

**NANYANG
TECHNOLOGICAL
UNIVERSITY**

SINGAPORE

**VIRTUAL EYE: HELPING THE VISUALLY IMPAIRED MAP
THE REAL WORLD**

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VIRTUAL EYE: HELPING THE VISUALLY IMPAIRED MAP
THE REAL WORLD

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Bachelor of Engineering in Computer Engineering of the Nanyang
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ABSTRACT

This research paper discusses the design and implementation of an enhanced indoor navigation system, aimed towards improving the existing technology by aiding the visually impaired. Loss of vision can drastically impair an individual's direction and mobility, especially in unfamiliar surroundings. Due to this, visually impaired individuals often find themselves needing further support and time to gain familiarity with new indoor settings. The objective of this paper is to present an enhanced indoor navigation system, customized to cater to the needs of the visually impaired. This has been achieved through the use of Bluetooth Low Energy (BLE) beacons, a BLE-supported Android device with in-built motion sensors and an Android Mobile Application.

The mobile application can be operated in three different modes – regular navigation, assisted navigation and free-roam mode. Regular Navigation has been designed for the visually abled

ACKNOWLEDGEMENTS

The author of this research paper would like to like to express her heartfelt gratitude to the following individuals and organizations for their support and contributions to this project:

Firstly, the author would like to thank her advisor and mentor Dr. SMITHA Kavallur Pisharath Gopi for her guidance and support throughout the entirety of the research. Her advice and constructive feedback were invaluable in shaping the direction and quality of the work presented in this paper.

The author would also like to like to express her appreciation for Fujitsu for the production of their Bluetooth Low Energy beacons and detailed hardware documentation. The clear setup instructions and hardware specifications significantly aided the implementation of the system.

Finally, the author would like to express her gratitude to her friends and family for their unwavering support throughout the year.

ACRONYMS

BLE	Bluetooth Low Energy
GPS	Global Positioning System
GLONASS	Global Navigation Satellite System
WLAN	Wireless Local Area Networks
RFID	Radio-Frequency Identification
VM	Virtual Machine
UI	User Interface
TTS	Text-to-Speech
LTS	Long-Term Support
SCSE	School of Computer Science and Engineering
IPS	Indoor Positioning System
RSSI	Received Signal Strength Indicator
IDE	Integrated Development Environment
MAC	Media Access Card

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CHAPTER 1: INTRODUCTION

1.1 Background

Over the past decade, the popularity of navigation tools as resources for accurate route planning and wayfinding has grown immensely. The major tools in the market today have enabled accurate navigation and demonstrated advances in path planning and movement control, and most importantly, in localization. Localization accomplishes the complex goals of accurate navigation by necessitating the support of precise topographic representation of space [1].

Localization can be broadly classified into outdoor and indoor variants. Outdoor localization has experienced a surge in technological advancements, as traditional celestial navigation techniques have grown to depend on satellites, such as – Global Positioning System (GPS), Galileo and the Global Navigation Satellite System (GLONASS) [2]. The needs of these modern outdoor localization techniques have been met through efficient data collection using mobile mapping technologies and advancements in modelling and data storage. This has led to outdoor navigation becoming ubiquitous, with GPS receivers included in a variety of consumer electronic devices such as smartphones and tablet computers.

Innovations in outdoor navigation systems have encouraged researchers to explore indoor navigation techniques to assist pedestrians in finding their way through complex indoor environments such as airport terminals, subways, and retail malls. GPS signal blockages by building walls and ceilings and multi-path interferences have increased the complexity of indoor navigation systems. As a result of this, the plethora of such existing systems rely heavily on electromagnetic signals, which are customised on the basis of their range, accuracy, and their capacity to penetrate solid objects [3]. One of the fundamental techniques for indoor localization is the use of Wireless Local Area Networks (WLAN). Wi-Fi technology, in particular, is frequently used for this purpose, where an accuracy of several decimetres has been achieved. Radio-Frequency Identification (RFID) is another option for highly

accurate indoor localization, primarily up to several centimetres if smart floors are used [4].

Despite the fast-paced innovations in the field of indoor navigation, existing solutions do not completely cater to the needs of those with visual disabilities. According to the World Health Organization, 285 million people worldwide are visually impaired, with 39 million blind and 246 million with poor vision [5]. The loss of vision can severely diminish an individual's orientation and movement – particularly in uncharted, environments. While guide dogs and canes are strong current resources to support their navigation, visually impaired people often encounter the need for further support and time to gain familiarity with new indoor settings. Existing indoor navigation applications are yet to address the greatest challenges of obstacle navigation and landmark identification faced by the visually impaired.

The aim of this **study** was to improve the existing solutions for indoor navigation, by customizing them to cater to the needs of the visually impaired. This was achieved by incorporating existing RFID beacon localization techniques with computer vision-based object detection to create a real-time voice-enabled assistant. The objective of this assistant is to aid the visually impaired in capturing vital information about their surroundings and navigating them through unknown indoor settings.

1.2 Objective

The fundamental objective of this **study** is to design and implement an indoor navigation system, consisting of a client-side Android Application and a cloud-based server. The application serves the purpose of providing both map-based visual indoor navigation as well as auditory and kinaesthetic navigation for the visually impaired.

The Android smartphone application, *VirtualEYE*, interacts with FUJITSU FWM8BLZ02 BLE Beacons to aid in indoor navigation. The application is also

connected to a remote Flask Server running on an Azure Cloud Virtual Machine (VM). The server functions as the ‘brain’ of the entire system, enabling real-time calculation of paths, distances, and directions for the Android client. The system in its entirety is able to perform the following features –

- Receive Instructions/Commands from the user via:
 - User Interface (UI) input
 - Kinetic input
 - Voice input
- Interact with the BLE beacons placed around the test area to:
 - Retrieve the landmark in the closest proximity to the user
 - Calculate the distance between the user and the retrieved landmark
- Perform obstacle detection to:
 - Warn the user under assisted navigation of obstacles in the path
- Provide Tactile and Audio feedback for the visually impaired users:
 - Vibrate the phone to indicate the correct direction during navigation
 - Give audio warnings and instructions using Text-To-Speech (TTS) to provide easier interaction with the application
- Display an interactable map of the test area for visual navigation:
 - Present a list of available locations the user can select and navigate to
 - Update the map with markers of selected locations and the path calculated
 - Provide written directions for navigation

1.3 Scope

The central focus of this **project** is the implemented indoor navigation system, where the system consists of the client-side Android application *VirtualEYE*, the remote Flask Server, and the BLE beacons. The purpose of the remote Flask server is to perform heavy, time-sensitive computations and reduce the burden on *VirtualEYE* to provide a more seamless and real-time experience to the user. It has been developed using Python version 3.9 and has been converted to a docker image.

This docker image has been uploaded on a Linux VM (Ubuntu Server 16.04 – Long Term Support (LTS)) on Azure Cloud. This is done to facilitate time-critical computations and communication.

VirtualEYE has been developed in Kotlin (**enter version**) using Android Studio (**enter version**). The tables below depict the permissions required by the application as well as the hardware features the application needs to function on the user's Android device.

Table 1-1: Permissions required by VirtualEYE, with stated reasons

Permission Required	Reason for Permission
BLUETOOTH BLUETOOTH_ADMIN BLUETOOTH_CONNECT BLUETOOTH_SCAN	A set of Bluetooth permissions is required to enable access to the smartphone's Bluetooth and to discover and interact with the BLE beacons.
ACCESS_FINE_LOCATION ACCESS_COARSE_LOCATION	The location data of the user is required to pair with the BLE beacon data to approximate the user's current location during indoor navigation
CAMERA	Required to perform Obstacle Detection for Assisted Navigation
INTERNET	Required to communicate with the remote Flask Server on Cloud – connect and stream data and response
RECORD_AUDIO	Required for enabling voice commands for the visually impaired users to set their destinations using speech
VIBRATE	Required to provide tactile feedback for the visually impaired user during Assisted Navigation

Table 1-2: Hardware features required by VirtualEYE, with stated reasons

Hardware Feature Required	Reason for requirement
bluetooth_le	Required to specifically interact with BLE-type beacons
camera	Required to perform obstacle detection for Assisted Navigation

The BLE beacons used in the indoor navigation system have been provided by FUJITSU. The beacons have been configured manually in *VirtualEYE*'s source code, and the communication between the two has been enabled via the Bluetooth Adapter present in the Android smartphone. The aforementioned test area has been set to Level 1 of the School of Computer Science and Engineering (SCSE) building. The beacons have been placed in the following important locations (venues with greater footfall) –

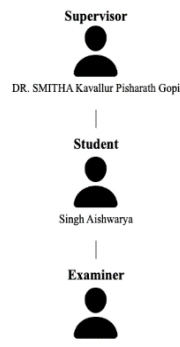
1. Cybercrime Analysis & Research Alliance @ NTU (CARA)
2. Student Lounge
3. Software Lab 1
4. Hardware Lab 1
5. Hardware Lab 2
6. Software Lab 2
7. Hardware Projects Lab

1.4 Project Plan

1.4.1 Project Organization

This project, and all of its components, were managed and accomplished completely by the author under the supervision and guidance of her supervisor, Dr. SMITHA Kavallur Pisharath Gopi. The project will be evaluated by the supervisor and an examiner from the faculty of the School of Computer Science and Engineering at the end of the Academic Year 2022/2023 Semester 2 examinations.

Figure 1-1: Project Organisation



1.4.2 Work Breakdown Structure

Table 1-3: Work Breakdown Structure

S/N	Phase	Task and Description	Effort Estimation
1	Project Initiation	<ul style="list-style-type: none"> • Arrange the first meeting with the supervisor • Post-meeting research and establishment of project outline and expectations 	1 week
2	Research and Exploration	<ul style="list-style-type: none"> • Indoor Navigation <ul style="list-style-type: none"> - Path Finding Algorithms - Different indoor navigation techniques - Calculating orientation and user direction - Localization • BLE beacons • Obstacle Detection in Android <ul style="list-style-type: none"> - Trade-offs with accuracy and speed - Captured frame analysis • Client-Server Architecture • Map Rendering in Android 	7 weeks
3	Software Development	<ul style="list-style-type: none"> • Develop and Implement System Architecture • Server Side: <ul style="list-style-type: none"> - WebSocket-based communication - HTTP communication - Flask Server setup - Develop path-finding algorithms - Create a communication protocol with the client • Client Side: <ul style="list-style-type: none"> - Bluetooth initialization and configuration - Sensor initialization and configuration - Create and customize the TTS manager 	26 weeks

		<ul style="list-style-type: none"> - Initialize and prepare 'SpeechRecognizer' - Server (HTTP) communication - Camera configuration - Utilizing the Obstacle Detection model - Initialize a map of the test area - UI considerations • Develop, Test, and Improve 	
4	Project Closure	<ul style="list-style-type: none"> • Final Report Preparation • Oral Presentation Preparation • Videos 	TBA

