Experimental Evaluation of Low-Cost BLE-based Indoor Positioning System

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CONTENTS

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***Abstract*—Recent global health events have underscored the need for accurate indoor tracking systems in healthcare facilities. Current GPS-based solutions excel in outdoor navigation but fall short in offering precise indoor positioning. Existing indoor positioning system solutions often come with high costs and complex implementation processes that pose barriers to widespread adoption in healthcare facilities. This study evaluates the feasibility of a cost-effective Indoor Positioning System (IPS) using Bluetooth-Low-Energy (BLE) technology in healthcare contexts by leveraging BLE beacons and the trilateration algorithm based on Received Signal Strength Indicator (RSSI) measurements. Tested in Rumah Sakit Nasional Diponegoro, an Indonesian hospital, from December 2021 to February 2022, our results show that the data collected from the system is infeasible for real-time indoor positioning tracking. The main issue is low data completeness, leading to missing data points that introduce inconsistencies. Furthermore, the dataset fails to accurately capture the healthcare facility's dynamic nature and multifaceted environment, rendering it less reliable for nuanced applications.**

***Index Terms*—indoor positioning system, bluetooth low energy, hospital environment**

I. Introduction

Indoor positioning systems (IPS) aim to locate an object, person or target in a closed environment using real-time waves, signals, or other sensory information. In response to the pressing challenges of the COVID-19 pandemic, the healthcare sectors have pushed the urgent need to adapt and strengthen internal monitoring measures. One is the demand for meticulous indoor tracking, especially within healthcare facilities [1]. Such systems serve critical functions by enabling healthcare providers to:

- Prevent unauthorised patient departures [2];
- Enforce strict supervision of quarantined individuals [2];
- Optimise resource allocation and management [1], [3];
- Significantly reduce the time in identifying the location of personnel and crucial assets [4].

In the life-and-death nature of healthcare, where moments can be pivotal, integrating an effective IPS can profoundly elevate the quality of patient care and broader public health services [1], [5]. While IPS solutions are available, their substantial costs and high maintenance deter healthcare facilities from adopting them. Developing IPS to be accessible and feasible is required for broader implementation.

One of the critical criteria for an ideal IPS is the provision for high accuracy and precision of a target's location. To this end, one of the most prevalent and accessible forms of navigation, the Global Positioning System (GPS), is insufficiently equipped to be an ideal IPS as they are unable to yield the high level of precision required for indoor tracking [2]. Issues such as signal attenuation from infrastructures and changing environmental factors make it an exceptional task for GPS to handle [6].

However, the last decade has witnessed monumental growth in the Internet of Things (IoT), creating affordable and efficient ways for devices to communicate and interact with each other. One of these developments is the Bluetooth Low-Energy (BLE) wireless technology, distinguished for its energy efficiency. BLE-enabled devices can sustain operations over extended periods of time, potentially spanning over years, whilst managing, transmitting, and processing substantial data streams [7]). Additionally, their cost-effectiveness makes them a viable choice for operational IPS deployment. Hence, this has paved the possibility of deploying a real-time IPS that is cost-effective and accessible [8].

An approach for developing IPS that has garnered considerable attention is the use of range-based localization algorithms, notably the trilateration method [9]. This method utilises the distance data from multiple reference points to estimate a target's position. While the theory of trilateration promises precision, the real-world application faces many challenges. In practice, the introduction of noise and environmental interference makes pinpointing a target a tremendous task. This study aims to formulate and evaluate the effectiveness of a low-cost IPS within authentic operational environments. To achieve this, BLE-beacons and scanners were calibrated and positioned for the trilateration technique. Between December 2021 and February 2022, an extensive data collection initiative was launched at Rumah Sakit Nasional Diponegoro, a hospital located in Indonesia. For this study, numerous hospital staff members were equipped with BLE-enabled wristwatches. As the staff went about their routine, adhering to social distancing protocols, these devices continuously transmitted signals every second, enabling the scanners to gather data within the dynamic hospital environment. The data will be analysed to validate the system's functionality and critically assess and examine the pragmatic applicability of the approach for indoor tracking.

If the data does not meet real-time indoor positional tracking expectations, this study will conduct a rigorous exploration of methodologies tailored for data optimisation. The objective is not just to fix data imperfections but to identify and implement solutions that can function given the bounds of data constraints. Furthermore, the potential limitations and factors that could have affected the data will be investigated. To this end, this study will address the data's immediate concerns and serve as a stepping stone for future advancements in developing low-cost IPS.

II. Background

A. Internet of Things in Healthcare

The concept of the Internet of Things (IoT) has emerged as a notable topic of discourse in both academia and industry. While interpretations vary, the central theme consistently revolves around a system where real-world objects connect and communicate via the Internet. Various literature like [10] and [11] accentuate IoT's transformative potential. While most contemplate the vast implications of IoT across numerous sectors, [4] delve profoundly into its healthcare applications. Such applications can seamlessly interconnect distinct healthcare touchpoints such as doctor visits, chiropractor interventions or rehabilitation sessions to enhance patient data integration. Despite the emphasis on medical data integration, the potential for IoT real-time tracking of patient, staff, and resources remain comparatively under-explored [3], [4]. Many healthcare advantages are lost due to the lack of real-time tracking. For instance, the ability to prevent unauthorised patient departures, which poses potential risks to the safety of both the patient and the public, seen during the global pandemic, becomes an arduous task without efficient tracking mechanisms [2]. Additionally, the immediacy of real-time tracking can drastically reduce the time spent locating key personnel and crucial assets, leading to enhanced operational efficiency and improved patient care [4].

B. Previous Challenges with Indoor Positioning Systems

Several works have aimed to refine IPS to optimise their application in healthcare contexts. For instance, a study by [1] employed an IPS in a healthcare setting that faced technological impediments involving energy-intensive costs. Moreover, the evaluation criteria in their work were primarily centred on staff satisfaction rather than objective tracking results. On the other hand, [12] employed a WLAN-based IPS framework that was grappled with computational challenges. Notably, both endeavoured to demonstrate the feasibility of real-time IPS within healthcare settings by deploying their real-time IPS solutions. However, they were met with challenges ranging from resource constraints to technological impediments. Distinctively, an attempt by Kyoto University Hospital faced substantial technical barriers, inhibiting a comprehensive system deployment [3], underscoring the need for more extensive research. Additionally, [3] caution about the legal and ethical entanglements when deploying an IPS in healthcare facilities, seemingly stifling research advancements due to increased regulatory scrutiny.

C. Bluetooth Low-Energy Technology and Received Signal Strength Indicator

With the emergence of Bluetooth Low Energy (BLE) and its economic feasibility and energy efficiency, as delineated by [7], [8], there remain questions about its potential use in developing accessible IPS for healthcare facilities. In this light, our work builds upon the approach of the works of [2], [7], where the authors simulate indoor tracking with BLE technology, evaluate its effectiveness and lay out the foundation for future IPS solutions.

Despite the merits of BLE, its actual litmus test lies in implementation. A central theme in BLE application revolves around distance measurement between devices, estimated using the Received Signal Strength Indicator parameter [8] Despite this, the complexities of deploying it in practical scenarios, like the methodology proposed by [7], have gaps. For instance, the readings for RSSI can fluctuate over time, be corrupted, or be lost before being read by the scanner. These factors, combined with frequent broadcasts, can impact the reliability of real-time tracking.

While some, like [13], underscore RSSI's consistency, an overwhelming number of studies suggest otherwise about RSSI's reliability as a distance estimator. For instance, the proposition by [14] about RSSI's robustness for measuring distance is counterbalanced by [15], finding that RSSI's accuracy wavers in varied environments. These challenges are further magnified when we consider real-world scenarios. The most prevalent factor in disrupting RSSI accuracies is multipath fading/multipath propagation, which are environmental interferences that distort signal trajectories [9]. Humans are mostly composed of water, so they can absorb radio signals, leading to signal distortions, a phenomenon documented by [16]. These obstacles will be faced when deploying RSSI-based systems in dynamic environments, such as hospitals.

