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Indoor Localization for Smart Museum Environments

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Abstract

Source Code

All source code developed as part of this master thesis has been open-sourced under the MIT license, in alignment with research standards and personal open-source convictions. The repositories include:

- **Flutter Application**: The cross-platform mobile application for data collection and interaction.
  `https://github.com/BhasherBEL/master-thesis-scanner`
- **Writing (LaTeX)**: The LaTeX source code of this master thesis.
  `https://github.com/BhasherBEL/Master-thesis---writing`
- **ESP Code**: The firmware developed for the ESP microcontroller
  `https://github.com/BhasherBEL/master-thesis-esp`
- **Data Analysis**: The scripts and tools used for analyzing the collected data.
  `https://github.com/BhasherBEL/master-thesis-analysis`

These repositories are publicly accessible to ensure transparency, reproducibility, and to contribute to the broader research and open-source communities. We would be pleased for any reuse of the provided code and encourage it, while still respecting the terms of the MIT license.

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Chapter 1

Introduction

1.1 Motivations

Over the past decade, museums have faced increasing competition and financial challenges due to decreased government funding, pushing many to adopt a more consumer-oriented approach [7]. Information and Communication Technologies (ICT) have become essential in enhancing visitor experiences, making exhibits more interactive and engaging. When designed intuitively, such technologies can improve cognitive engagement and positively impact learning outcomes [15].

Indoor localization presents a promising solution by enabling seamless navigation and interaction with exhibits, enriching the visitor experience. Additionally, it allows museums to collect valuable data to optimize exhibit layouts and visitor flows. However, challenges remain, including concerns about social acceptability and reduced interaction between visitors [20]. Furthermore, the environmental impact of indoor localization systems, such as energy consumption and hardware requirements, must be carefully considered.

Balancing engagement, sustainability, and social interaction is crucial for museums adopting new technologies. Indoor positioning systems, if well-designed with sustainability in mind, such as using energy-efficient devices, minimizing infrastructure demands and avoid extensive algorithm training, can enhance accessibility and personalization while fostering a more integrated and sustainable visitor experience.

1.2 Introduction to indoor localization

Indoor localization is a widely researched field with diverse approaches, many of which enable the collection of valuable analytics, such as visitor retention time [19]. Some methods leverage existing infrastructure, such as Wi-Fi or FM signals and users' devices, while others require dedicated installations or operate independently of user devices [1]. Each approach involves trade-offs in terms of accuracy, hardware requirements, and environmental impact, an often-overlooked factor despite its potential significance [12].

The terminology varies, with *Indoor Positioning Systems (IPS)* referring to the technology, *indoor positioning* describing the process, and *Indoor Location-Based Services (ILBS)* using location data for added functionalities. Finally, *Indoor localisation* is simply a spelling variant.

1.3 Research objectives and organization

This research aims to develop an indoor positioning system for the Musée L of Louvain-la-Neuve to enhance visitor experience while considering environmental and social impacts. A key goal is to improve navigation and accessibility by designing a user-friendly system that enhances engagement and knowledge retention.

To achieve this, the study will evaluate various indoor localization technologies, assessing their accuracy, infrastructure compatibility, and sustainability. Particular attention will be given to energy consumption, hardware requirements, and privacy concerns. The necessary background information and existing solutions will be presented in chapter 2.

A prototype tailored to the Musée L will be developed and tested, with a focus on reliability, ease of deployment, and minimal disruption to exhibits. In addition, an Android application will be designed to leverage the location information, enhancing visitor experience through personalized guidance and contextual information. The research methodology will be outlined in chapter 4, and the implementation details will be explained in chapter 3.

The system's performance will be evaluated through technical and some user-based assessments, analyzing visitor movement patterns and engagement. The results and their implications, including limitations, will be discussed in chapter 6. Finally, conclusions and future research directions will be provided in chapter 7. This study aims to create an effective and sustainable indoor localization solution for the Musée L while offering a framework applicable to other cultural institutions.

Chapter 2

Background and Related Work

2.1 Localization Technologies

Indoor localization encompass a wide range of technologies designed for tracking and positioning within indoor environments. This chapter provides an overview of key technologies, comparing them based on multiple factors, including whether the user needs to carry a device, accuracy, sustainability, cost, and infrastructure requirements. Various methods such as GPS, QR codes, RFID, NFC, infrared, ultrasound, ultra-wide band, Wi-Fi, Bluetooth, and hybrid approaches are examined in terms of their feasibility and trade-offs. A summary table at the end of the chapter will provide a comparative overview to facilitate the selection of the most suitable approach for specific indoor environments.

