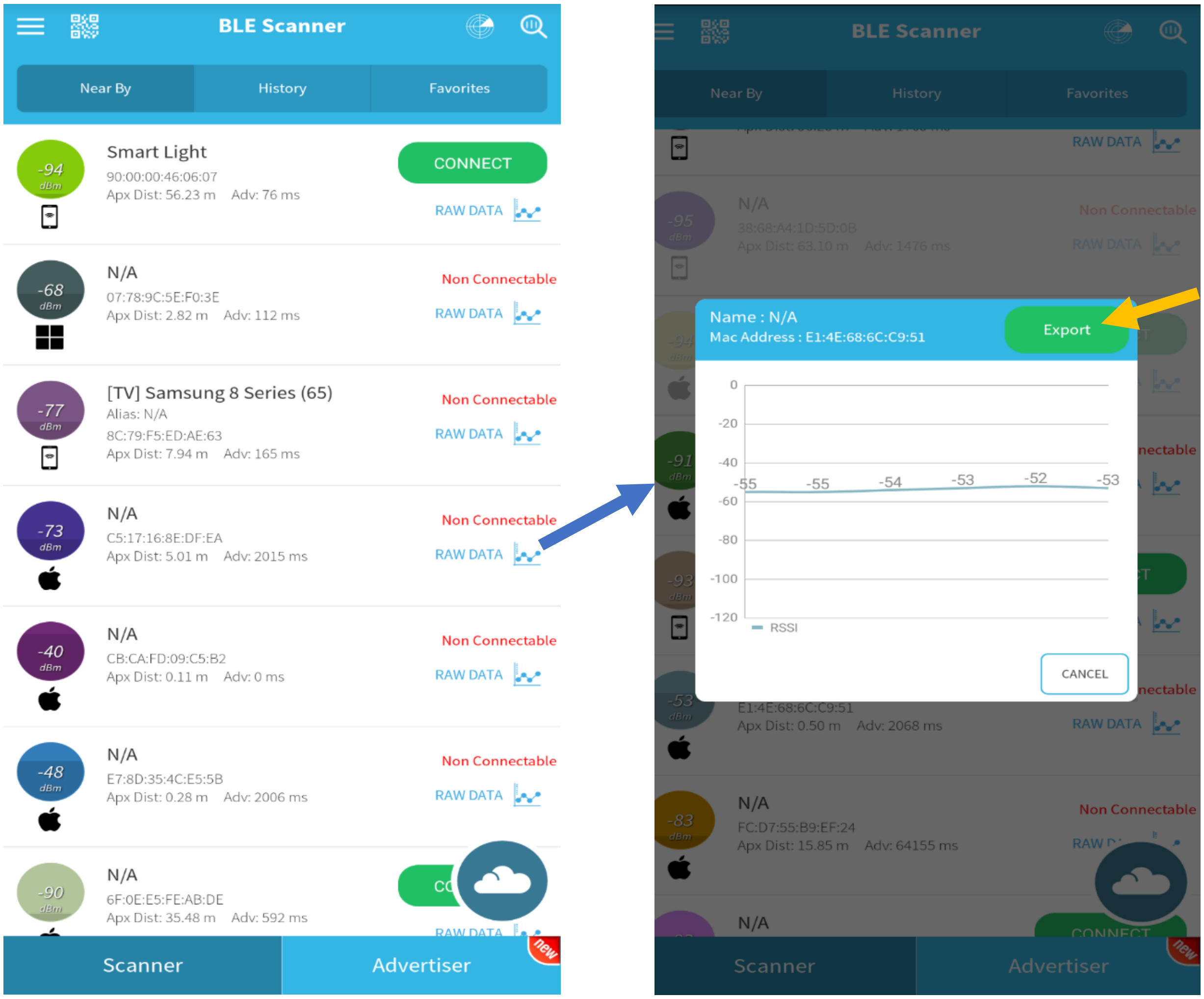


Figure 3.2: BLE Scanner 4.0 app interface

By clicking on the graph beside the raw data, we can collect RSSI data for a given time with timestamps. We can also export the data as a CSV file. Figure 3.3 shows a sample output of the RSSI data tracked over time. More negative values are indicative of the AirTag being further from the phone and less negative values indicate that the tag is closer to the phone.

	A	B	C	D	E
1	BLE Scanner Chart Data				
2	Device Name	N/A			
3	Mac Address	D7:DD:74:A2:33:F7			
4					
5	Time	RSSI			
6	07-11-2024 13:52:35:644	-42			
7	07-11-2024 13:52:37:654	-45			
8	07-11-2024 13:52:39:651	-45			
9	07-11-2024 13:52:41:651	-45			
10	07-11-2024 13:52:43:645	-46			
11	07-11-2024 13:52:45:638	-50			
12	07-11-2024 13:52:47:648	-56			
13	07-11-2024 13:52:49:648	-66			
14	07-11-2024 13:52:51:645	-75			
15	07-11-2024 13:52:53:648	-75			
16	07-11-2024 13:52:55:642	-82			
17	07-11-2024 13:52:57:648	-86			
18	07-11-2024 13:52:59:643	-89			
19	07-11-2024 13:53:01:653	-89			
20	07-11-2024 13:53:03:646	-87			
21	07-11-2024 13:53:05:648	-85			
22	07-11-2024 13:53:07:650	-81			
23	07-11-2024 13:53:09:647	-75			
24	07-11-2024 13:53:11:647	-67			
25	07-11-2024 13:53:13:655	-60			
26	07-11-2024 13:53:15:646	-60			

D7DD74A233F7_RSSI_DATA

Figure 3.3: Illustration of an example of the CSV file format recorded by one of the phones.

The CSV file data includes time-stamped RSSI (Received Signal Strength Indicator) values for the AirTag, showing how the signal strength changed over the course of one minute. This data provides insight into the person's movement patterns within the environment, as fluctuations in RSSI values indicate changes in proximity to the recording device. In order to calibrate the RSSI data to a physical distance, the AirTag and smartphone were placed a known distance apart and the RSSI was measured as shown in Figure 3.4. The distance from the AirTag-embedded wristband to the phone is recorded as 10 feet. At this distance the RSSI value was determined to be between -65 to -70.

Figure 3.4: In this figure, the distance (10 feet) is measured using a tape measure.

3.3 Research Environment

Figure 3.5 illustrates the floor plan of our research environment, which is designed to resemble a typical one-bedroom apartment. The pictures in Figure 3.6 showcase the various rooms in this environment. Upon entering through the front door, the bathroom is located on the left, while the kitchen is situated on the right. Moving further inside, there is a small dining area adjacent to a compact living room. The living room serves as a central space, providing access to the bedroom. This setup allows us to simulate real-world indoor environments, making it ideal for testing and evaluating our research objectives in a practical setting.

Three smartphones are strategically placed at fixed locations in the room, such as beside the couch and the dining table, to act as reference points for tracking. Using the "BLE Scanner 4.0" app, the smartphones continuously monitor the Received Signal Strength Indicator (RSSI) values from the AirTag, along with corresponding timestamps.

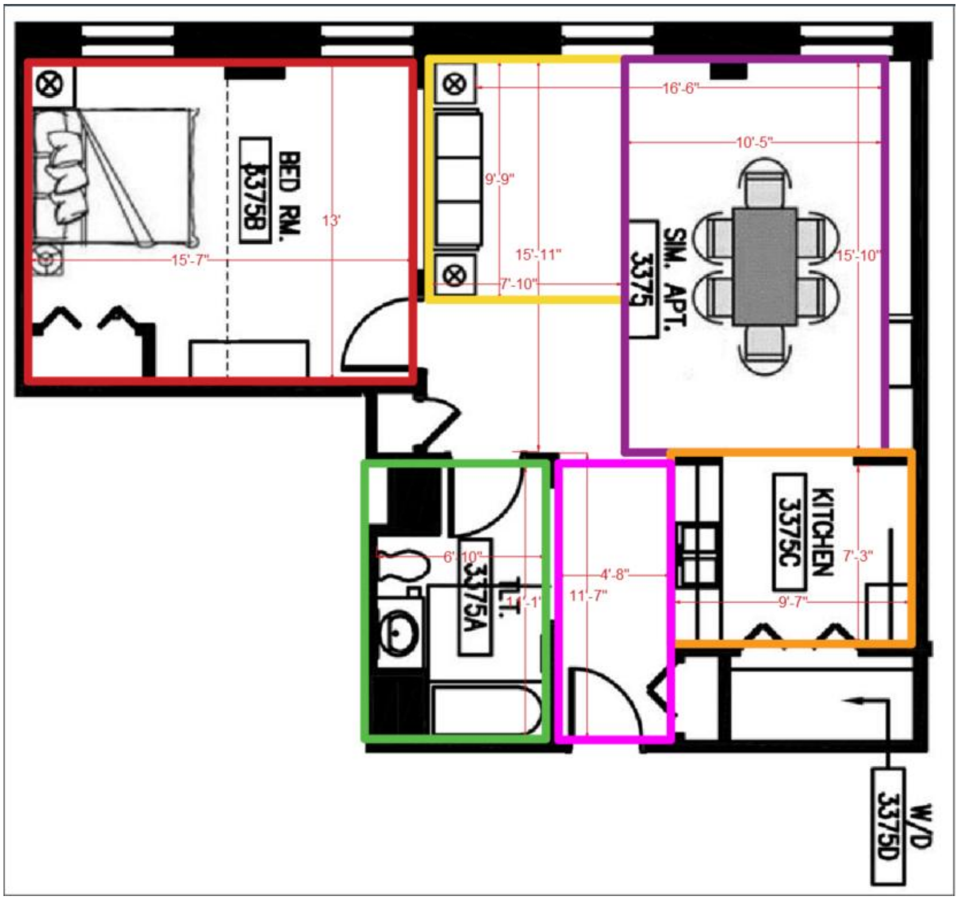


Figure 3.5: Floor plan of our research environment

Figure 3.6: Research environment

3.4 Data Collection and Movement Script

To validate the data, participants' movements are simultaneously tracked in the BLE Scanner app and video recorded from multiple camera angles. The script of movements tracked to demonstrate the effective use of RSSI for movement tracking include:

1. Moving from the bedroom to the dining table (spending 2 minutes at each location).
2. Transitioning from the dining table to the kitchen.
3. Walking from the dining table to the living room.
4. Moving from the couch to the bathroom and then to the bedroom.
5. Traveling between the bedroom and the bathroom.

Figure 3.7: Screen capture from the video recording

The collected RSSI data is used to estimate the participant's location. For example, if the RSSI value is recorded as -70 for device 1 and -50 for device 2, it indicates that the AirTag is approximately 15 feet away from device 1 and 1 foot away from device 2, suggesting the participant is near the couch. This setup enables precise localization by triangulating the RSSI values relative to the fixed devices. This methodology allows for real-time tracking of a person's movement patterns, providing a foundational dataset for understanding in-home behavior and identifying potential changes over time.

After collecting several days of movement data, the RSSI readings and timestamps are analyzed using MATLAB to visualize the participant's movement patterns within the home. The localization process is based on plotting the data points and creating an animated representation to observe movements over time.