Despite these shortcomings, the literature is far from pessimistic. While [15], [17] highlight the current limitations of RSSI, they remain optimistic about its future potential, especially when multiple scanners are incorporated. Furthermore, experimental studies like [7], [12] support that distance estimation from RSSI becomes highly accurate with a small margin of error with proper calibration and positioning of scanners. As such, the RSSI distance model

$$RSSI = -(10n \log_{10} d + A) \tag{1}$$

where n is the signal propagation constant, d is the distance from the sender and A is the measured RSSI at 1m, is agreed upon to be an accurate depiction of the relationship between RSSI and distance [6], [18]. Our study seeks to integrate BLE technology and its RSSI capabilities within a hospital setting, transitioning the evaluation of RSSI as a distance estimator from controlled experimental settings to a real-world context, bridging the gap in the literature.

D. Trilateration as a Localization Method

Every IPS solution requires a localization method to determine the position of a target. [9] outlines the IPS deployment process into three methodological stages:

- Beacon/Scanner Placement: This phase focuses on strategically positioning scanners/beacons. [19] illustrate the significance of optimal node layout, demonstrating a localization error range of around 5-10% in environments with minimal external interference.
- Calibration: The step aims to define and establish all configurations that best align with the model provided by [6].
- Positioning: At its core, positioning encapsulates the selection and implementation of a localization method.

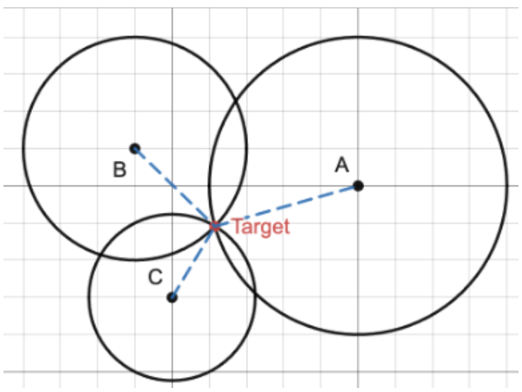


Fig. 1: Trilateration technique demonstrating target localization using three reference nodes.

The project will primarily focus on the trilateration method. Defined by [20], trilateration leverages the spatial arrangement of three or more reference nodes to determine a target's location. The method requires two main components: beacons and scanners. Beacons broadcast a signal periodically and can be in the form of a mobile phone or a watch. The scanners will record any signals received by the beacon's broadcasts. As illustrated in Fig. 1, the trilateration technique operates based on distance measurements derived from signal strength. In this case, BLE-enabled technology measures signal strength through a Received Signal Strength Indicator (RSSI). Specifically, when a beacon/target broadcasts a signal, multiple scanners (at least three for two-dimensional localization) at known static locations detect and record the signal. Fig. 1 demonstrates this by placing three scanners, A, B and C, at known locations to receive an RSSI measurement from the beacon/target. By evaluating the RSSI, each scanner computes its distance from the beacon, represented by the radii of circles. Ideally, the circles intersect in one convergent point indicating the beacon/target's exact position [7], [18]. A centroid positioning algorithm is required for non-ideal trilateration results [18]. Crucially, there is a distinction between the trilateration and triangulation methods; some studies, such as [21], use the terms interchangeably. Thus, our work uses the trilateration method, not triangulation, to prevent ambiguity.

E. Current State of Literature

The existing literature underscores a void in the application of cost-effective IPS solutions leveraging BLE technology in healthcare settings. Studies often gravitate towards more costly IPS solutions [3], [12] that pose financial barriers for healthcare institutions. Furthermore, most studies conduct their experiments in synthetic environments [9] to evaluate IPS performance and cannot capture the nuance and complexities of operational scenarios. With the absence of a practical, financially accessible IPS solution, our work addresses this gap, probing the feasibility of a cost-effective IPS built upon BLE technology and anchored by the trilateration method. Through evaluating our IPS deployment in an authentic environment, whether they underline the feasibility or highlight challenges, the results will be instrumental in bridging the existing gaps and laying the foundation for future endeavours in accessible IPS solutions.

III. Details of the Purposed System

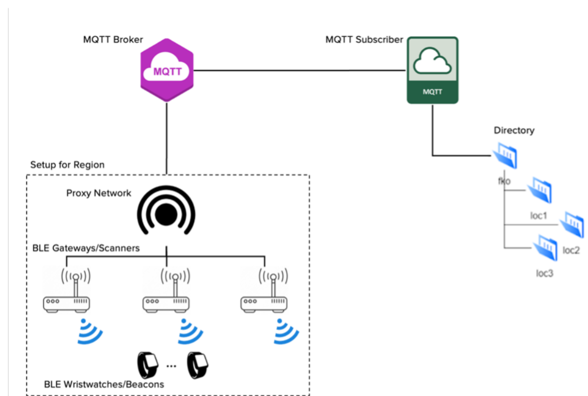


Fig. 2: General design overview of proposed Indoor Positioning System.

Our low-cost Indoor Positioning System, outlined in Fig. 2, consists of the following elements:

- Bluetooth Low Energy Scanners/Gateway – these are positioned throughout a targeted vicinity. Details about the positioning method will be discussed in the next section. The scanners are analogous to satellites in a GPS set-up [2]. By operational principle, the scanner captures the signals from the beacons containing Received Signal Strength Indicator (RSSI) data through a transparent proxy network for trilateration. The experimental study uses MKGW1-BW Pro Bluetooth Gateway as a scanner and sends the data to an MQTT broker.
- BLE wristwatches – operationally, these emit BLE signals every second for BLE scanners to receive. They are distributed amongst hospital staff, particularly those who work near the scanners. The BLE wristwatch used in the experimental study is a W5 Bluetooth Beacon Tracker fitted with a nRF52 chipset.
- Proxy Network – technical and legal complications are faced when integrating our system into the hospital net-

work; thus, a proxy network must be set up for our beacon and scanners to broadcast and receive signals. This is set up using a wireless access point and is needed for the scanners to upload the data to the MQTT broker.

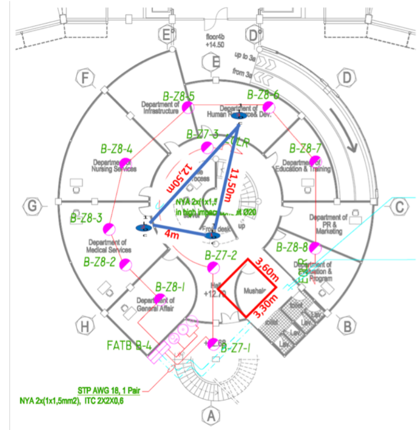
- MQTT Broker/Server – acting as a central hub where all scanner data is uploaded to and sent to the subsequent MQTT subscriber. In the study's context, the broker is MQTT Eclipse Mosquito, a web service designed to send messages to an MQTT subscriber. In future practice, the broker will cater for data transmission in real time so that data can be streamed for real-time processing.
- MQTT Subscriber –the application that receives and organises the data from the MQTT broker.

Once the components are all set up in the desired location, the BLE wristwatches are given to hospital staff as they proceed with their usual operations. The wristwatches will act as beacons, sending RSSI data to the Bluetooth Low Energy Scanners or BLE Gateway. The gateway device will send the recorded data to the MQTT broker through the proxy network. The broker publishes the collected data in a structured JSON format. The JSON encompasses information such as RSSI values, the associated timestamp and the base RSSI, among other relevant data points. The MQTT subscriber is configured to batch the received messages, and every 5 minutes, the accumulated messages are systemically written into a .txt file and stored within the appropriate directory.