1.4.3 Project Schedule

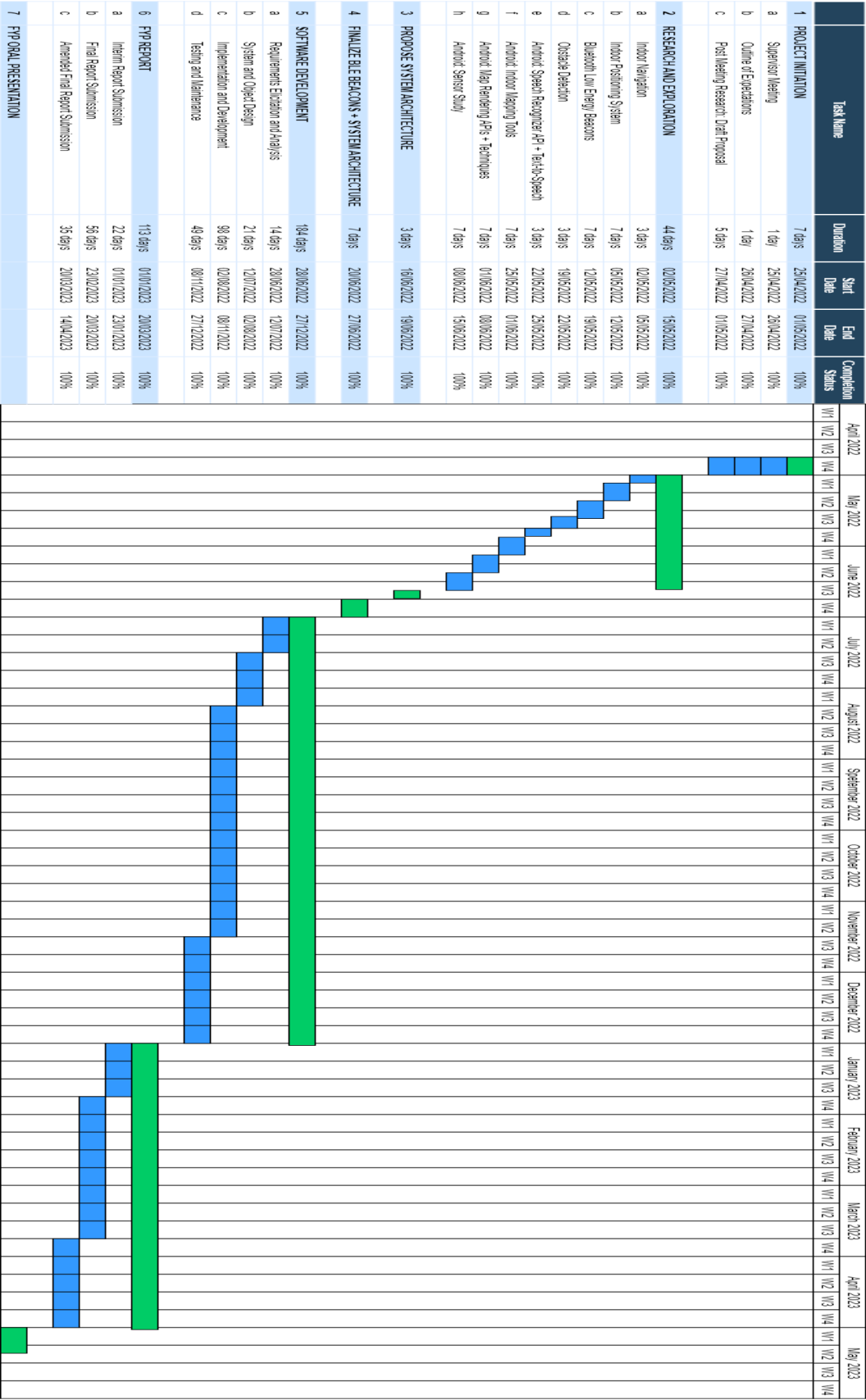


Figure 1-2: FYP Schedule

CHAPTER 2: LITERATURE REVIEW

Indoor mapping is the process of making interior locations and landmarks discoverable, using indoor positioning and navigation techniques. Each of these techniques has its own set of advantages, which have been explored in this chapter and have motivated the implementation of this project.

2.1 Indoor Positioning System (IPS)

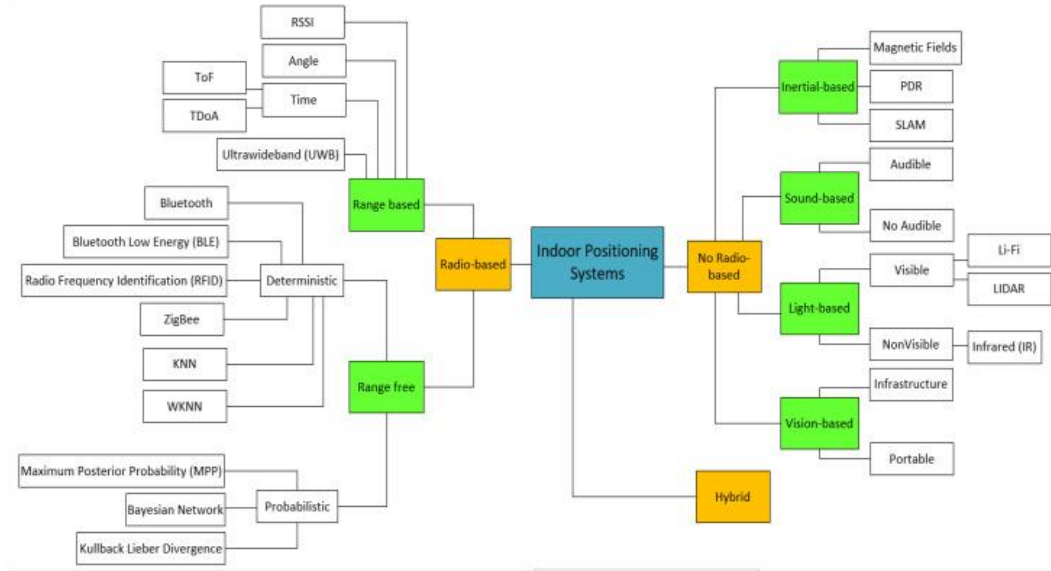
Positioning Systems, based on the tools employed, can be grouped into outdoor or indoor. Most navigation systems today are well-established in outdoor contexts, delivering accurate positioning and navigation assistance with negligible errors [6]. On the other hand, in indoor settings, satellite-reliant positioning systems such as GPS and GLONASS are ineffective. The accuracy of these systems suffers considerably as a result of signal loss due to collisions with indoor structures and can therefore not be used as reliably in indoor environments [7].

Indoor positioning systems (IPS) can be thought of as GPS, but for indoor locations. While GPS is utilized outside, IPS can detect real-time positions inside a facility to correctly establish the coordinates of people or assets. IPSs can be used for a variety of purposes, including identifying and tracking individuals, enabling medical monitoring, and supporting visually impaired individuals in their everyday routines. Indoor positioning approaches have gained a lot of traction, allowing the development of systems for a wide range of model situations. This has allowed IPSs to be classified in a variety of ways based on numerous parameters [8].

IPS can be grouped based on architectural design: self-positioning, infrastructure positioning, and supported by self-directed infrastructure. Devices choose their own placements in self-positioning architecture. The positions of devices released in the environment are used to estimate device placements in infrastructure positioning architecture. Lastly, in self-directed infrastructure-aided architecture, an external system calculates the position and delivers it to the monitored user in response to a request.

Additionally, most IPS employ radio frequency, vision-based, audible, and inaudible sound, inertial and light-based technologies. A complete classification of IPSs is shown below in Figure 2-1 [9].

Figure 2-1: Classification of IPS



To choose an appropriate IPS for the blind, it is critical to understand the efficiency and limits of different alternatives. Despite accuracy being a crucial performance parameter, other factors such as response time, availability, and scalability are equally significant and must be addressed. The following sections outline different systems, focusing on their most prominent characteristics and drawbacks.

2.1.1 Radio Frequency-based IPS

There are a number of diverse devices and wireless networks that can be deployed in indoor environments for indoor positioning. Some of these include Internet of Things (IoT) devices, RFID devices, Bluetooth beacons, and traditional Wi-Fi networks. The method of obtaining information in Radio Frequency-based IPS is the categorization parameter to classify the system into range-based and range-free Radio Frequency IPS.

2.1.1.1 Range-based Radio Frequency IPS

Methods based on range extract geometric information (distance or angle) from different nodes and then combine the geometric restrictions of each anchor to derive the user's location [10]. There are several methods for extracting geometric information from these signals. The most popular are approaches based on signal propagation time between the transmitter and the receiver, the angle of arrival (AoA), or received signal intensity (received signal strength indicator, RSSI). The focus of this study will be on RSSI.

RSSI-based location algorithms employ the intensity of the received signal to calculate the distance between the user and a node. These approaches assume that the attenuation of a signal as it travels from a transmitter to a receiver is proportional to the distance travelled [11]. To determine the distance between two places, a signal propagation model must be used to represent the environment with Bluetooth devices. The log-distance trajectory loss model is perhaps the most used model, with attenuation (in dB) equal to the logarithm of the distance traversed –

$$RSSI = P_{1m} - 10\alpha \log_{10} d - \gamma$$

In the equation above, P_{1m} is the reference power value measured in dBm at a distance of one meter from the transmitter, α is the exponent of the loss of path γ , and d is the distance between the receiver and transmitter. P_{1m} and α are model parameters that must be determined via calibration. This is done by collecting the RSSI values at predefined positions, with known distances to the positioned nodes, which is usually done using regression methods. After this, the distance can be estimated according to the path-loss model using the Maximum Likelihood Estimator [12].

2.1.1.2 Range-free Radio Frequency IPS

Range-free approaches rely on data collected from connections. The resulting values may be utilized to estimate the position without having to calculate any

measure of reach at a node. This can be done in two ways: proximity algorithms and digital printing methods.

Proximity algorithms employ connection information to determine the user's position based on the number of nodes in the vicinity. Proximity algorithms are based on a basic concept: if a user receives a signal from a node, the user's position must be close to the position of the said node [13]. The procedure is carried out in the following steps: The user initially scans the channel for radio signals from the placed nodes. The user's position is calculated to the position of the node when it is detected. When many nodes are available, the model will choose the one with the strongest signal.

Figure 2-2: Diagrammatic representation of the proximity algorithm

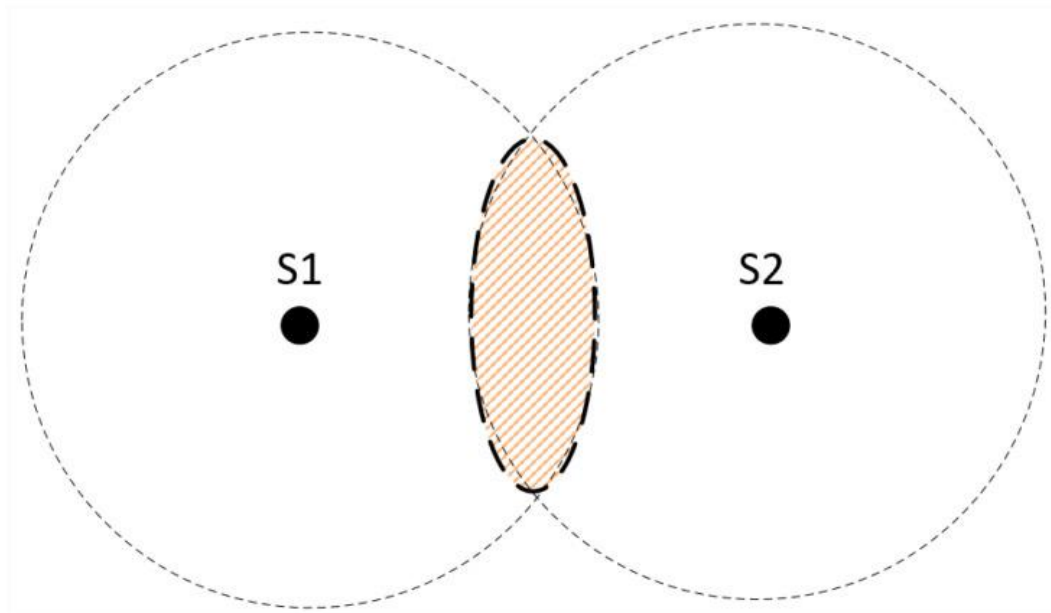


Figure 2-2 represents the working of the proximity algorithm. The circles reflect the coverage area of the placed nodes, and an intersection between them is required. When a user moves around the circle maintained by node S1, their location is estimated using placed node S1 as a reference. When a user enters the circle of node S2, the position of placed node S2 is calculated. The placed node will be chosen based on the RSSI at the junction of the two circles. Thus, the amount of inaccuracy offered by proximity algorithm approaches is proportional to the coverage area size. In other words, if the coverage area is wide, the error increases, and if the coverage

area is small, the number of anchor nodes required for total internal area coverage grows.