For this analysis, the positions of the three smartphones are fixed and known. Circles are drawn around each device in MATLAB based on the RSSI values, with the radius representing the estimated distance of the AirTag from the respective device. The intersection point of these circles indicates the participant's location in the home environment.

By generating an animation of these plotted data points over time, it becomes possible to visualize the participant's movement trajectory through different rooms. This dynamic representation allows for a clear understanding of where the rooms are located and where the participants were at any given moment during the observation period.

3.5 Data Visualization

Figure 3.8 shows the variation in Received Signal Strength Indicator (RSSI) values over time for three different phones: RC phone, TT phone, and YK phone. These phones were placed in corners of the living room in the test environment as depicted in Figure 3.8. The RSSI values, measured in dBm, indicate the signal strength received from a Bluetooth device over a one-minute period. Each line represents the RSSI readings recorded by a specific phone at different timestamps. The fluctuations in RSSI values suggest variations in signal reception due to factors such as interference, obstacles, or minor changes in the relative positioning of the devices.

Overall, while the signal strength for each phone follows a similar trend, slight differences are observed, possibly due to variations in hardware sensitivity or environmental conditions.

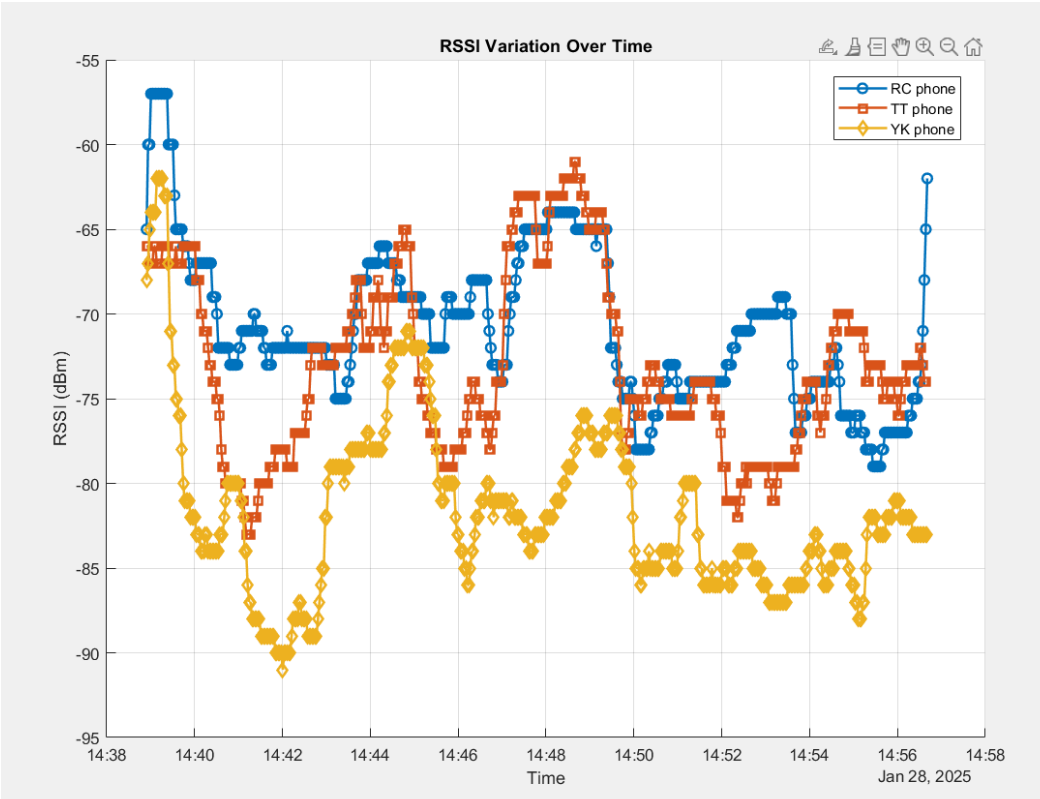


Figure 3.8: Variation in RSSI values over time for three devices

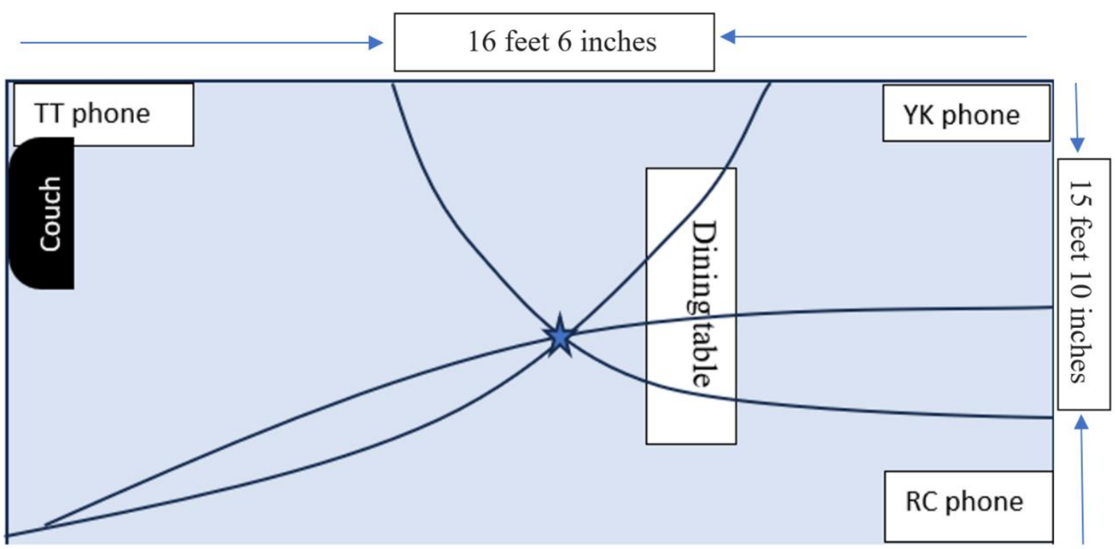


Figure 3.9: Intersection point of three device areas/possible location of the participant

In this MATLAB code, we implemented a **trilateration algorithm** to determine the estimated position of an unknown point using distance measurements from three known reference points (phones). Each phone represents a fixed beacon, and the distances to the target point are used to compute its location. Figure 3.9 depicts the use of triangulation to identify the location of a person.

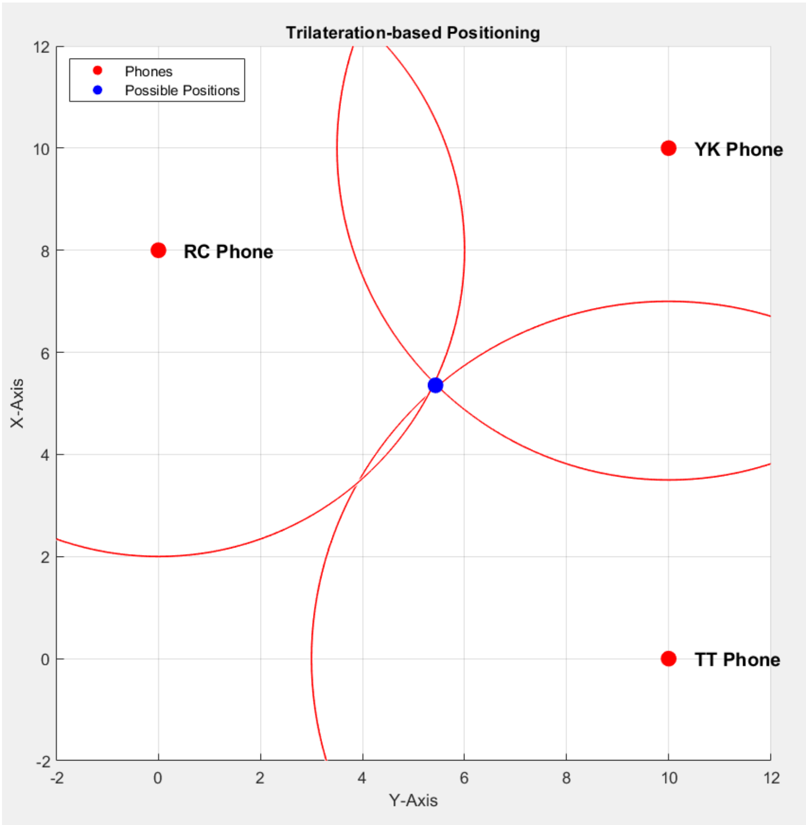


Figure 3.10: Trilateration-Based Position Estimation

The Methodology for the trilateration algorithm is given below.

1. **Defining Reference Points:**
   - Three phones are placed at known positions in a 2D space:
     - TT Phone at (0,10) feet
     - YK Phone at (10,10) feet
     - RC Phone at (8,0) feet

2. **Distance Measurements:**
   - The measured distances from the target to each phone were recorded as:
     - d1 = 7 feet (from TT Phone)
     - d2 = 6.5 feet (from YK Phone)
     - d3 = 6 feet (from RC Phone)
3. **Mathematical Approach:**
   - Initially, we formulated three circle equations, each representing the possible location of the target based on the given distances. However, due to potential measurement errors or small inaccuracies, the three circles do not intersect perfectly at a single point.
4. **Least Squares Optimization:**
   - To resolve this issue, we employed a **least squares optimization technique (using the MATLAB lsqnonlin function)** to determine the best-fit intersection point that minimizes the distance error across all three reference circles.
   - The optimization function calculates the point (x, y) that best satisfies all three distance constraints, ensuring an accurate and robust estimate of the target's position.
5. **Visualization:**
   - The phones' positions and distance circles are plotted for visualization.
   - The final estimated intersection point is highlighted, representing the computed target location.

By using nonlinear least squares optimization**,** we achieved a highly accurate estimation of the target's position. This approach enhances precision, making it suitable for real-world indoor localization applications**,** such as position tracking in smart homes, robotics, or beacon-based navigation systems**.** This method not only provides a spatial understanding of the individual's movements but also highlights behavioral patterns and time spent in different areas, offering valuable insights for further analysis of in-home activity and mobility.

3.6 Time Based Integration of Data

In this approach, we will begin by selecting a set of three points, each corresponding to a distinct device (e.g., YK phone, TT phone, and RC phone). For each set of three points, we will plot circles representing the distance from each phone to the person. The process will be repeated for subsequent sets of three points, with each new set of circles plotted accordingly. Over time, this series of plots can be compiled into a video file, where each frame corresponds to a set of three circles, showing how their intersections change as the person moves.

The initial set of points should ideally be aligned precisely. The distances indicated by the red, green, and blue circles correspond to the distance as approximated by the RSSI (Received Signal Strength Indicator) values from the RC phone, TT phone, and YK phone, respectively. From these distances, we can project the three circles and determine the person's location based on their intersection.

This represents the first frame in the animation. The process will be repeated for each subsequent frame: new points are plotted, the circles are redrawn, and the intersection is recalculated to track the person's movement. As the person moves—whether toward the couch, the table, or another area in the environment, the intersection of the circles will shift accordingly, providing a visual representation of the person's location.