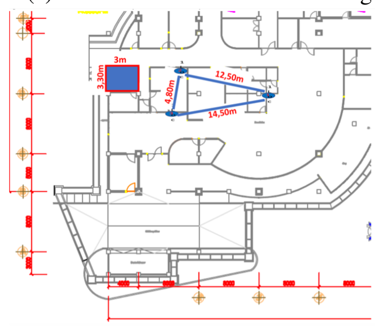
IV. Calibration and Placement of BLE Scanners

It is common practice to calibrate the BLE beacons. As found by [7], proper calibration of the beacons dramatically affects the accuracy of locating a target. Furthermore, the RSSI distance estimation model by [6] requires calibration in the form of the base RSSI. The base RSSI is the expected signal strength if the scanner and beacon were 1m apart. Ensuring that these values align is paramount to estimating the distance.

To obtain the optimal placement of BLE scanners within the premises, it is essential to heighten total coverage without oversaturating the environment with excess scanners. Excessing scanners is counterintuitive to producing a low-cost IPS as it costs more to build and maintain the solution. The approach for the positioning method is inspired by and adapted from the heuristic algorithm presented by [2] for determining the number and distribution of BLE beacons or scanners. While their algorithm is designed for expansive floor-wide coverage, our scope of focus is a room and its surrounding premises. In principle, we position the scanners to want optimal coverage of a desired room; this often comes in triangulating around the room. As such, no room is to have more than one scanner. As depicted in Fig. 3(a), the scanners are positioned such that the UGD RSND is triangulated but are also in separate rooms. The FKO scanners are also positioned similarly, as seen in Fig. 3(b), where each scanner is placed in a separate room but attempts to cover as much of the area as possible. Each region has a total of three scanners. Another factor when determining scanner positions is the power supply requirement. BLE gateways need a power supply; thus, the scanner locations will be selected to be close to specific power sources or outlets.



(a) Scanner locations of RSND region



(b) Scanner locations of FKO region.

Fig. 3: Building blueprint illustrating placement of BLE scanners through key hospital regions.

A prerequisite of the trilateration method is knowing the location of the scanners. This experiment measures each scanner's exact latitude and longitude and uses it as the known location. Measuring the coordinates of the scanners requires a high degree of precision and is affected by the measurement application and height or floor level.

V. Extraction and Utilisation of Essential Data for Trilateration

In data extraction for our IPS, several values are required to facilitate the trilateration localization technique. On top of the known location for the scanners, the values required are the recorded instance of RSSI value, the timestamp of when the data was recorded and the base RSSI. The nRF52 chipset also embeds 3-axis data, a value not central to this experiment, providing a three-dimensional representation of the beacon. The breadth of data from the BLE beacons offer potential for future extensions or additional use cases, making our IPS adaptable and forward-looking.

Since the trilateration technique is a range-based localization method, converting from RSSI to distance (in meters) is necessary. Solving for distance in the RSSI distance estimation model provides

$$d = 10^{(\frac{A-RSSI}{10n})} \tag{2}$$

where d is the estimated distance, A is the base RSSI, n is the environment factor ranging from 2 to 4. An environment factor of 2 indicates low external interferences and is best used when there are few obstacles to cause multipath propagation. In contrast, an environment factor of 4 suggests high levels of interference and is more appropriate in a bustling environment like a hospital. Since the environment factor is user-controlled, extensive trial-and-error will be conducted to observe the localization behaviour to determine the most appropriate value.

Since the trilateration method requires the known location of the scanners, we employ the distance degrees method. Distance is represented in degrees rather than linear measurements when working with geographic coordinates. Given that the RSSI distance model furnishes distances in meters, a conversion to degree distance is required. This conversion is made through the following formula:

$$d_\theta = \frac{d_m}{R} \tag{3}$$

where d_θ denotes the distance in degrees, d_m is the distance in meters, and R is distance covered in meters by an arc degree i.e. the total distance covered by one degree of latitude or longitude. This relies on the assumption that the scanner locations are situated on a flat plane, allowing for R to be a constant value. Since the experiment covers a relatively small area, the curvature of the Earth is considered negligible. The study's chosen value for R is 111,113, an approximate representation of the distance covered by an arc degree around the equator. Note that R varies depending on geographic location as the distance covered by an arc degree decreases towards the poles of the Earth.

VI. Implementing Trilateration Localization Technique

In implementing the trilateration localization technique, it is vital to adopt a systematic approach that caters for both precision and handling of possible anomalies in the data.

A. Procedure

For each timestamp or time increment, the respective RSSI values from each scanner are gathered and aggregated appropriately, usually through the mean. With the aggregated RSSI value from each scanner, the estimated distance is computed through the RSSI distance model (2). The derived distances, being the distance from the scanner to the target, represent the estimated radius of a circle, with the scanner positioned in the centre. From a more mathematical perspective, let $\xi = \{S_1, ..., S_{n_\xi}\}$ be the set of all reference nodes or scanners and $n_\xi = n(\xi)$, the number of scanners. The solution to

$$\begin{gathered} (x - x_{S_1})^2 + (y - y_{S_1})^2 = d_{S_1}^2 \\ \dots \\ (x - x_{S_1})^2 + (y - y_{S_1})^2 = d_{S_1}^2 \end{gathered} \tag{4}$$

where d_{S_i} is the distance between the target and scanner S_i and $i \in \{1, ..., n_\xi\}$, provides the coordinates to the target.

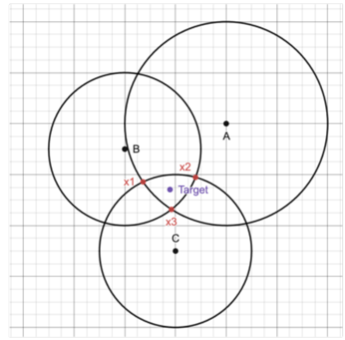


Fig. 4: A more realistic scenario of using the trilateration method. Instead of a single point, the target's estimated location is represented within the region where the circles intersect.

However, as Fig. 4 depicts, real-world applications often present a more complex situation. External interferences, measurement inaccuracies, and noise can all lead to deviations from the expected outcome. Consequently, rather than an exact singular point of intersection, it is expected to find an overlapping area indicative of the target's potential location. As such, the solutions to (4) form the vertices of a polygon, and the target's position is expected to be in the centroid. The centroid positioning algorithm provided by [18] computes the mean of the intersections for predicting the target's exact location. This algorithm comes with the assumption that all circles intersect each other.

Let $(x_1, y_1), ..., (x_{n_I}, y_{n_I})$ be the respective x and y values of the vertex coordinates and n_I the number of vertices of the polygon formed by the overlapping of circles, the estimated target position is

$$(x, y) = (\frac{x_1 + ... + x_{n_I}}{n_I}, \frac{y_1 + ... + y_{n_I}}{n_I}) \tag{5}$$

This method is computationally cheap and results in a relatively robust solution. Considering the motivation to study the different outcomes of the low-cost IPS data, working with the target's area range will provide greater oversight for evaluation.

B. Timestamp Windowing/Incrementation

When working with real-life data, anomalies in the data will occur, especially on a second interval. These anomalies can include sudden data spikes and invalid or missing data. Furthermore, the clocks in each scanner may not be fully in sync. It follows that an essential step in data processing is to decide upon an increment or window of time to address these occurrences by smoothing out anomalies and synchronising scanner time frames. The windowing size or incrementation choice depends on the data. In this study, a baseline of 5-second windows has been chosen so that it is enough to smooth the data whilst being small enough to have precision for real-time tracking. The choice of windowing size is versatile to cater for any circumstance and can be used to investigate the patterns in target movement at chosen intervals.