The fingerprinting location system on the other hand makes use of information sensed in certain areas, which must first be determined. As a result, the approach necessitates the observation of two phases: offline and online. The region is divided into small cells in the first phase to specialize in the identification of each point of interest, allowing data to be collected to establish a database. The core concept of digital printing is to record a signal pattern in a manner akin to a relational database. This pattern is used as a guideline when looking for a value via equivalence or approximation. The position is approximated in the second phase by comparing the collected data to the records stored in the database. The biggest downside of the approach, regardless of the origin of the fingerprints, is the work necessary to gather samples to build the database, which raises the cost and restricts scalability.

2.1.2 Inertial Sensors-based IPS

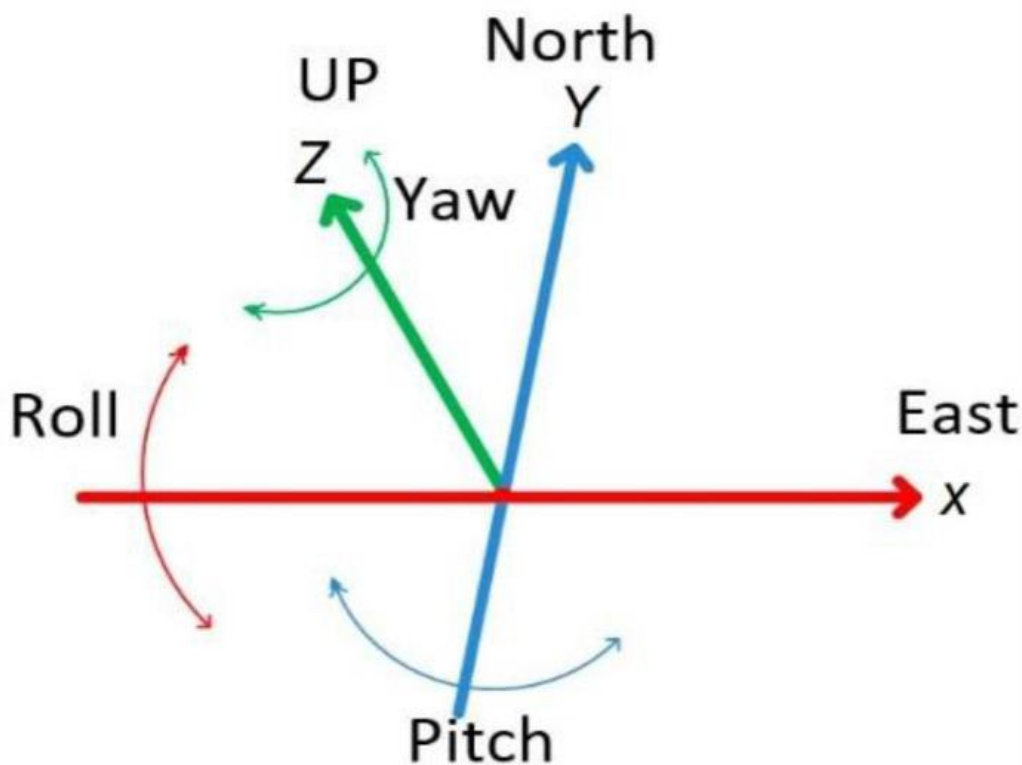
Network-based systems determine user locations by analysing the resources of wireless network signals. This paradigm necessitates intervention in the environment in the form of physical infrastructure. Inertial information-based systems determine their locations without the need for external resources.

Accurate information about a target's location is required, which is why these models use the geographic coordinate model, which includes latitude, longitude, and altitude, to determine the absolute (inertial) position. The sensors enable the absolute (inertial) location to be experienced instantaneously in the roll, pitch, yaw (RPY) system utilizing the x-, y-, and z-axes (Figure 2-3) [14]. The x-axis represents the nominal orientation (front), the y-axis is orthogonal to the x-axis and points to the left side, and the z-axis (yaw) points up.

Inertial sensors are typically built into units of inertial measurement (IMUs), which include an accelerometer, a gyroscope, and a magnetometer with three axes each. The magnetometer is not an inertial sensor; but, because it is part of the IMU, it will be considered in combination with the other sensors in this study. To create an

address, the magnetometer sensor employs the earth's natural magnetic field or artificial magnetic fields of alternating current. When acceleration in each direction is sensed, accelerometers may be used to calculate changes in the user's location. This is a very approximate estimate that may be improved by observing variations in a course with a gyroscope.

Figure 2-3: Roll-Pitch-Yaw Reference



Since there is no requirement to put equipment in the environment, inertial systems are completely scalable in terms of size and number of users. Furthermore, smartphones now include inbuilt IMUs. As a result, the system has a low cost. However, it is critical to consider the lower accuracy that is caused by inertial drift.

2.1.3 Computer Vision-based IPS

IPS that employ computer vision recognize, monitor, and steer persons in indoor spaces using information gathered by cameras and a set of image processing algorithms [15]. The camera on a smartphone is used by the user to observe and

take photographs or videos from that user's point of view. The collected data may be compared to previously saved files or taught models – decision trees, neural networks, etc.

Indoor locating techniques that rely on a single sort of sensory perception are more prone to failure under specific physical and logical situations and dispositions [16]. One method for reducing the errors or limits of these systems is to combine distinct sensory experiences, resulting in a hybrid arrangement that, while more expensive to install, gives more accurate and dependable findings. To test the degrees of accuracy and constraints, the scientists created an indoor positioning system that integrated camera sensors, inertial sensors, and the Wi-Fi sensor found on smartphones.

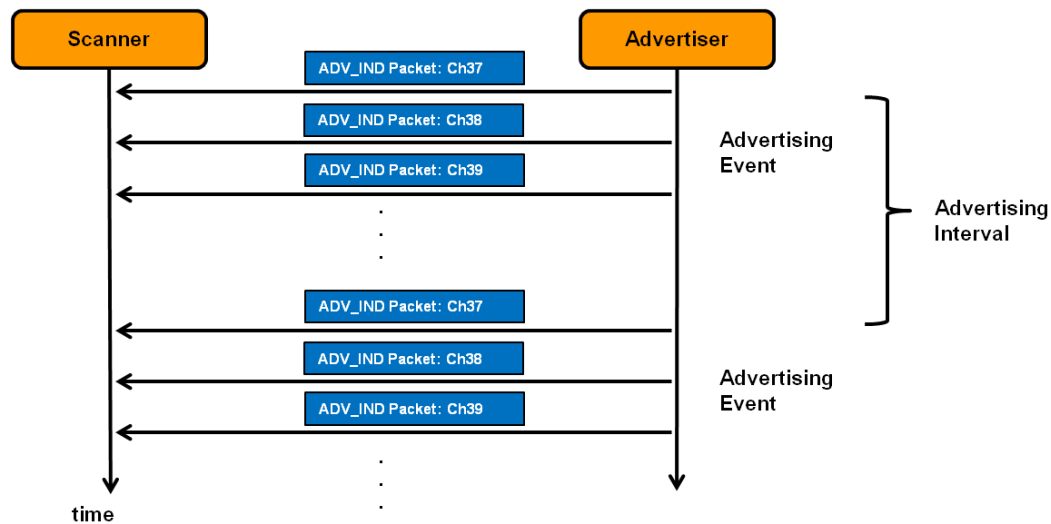
2.2 Bluetooth Low Energy (BLE) Beacons

A Bluetooth beacon is a tiny wireless device that uses Bluetooth Low Energy (BLE) technology to communicate. It sends a radio signal composed of letters and numbers that are broadcasted at short, regular intervals. Once in range, a Bluetooth-enabled device such as a smartphone, gateway, or access point may identify the beacon. BLE technology is a new wireless personal area network technology standard that is part of the Bluetooth 4.0 standard. Both Bluetooth and BLE technologies operate at 2.4GHz and use the same modulation mechanism, Gaussian Frequency Shift Keying. In theory, BLE application throughput is roughly 300kbps, which is up to seven times less than traditional Bluetooth [17]. It is therefore more power efficient than classic Bluetooth – allowing beacons to run for years on small coin-cell batteries.

BLE beacons are programmed to broadcast ‘IDs’ at set frequencies (configurable by the user). This ID serves as a unique identifier, which is used by a Bluetooth-enabled device to perform an action function based on the ID received. With this, the entire BLE architecture can be explained in terms of three processes – advertising, scanning and connection. Advertising and Scanning make up the discovery process in the BLE architecture. In this, devices use advertising channels

to identify each other, where one device performs advertisement and the other performs scanning. The discovery process pertinent to this **project** is Passive Scanning – where the advertiser is not informed if the advertised packet has been received by the scanner or not. This has been illustrated in *Figure 2-4* [18].

Figure 2-4: Illustration of Passive Scanning



Based on the advertising data (device name, service UUID, RSSI, and so on), the Scanner chooses an appropriate Advertiser to connect with and start an exchange. Once a Scanner has gathered enough information to determine which Advertiser to connect to (including its MAC address), it becomes an Initiator, commencing a BLE Link Layer connection procedure. The devices are then linked, and data packets may be transferred. The Initiator then becomes the Link Layer Master, while the Advertiser becomes the Link Layer Slave.

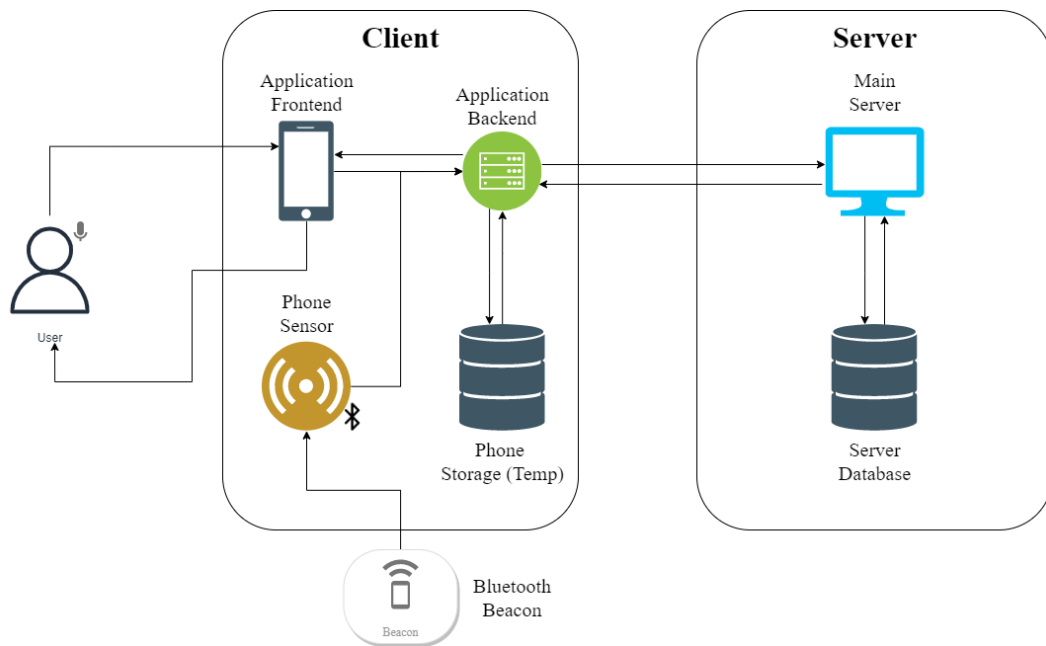
CHAPTER 3: SYSTEM ARCHITECTURE

This chapter discusses the architecture of the proposed indoor navigation system. The discussion begins with details on the initial plans and considerations for the system and continues towards the description of the final architecture of the system, consisting of the path planning server and the client-side Android application, *VirtualEYE*.