In the final video, the person’s position can be marked with a symbol (such as a star or another appropriate marker) at each intersection. By observing the movement of these intersections across frames, we will be able to see the path the person takes over time through the space, from the couch to the table and down to the kitchen area, for example, in Figure 3.11, Screen capture from the trilateration-based positioning movie showing the estimated location of the participant (star) derived from the intersection of distances to three phones (red, green, and blue). The circles represent the calculated ranges from each phone, while the timestamp indicates the precise recording time. Consecutive frames from the movie allow visualization of the participant's movement path through the environment.

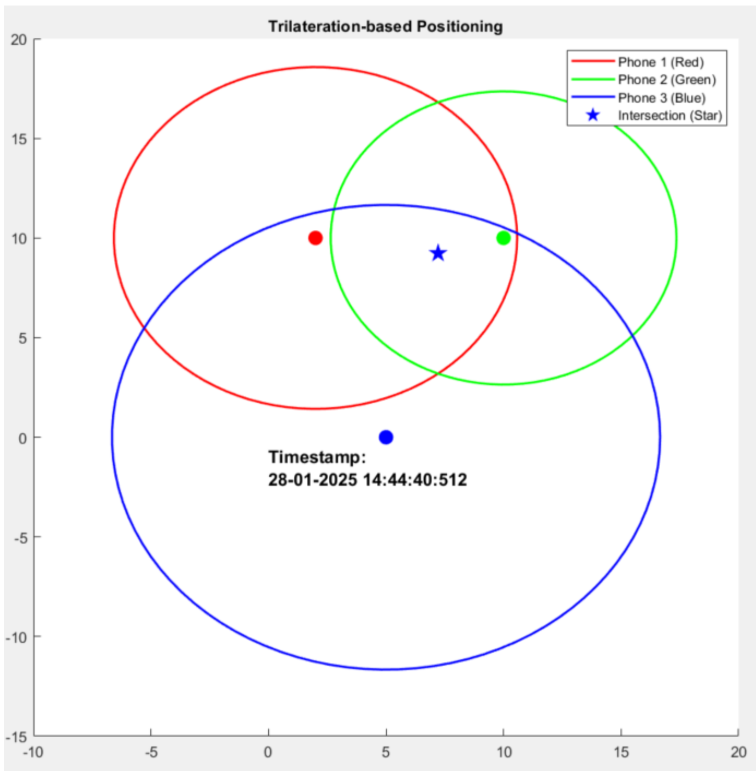


Figure 3.11: Screen capture from the movie

Chapter 4 - Data Analysis

4.1 Evaluation of Methodology

A series of controlled movement scripts were developed to simulate realistic human activity within the research environment. These scripts involved transitioning between various rooms while collecting Received Signal Strength Indicator (RSSI) data using the designated devices. The goal was to assess how well the system could capture and reflect relative location changes over time while people were making natural movements like someone would do in their own home.

The movement sequences were structured to include stationary periods (to establish signal baselines) and transitions (to observe signal dynamics). The following scenarios were implemented:

1. Bedroom to Dining Table

   The participant remained seated on the bed for two minutes, then transitioned to the dining table and remained seated there for another two minutes.

2. Dining Table to Kitchen

   After spending two minutes at the dining table, the participant moved into the kitchen and remained there for two minutes.

3. Dining Table to Living Room

   The participant returned to the dining table briefly, sat for two minutes, then proceeded to the living room, sitting on the couch for another two minutes.

4. From the couch to Bathroom and Bedroom

   From the couch, the participant entered the bathroom and remained there for two minutes, then returned to the bedroom for another two-minute interval.

5. Bedroom to Bathroom and Back

   During a simulated midnight trip, the participant moved from the bed to the bathroom, spent two minutes there, and then returned to the bedroom for another two minutes.

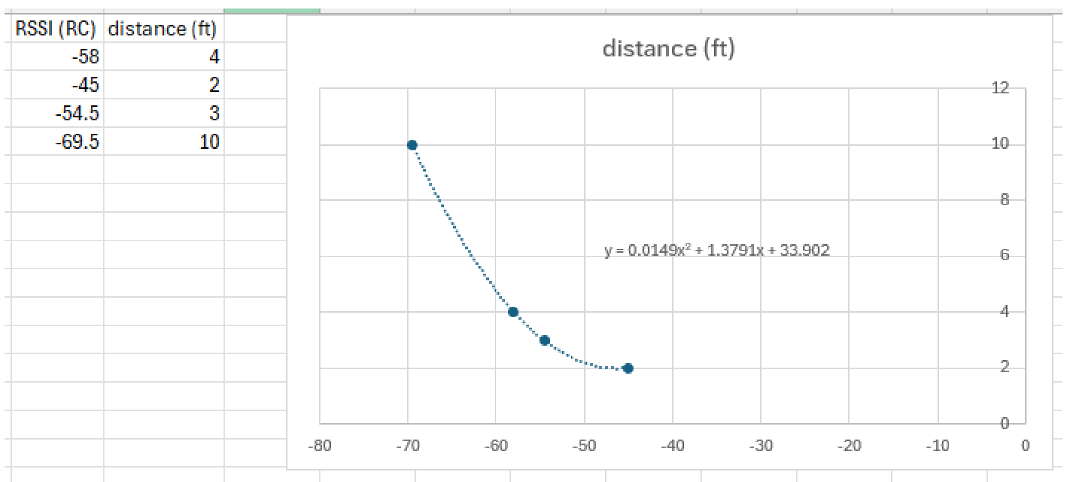
These movements provided a varied yet consistent set of positional changes that allowed us to analyze the system's tracking accuracy and responsiveness under semi-controlled residential conditions.

Figure **4.1** shows the smoothed RSSI values (5-point moving average) over time for three phones (RC, TT, and YK). The RSSI values were smoothed using a five-point moving average to reduce variability and minimize signal noise in the data. Each data point represents the averaged signal strength at a given timestamp during the movement sequences.

	A	B	C	D
1	Time	RC avg	TT avg	YK avg
2	28-01-2025 14:38:54:443	-59.8	-66.6	-65.6
3	28-01-2025 14:38:56:461	-58.2	-66.6	-64.8
4	28-01-2025 14:38:58:456	-57.6	-66.6	-64.2
5	28-01-2025 14:39:00:453	-57	-66.6	-63.6
6	28-01-2025 14:39:02:448	-57	-66.6	-63.2
7	28-01-2025 14:39:04:449	-57	-66.6	-62.8
8	28-01-2025 14:39:06:442	-57	-66.8	-62.4
9	28-01-2025 14:39:08:450	-57	-66.8	-62
10	28-01-2025 14:39:10:447	-57	-66.6	-62.2
11	28-01-2025 14:39:12:451	-57	-66.4	-62.4
12	28-01-2025 14:39:14:457	-57	-66.2	-62.6
13	28-01-2025 14:39:16:459	-57.6	-66	-63.6
14	28-01-2025 14:39:18:450	-58.2	-66.2	-65.4
15	28-01-2025 14:39:20:450	-58.8	-66.4	-67
16	28-01-2025 14:39:22:456	-59.4	-66.6	-69
17	28-01-2025 14:39:24:454	-60.6	-66.8	-71
18	28-01-2025 14:39:26:457	-61.6	-66.8	-72.6
19	28-01-2025 14:39:28:460	-62.6	-66.8	-73.4
20	28-01-2025 14:39:30:449	-63.6	-66.8	-74.4

Figure 4.1: Sample smoothed RSSI values over time for three phones (RC, TT, and YK).

Figure 4.2 shows RSSI data collected at known distances (in feet) from one of the phones used in the experiment (RC). These measurements were used to derive an empirical equation relating RSSI values to physical distance for interpolation purposes. The interpolation curve shows the relationship between RSSI values and physical distance. The best-fit equation was used to estimate distances from RSSI values collected during movement experiments. Similar datasets were collected by measuring RSSI values at known physical distances (in feet) from each of the three phones (RC, TT, and YK). From these datasets, a best-fit curve was derived for an equation correlating RSSI to distance. For each of the phones used, RC, TT, and YK, a quadratic curve was the best fit.



RSSI (RC)	distance (ft)
-58	4
-45	2
-54.5	3
-69.5	10

Figure 4.2: Sample RSSI data collected at known distances (in feet) from one phone (RC)and the interpolation curve showing the relationship between RSSI to distance

The following three equations were derived from the RSSI calibration data. Equation 4.1 is the calibration for phone RC, equation 4.2 is for TT phone and equation 4.3 is for YK phone.

$$y = 0.0149x^2 + 1.3791x + 33.902 \tag{4.1}$$

$$y = 0.0033x^2 - 0.1443x - 14.705 \tag{4.2}$$

$$y = 0.037x^2 + 4.8426x + 163.29 \tag{4.3}$$

Using these equations, interpolation and estimation of physical distances were performed based on the RSSI values collected during the movement trials. This process allowed conversion of signal strength data into spatial estimates, which were later used for trilateration and position tracking.

4.2 Visualization of Movement Using MATLAB-Based Trilateration Animation

In this approach, the estimated distance of the person from each of the phones (e.g., YK phone, TT phone, and RC phone) was computed using equations 4.1-4.3 to translate from RSSI data into physical distance estimates. From this data, circles could be drawn around the phone locations to project estimated positions of the AirTag over time relative to the location of the tracking phones. This process is repeated for subsequent sets of three points, with new circles plotted accordingly. Over time, the resulting series of plots is compiled into a video file, where each frame visualizes a unique set of three circles and their intersections, illustrating the person's movement.

To ensure accuracy, the initial positions of the devices should be precisely aligned. The red, green, and blue circles correspond to distance estimates derived from the RSSI values of the TT phone, YK phone, and RC phone, respectively. These distances define the radii of the circles, and the intersection point of the three indicates the estimated position of the person at that time.

This first set of circles represents the initial frame of the animation. For each subsequent frame, updated RSSI values generate new distances, new circles are drawn, and a new intersection point is calculated. This ongoing process visualizes the changing location of the individual over time.

As the person moves through the environment—such as from the couch to the table, and eventually toward the kitchen—the intersection points shift accordingly.

In the final animation, the person's estimated position can be marked with a symbol (such as a star) at each intersection point. Observing the progression of these markers across the video frames provides a clear visual representation of the individual's path through the space.

4.2.1 Projection Constraints to Maintain Environmental Boundaries

To ensure the predicted position of the participant remained within the defined boundaries of the research environment, spatial constraints were incorporated into the position estimation algorithm. Specifically, the environment was bounded by a fixed rectangular area, and any estimated coordinates falling outside of this area were either clipped to the nearest valid boundary or discarded from visualization. Additionally, logical constraints were applied to restrict movement beyond physical structures, such as walls or predefined zones (e.g., the participant's position could not exceed the window at y=20 or enter regions beyond the bedroom or kitchen layout). These safeguards helped maintain the realism and validity of the projected trajectory and allowed for more accurate visual validation when compared to ground truth video data.