C. Tolerance for Errors

In practical settings, measurement errors and deviations are expected and should be considered when applying the trilateration technique. A tolerance range of 5%-10% is chosen for the calculations, informed by the error margins observed in [19]. Enabling a broader tolerance range could undermine the accuracy of our assessment regarding the data's feasibility. Of course, this range offers a buffer, allowing for minor measurement deviations. For instance, if a measured distance is 10m, we enable a range of 9.5 to 10.5 meters (for a 5% tolerance) for trilateration. Fig. 5 demonstrates how enabling a tolerance range can allow for closed-form solutions to be possible for certain trilateration cases. By accounting for this range, the trilateration technique remains resilient to minor fluctuations in the readings.

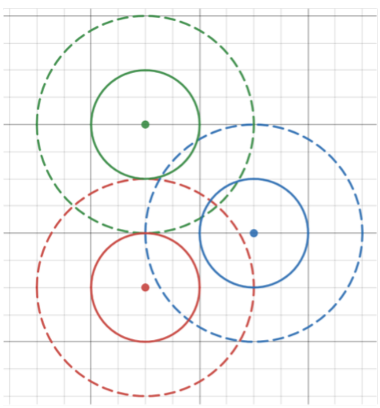
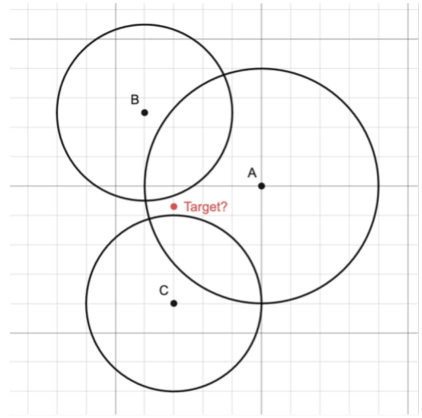


Fig. 5: A demonstration of how the tolerance range, depicted by the dashed circles, can overcome scenarios that have no solutions.

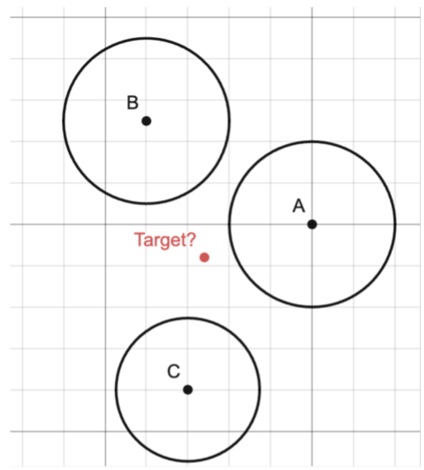
D. Expectations of Failures and Oddities

Our motivation to assess the feasibility of the implemented IPS solution requires prioritising understanding, investigation and mitigation of failures, faults and oddities occurring. The approach is twofold by assessing the reliability of the current methodology whilst building a robust foundation for future advancements in this realm of work. For instance, Fig. 6(a), 6(b) and 6(c) showcase an expected failure that may occur during the trilateration application. These scenarios may occur frequently in the data; thus, understanding the cause and determining a solution is important for developing low-cost IPS.

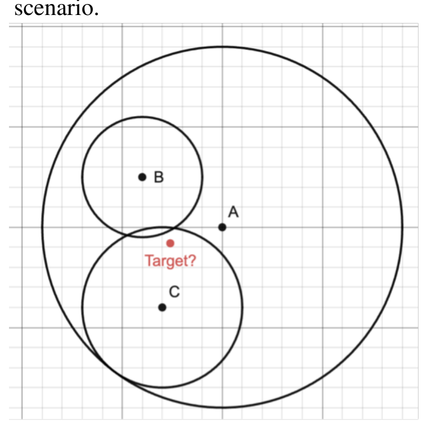
A noteworthy constraint in the current experiment is the lack of a well-defined 'truth value' or dependable reference point to benchmark the trilateration results. Initially, the project aimed to use CCTV footage for ground truth validation; however, legal challenges made this approach out of the question.



(a) A visual depicting a semi-overlapping scenario.



(b) A visual depicting a non-overlapping scenario.



(c) A visual depicting a sporadic scenario.

Fig. 6: Building blueprint illustrating placement of BLE scanners through key hospital regions.

Without this comparative standard, gauging the accuracy and dependability of our findings becomes challenging to evaluate.

VII. Achieved Results from Calibration Testing

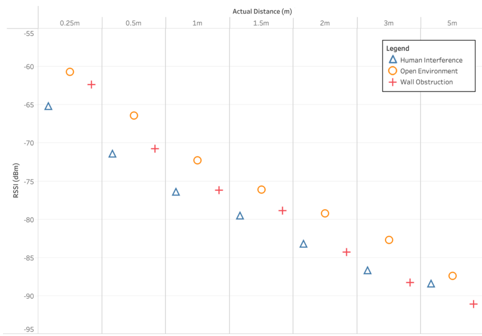


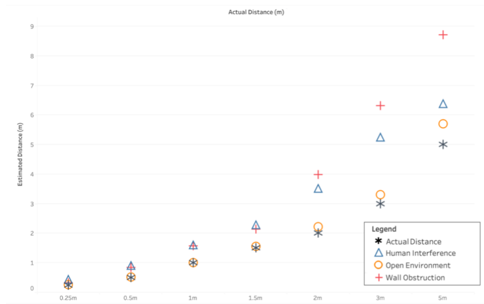
Fig. 7: Measured RSSI values in an open environment with human interference and wall obstruction.

A thorough evaluation of how RSSI values vary with different distances and under assorted conditions is needed to confirm that the technology behaves as expected and to unravel the nuances behind distance estimation. Thus, an external calibration test on one of the BLE wristwatches is conducted. Beacon calibration hinges on the RSSI baseline reading, representing the anticipated RSSI when positioned 1 meter away from the scanner. The baseline reading in this external testing is -72.3 dBm.

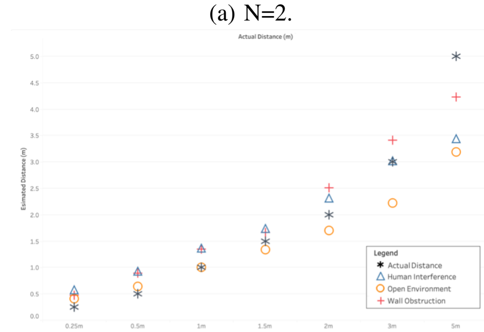
In the calibration phase, the BLE wristwatch is placed in a single location with the scanner, an iPhone 14 with nRF Connect application, situated at varying distances from the beacon. The RSSI average, captured over one minute, is recorded. The following experiment spans three conditions: an open space, one with human interference, and another with a wall as an obstruction. For context, the person is a 73kg individual, and the wall is plaster. Fig. 9(a), 9(b) and 9(c) offer a graphical representation of the experimental setup.

Fig. 7 shows that RSSI values closely estimate the distance in an open environment, particularly at closer proximity. Nevertheless, this correspondence weakens as distance grows, a trend consistent across all conditions. Despite this, the current results align with the outcomes seen by [7], stating that there is a high probability of the locating error is less than 1.5m. Fig. 8. suggests that the deviation level correlates with the obstruction's nature and distance from the beacon. These deviations become more significant the more distant the scanner is from the beacon. Interestingly, the wall obstruction proved a greater hindrance from a human subject. This is likely due to signals diffracted around a human that can reach the scanner at a greater strength than those having to traverse through a wall. As observed in Fig. 8(a), an environmental factor of N=2 is an excellent choice for open environments but causes overestimation when there are external interferences.