3.1 Initial Considerations

The figure below illustrates the first proposed architecture for the indoor navigation system –

Figure 3-1: Initial proposed System Architecture



The system architecture in *Figure 3-1* illustrates how all the components are connected to each other. The user interacts solely with the client-side Android application *VirtualEYE*, via audio or UI input. In the above architecture, the client will be connected to the server via a WebSocket connection. The backend of *VirtualEYE* will initiate a connection with the Python WebSocket and start communication once the user has given instructions to the application. For the

detection of BLE beacons, the Bluetooth manager of the smartphone will initialize the scanner and start scanning for nearby beacons. This information will be sent to the server, where the server will check its database against the received BLE beacon 'fingerprint' and send back an appropriate response. In addition to this, obstacle detection will also be performed by the server, where images are streamed from *VirtualEYE* to the server via the same WebSocket. The image frames from the camera stream will be encoded in Base64 format and will be then sent to the server for obstacle detection. The smartphone's temporary storage is used to hold these encoded frames temporarily before sending them for obstacle detection. The server, after receiving the encoded images, performs obstacle detection using the ImageAI API and YoloV4 model. The obstacles detected are then sent back to the application's backend, where the TTS engine is used to alert the user of the same.

This architecture solely relies on BLE beacons for indoor navigation. Based on the BLE beacon detected, along with its fingerprint data, the server will calculate the shortest path to the chosen destination in real time. It relies on basic RSSI-distance calculations to estimate the distance to the next beacon/node. Upon implementing this architecture, there were several pitfalls identified -

- User Interaction:
 - Using only audio input for the visually impaired proved to be unreliable as the input captured was not accurate for most trials.
 - The use of only BLE beacons did not provide enough information about the visually impaired user's environment – it was also not able to accurately localize and determine where the user was heading.
 - Audio feedback being the only medium of feedback for the visually impaired user was not very efficient in terms of providing timely instructions and alerts of their surroundings – there was an overwhelming amount of feedback being given, at a noticeable delay as well.
- Client – Server Communication:
 - There was a significant delay in obstacle detection with the initial system architecture. Despite adjusting the frame rate on the client

side and tuning the model parameters on the server side, there was a noticeable lag in the results received. This had a major impact on the application's performance.

- Using the same WebSocket connection also leads to an added delay in real-time path calculation for indoor navigation. The user would be alerted of the location much after passing it – another damper on seamless user experience.
- BLE Beacons:
 - The RSSI value received from the BLE beacons was not precise – there were a lot of fluctuations in the value received by the Android application.
 - The values of RSSI varied significantly depending on the location it was placed, despite being the same physical distance from the phone.
 - The distance calculated from the RSSI value received was not enough to accurately localize the user in the indoor setting.
 - There were no checks/algorithms to determine turns taken by the user – the beacons were not enough to determine this information.

Based on the observations from the first round of testing of different functions from the initially proposed system architecture, the conclusion was to modify the system architecture to address the pitfalls observed during testing.

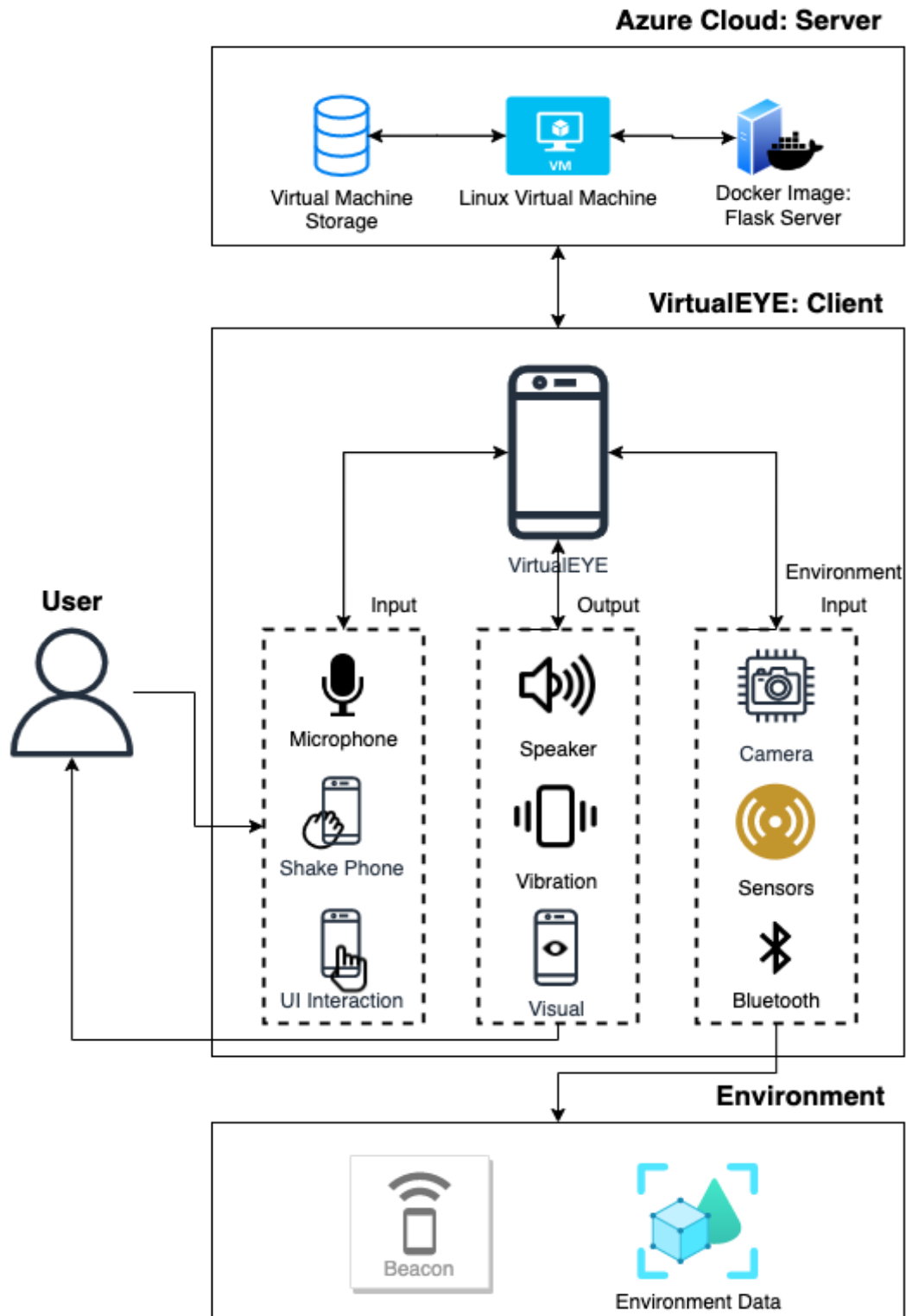
3.2 Final Architecture

This section provides a detailed outline of the final, implemented system architecture. The changes made to the architecture proposed in Section 3.1 are listed in this section, along with the reasons for the same. The final system architecture, along with its individual components has been discussed in detail in the upcoming sub-sections.

3.2.1 Final System Architecture

Figure 3-2 illustrates the final system architecture that has been implemented.

Figure 3-2: Final implemented System Architecture



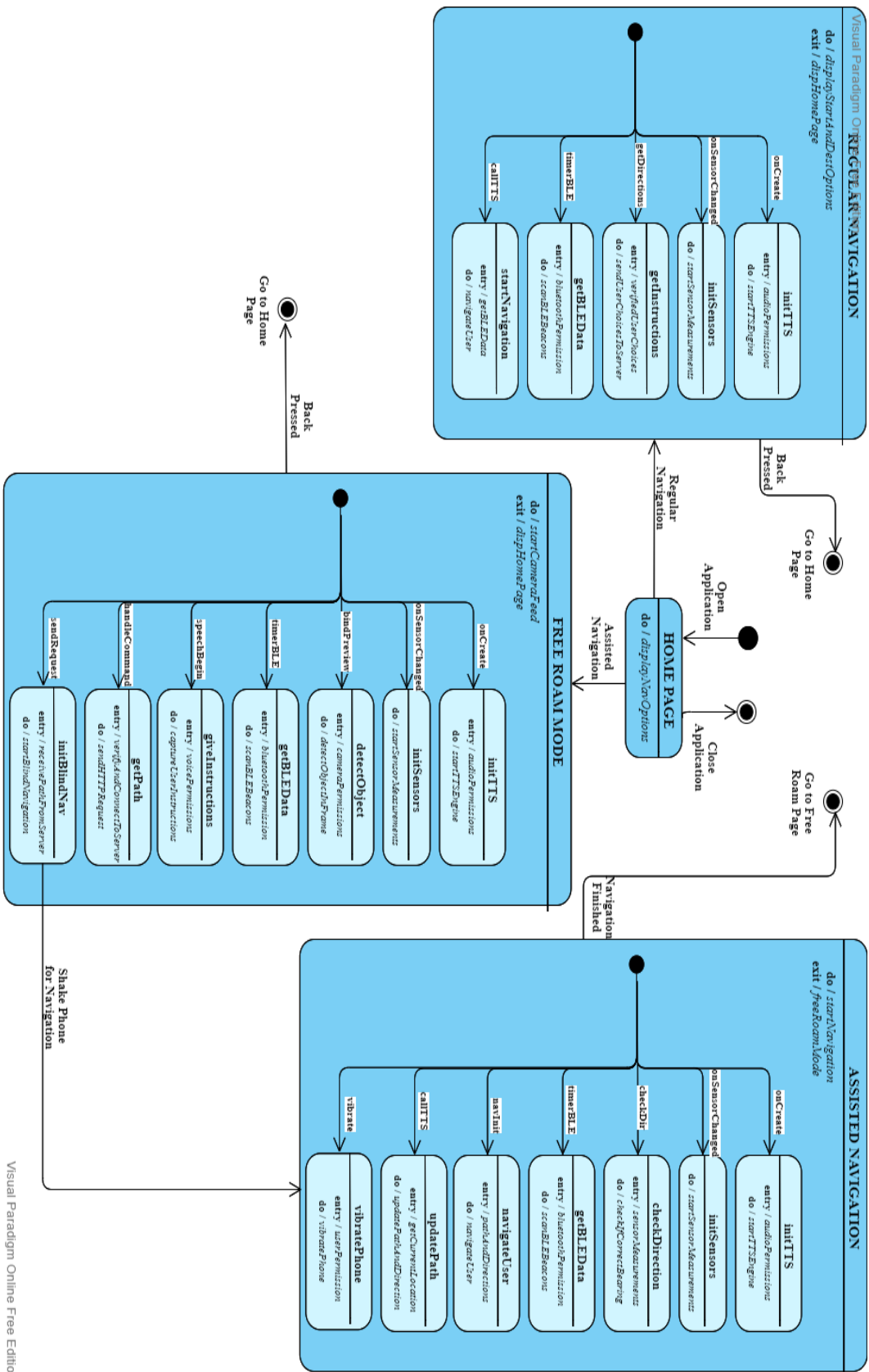
In this final architecture, new input sources and feedback mediums have been introduced to address the issues of the initial architecture. The user can interact with VirtualEYE via three input sources: UI Interaction (interacting with buttons, dropdown menus, etc for the visually abled), audio input (via microphone to set destination for navigation) and shake input to navigate to other parts of the application or enable microphone for audio detection. The feedback given by the application is also done in three ways: visual feedback (output presented on screen for the visually abled), audio feedback via phone speakers to provide instructions and alerts during navigation, and tactile feedback via phone vibration to navigate the user in the correct direction.