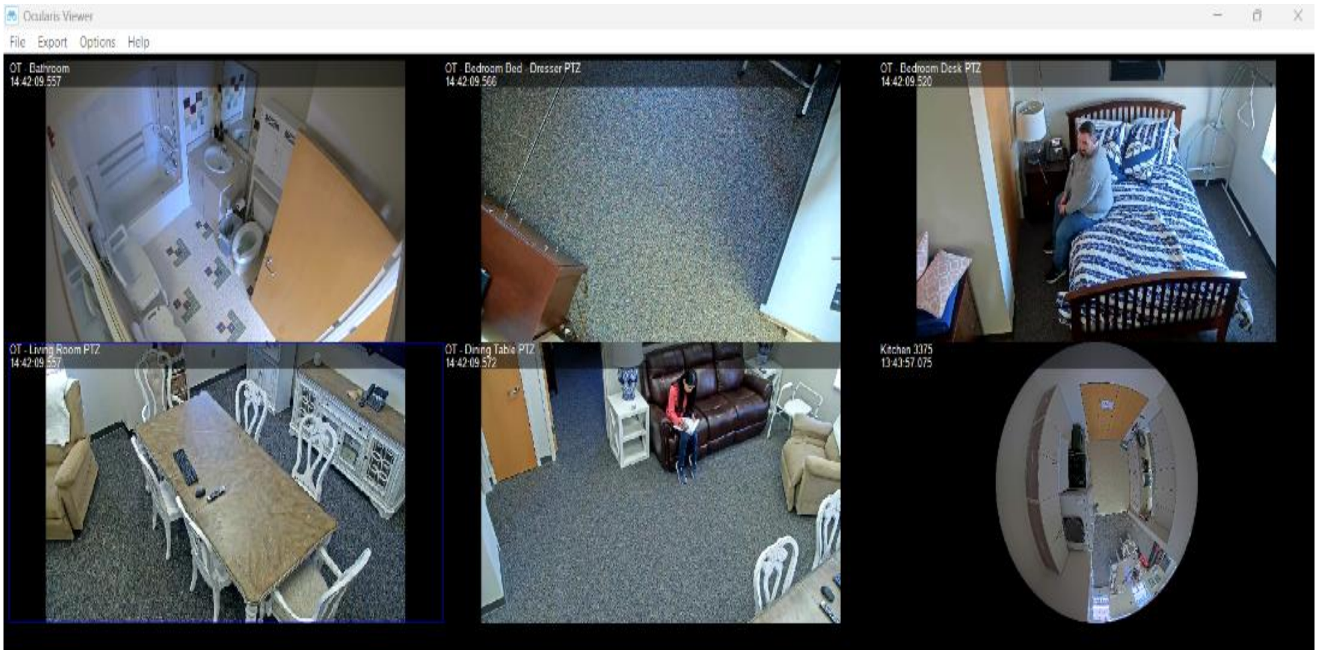
4.3 Visual Validation Through Side-by-Side Video Comparison

The research environment has several cameras to track participant activities using the Ocularis video surveillance system. To validate the accuracy of the MATLAB-based trilateration visualization, selected screen captures from the Ocularis video surveillance system were compared side-by-side with frames from the MATLAB-generated movement video. This comparison enables a qualitative assessment of whether the estimated positions—represented by the intersection point (star) in the MATLAB video—correspond to the actual physical locations observed in the real-world footage.

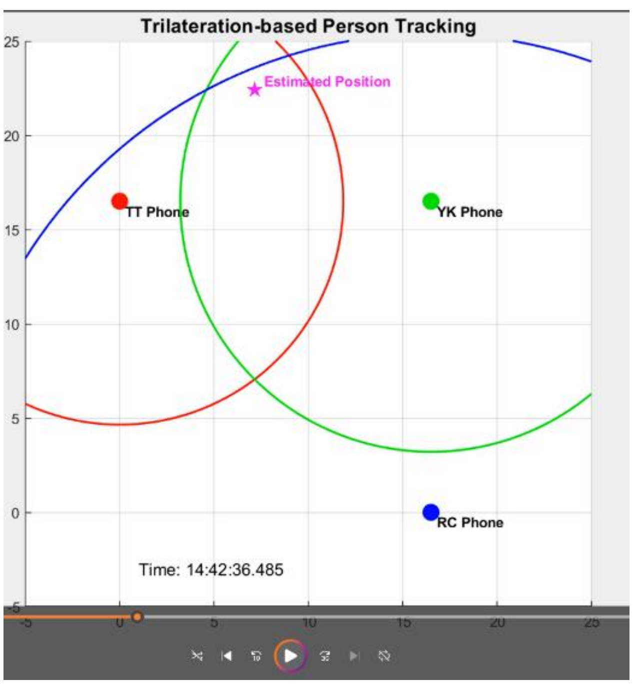
In Figure 4.3 (a) at **14:42**, the participant (the man in gray shirt, RC) is observed sitting on the bed in the Ocularis capture, however the MATLAB video at this timestamp, Figure 4.3 (b) indicates that the participant is located outside of the research area. This indicates that some refinement was necessary to improve the algorithm to ensure that the projected location of the intersection of circles is within a feasible region. Once this was observed, the MATLAB script was revised to restrict the placement of the star to locations inside the research environment, and the regions were labeled in the MATLAB plots. Figure 4.3 (c) shows an improved estimation of the location of the participant at 14:42.

As can be seen in Figure 4.4, at timestamp **14:39**, the Ocularis video shows the participant positioned in the dining area. The corresponding frame in the MATLAB video also places the intersection point (star) in the dining area, indicating close alignment between the estimated and actual positions. Similarly, at **14:44** in Figure 4.5, RC is shown sitting at the dining table according to the surveillance footage, with the MATLAB video placing the intersection point near the dining table as well.

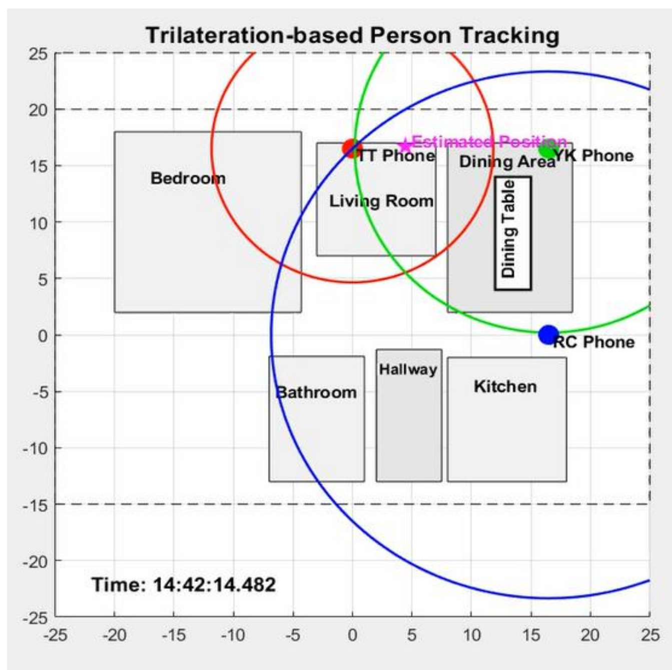
Figures 4.6 and 4.7 illustrate examples of the localization process at two time points. At 14:47, RC was seated on the couch, as shown in the Ocularis screen capture and the MATLAB video capture, which places his estimated position near the couch in the living room area. Two minutes later, at 14:49, RC was in the bathroom, according to the Ocularis screen capture, and the MATLAB video also reflects the transition toward that area. As mentioned previously, when participants moved between rooms or when walls separated spaces, some noise was observed in the localization data, occasionally affecting the precision of the estimated position.



(a)

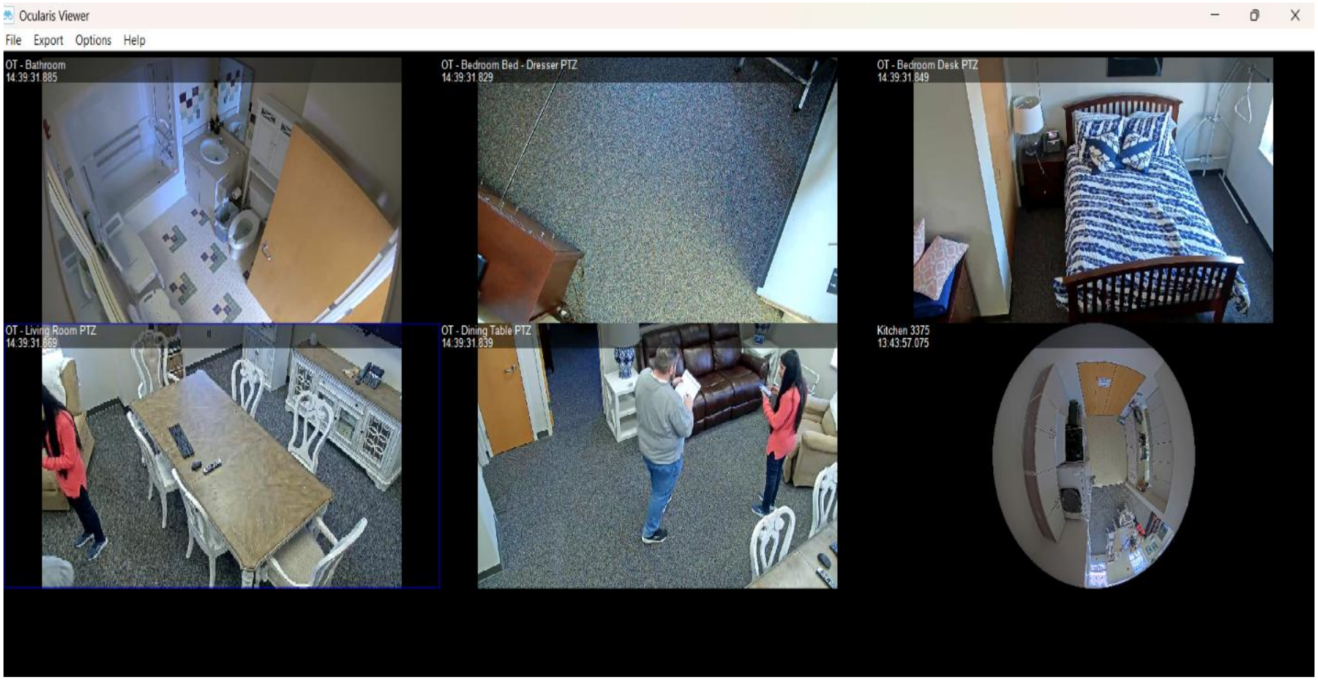


(b)

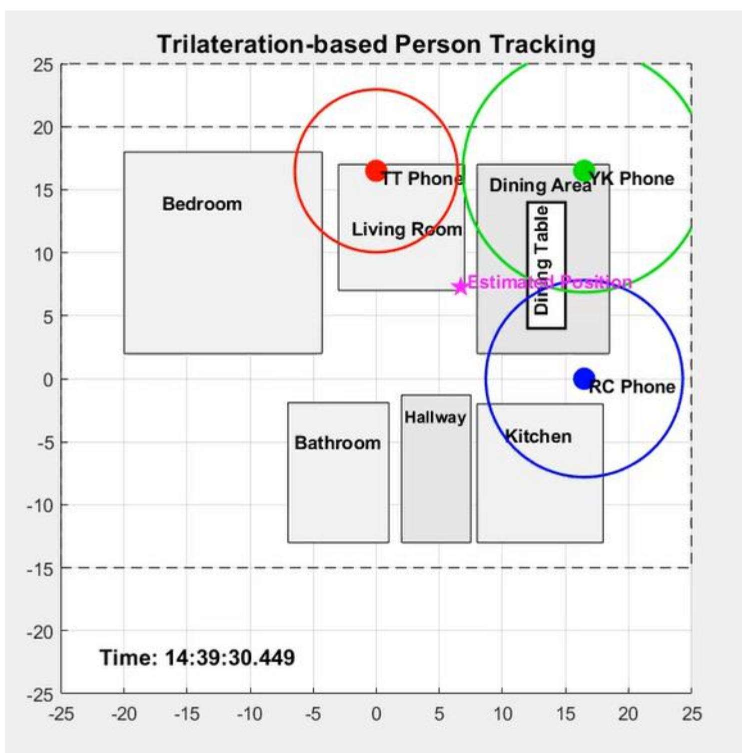


(c)