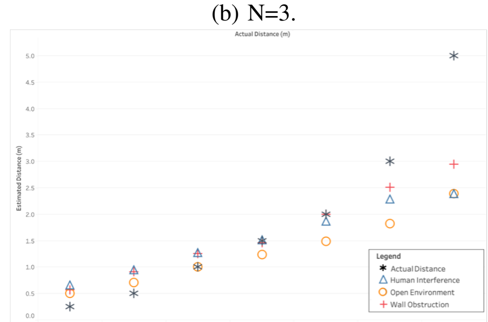
Fig. 8(b), positing an environmental factor of N=3, underscores its ability to mitigate external interference. The estimated distances between each condition are smoothed,



(a) N=2.

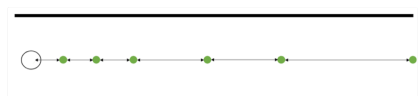


(b) N=3.

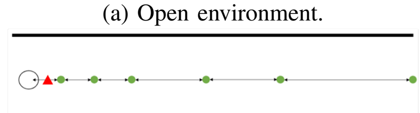


(c) N=4.

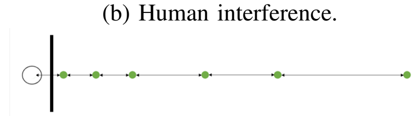
Fig. 8: Computed distances, using different environmental factors, from RSSI against measured distances in different environments.



(a) Open environment.



(b) Human interference.



(c) Wall obstruction.

Fig. 9: A visual of the calibration testing experiment for each environment.

resulting in tighter predictions. Consequently, the computed distances are underestimated, particularly in more distant measurements. Fig. 8(c), using N=4, displays a more smoothed and underestimated distance estimation. While N=3 appears to be the best-fitting model for the experiment, it is crucial to consider that N=4 assumes high levels of interference. Given a hospital's bustling atmosphere, such underestimation may be crucial when applied to the dataset.

While modulating N might refine readings at specific RSSI levels, RSSI's reliability as a distance gauge is tenuous over long distances. This observation feeds directly into the trilateration method's potential efficacy and the adaptations required to make it feasible with the data.

Some points must be made regarding the calibration testing. Conditions in the experiment may not mimic those in a healthcare environment. Variables such as the angle of the beacon or scanner, ambient signal interference, or even the type of scanner used can all influence the outcome. However, the initial findings explain the challenges of applying the trilateration method to the dataset.

VIII. Data Quality and State Analysis

Of course, the foundation of determining the feasibility of our low-cost IPS lies in the integrity and quality of the data. Analysing the data to discern the readiness and precautions needed for the intended application is crucial.

A. Data Incompleteness

For precise tracking, it is crucial that each scanner simultaneously provides RSSI readings. Our experimental study deployed six scanners across regions FKO and RSND, three each. Suppose a scanner fails to send data through the network for a day; we are left with only two RSSI readings for that period. Since trilateration necessitates a minimum of three RSSI values, such a failure renders indoor tracking infeasible for that entire day.

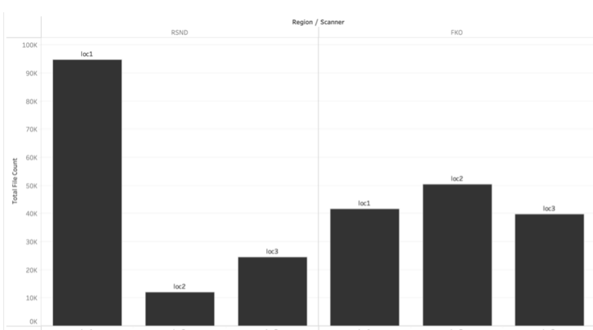
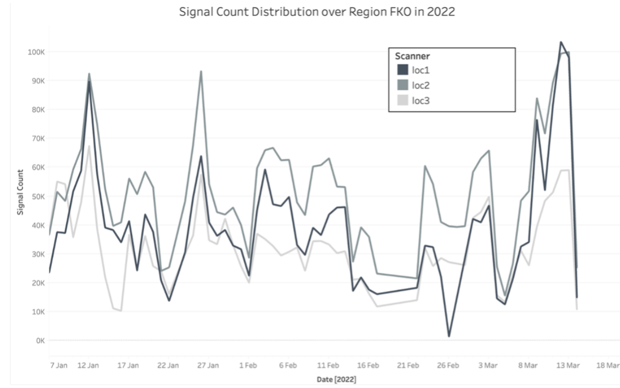
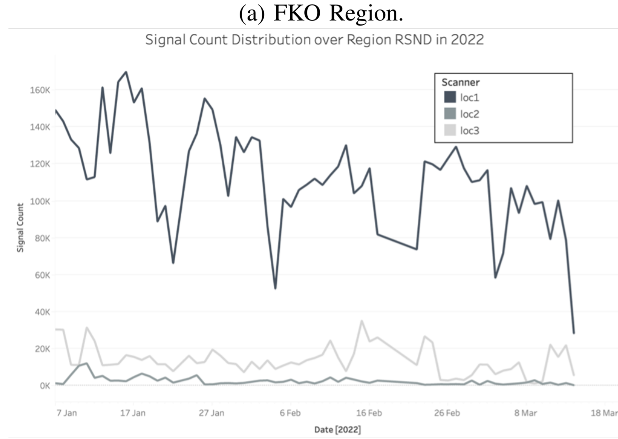


Fig. 10: Distribution of file counts recorded by individual scanners across regions FKO and RSND.

Each batch of data given to the MQTT subscriber produces a .txt file and is stored within a directory associated with a scanner. Fig 10. presents a notable disparity in file counts across different locations within the same region. The lack of uniformity suggests a disproportionate amount of RSSI readings required for trilateration.



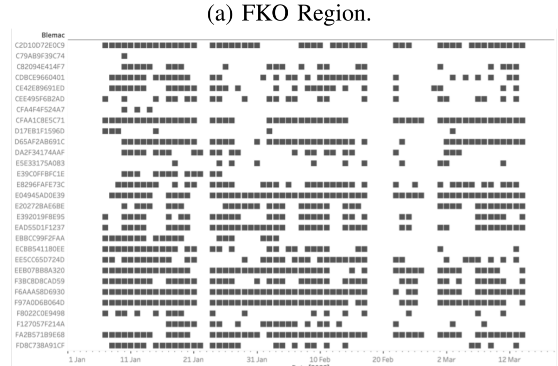
(a) FKO Region.



(b) RSND Region.

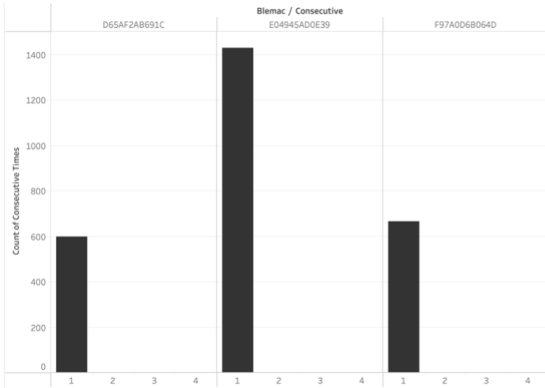
Fig. 11: Signal count distribution in 2022.

(a) FKO Region.

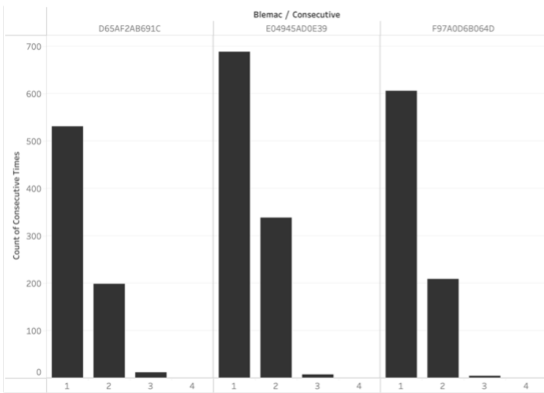


(b) RSND Region.