For interacting with the environment, additional sensors – magnetometer and accelerometer – are used in conjunction with the Bluetooth scanner and camera. The sensors provide additional information about the user's current bearing and direction, as well as the speed and movement of the user that aids in localization during indoor navigation. The Bluetooth scanner remains from the previous architecture to interact with the BLE Beacons placed in the test environment and the camera is used to perform obstacle detection.

To address the client-server communication issues in Section 3.1, the WebSocket has been replaced with a Flask server in the final architecture. The communication speeds with the Flask requests are much more efficient and provide a better user experience by reducing calculation delay. To further improve the efficiency of the communication, the server has been shifted from a local IP to a Linux Virtual Machine on Azure Cloud. This was done by creating a docker image of the Flask server and then hosting it on the cloud. This allows any device with the application to connect to the server via the Internet and eliminated the need to be connected to the same network to perform localization.

The aforementioned details can be visualized in the overall dialog map of the indoor navigation system in *Figure 3-3*. The sections following *Figure 3-3* continue the discussion of the final architecture in detail by providing relevant illustrations to explain the program flow of the application.

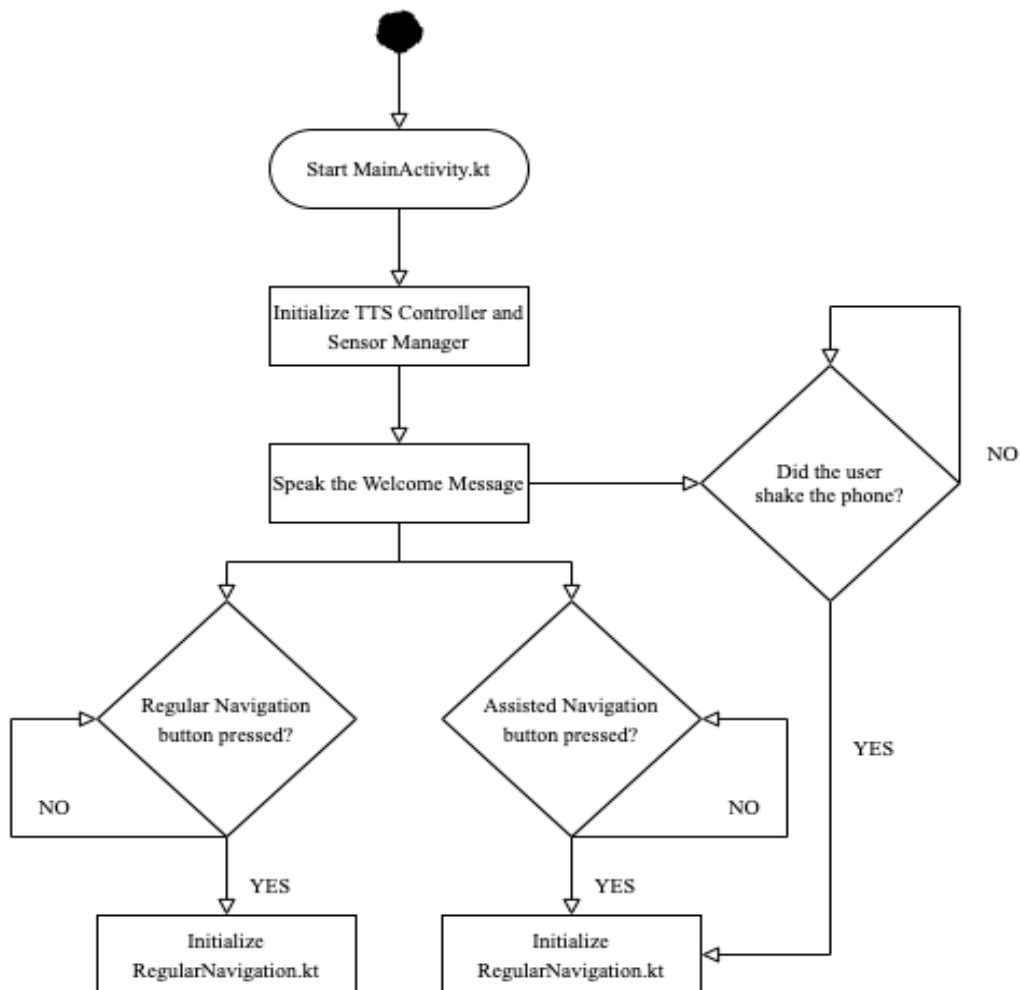
Figure 3-3: Complete System Dialog Map



3.2.2 Home Screen: MainActivity.kt

The application opens up to the Home Screen, or MainActivity.kt. *Figure 3-4* illustrates the dialog map for the same. Upon the creation of the activity, the TTS controller and sensor manager are initialized in the application. After this, the welcome message is spoken (providing instructions and further context for the visually impaired users). Next, the application awaits user input. The application can accept two different types of inputs – kinetic (shaking the phone) or UI interaction (buttons). Kinetic input is provided for the visually impaired – once the user shakes the phone, the user is redirected to Free Roam Mode (AssistedNavigation.kt). Apart from this, there are two on-screen buttons – one that redirects the user to Regular Navigation Mode (RegularNavigation.kt) and one that redirects the user to Free Roam Mode.

Figure 3-4: MainActivity.kt: Dialog Map



3.2.3 Regular Navigation (Vision-Based): RegularNavigation.kt

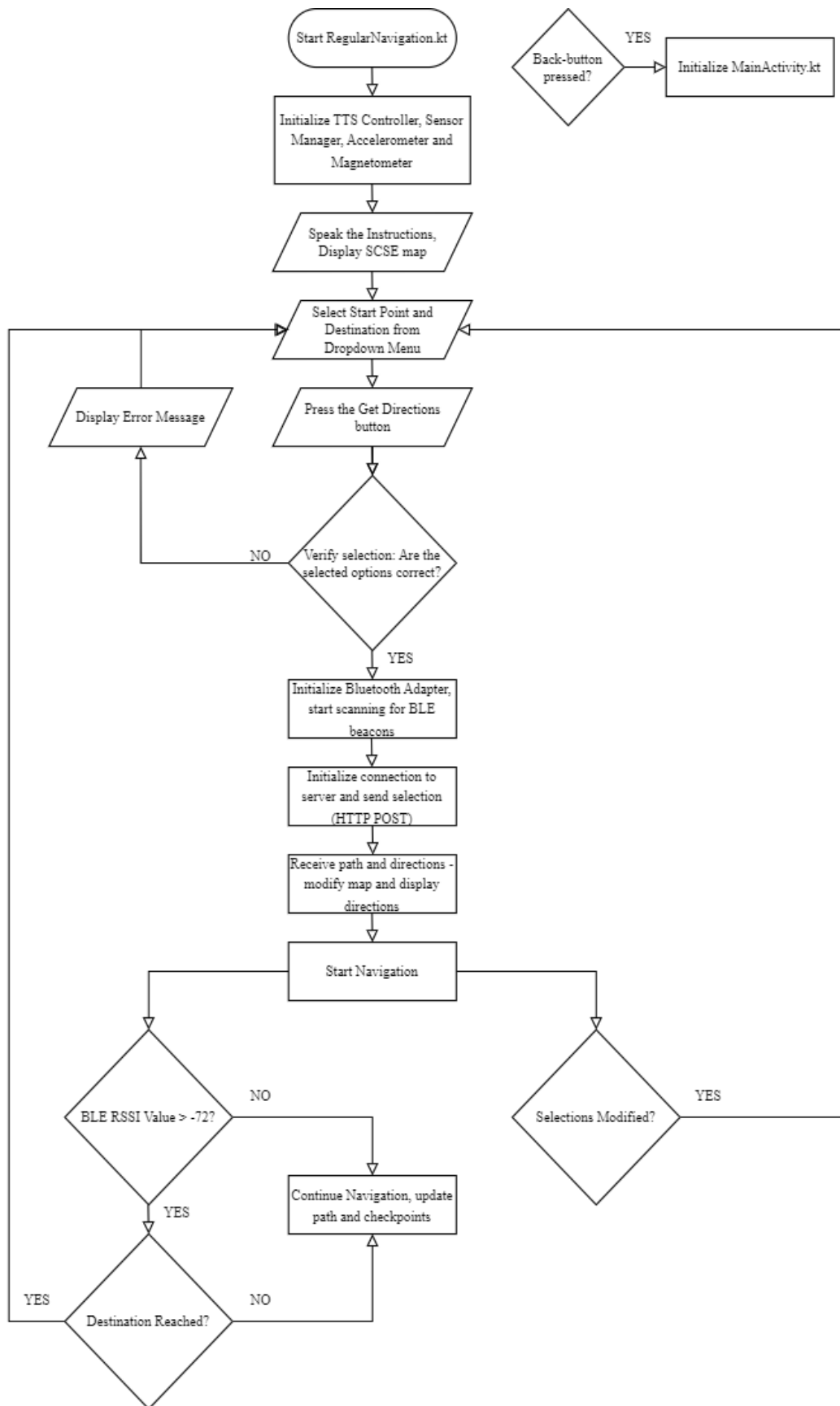
Regular Navigation mode supports vision-based indoor navigation. The screen consists of an indoor map of the test environment – SCSE Level 1 – as well as drop-down lists for users to select the start location and destination. *Figure 3-5* illustrates the flow of the program in RegularNavigation.kt.

Upon initialization of the activity, the TTS controller, sensor manager, accelerometer, and magnetometer are loaded, and the welcome message is spoken as well. At this point, the application awaits user input. Back press on the smartphone redirects the user back to the Home Screen. The start location and destination can be selected from the drop-down menu, and upon pressing the Get Directions button, an HTTP request is made to the server, sending the verified selected options. The server responds with the directions and the path, and the UI updates the map with the same. At the same time, the Bluetooth Manager is initialized and BLE beacon scanning begins.

In this activity, BLE beacons are used with the other aforementioned sensors to perform localization. The sensors aid in calculating the direction and bearing, as well as the distance based on the steps taken by the user. This is used in conjunction with the data received from the BLE beacons that are scanned by the application. The BLE beacons are used for proximity ranging and the sensors are used to re-affirm and validate the information calculated from the BLE beacon data.

Based on the testing methods described in Chapter 5, if the BLE RSSI value exceeds -72, the beacon is considered in range and its information is used to calculate the distance to the beacon. This process continues until the destination node or beacon has been detected. Every time a beacon is detected, the application sends the corresponding node/location to the server and the navigation takes place seamlessly, in real-time for the user.