Figure 4.3: RC in the bedroom area at 14:42 in Ocularis screen capture (a) but MATLAB intersection is outside of the research window in (b) and improved movie capture in (c) with room labels

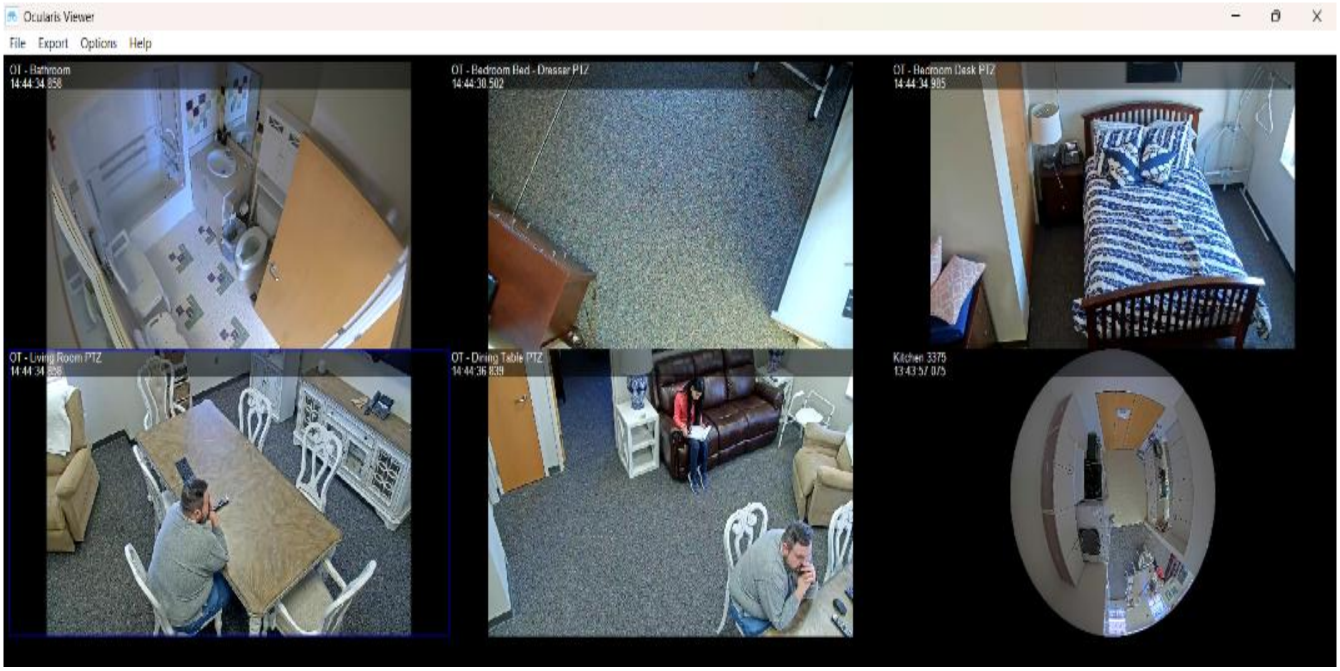


(a)

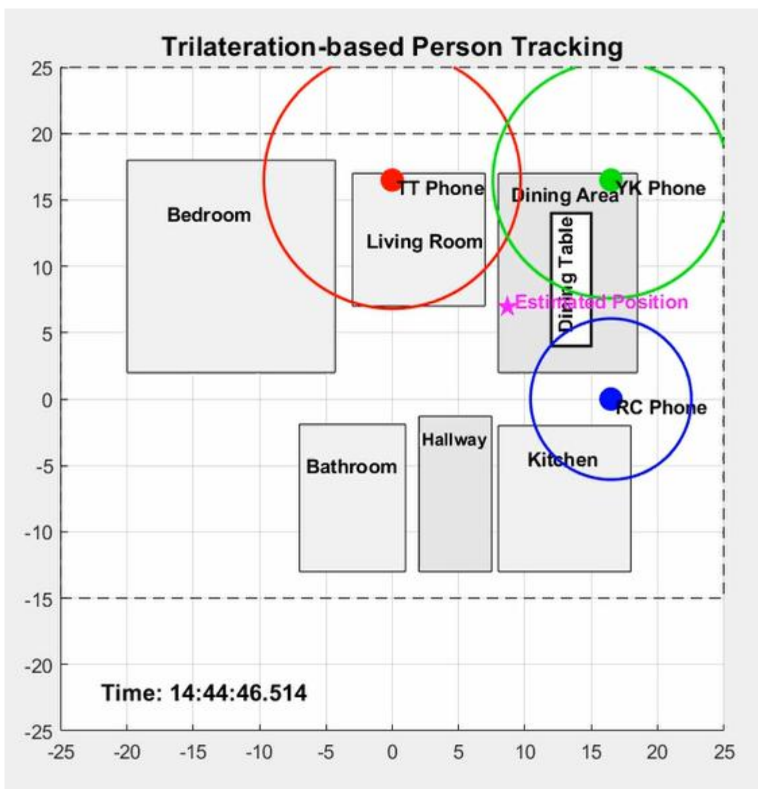


(b)

Figure 4.4: RC in Living room area at 14:39 in Ocularis screen capture (a) and in MATLAB video capture (b)

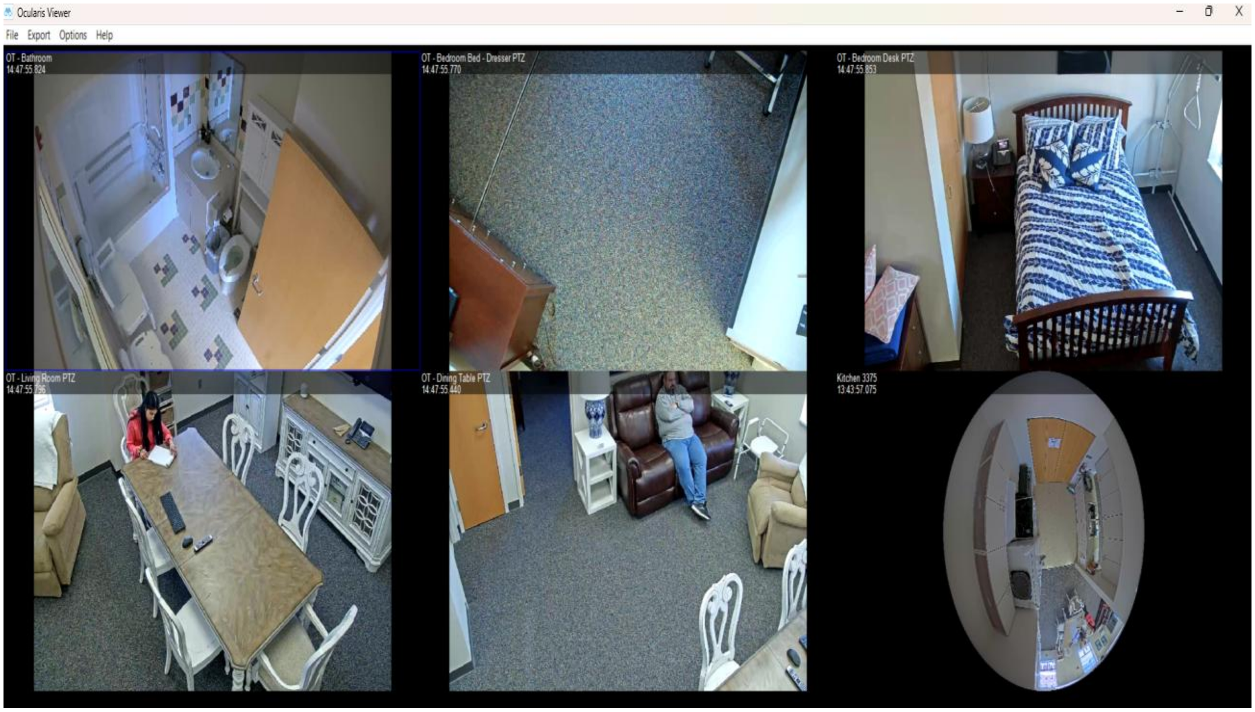


(a)

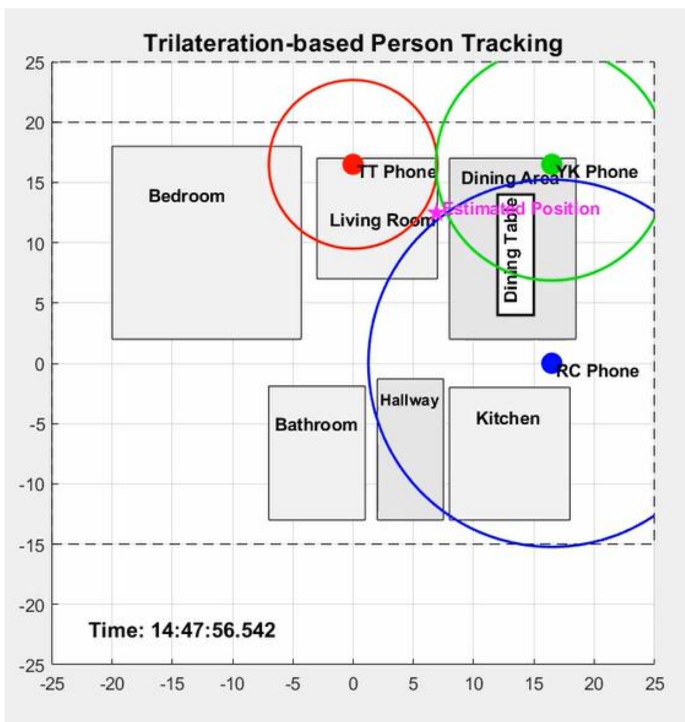


(b)

Figure 4.5: RC at dining table at 14:44 in both Ocularis screen capture (a) and MATLAB video capture (b)