Fig. 12: Daily data available for trilateration for each beacon from January to March 2022.



(a) Distribution of consecutive time with no incrementation .



(b) Distribution of consecutive time with a 5-second incrementation.

Fig. 13: Distribution of consecutive times across selected BLE beacons in the FKO region.

Fig. 11 and 12 further reinforce the imbalance in the distribution of RSSI readings across different regions. Uniformity in file and signal counts suggests that the trilateration criterion of at least three simultaneous RSSI readings from distinct scanners is satisfied. However, these readings are unavailable, rendering much of the data nonviable for trilateration processes.

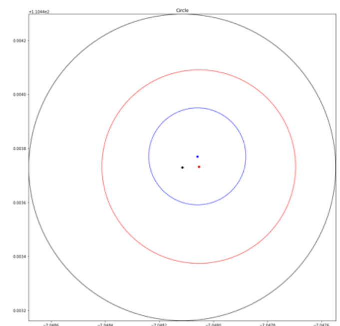
Region RSND exemplifies this challenge distinctly. In Fig. 11, the loc1 scanner records a voluminous amount of data but needs concurrent readings from the other scanners, making a sizable chunk of it unsuitable for the following process. This non-uniformity raises concerns about the potential inefficiencies and gaps in the data collection process.

Region FKO presents a more balanced collection for signal and file counts. The steady and concurrent readings from FKO's scanner make it the most robust and suitable for exploration.

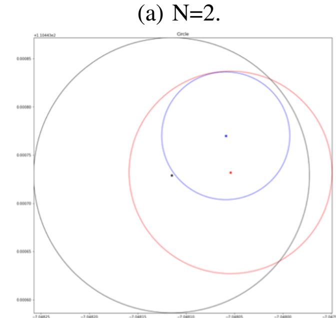
The presented counts unveil the need for proper data collection. Region RSND faced network limitations that could have affected the data collection process and caused lost packages. These technical difficulties can be challenging to maintain but require more attention to ensure consistency. This hints at the potential operational and infrastructural disparities that future advancements in IPS deployment can face.

A method of validating the outcome of our results, without known truth values, is observing the target's movement over a timespan. Given a small timeframe, the target's movement should be minimal. Any significant erratic movement is indicative of poor data. The data must be continuous to observe movement patterns, ensuring no gaps or missing entries during the observation period. Fig. 13 illustrates an issue with data continuity. Most of the usable data is not sequenced in consecutive order. Furthermore, the figure further displays the usefulness of time incrementation in fixing the continuity issue. This inconsistency in the data will become problematic in analysing movement patterns.

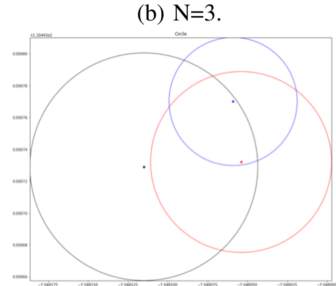
IX. Achieved Trilateration Results From Indoor Positioning System Solution



(a) N=2.



(b) N=3.



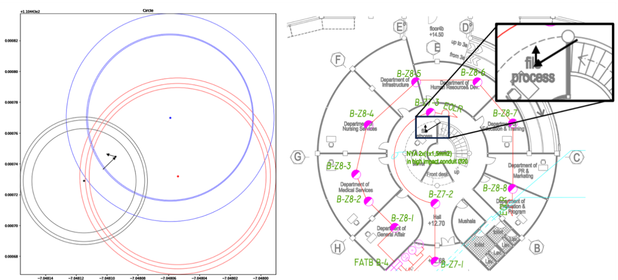
(c) N=4.

Fig. 14: Environmental factor effect on trilateration outcome at a selected timestamp in region FKO.

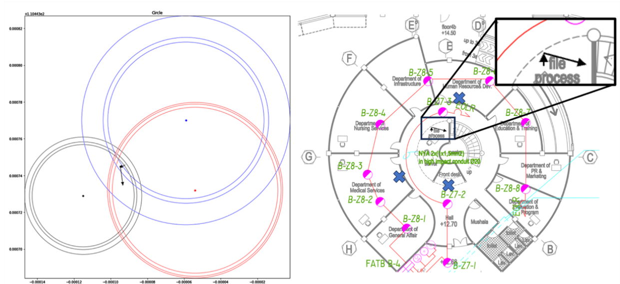
A. Results

Around 90% of the data being fragmented, with only occasional sequences of continuous data, meant that movement patterns could only have a brief span of up to 30 seconds. Based on Fig. 15, these indicate that the IPS solution can deduce the target's location. The following figures indicate that the target would have worked within the server and file room. However, without the ground truth to compare against, we cannot definitively confirm whether the system has accurately tracked the target's location. Fig. 15(c), presents this uncertainty where it is unclear which room the target was in before moving into the file room.

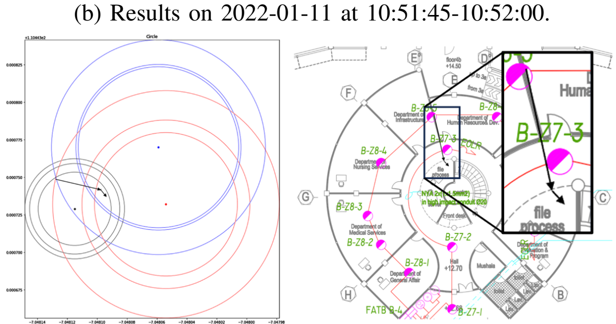
While there are evident successes in the data representation, the results are underwhelming to assert any feasibility of the data for precise indoor tracking. The sheer scarcity of incompleteness of the data and its plethora of isolated data points, greatly undermines the system's reliability. The fragmented nature of the data offers small glimpses into the potential movement patterns, but without continuity or context, it is unlikely to argue for its practicality.



(a) Results on 2022-01-10 at 10:55:15-10:55:30.



(b) Results on 2022-01-11 at 10:51:45-10:52:00.

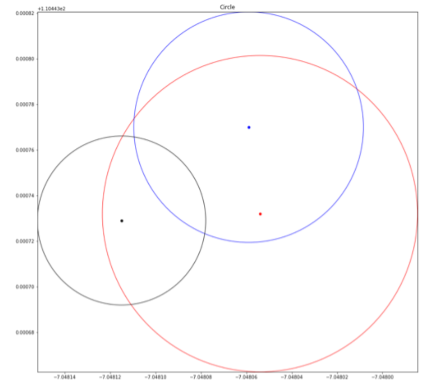


(c) Results on 2022-01-11 at 2:09:45-2:10:00.

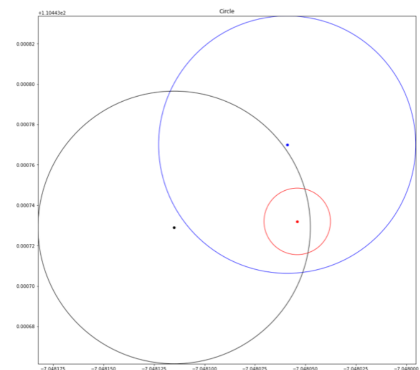
Fig. 15: Tracking results taken over 15 seconds in FKO.

B. Resolving Difficult Scenarios

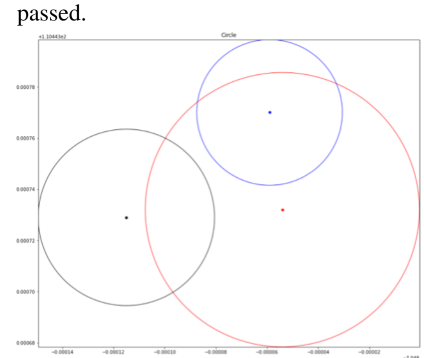
In the process of trilateration application, a significant number of outcomes presented challenges that rendered them unsolvable.