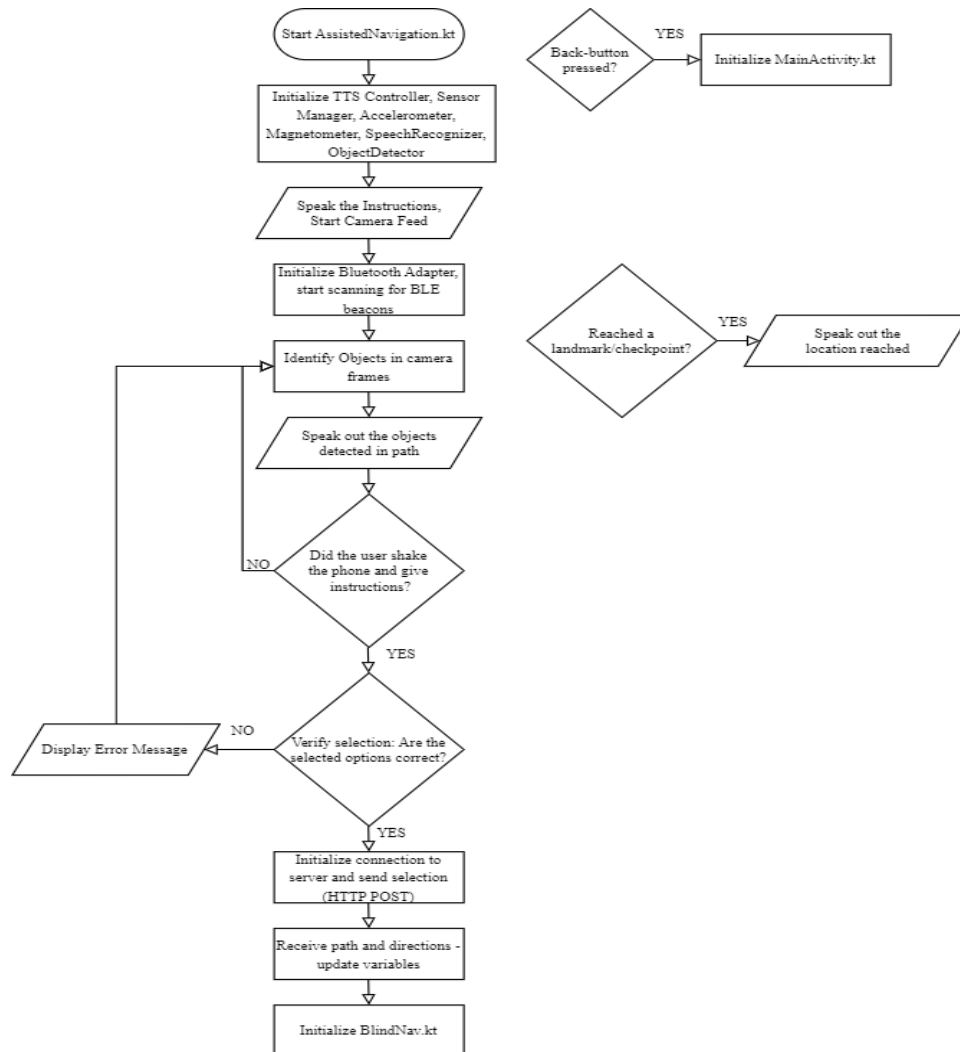
Figure 3-5: RegularNavigation.kt: Dialog Map



3.2.4 Free Roam Mode: AssistedNavigation.kt

Free Roam Mode can be accessed from the Home Screen as described in Section 3.2.2. *Figure 3-6* illustrates the logic flow in the activity. Most initializations remain the same from the previous activities, however, in addition to them, the camera stream is booted up in this activity. Obstacle detection takes place in this activity, where frames are analysed from the camera stream, and the obstacle detected is spoken out to alert the user. Additionally, the activity awaits user input (kinetic – phone shake) to begin Assisted Navigation (BlindNav.kt) for visually impaired users. The verification and request processes are similar to that in Section 3.2.3, and the results from the same are used to update the global variables before the next activity is initialised.

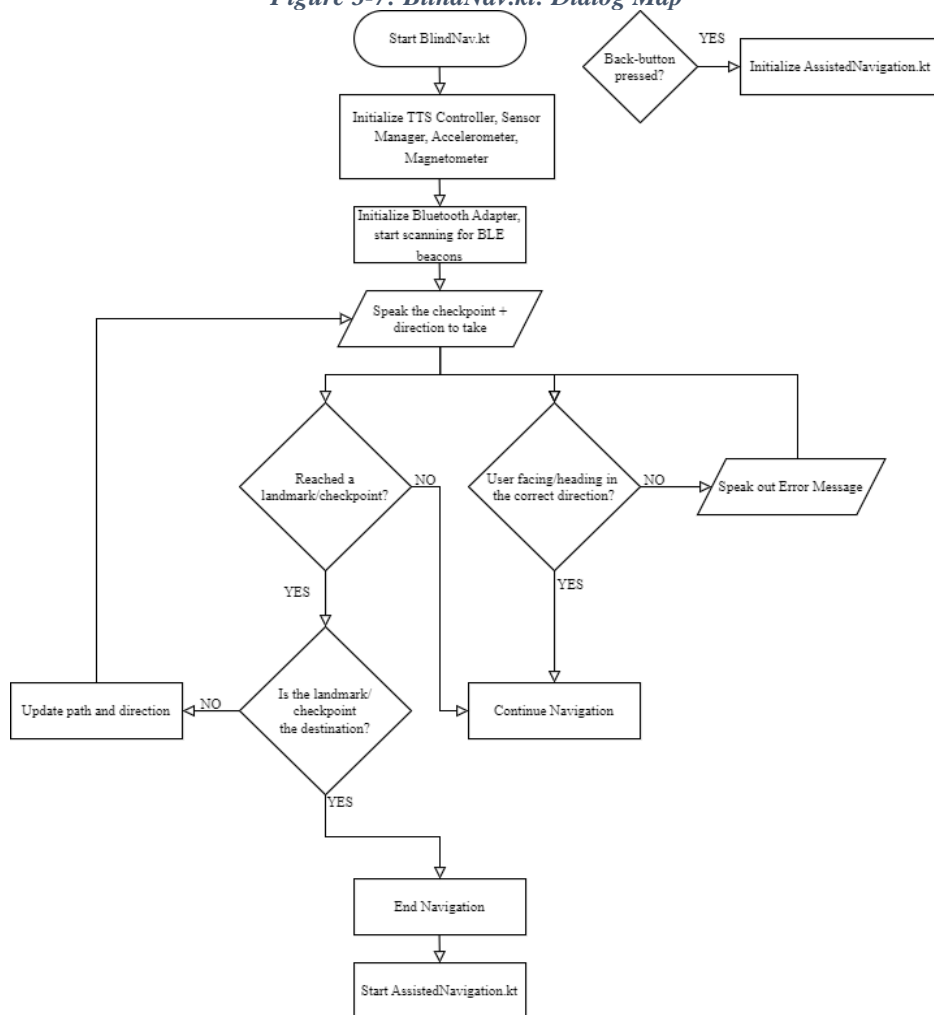
Figure 3-6: AssistedNavigation.kt: Dialog Map



3.2.5 Assisted Navigation (Visionless Navigation): BlindNav.kt

This activity is similar to the Regular Navigation mode in terms of navigation algorithms and logic. Figure 3-7 illustrates the algorithmic flow of this activity. Sensor and TTS initializations remain the same as previous activities. The significant difference in this activity is the feedback given from the application. Visually impaired users struggle to navigate in uncharted, indoor settings, and thus the purpose of this activity is to provide as much information about the user's surroundings. This activity tells the user how far they are from the next checkpoint, provides tactile (vibration) feedback to indicate if the user is heading in the right direction, and continues to give information about the user's immediate surroundings to safely guide the user to their destination.

Figure 3-7: BlindNav.kt: Dialog Map



CHAPTER 4: SYSTEM IMPLEMENTATION

This chapter discusses the implementation of the final architecture discussed in Chapter 3. It will cover the tools and how they were utilized in implementing the architecture.

4.1 System Implementation Tools

Table 4-1 illustrates the tools and APIs that were used to implement the final architecture in Section 3.2 –

Table 4-1: System Implementation Tools

Tool/API	Description
Android Studio	<ul style="list-style-type: none">• Integrated Development Environment (IDE) used to develop <i>VirtualEYE</i> Android application• Programming Language: Kotlin + XML
SketchFab	<ul style="list-style-type: none">• Modelling software used to construct indoor maps for the test environment
Tensorflow Lite	<ul style="list-style-type: none">• Open-source smartphone library to deploy models on devices (smartphones)
Firebase ML Kit	<ul style="list-style-type: none">• Ready to use smartphone APIs to perform machine learning tasks on the device
Visual Studio	<ul style="list-style-type: none">• IDE used to develop the Flask Server• Programming Language: Python 3.9• Dependencies used: Flask Framework,
Docker	<ul style="list-style-type: none">• Tool to allow the server, with its dependencies, to run in packages called containers without the need to set up the environment.
Azure Cloud	<ul style="list-style-type: none">• Cloud platform that provides Linux VM to host the server on the Internet

4.2 Indoor Mapping

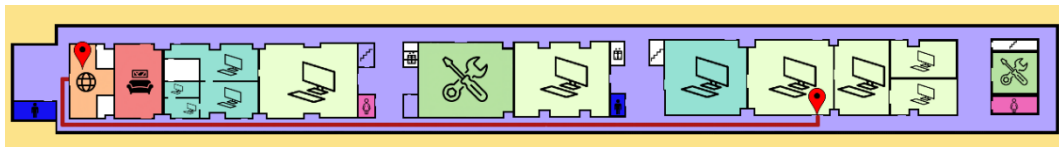
The chosen test environment, SCSE Level 1, was mapped using the aforementioned tool SketchFab. The building and indoor map reference was taken from NTU Maps [19] as seen in *Figure 4-1* –

Figure 4-1: Screenshot of SCSE Level 1 from NTU Maps



This reference was used in the SketchFab software to create indoor environments to an appropriate scale with labels to identify important landmarks and checkpoints. To add this map to the Android application, an external library - Subsampling Scale Image View [20] – was used. This is a library created by David Morrissey to view images in a custom view. These views are designed to display large images (such as maps and building data) without affecting the application's performance and image quality. The library also allows the zooming and panning of images, as well as the addition of custom markers – features that are used in *VirtualEYE* for indoor mapping and navigation. This is illustrated in *Figure 4-2* –

Figure 4-2: Screenshot of the map from VirtualEYE, displayed using the library



4.3 Beacon Configuration and Placement

The beacons used in this study fulfilled the bare minimum requirements of a BLE beacon – it only advertises the device name, MAC (Media Access Card) Address, and its RSSI value. The manufacturing company only provides a technical specification document [21] to understand the hardware capabilities of the beacons. The user of the beacons must write their own code, tailored for their use case, in order to effectively use the beacons (as no SDK is provided). Hence, these beacons

had to be configured and tested multiple times to choose the best parameters for indoor navigation and localisation.