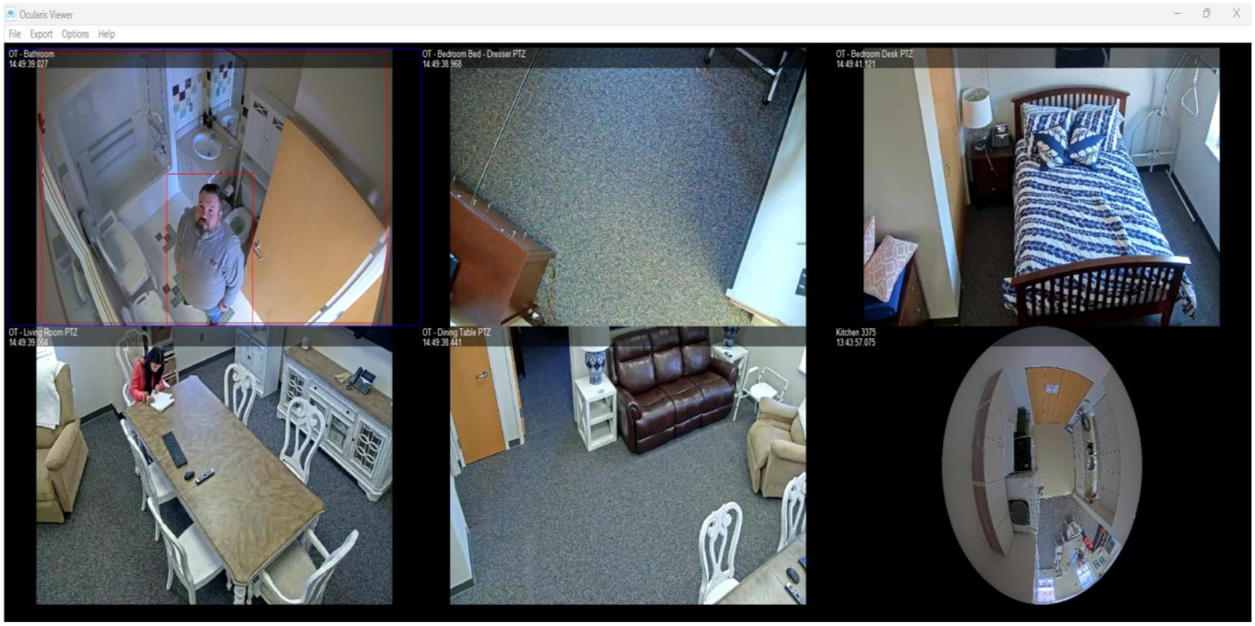


(a)

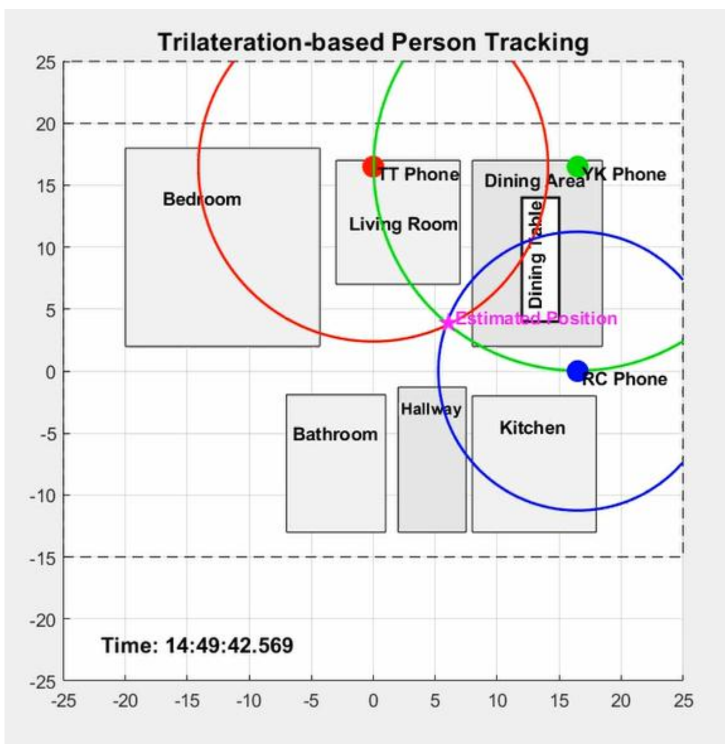


(b)

Figure 4.6: RC on the couch at 14:47 in both Ocularis screen capture (a) and MATLAB video capture (b)

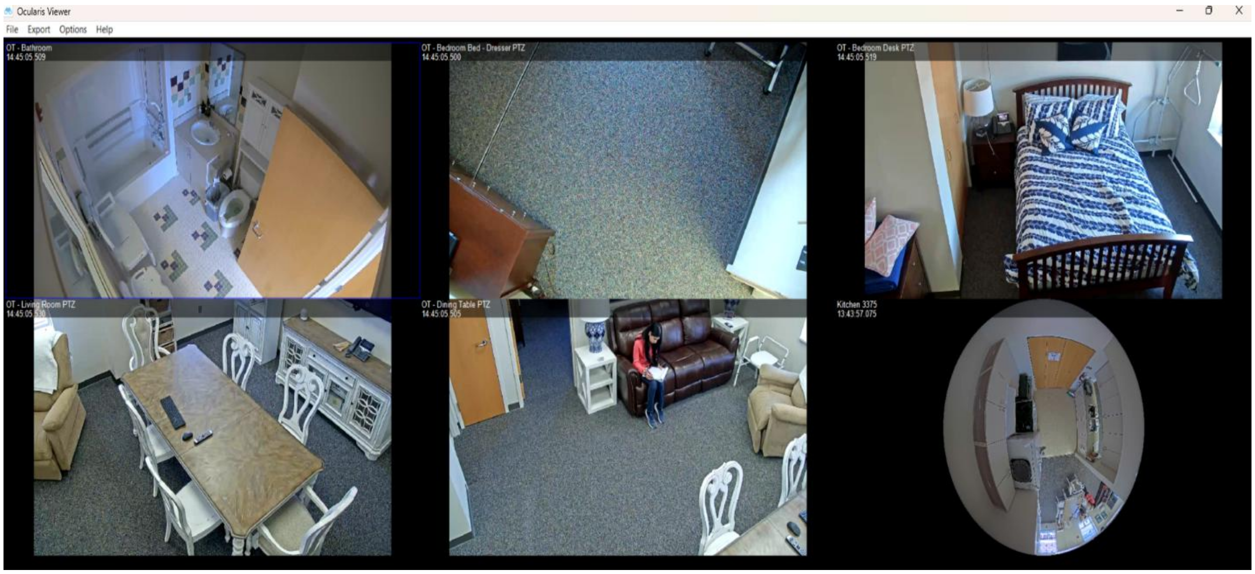


(a)

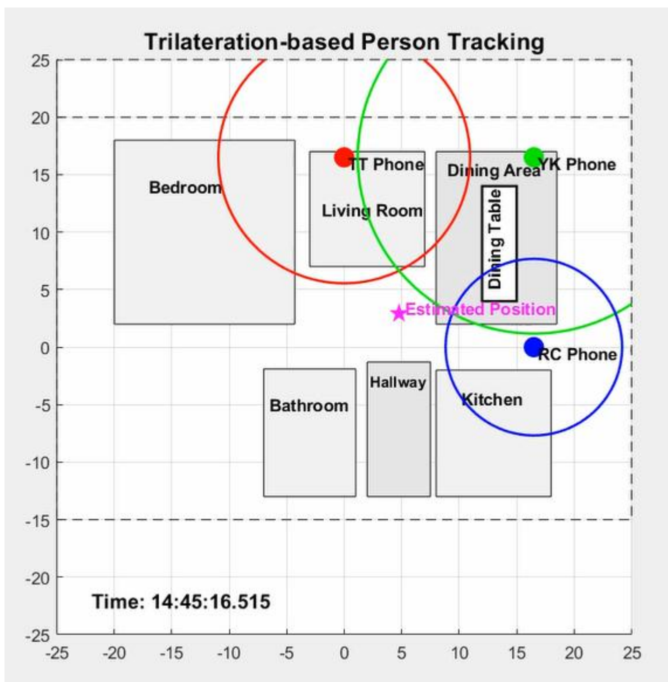


(b)

Figure 4.7: RC at bathroom at 14:49 in both Ocularis screen capture (a) and closer to bathroom in MATLAB video capture (b)



(a)



(b)

Figure 4.8: RC in the kitchen area at 14:45 in both Ocularis screen capture (a) and closer to the kitchen in MATLAB video capture (b)

Figure 4.8 shows RC in the kitchen area at 14:45, as indicated by the Ocularis audio recording and our data collection script (a), with the MATLAB video capture (b) also placing his estimated position near the kitchen. However, there was an issue with the Ocularis video capture system in this location. Although the data collection scripts were designed to record both video and RSSI data in the kitchen, the Ocularis system experienced limitations that prevented accurate video recording and time-stamping for this area. As a result, while the MATLAB capture reflects RC's position appropriately, the Ocularis video data for the kitchen is incomplete.

To assess the accuracy of the estimated positions derived from RSSI-based trilateration, a visual validation was performed. A MATLAB-based simulation environment was developed to generate a movie of estimated positions over time, based on RSSI data from three fixed-location smartphones. This movie was compared side-by-side with a video recording captured through the Ocularis surveillance system.

The comparison allowed for a qualitative evaluation of the system's performance. The estimated trajectories, shown as a moving marker within the simulated floor plan, were visually aligned with the subject's actual movement recorded by the surveillance footage. Notable consistencies between the two videos support the reliability of the estimation algorithm in tracking relative movement patterns within the indoor environment. Minor discrepancies were observed, likely due to signal noise, occlusions, or physical barriers not modeled in the simulation. Overall, the side-by-side video comparison served as an effective tool for intuitive validation of the algorithm's spatial accuracy. These time-synchronized comparisons reinforce the credibility of the trilateration method and the reliability of RSSI-based position estimation when visualized through MATLAB.

Chapter 5 - Results and Discussions

This chapter presents the outcomes of the indoor positioning framework implemented using MATLAB and visually validated through synchronized video comparison. The developed system integrates trilateration techniques based on RSSI values received from three smartphones (RC, TT, and YK) strategically placed in a residential environment. The accuracy of the predicted positions was assessed using a side-by-side comparison with the participant's actual movement recorded via Ocularis video capture.

5.1 Environment Layout and Constraint Modeling

A detailed 2D layout of the experimental environment was constructed in MATLAB, replicating key spatial zones including the Bedroom, Living Room, Dining Area, Kitchen, and Bathroom. These room boundaries were incorporated using precise rectangle and line segment definitions based on architectural dimensions.

To ensure realism and accuracy in the predicted positioning, constraints were introduced into the projection algorithm:

- The participant's estimated position (marked as a star) was bounded within the logical confines of the mapped environment.
- To reflect the physical constraints of the room, the algorithm capped the y-axis at 20 (representing the wall with the window) and restricted projections into inaccessible areas such as beyond walls or outside the bounding rectangle of the floor plan.

These spatial restrictions were critical in avoiding implausible location predictions and in aligning the system behavior with real-world physical constraints.