(a) Example of non-convergent circle intersections.



(b) Example of circle entirely encompassed.



(c) Example of circles having a lack of intersections.

Fig. 16: Most common trilateration scenarios where centroid positioning algorithm cannot be applied immediately.

Fig. 16 showcases the predominant scenarios observed within both sequences of continuous data and individual standalone data points. We define the scenario in Fig. 16(a) as Case 1, Fig. 16(b) as Case 2 and Fig. 16(c). as Case 3. Additionally, the ideal trilateration case will be defined as Case 0.

In Case 1, applying the centroid positioning algorithm cannot be executed as easily. Thus, we cannot pinpoint an exact location where the target is. This is potentially caused by a high level of interference where the signal strength to a scanner is weakened, resulting in an overestimated distance. Another factor to consider is that the current IPS solution operates on a 2D plane. If the target were to be on another level, complications will arise, introducing more obstacles for further multipath fading.

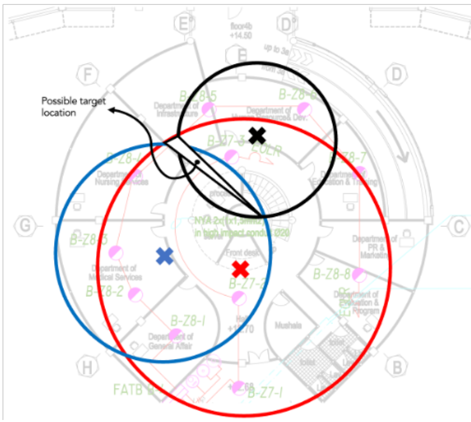


Fig. 17: Resolving Case 1 through forming a polygon along the existing intersections.

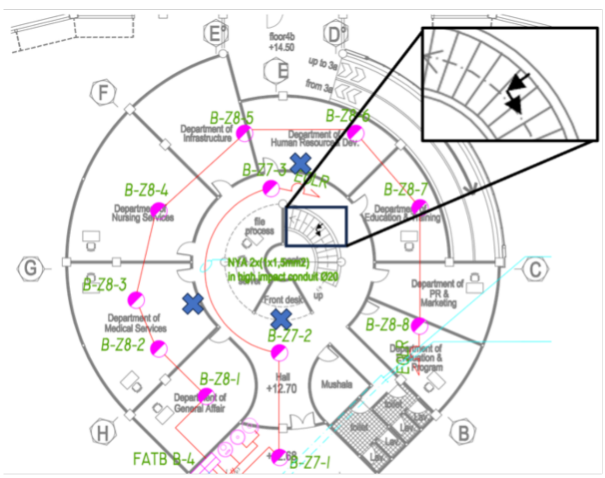


Fig. 18: Tracking results taken over 15 seconds on 2022-01-12 at 22:19:25-2:19:45 dealing with Case 1 scenarios in FKO.

Whilst unlikely to resolve Case 1 due to its lack of impact, examining the tolerance range can enable the use of the centroid positioning algorithm. This can be done by decreasing the overestimated distance and increasing the subsequent scanners by 10%. Increasing the tolerance range further than 10% has been observed to complicate Case 1 into another unresolvable case. Case 1's sensitivity to tolerance range should be limited by restricting it to at most 10%. Another solution is illustrated in Fig. 17 by forming a polygon along the existing intersections and finding the centroid for the target location. Forming a polygon forms a smaller area of where the target location is, creating another degree of uncertainty and thus is not reliable in accurate tracking. Applying the 10% tolerance range can alleviate this uncertainty by widening the localization area. Fig. 18 reflects this with subtle target movements. Moreover, the target appears to be on the stairs at a lower height, reinforcing that the scenario can occur if the target is on a different level.

Case 2's numerous occurrences indicate that this scenario is not a result of a spike noise but instead the environment. The distance estimated for the scanner encompassed is generally too small for setting N=2 to increase the circle radius. What can be surmised is that the target is close to a scanner, but high levels of interference cause the other scanners to receive a significantly weakened signal, producing significant distance estimates. In such scenarios, a more extensive tolerance range is required. We find that a 20-25% error range is optimal for determining the target location in these cases. For instance, Fig. 19. showcases how Case 2 can be decomposed into Case 0 and Case 1. In fact, due to many scenarios having decomposed into Case 1 through the tolerance range, we refrain from further applying it to Case 1 scenarios. Adding a degree of uncertainty is ill-advised for indoor tracking. Fig. 20 shows the resolution of using tolerance ranges to handle Case 2 scenarios.

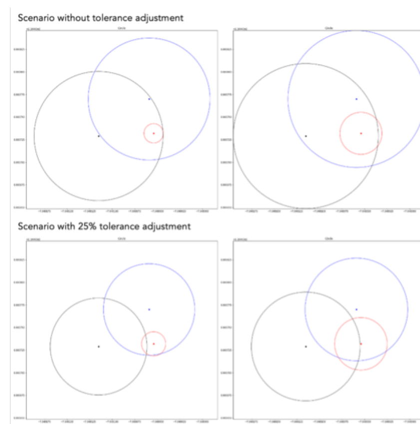


Fig. 19: The effects of tolerance range adjustments on Case 2 scenarios.

Fig. 20: Tracking results taken over 15 seconds on 2022-02-02 at 12:55:40-12:55:55 dealing with Case 2 scenarios in RSND.

Case 3 poses an interesting scenario. Once again, due to its frequent occurrence, this is not a result of a sudden noise spike. Varying degrees of environmental interference cause some scanners to underestimate the distance. The results from calibration testing imply that using environmental factors cannot sufficiently capture the dynamic nature of a healthcare facility. A solution exists in modifying the environment factor for specific scanners. In Case 3, scanners with low distance estimations are potentially underestimated by N=4. Using N=2 or N=3 can reduce this and provide ideal trilateration outcomes. However, this resolution method is found to be unreliable in most cases. Changing the environmental factor is often insufficient to change the scenario to Case 0 or 1. In this light, Case 3 can be quickly resolved using a tolerance range of 20-25% and decomposing it into Case 0 or 1.

Analysing movement patterns over 30 seconds, represented by three consecutive data points, offers limited insight into resolution accuracy. Fig. 21 showcases the target's oscillatory motion, which, within the brief timeframe, may suggest that the tracking is successful. If the movement pattern is extrapolated under the same dataset, the target could appear to be moving back and forth. This inconsistency implies that the data, along with the method of case resolution, is unreliable for indoor tracking.

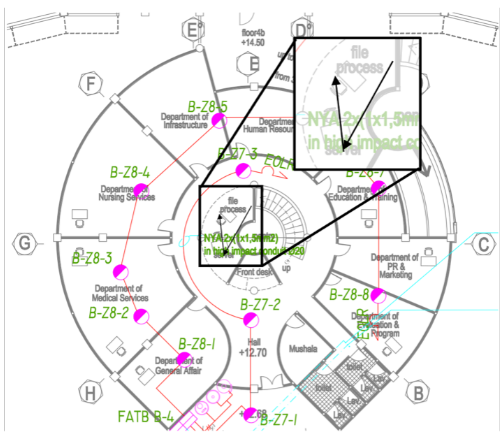
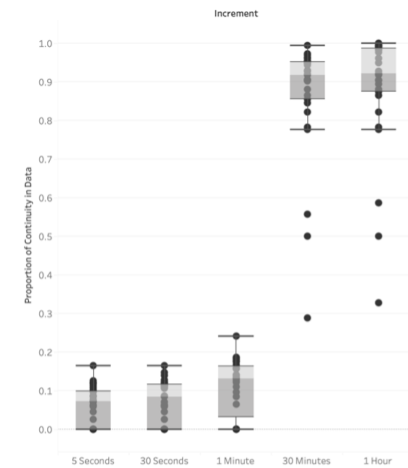


Fig. 21: Tracking results taken over 15 seconds on 2022-01-10 at 10:55:15-10:55:30 dealing with Case 3 scenarios in FKO.