4.3.1 Beacon Detection

To communicate with the beacons, the Android's BluetoothAdapter has been utilised. *Figure 4-3* is the code snippet used to initialize and define the aforementioned adapter –

Figure 4-3: Screenshot from Android Studio: Initialising Bluetooth Adapter

```
// BLE Scanner Init
val bluetoothAdapter: BluetoothAdapter? = BluetoothAdapter.getDefaultAdapter()
if (bluetoothAdapter == null) {
    finish()
}

mBluetoothLeScanner = bluetoothAdapter?.bluetoothLeScanner
mScanCallback = initCallbacks()

val settings = ScanSettings.Builder()
    .setScanMode(ScanSettings.SCAN_MODE_LOW_LATENCY)
    .build()

val filter1 = ScanFilter.Builder()
    .setDeviceName("FCL Beacon1")
    .build()

val filter2 = ScanFilter.Builder()
    .setDeviceName("FWM8BLZ02")
    .build()

val filters = mutableListOf(filter1, filter2)

mBluetoothLeScanner?.startScan(filters, settings, mScanCallback)
```

If the adapter is null, the scanning does not start up. If not null, it launches a BluetoothLeScanner, which searches for BLE devices. The code also includes a callback method (mScanCallback) that is invoked when a BLE device is discovered.

The code then uses `ScanSettings.Builder` to configure the scan settings. The scan mode is set to `SCAN MODE LOW LATENCY` for this use case, which implies that the scan will be performed at a high pace but will require more power (which ensures a more real-time scanning algorithm).

The Builder then constructs two `ScanFilter` objects, `filter1`, and `filter2`, which are used to filter BLE devices based on their names. Filter1 is seeking for a device called "FCL Beacon1", whereas `filter2` is looking for a device called "FWM8BLZ02" – to filter out the required beacons from other BLE devices in the vicinity. The filters, together with the settings and the callback function, are added to a list and sent to the `startScan` method. This initiates the search for BLE devices that meet the provided filter conditions.

Figure 4-4: Screenshot from Android Studio: Scan Method

```
private fun initCallbacks(): ScanCallback {  
  
    return object : ScanCallback() {  
        @SuppressWarnings("MissingPermission", "NewApi")  
        override fun onScanResult(  
            callbackType: Int,  
            result: ScanResult  
        ) {  
            super.onScanResult(callbackType, result)  
  
            if (result.device != null) {  
                if (result.device.name != null) {  
                    //addDevice(result.getDevice(), result.getRssi());  
                    Log.i(tag: "BLE NAME: ", result.device.name)  
                    //println(result.device.name)  
                    Log.i(tag: "BLE MAC: ", result.device.toString())  
                    bleMAC = result.device.toString()  
                    //println(result.device)  
                    Log.i(tag: "BLE RSSI: ", result.rssi.toString())  
                    rssiVal = result.rssi  
                    //println(result.rssi)  
                }  
            }  
        }  
    }  
}
```

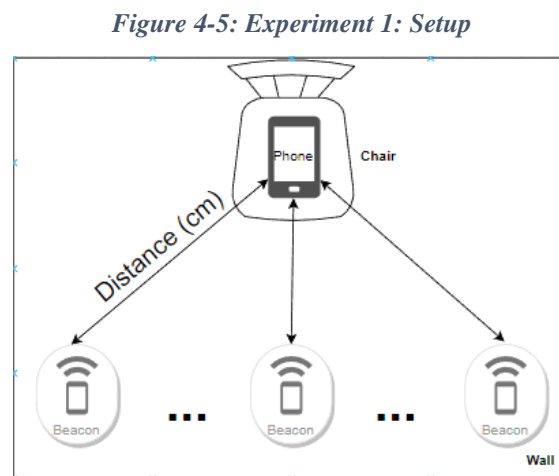
The code snippet in *Figure 4-4* defines the method "initCallbacks()" that returns a ScanCallback object. The ScanCallback class is used to receive callbacks when a BLE device is discovered [22]. The code overrides the ScanCallback class's onScanResult method. When a BLE device is discovered, this function is invoked. The callbackType and result arguments are required by the method. The callbackType parameter is an integer representing the kind of callback (e.g., SCAN FAILED ALREADY STARTED), and the result parameter is an instance of the ScanResult class containing information about the discovered device. The if-condition then checks if a device has been detected, and Log statements are used to view results for debugging and performing tests.

4.3.2 Beacon Configuration and Distance Estimation

Using the boilerplate scanner code in Section 4.3.1, multiple experiments were conducted to come up with a suitable calculation for distance estimation in the proximity ranging function for indoor localisation. Before using the literature method described in Section 2.1.1.1, the initial approach was to derive a custom relationship between RSSI value and Distance from the beacon (in centimetres).

4.3.2.1 Experiment 1: Base Case

Figure 4-5 illustrates the setup for the base case –



To calculate the relationship between distance and RSSI value, keeping distance constant, the RSSI value was noted at constant time intervals. This process was repeated for 5 trials. The angle of the beacons placed from the phone was also changed for the same distance to observe any changes in the RSSI values scanned. The results have been summarised in the tables below –

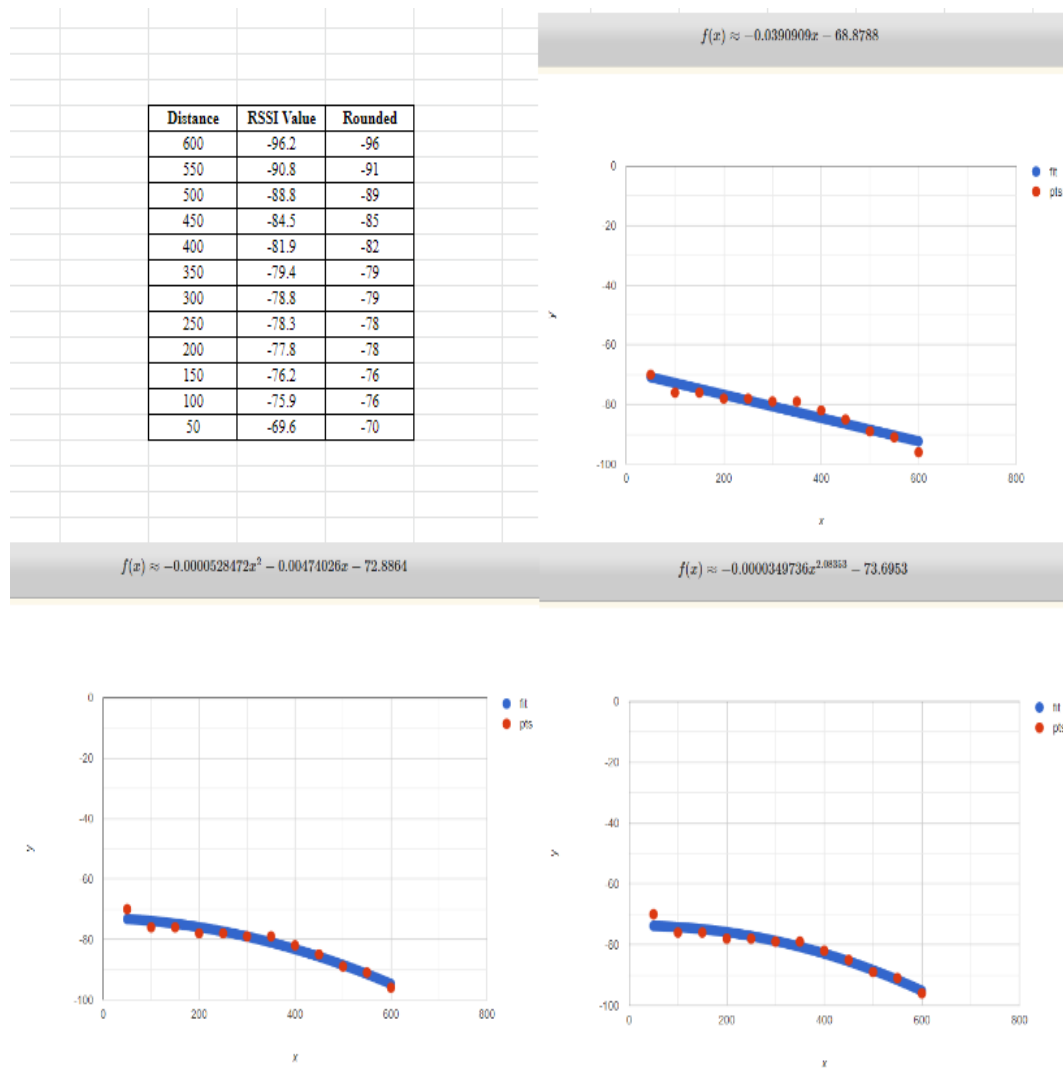
Figure 4-6: Experiment 1: Scan Results

Distance 600cm					
Time (Seconds)	RSSI Values				
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5
0	-91	-95	-92	-96	-96
30	-91	-95	-94	-98	-95
60	-92	-92	-93	-98	-98
90	-95	-93	-95	-98	-96
120	-92	-93	-95	-104	-98
150	-98	-95	-95	-106	-104
180	-95	-95	-95	-98	-110
Average	-93.42857143	-94	-94.14285714	-99.71428571	-99.57142857
	Final Avg -96.17142857				
Distance 500cm					
Time (Seconds)	RSSI Values				
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5
0	-89	-92	-91	-90	-90
30	-87	-89	-89	-90	-87
60	-87	-90	-85	-90	-90
90	-87	-89	-87	-90	-90
120	-89	-87	-89	-90	-90
150	-89	-85	-91	-89	-90
180	-87	-89	-85	-89	-90
Average	-87.85714286	-88.71428571	-88.14285714	-89.71428571	-89.57142857
	Final Avg -88.8				
Distance 400cm					
Time (Seconds)	RSSI Values				
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5
0	-81	-81	-81	-81	-87
30	-85	-84	-81	-79	-85
60	-84	-84	-85	-79	-82
90	-81	-81	-85	-84	-82
120	-81	-82	-83	-80	-81
150	-82	-82	-79	-80	-81
180	-81	-82	-79	-80	-81
Average	-82.14285714	-82.28571429	-81.85714286	-80.42857143	-82.71428571
	Final Avg Distance -81.88571429				
Distance 300cm					
Time (Seconds)	RSSI Values				
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5
0	-78	-78	-81	-83	-77
30	-80	-78	-77	-77	-77
60	-77	-78	-76	-77	-78
90	-75	-79	-81	-82	-78
120	-80	-77	-77	-77	-78
150	-80	-77	-88	-84	-78
180	-79	-78	-77	-78	-84
Average	-78.42857143	-77.85714286	-79.57142857	-79.71428571	-78.57142857
	Final Avg -78.82857143				
Distance 200cm					
Time (Seconds)	RSSI Values				
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5
0	-78	-78	-75	-84	-77
30	-78	-78	-79	-77	-77
60	-78	-78	-76	-77	-79
90	-76	-79	-79	-77	-78
120	-76	-76	-78	-77	-78
150	-76	-76	-78	-81	-78
180	-79	-76	-77	-82	-77
Average	-77.28571429	-77.28571429	-77.42857143	-79.28571429	-77.71428571
	Final Avg -77.8				
Distance 100cm					
Time (Seconds)	RSSI Values				
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5
0	-77	-77	-78	-74	-76
30	-77	-77	-74	-75	-76
60	-75	-78	-74	-75	-75
90	-77	-77	-77	-75	-79
120	-76	-76	-78	-76	-77
150	-76	-73	-74	-74	-75
180	-76	-78	-74	-74	-76
Average	-76.28571429	-76.57142857	-75.57142857	-74.71428571	-76.28571429
	Final Avg -75.88571429				