5.2 Positional Estimation Results

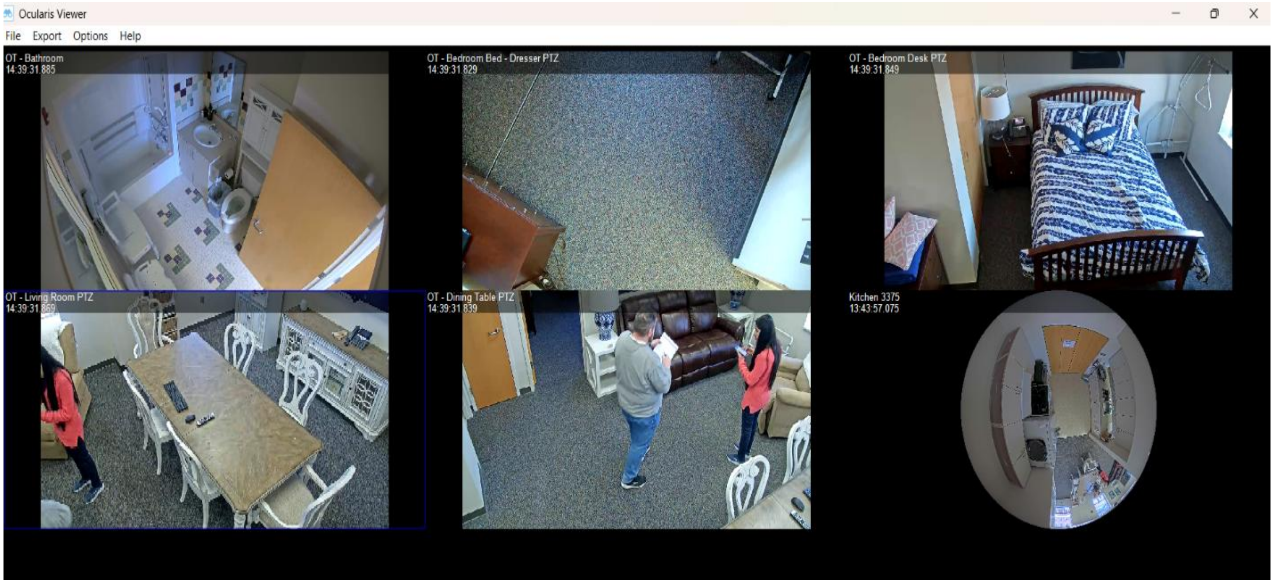
Over a sequence of timestamps, the MATLAB simulation successfully estimated the participant's location using trilateration principles in most circumstances. Each frame of the generated movie plotted:

- Real-time distances (circles) from RC, TT, and YK phones
- The intersection zone estimate (the star)
- A room-labeled floor plan
- Environmental elements like the dining table and kitchen walls

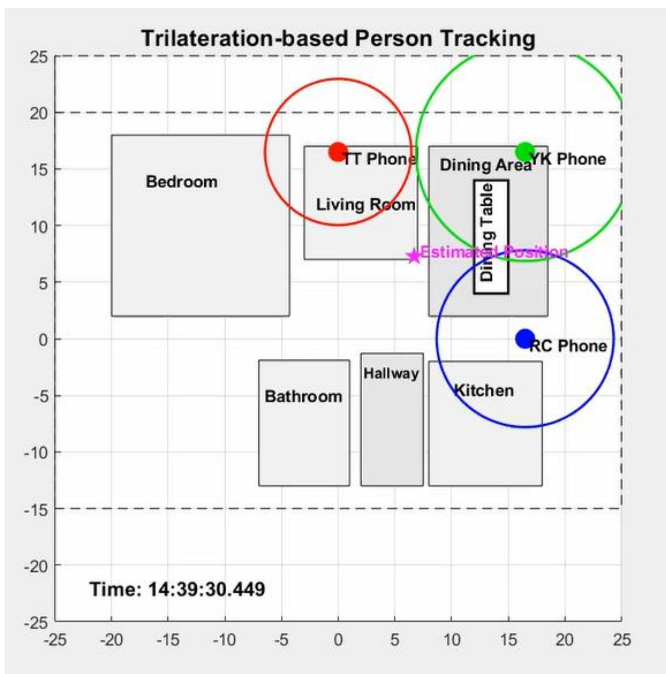
In general, the star closely followed the movement trajectory seen in the reference Ocularis video, particularly in zones like the Dining Area, Living Room, and Kitchen. The dynamic update of distances helped capture moment-to-moment fluctuations due to RSSI variability. The algorithm prevented projections into logically inaccessible areas (e.g., through walls or outside the bounding rectangle of the floor plan). A notable challenge was the occurrence of significant distance estimates that placed projected positions well outside the room where the phones were located, requiring careful handling to maintain logical consistency with the floor plan.

5.3 Visual Validation and Interpretation

To validate the system's performance, a side-by-side comparison between the MATLAB movie and the actual surveillance footage was conducted. Figure 5.1, at timestamp 14:39, shows the participant standing in the dining area in the Ocularis video. The corresponding MATLAB frame similarly places the intersection point (star) in the dining area, demonstrating strong agreement between the estimated and observed positions.



(a)



(b)

Figure 5.1: The participant (The man in gray shirt, RC) in Living room area at 14:39 in Ocularis screen capture (a) and in MATLAB video capture (b)

Key observations include:

- **High agreement** during transitions between Dining and Living room areas.
- **Occasional mismatch** in bedroom and bathroom transitions. Although the participant entered the bedroom and the bathroom several times (as per video), the estimated positions rarely reached that zone.
- Limitations were noted in the kitchen area. Although our data collection scripts were designed to capture both video and RSSI data, the Ocularis system experienced difficulties recording and time-stamping videos in that location. As a result, while the MATLAB captures generally placed the participant near the kitchen, the Ocularis video data was incomplete, reducing the ability to validate positions in that zone.

This discrepancy is likely due to:

- Weak RSSI coverage or noisy signals from phones placed near walls (e.g., TT and RC).
- Overly restrictive distance convergence, possibly misplacing the centroid.
- Potential signal attenuation caused by furniture or walls not modeled as signal-blockers.

This limitation suggests that while the algorithm reliably detects motion within open spaces, improvements are needed for edge or corner zones like the bedroom and the bathroom.

5.4 Accuracy Analysis of Movement Tracking

To evaluate the accuracy of the trilateration-based position estimation, a detailed comparison was conducted between the MATLAB-generated movement video and the Ocularis camera recordings. Table 5.1 summarizes the results of this comparison, showing timestamped locations obtained from both sources, along with notes on signal quality and accuracy classification.

In this study, *localization accuracy* was defined as the degree of agreement between the estimated position obtained from the MATLAB trilateration model and the actual position of the participant observed in the Ocularis video footage. For each time segment, the estimated position was classified as *accurate* when the intersection point (represented by the star marker) corresponded to the correct physical zone or activity area (e.g., couch, dining table, kitchen) as observed in the Ocularis video. The percentage of time the system correctly identified the participant's zone was calculated to represent the model's accuracy for each location.

The results indicate that the system achieved high accuracy in open areas such as the dining area, living room, and couch, where Bluetooth signals were stable and unobstructed. In contrast, accuracy decreased in regions such as the bedroom and bathroom, primarily due to signal attenuation and multipath interference caused by walls and obstacles. Instances where the estimated position partially matched the actual position typically occurred during transitions between rooms, particularly in the hallway, where overlapping signal strengths from multiple phones caused ambiguity.

Table 5.1: Comparison of Actual and Estimated Locations for Accuracy Analysis

Timestamp (min)	Actual Location (Ocularis Video)	Estimated Location (MATLAB video)	Accurate? (Yes/No)	Notes
28-01-2025 14:38:54	Dining area	Dining area	Yes	Stable reading
28-01-2025 14:39:00	Living room area	Living room area	Yes	Stable reading
28-01-2025 14:39:30	Living room area	Living room area	Yes	Stable reading
28-01-2025 14:40:00	Bedroom	Living room area	No	Weak signal near wall
28-01-2025 14:40:30	Bedroom	Living room area	No	This time, the star was between bedroom and living room
28-01-2025 14:41:00	Bedroom	Living room area	No	Closer to bedroom
28-01-2025 14:41:30	Bedroom	Window area near bedroom	No	Weak signal near wall
28-01-2025 14:42:00	Bedroom	Window area near bedroom	No	Weak signal near wall
28-01-2025 14:42:30	Dining table	Window area near bedroom	No	Weak signal near wall
28-01-2025 14:43:00	Dining table	Dining area	Yes	Stable reading
28-01-2025 14:43:30	Dining table	Dining area	Yes	Stable reading
28-01-2025 14:44:00	Dining table	Dining area	Yes	Stable reading
28-01-2025 14:44:30	Dining table	Dining area	Yes	Stable reading

28-01-2025 14:45:00	Kitchen area	In the Hallway	Partially	The star is in the hallway towards the kitchen
28-01-2025 14:45:30	Kitchen area	In the Hallway	Partially	The star is in the hallway towards the kitchen
28-01-2025 14:46:00	Kitchen area	In the Hallway	Partially	The star is in the hallway towards the kitchen
28-01-2025 14:46:30	Kitchen area	In the Hallway	Partially	The star is in the hallway towards the kitchen
28-01-2025 14:47:00	Living room area	Living room area	Yes	Stable reading
28-01-2025 14:47:30	On the Couch	Living room area	Yes	Stable reading
28-01-2025 14:48:00	On the Couch	Living room area	Yes	Stable reading
28-01-2025 14:48:30	On the Couch	Living room area	Yes	Stable reading
28-01-2025 14:49:00	On the Couch	Living room area	Yes	Stable reading
28-01-2025 14:49:30	Bathroom	Hallway near the bathroom	Partially	The star is in the hallway near the bathroom
28-01-2025 14:50:00	Bathroom	Hallway near the bathroom	Partially	The star is in the hallway near the bathroom
28-01-2025 14:50:30	Bathroom	Hallway near the bathroom	Partially	The star is in the hallway near the bathroom
28-01-2025 14:51:00	Bedroom	Hallway near the bathroom	Partially	The star is in the hallway near the bathroom
28-01-2025 14:51:30	Bedroom	Living room area	No	Weak signals as walls are between them
28-01-2025 14:52:00	Bedroom	Living room area	No	Weak signals as walls are between them
28-01-2025 14:52:30	Bedroom	Living room area	No	Weak signals as walls are between them
28-01-2025 14:53:00	Bedroom	Living room area	No	Weak signals as walls are between them
28-01-2025 14:53:30	Bathroom	Living room area	No	Weak signals as walls are between them
28-01-2025 14:54:00	Bathroom	Living room area	No	Slight drift
28-01-2025 14:54:30	Bathroom	Living room area	No	Slight drift
28-01-2025 14:55:00	Bathroom	Window area near bedroom	No	Slight drift
28-01-2025 14:55:30	Bedroom	Dining area	No	Weak signals as walls are between them
28-01-2025 14:56:00	Bedroom	Dining area	No	Weak signals as walls are between them
28-01-2025 14:56:30	Bedroom	Dining area	No	Weak signals as walls are between them

Overall, the movement tracking algorithm demonstrated reliable performance in open spaces but highlighted the limitations of Bluetooth-based trilateration in enclosed or obstructed environments.

As shown in **Table 5.2**, the model achieved the highest accuracy in open areas such as the living room, dining area, and couch (100%), where line-of-sight and signal stability were optimal. In contrast, accuracy declined in partially enclosed spaces like the dining table (75%) and kitchen (50%). The lowest performance was observed in the bathroom (37.5%) and bedroom (4.5%), where walls and doors caused significant signal attenuation. These findings confirm that signal obstruction and multipath effects are key limitations for BLE-based indoor localization in multi-room environments.