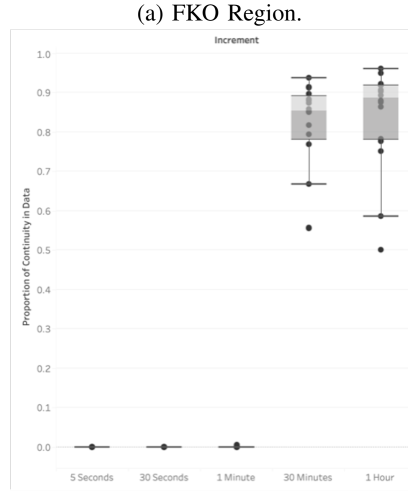
It is noteworthy to highlight that many scenarios can be addressed by adjusting the tolerance range appropriately. However, each case will necessitate distinct modifications. While these resolutions may be enough to pinpoint the target location, we cannot conclude that the data is feasible using time increments of 5 seconds. In addition, using a 20-25% tolerance range signifies a significant error in the data. The data's intermittent nature and quality present a severe challenge in achieving consistent indoor positioning tracking.

X. Precision Trade-off for Indoor Positioning Tracking

Real-time indoor positioning tracking requires grappling with the intricacies of leveraging data in small increments. A system that tracks a target in real-time hourly is not considered an effective real-time IPS compared to one that can perform every 5 seconds. However, given that the current dataset is infeasible to produce appropriate results for accurate indoor tracking on such granularity, an intuitive recourse is to transition to larger time increments to resolve data continuity issues. Fig. 22 illustrates this adaptive approach, whereby extending the windowing time helps bridge data discontinuities.



(a) FKO Region.



(b) RSND Region.

Fig. 22: Proportion of data continuity for each beacon. We define data continuity as having at least three consecutive data points available for trilateration.

This strategy necessitates a trade-off in precision, needed in real-time indoor tracking, for a coherent representation of indoor trajectories. This decision is not a compromise but rather a well-considered recalibration to maximise the utility of the current dataset. Fig. 22 illustrates this adaptive approach, whereby extending the windowing time helps bridge data discontinuities. By losing precision for larger time windows, we end up achieving, on average, 90% data continuity. It was found that using hourly time increments produced plentiful sequenced data. However, tracking the exact target location hourly is impractical as the target could have moved to many different locations. To compensate for the lack of precision, it is appropriate to examine the area that the target has, on average, spent the most time at.

Fig. 23 serves as a representative example of the outcomes achieved when employing extended time increments. A notable observation is the reoccurring centrality of the localization areas. Consequently, all beacons within the FKO region predominantly signal activity in the file and server room, on the stairs and at the reception desk. Despite observing days' worth of data, there is an evident lack of significant movement. This raises questions about the dataset's ability to represent the environment's intricacies. Even with broader time windows, we still encounter scenarios necessitating adjustment of tolerance ranges of up to 25%. This brings to light the potential inadequacies in the RSSI distance model used.

While larger time increments are impractical in indoor tracking, they address particular challenges and bring new considerations. The centralised behaviour of the data suggests either a limitation in data capture or potential inadequacy in the RSSI distance model.

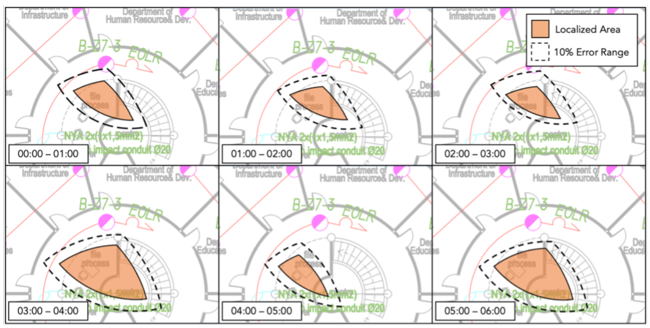


Fig. 23: Hourly localization snapshots of a target's area in the FKO region over a 6-hour duration.

XI. Future Work

The evaluation of our cost-effective IPS solution revealed several areas of improvement. As it stands, future advancements in exploring the realm of cost-effective IPS solutions using BLE technology need to establish its feasibility first. As such, evaluating a dataset over a shorter period is recommended, as having a concise timeframe offers preliminary validations of IPS functionality, such as obtaining the ground truth on where the target is during a specific time. An immediate comparison between the estimated target location and ground truth will allow for proper system evaluation. This step ensures that the deployed system is feasible for tracking before undertaking more extensive projects. The most outstanding issue that prevented the data from being suitable for tracking is the gaps in the dataset. Moving forward, meticulous planning and rigorous setup procedures need to be addressed. Ensuring that the scanners and network effectively capture data can significantly reduce incompleteness. Accurately pinpointing the scanner's known location is crucial in using the trilateration algorithm. While our study operated on the assumption of correct latitude and longitude values, there is potential that they were not exact. Alternative methods for identifying known locations, such as employing a Cartesian grid-based approach on the building's blueprint, might offer advantages.

Exploration of incorporating more than three scanners can alleviate the constraints posed by the trilateration algorithm, which mandates a minimum of three RSSI readings. Deploying additional scanners can achieve a more robust system, especially if data inconsistency continues to be a pressing issue. Moreover, using other localization strategies, such as fingerprinting, as suggested by [2], should be investigated to enhance indoor positioning accuracy.

The dataset reflecting different reoccurring scenarios and using high tolerance ranges is due to the need to understand the environment. Hence, our work encourages environment profiling to understand how different areas within the facility might have distinct signal propagation characteristics. Moreover, exploring other RSSI distance models can also aid in encapsulating environmental interferences. Conducting a thorough environmental profile can help adjust system parameters for specific zones.

XII. Conclusion

Our research evaluates the feasibility of a Bluetooth-Low-Energy (BLE) based Indoor Positioning System (IPS) in a real-world healthcare setting, the Rumah Sakit Nasional Diponegoro Hospital. The trilateration algorithm, utilising the Received Signal Strength Indicator (RSSI) measurements, provided a promising avenue for cost-effective indoor tracking. Data completeness emerged as a principal concern, with gaps in the dataset significantly impacting the system's reliability. Moreover, this system's capacity to authentically capture the complexities of a dynamic hospital environment proved challenging.

Notwithstanding these shortcomings, our study lays the foundation for iterative improvements. Meticulous setup procedures, ensuring optimal data collection, and building an environment profile stand out as pressing avenues for improvement. Future work should delve into shorter timeframes to ascertain IPS efficacy promptly, emphasise augmenting data collection protocols to prevent data losses and form a reference to benchmark the accuracy of the data. Additionally, exploring alternate positioning algorithms and deploying a more extensive scanner array may enhance accuracy. While revealing certain limitations of the current system, this research underscores the potential of implementing cost-effective IPS solutions. With iterative refinements, there is a prospective realisation of an efficacious and economically viable indoor positioning system.

Acknowledgment

We thank Dr. Kiki Adhinugraha and Dr. David Taniar not only for navigating the intricate legal paperwork and communication necessary for the design and deployment of the BLE-based indoor positioning system in Rumah Sakit Nasional Diponegoro but also for their invaluable guidance on the dataset evaluation. Their expertise and insights played a pivotal role in thoroughly exploring and understanding our collected data.

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