Distance 550cm					
Time (Seconds)	RSSI Values				
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5
0	-91	-90	-91	-91	-91
30	-91	-90	-90	-91	-92
60	-90	-90	-90	-91	-91
90	-91	-90	-92	-91	-91
120	-90	-91	-90	-90	-91
150	-90	-91	-93	-91	-90
180	-91	-91	-93	-90	-90
Average	-90.57142857	-90.42857143	-91.28571429	-90.71428571	-90.85714286
	Final Avg -90.77142857				
Distance 450cm					
Time (Seconds)	RSSI Values				
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5
0	-83	-82	-83	-83	-84
30	-88	-87	-82	-83	-87
60	-82	-82	-83	-82	-89
90	-87	-82	-87	-82	-84
120	-87	-87	-88	-88	-83
150	-82	-85	-82	-83	-88
180	-88	-82	-82	-82	-90
Average	-85.28571429	-83.85714286	-83.85714286	-83.28571429	-86.42857143
	Final Avg -84.54285714				
Distance 350cm					
Time (Seconds)	RSSI Values				
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5
0	-83	-78	-76	-83	-81
30	-85	-78	-76	-78	-81
60	-85	-78	-76	-79	-78
90	-84	-80	-81	-76	-78
120	-84	-82	-77	-77	-78
150	-80	-82	-77	-78	-78
180	-82	-78	-77	-78	-78
Average	-83.28571429	-79.42857143	-77.14285714	-78.42857143	-78.85714286
	Final Avg Distance -79.42857143				
Distance 250cm					
Time (Seconds)	RSSI Values				
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5
0	-78	-78	-79	-78	-77
30	-80	-78	-79	-77	-77
60	-78	-78	-76	-77	-78
90	-78	-82	-79	-77	-78
120	-78	-82	-78	-77	-78
150	-78	-82	-78	-78	-78
180	-78	-82	-77	-78	-77
Average	-78.28571429	-80.28571429	-78	-77.42857143	-77.57142857
	Final Avg -78.31428571				
Distance 150cm					
Time (Seconds)	RSSI Values				
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5
0	-74	-79	-79	-74	-76
30	-76	-74	-74	-75	-76
60	-79	-78	-74	-75	-76
90	-79	-79	-77	-76	-83
120	-75	-77	-76	-76	-83
150	-73	-73	-74	-74	-76
180	-78	-75	-74	-74	-76
Average	-76.28571429	-76.42857143	-75.42857143	-74.85714286	-78
	Final Avg -76.2				
Distance 50cm					
Time (Seconds)	RSSI Values				
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5
0	-75	-73	-71	-67	-69
30	-73	-71	-71	-69	-68
60	-65	-65	-70	-69	-68
90	-65	-73	-70	-69	-69
120	-74	-71	-67	-68	-68
150	-72	-78	-67	-68	-69
180	-65	-76	-67	-68	-69
Average	-69.85714286	-72.42857143	-69	-68.28571429	-68.57142857
	Final Avg -69.62857143				

The final average values from this experiment were then taken (rounded up to the nearest whole number) and multiple equations were derived to estimate the relationship between distance and RSSI values (Linear, Quadratic, Root) [23]. The results from this have been illustrated below –

Figure 4-7: Experiment 1: Final Results

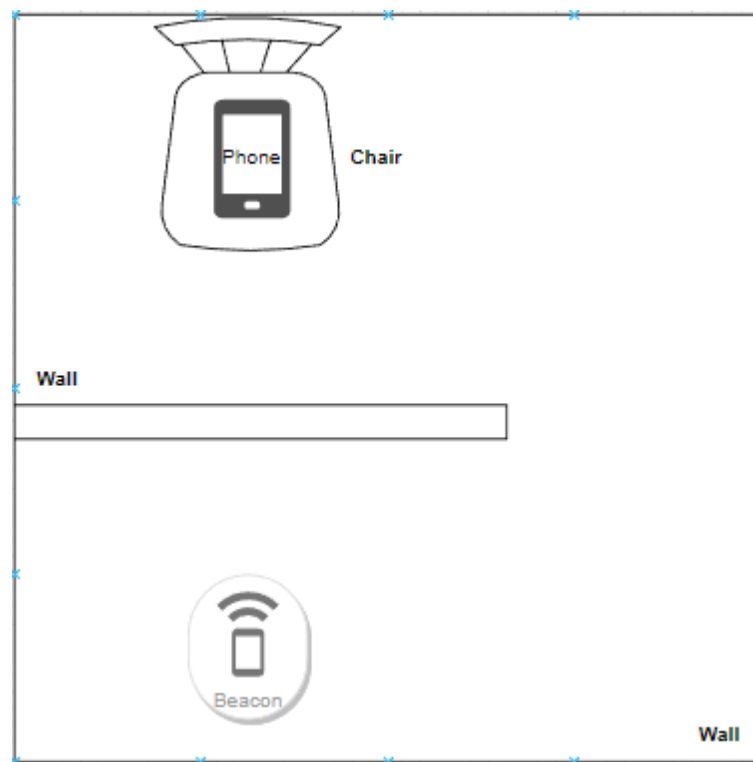


Despite doing multiple trials and averaging across multiple observed values, there was still a significant difference in the accuracy of the distance estimated using this method (for all three derived curves). The distance estimated was only accurate for a specific range of values (for distances less than 200cm). The next step was to conduct another experiment to further analyse the results and try to improve the derived equations.

4.3.2.2 Experiment 2: Base Case + Obstacle (Wall)

The setup in this experiment was similar to that in Experiment 1, however, an additional obstacle (a wall) was introduced in the experiment area. This was to cater to a more realistic scenario, where the beacons and scanner would be interacting with each other with multiple obstacles, the main one being walls. *Figure 4-8* illustrates the setup –

Figure 4-8: Experiment 2: Setup



The scan results and final calculations were conducted in the same manner as Experiment 1. The introduction of the obstacle did bring variations in the derived equations, however, upon testing, the same problem as in Experiment 1 was encountered. For this experiment, the estimated distances were only accurate up to 165cm – still not ideal for the study's use case.

4.3.2.3 Experiment 3: Literature Method

4.4 Server Implementation

4.5 Client Implementation

4.5.1 Class Diagram

4.5.2 Main Activity

4.5.3 Regular Navigation

4.5.4 Assisted Navigation

4.5.5 Blind Nav

4.6 Placeholder

CHAPTER 5: TESTING AND EVALUATION

5.1 Test Case 1

5.1.1 Setup

5.1.2 Results

5.1.3 Analysis

5.2 Test Case 2

5.2.1 Setup

5.2.2 Results

5.2.3 Analysis

5.3 Test Case 3

CHAPTER 6: CONCLUSION

CHAPTER 7: FUTURE WORK

REFERENCES

- [1] T. Becker, C. Nagel, and T. H. Kolbe, "Supporting contexts for indoor navigation using a multilayered space model," 2009 Tenth International Conference on Mobile Data Management: Systems, Services and Middleware, 2009.
- [2] A. Satan and Z. Toth, "Development of Bluetooth based indoor positioning application," 2018 IEEE International Conference on Future IoT Technologies (Future IoT), 2018.
- [3] F. Zafari, I. Papapanagiotou, and K. Christidis, "Micro-location for internet of things equipped smart buildings," IEEE Internet of Things Journal, vol. 3, no. 1, pp. 96–112, 2016.
- [4] J. Hvizdos, J. Vascak, and A. Brezina, "Object identification and localization by smart floors," 2015 IEEE 19th International Conference on Intelligent Engineering Systems (INES), 2015.
- [5] D. Pascolini and S. P. Mariotti, "Global Estimates of Visual Impairment: 2010," British Journal of Ophthalmology, vol. 96, no. 5, pp. 614–618, 2011.
- [6] Dardari D., Closas P., Djuric P.M. Indoor tracking: Theory, methods, and technologies. IEEE Trans. Veh. Technol. 2015;64:1263–1278. doi: 10.1109/TVT.2015.2403868.
- [7] Navarro A., Sospedra J., Montoliu R., Conesa J., Berkvens R., Caso G., Costa C., Dorigatti N., Hernández N., Knauth S., et al. Geographical and Fingerprinting Data to Create Systems for Indoor Positioning and Indoor/Outdoor Navigation. Challenges, Experiences and Technology Roadmap Intelligent. Data Centric Syst. 2019;2019:1–20. doi: 10.1016/B978-0-12-813189-3.00001-0.
- [8] Alarifi A., Al-Salman A., Alsaleh M., Alnafessah A., Al-Hadhrami S., Al-Ammar M.A., Al-Khalifa H.S. Ultra-Wideband Indoor Positioning Technologies: Analysis and Recent Advances. Sensors. 2016;2016:707. doi: 10.3390/s16050707.
- [9] Simões WCSS, Machado GS, Sales AMA, de Lucena MM, Jazdi N, de Lucena VF Jr. A Review of Technologies and Techniques for Indoor Navigation

Systems for the Visually Impaired. *Sensors* (Basel). 2020 Jul 15;20(14):3935. doi: 10.3390/s20143935. PMID: 32679720; PMCID: PMC7411868.

[10] Wang Y., Yang Q., Zhang G., Zhang P. Indoor positioning system using Euclidean distance correction algorithm with Bluetooth low energy beacon; Proceedings of the International Conference on Internet of Things and Applications (IOTA); Las Vegas, NV, USA. 22–24 January 2016; pp. 243–247.

[11] Palumbo F., Barsocchi P., Chessa S., Augusto J.C. A stigmergic approach to indoor localization using Bluetooth Low Energy beacons; Proceedings of the 12th IEEE International Conference on Advanced Video and Signal Based Surveillance (AVSS); Karlsruhe, Germany. 25–28 August 2019; pp. 1–6

[12] Zanella A. Best Practice in RSS Measurements and Ranging. *IEEE Commun. Surv. Tutor.* 2016;18:2662–2686. doi: 10.1109/COMST.2016.2553452.

[13] Zhao Y., Fritsche C., Yin F., Gunnarsson F., Gustafsson F. Sequential Monte Carlo Methods and Theoretical Bounds for Proximity Report Based Indoor Positioning. *IEEE Trans. Veh. Technol.* 2018;67:5372–5386. doi: 10.1109/TVT.2018.2799174.

[14] Munoz Diaz E. Inertial pocket navigation system: Unaided 3D positioning. *Sensors.* 2015;15:9156–9178. doi: 10.3390/s150409156.

[15] Fraundorfer F., Scaramuzza D. Visual odometry: Part II: Matching, robustness, optimization, and applications. *IEEE Robotics Autom. Mag.* 2012;19:78–90. doi: 10.1109/MRA.2012.2182810.

[16] Zhao Y., Xu J., Wu J., Hao J., Qian H. Enhancing Camera-Based Multimodal Indoor Localization With Device-Free Movement Measurement Using WiFi. *IEEE Internet Things J.* 2020;7:1024–1038. doi: 10.1109/JIOT.2019.2948605.

[17] Ji, M., Kim, J., Jeon, J., & Cho, Y. (2015). Analysis of positioning accuracy corresponding to the number of BLE beacons in indoor positioning system. 2015 17th International Conference on Advanced Communication Technology (ICACT). doi:10.1109/icact.2015.7224764

- [18] <https://microchipdeveloper.com/wireless:ble-link-layer-discovery>
- [19] <https://maps.ntu.edu.sg/#/ntu/d386ffa80e4e46f286d17f08/poi/search>
- [20] <http://davemorrissey.github.io/subsampling-scale-image-view/javadoc/>
- [21] Enter link to tech spec
- [22] <https://developer.android.com/reference/android/bluetooth/le/ScanCallback>
- [23] <https://www.dcode.fr/function-equation-finder>