Table 5.2: Location-wise Accuracy of the BLE-based Movement Tracking System

Actual Location	Accuracy (%)
Living room area	100.0
Dining area	100.0
On the couch	100.0
Dining table	75.0
Kitchen area	50.0
Bathroom	37.5
Bedroom	4.5

This table summarizes the percentage of accurate position estimations at each physical location, based on the comparison between MATLAB-estimated positions and Ocularis video recordings.

5.5 Discussion of Limitations and Future Directions

Despite promising visual validation in open regions, several limitations were identified:

- **Signal fluctuation**: RSSI data, being inherently noisy, led to jitter in the projected star even when the participant was static.
- **Environmental obstructions**: Physical elements like walls and furniture were not modeled for signal attenuation.
- **Floor plan scaling**: Inaccurate room dimension scaling may have influenced projection reliability near borders.
- **Latency** was also observed between RSSI measurements and the corresponding physical movements. This delay occasionally caused a lag in aligning estimated positions with the participant's actual location, particularly during faster transitions between rooms. While such latency raises challenges for capturing quick movements with high precision, it is less likely to significantly affect the tracking of Activities of Daily Living in older adults, where movements tend to be slower and more gradual.

One approach was used in this research to address the issue of unrealistic distance estimates outside the room was smoothing the RSSI data prior to position estimation. A five-point moving average was applied to reduce variability and minimize signal noise, as shown in Figure 4.1.This preprocessing step helped us stabilize the distance calculations and limited the frequency of extreme outliers that could otherwise project positions beyond the physical boundaries of the floor plan.

To address these, future work may involve:

- Incorporating **Kalman Filters** [18] for smoother tracking.
- Using **wall-aware attenuation models** [19] to reflect realistic signal behavior.

- Adding **more beacon nodes** for enhanced coverage and redundancy.

The MATLAB-based position estimation system demonstrated the capability to model indoor localization effectively. The visual validation confirms general agreement between the predicted and actual paths, particularly in central areas. However, enhanced modeling and signal handling are necessary to ensure accurate predictions near boundaries such as the bedroom and the bathroom.

Chapter 6 - Conclusions and Future Works

This thesis presented the development and evaluation of a MATLAB-based indoor localization system designed to estimate the position of a participant within a mapped residential environment using trilateration of RSSI values from three fixed smartphones. The system was validated through side-by-side visual comparison with actual video footage captured using an Ocularis surveillance system.

The key conclusions drawn from this research are as follows:

- **Successful Implementation of Indoor Position Estimation**:

  The proposed method effectively used signal strength data to generate real-time estimates of a participant's location. The visualization provided clear spatial context by overlaying the predicted positions (represented by a star) on a detailed floor plan of the environment, including rooms such as the Bedroom, Living Room, Dining Area, Kitchen, and Bathroom.

- **Accuracy and Visual Validation**:

  Visual comparison with actual movement captured on video demonstrated strong alignment between predicted and actual participant positions in central and open areas of the environment, particularly within the Kitchen and Dining Area. This confirmed the system's potential for real-time indoor tracking under favorable conditions.

- **Spatial Constraints Enhanced Realism**:

  The incorporation of environmental constraints—such as limiting position estimates within the defined floor plan and avoiding unrealistic placements through walls or beyond windows—significantly improved the realism of the estimated trajectories and prevented computational artifacts from distorting the results.

- **Enhancing Monitoring Accuracy for Assistive Device Users:**

  Beyond its technical validation, this study's findings suggest broader implications for health monitoring, particularly among individuals using assistive devices like canes or walkers. Since fitness trackers often struggle to capture movement accurately in such populations, the proposed approach offers a more inclusive and reliable alternative. This integration of engineering methods with healthcare objectives highlights a meaningful synergy between technology and human well-being.

- **Limitations in Peripheral Zone Detection**:

  Despite promising results, the system showed limited ability to predict positions accurately in boundary areas such as the Bedroom. This was likely due to factors such as weak signal coverage, unmodeled obstructions, or algorithmic constraints that favored central convergence zones. These issues underscore the challenges of RSSI-based localization in complex environments.

- **Path Forward for Future Work**:

In future work, the use of **Markov chains** can be explored to predict the participant's likely next actions based on previous location data [20]. By modeling the probability of transitioning between different rooms or activity zones, the system could anticipate future movements and detect deviations from normal behavior, which may serve as early indicators of health or mobility changes [21].

Enhancements such as advanced filtering (e.g., Kalman or particle filters), multi-node triangulation, and modeling of signal attenuation due to walls and furniture are recommended to improve tracking stability and coverage. Integrating additional data sources such as inertial measurement units (IMUs) or camera-based vision could further increase the accuracy of localization systems.

In summary, this work demonstrates a cost-effective, visually validated approach to indoor localization using readily available smartphones and signal-based trilateration. With further development, this framework can support various real-world applications such as monitoring older adults independently living in the community, monitoring older adults living in a facility such as an assisted living facility or skilled nursing facility, home automation, and emergency response in smart environments. This research is part of a broader smart home initiative focused on passive, non-invasive monitoring of older adult health. By using wearable wireless sensors for real-time indoor localization, the study demonstrates how activities of daily living can be tracked unobtrusively. Such data not only support early detection of health concerns but also provide a foundation for training AI models to identify behavioral changes over time.

In the future, this work will be integrated into other sensor data collection during activities including motion detectors, contact sensors, and activity trackers to further track the activities of daily living of older adults and to develop predictive analytics for early alert health warning systems.

The research team will keep track of their movement vs time, and vital signs indicative of health such as number of steps taken daily and heart rate. So, this timestamping will include - wireless sensor data, motion detector data, smartwatch data, contact sensor data, etc.

The team will be working toward establishing a schedule, like a routine of their activities of daily living, and then using that as a plan for tracking any significant changes in their activities which may indicate health complications such as arthritis pain, fatigue, falls, dementia, and other age-related health concerns. Our research objective will be to train an AI system to detect prominent changes in daily activities by a comparative assessment of the use of data from the motion detectors, contact sensors, etc. In the case of an emergency or any significant drift in their daily behavior, the residents of the smart home will be connected to a healthcare provider, and the family will be notified so that they may take appropriate action out of concern for their family member.

Table 6.1 depicts an example of timestamp data for a schedule of waking and sleeping times in a week:

Table 6.1: Example of timestamp data for a schedule of waking and sleeping times in a week

Day	Date	Waking Time	Sleeping Time
Monday	2024-04-01	07:00 AM	11:00 PM
Tuesday	2024-04-02	06:30 AM	10:45 PM
Wednesday	2024-04-03	07:15 AM	11:30 PM
Thursday	2024-04-04	08:00 AM	12:15 AM (next day)
Friday	2024-04-05	06:45 AM	11:45 PM
Saturday	2024-04-06	08:30 AM	12:30 AM (next day)
Sunday	2024-04-07	09:00 AM	11:00 PM

We can further ascertain the time intervals within which meals are typically consumed. This can be determined based upon periods of time spent in the dining area of the home. Additionally, metrics such as the average frequency of bathroom visits, estimated by the mean number of entries into the bathroom as determined by the sensors. This may vary day to day and will be reported as both a mean with standard deviation and a median with interquartile range.

Furthermore, we can gather data on their laundry frequency and microwave usage habits using contact sensors on the doors to appliances. To include additional data points related to daily activities, we can expand the table as depicted in Table 6.2.

Table 6.2: Example of Timestamp data of daily living activities

Day	Date	Waking Time	Sleeping Time	Meal Window	Bathroom Trips (Mean/Median)	Microwave Usage
Monday	2024-04-01	07:00 AM	11:00 PM	08:00 AM - 09:00 PM	10 times (9.5 median)	3 times a day
Tuesday	2024-04-02	06:30 AM	10:45 PM	07:30 AM - 08:30 PM	9 times (9 median)	4 times a day
Wednesday	2024-04-03	07:15 AM	11:30 PM	08:15 AM - 09:15 PM	11 times (10.5 median)	2 times a day
Thursday	2024-04-04	08:00 AM	12:15 AM (next day)	09:00 AM - 10:00 PM	12 times (11 median)	3 times a day
Friday	2024-04-05	06:45 AM	11:45 PM	07:45 AM - 08:45 PM	10 times (9.5 median)	4 times a day
Saturday	2024-04-06	08:30 AM	12:30 AM (next day)	09:30 AM - 10:30 PM	9 times (8.5 median)	2 times a day
Sunday	2024-04-07	09:00 AM	11:00 PM	10:00 AM - 11:00 PM	8 times (7.5 median)	3 times a day

This expanded table now includes meal windows, average and median bathroom trips per day, and microwave usage frequency.

By analyzing the timestamps of waking and sleeping times, meal schedules, bathroom trips, laundry frequency, and microwave usage, we can discern significant shifts in an individual's daily behavior. These timestamps provide a comprehensive view of their daily routine, allowing us to identify deviations or patterns that may indicate changes in lifestyle, health, or environmental factors. For example, a sudden alteration in waking or sleeping times could suggest disruptions in sleep patterns or lifestyle adjustments. Similarly, fluctuations in meal times or bathroom visits may indicate changes in dietary habits or health conditions such as an enlarged prostate. Monitoring these timestamps enables us to pinpoint crucial shifts in behavior, facilitating personalized interventions or support as needed.

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Appendix – IRB Approval Letter

EAST CAROLINA UNIVERSITY
University & Medical Center Institutional Review Board
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Notification of Amendment Approval

From: Biomedical IRB
To: Young Joo Kim
CC:

Date: 1/31/2025
Re: Ame4_UMCIRB 20-002770
UMCIRB 20-002770
Biosensors as a Basis for Development of a Virtual Nurse

Your Amendment to update this study according to the revised human research regulations (as of January 21, 2019) has been reviewed and approved using expedited review on 1/30/2025. It was the determination of the UMCIRB Chairperson (or designee) that this amendment does not impact the overall risk/benefit ratio of the study and is appropriate for the population and procedures proposed.

Please note that any further changes to this approved research may not be initiated without UMCIRB review except when necessary to eliminate an apparent immediate hazard to the participant. All unanticipated problems involving risks to participants and others must be promptly reported to the UMCIRB. The investigator must submit a Final Report application to the UMCIRB prior to the Expected End Date provided in the IRB application. If the study is not completed by this date, an Amendment will need to be submitted to extend the Expected End Date. The investigator must adhere to all reporting requirements for this study.

Approved consent documents with the IRB approval date stamped on the document should be used to consent participants (consent documents with the IRB approval date stamp are found under the Documents tab in the study workspace).

The approval includes the following items:

Document	Description
Smart Home consent form_012425.doc(0.07)	Consent Forms
SmartHome protocol_012425.docx(0.05)	Study Protocol or Grant Application
	Remove D. Roberson from study team
	Move H. Davis from study staff to a study sub-investigator
	Extend study end date to 6/30/2026

The Chairperson (or designee) does not have a potential for conflict of interest on this study.

IRB00000705 East Carolina U IRB #1 (Biomedical) IORG0000418
IRB00003781 East Carolina U IRB #2 (Behavioral/SS) IORG0000418