2.1.1 Satellite navigation

Satellite navigation systems, such as GPS, GLONASS, Galileo, and BeiDou, are the standard for global positioning and are widely integrated into smartphones, wearables, vehicles, and other devices. Recent advancements, including improved satellite constellations and correction techniques like SBAS (Satellite-Based Augmentation Systems), have significantly enhanced positioning accuracy, with some systems achieving precision within a few meters. However, these technologies still face major limitations in indoor environments due to signal degradation caused by multi-path interference, obstructions, and the lack of a direct line of sight to satellites, making them unreliable for accurate indoor localization [12].

2.1.2 QR code

QR codes are a widely used method for providing information to visitors. However, as an active technology, they require users to actively scan the code to access content, which may limit engagement and effectiveness, especially for the majority of visitors who may not take this extra step [19].

2.1.3 RFID

RFID is a widely deployed technology, used by most of the contactless tokens. In the context of indoor localization, it would require numerous inexpensive tags. It also works without direct LoS [12]. It's a nice alternative to QR-code, and allow a bit more interaction. However, it is also an active method, that as the same issues as discussed before. Its short range makes it also more efficient to determine if a user is near the tag rather than having a precise indoor localization [17].

2.1.4 NFC

NFC is a widely deployed technology, integrated into most modern smartphones. Like RFID, it has a very limited communication range and requires a dense network of beacons for indoor localization. However, NFC offers high precision and does not require visitors to carry any additional devices, making it a more interactive and user-friendly alternative to RFID [5].

2.1.5 Vision

Vision-based systems use cameras and image processing algorithms to detect and track objects or individuals within an environment. These systems can achieve high accuracy and provide rich contextual information, making them useful for applications like facial recognition, object identification, and augmented reality. However, they require significant computational resources, are affected by lighting conditions and occlusions, and raise privacy concerns in public spaces. Despite these challenges, advances in machine learning and computer vision continue to improve their reliability and applicability in various domains [12].

2.1.6 Infrared

Infrared-based indoor localization requires a direct Line of Sight (LoS) and is unable to penetrate walls, making it susceptible to occlusions and multi-path errors [12]. Additionally, it is highly sensitive to environmental factors such as heat sources and ambient lighting, which can interfere with signal accuracy [17]. Furthermore, the implementation of infrared systems often demands specialized and expensive hardware, limiting their practicality for large-scale deployments.

2.1.7 Ultrasound

Ultrasound is complex to set up in a large scale, is prone to multi-path errors and is highly sensitive to ambient temperature [12]. It uses the technique of the Time Of Flight (TOF) and can have an accuracy up to the centimetres, but the real efficiency can be affected by the humidity, the ambient temperature, the air density and the obstacles. It also require a tight synchronization between the devices [17] [12].

2.1.8 Ultra-Wide Band

Ultra-wide band can provide a very accurate localization, based on the Time-Of-Arrival (TOA) techniques. It's also power efficient, has a fine resolution and is robust in harsh environments. However, it requires a lot of extra hardware devices [19] and is expensive [17].

2.1.9 Wi-Fi

The Wi-Fi is one of the most used systems for indoor localization, as it's the most widely deployed indoor infrastructure and thus can partially rely on existing infrastructure. It's also cost-effective [12] and do not require extensive knowledge for users or maintainers [17]. The users don't have to carry any special device, except their own smartphone.

However, the devices are heterogeneous and may differ widely from the reference device(s) used for initial setup [11]. It doesn't require a direct LoS [12], even if the environment may have a huge impact on the precision, range and multi-path effect [11]. Most used techniques are Cell Of Origin (COO) method, triangulation and RSSI-based fingerprinting. It can achieve a theoretical precision of a few centimetres in a dense, errorless and open environment but usually achieve a precision of a few meters for more realistic ones [11].

More specifically, RSSI is the current mainstream system but is prone to noise and interfaces in a dense area [19]. The precision can be adjusted based on the density [17]. It offers a proper balance between efforts and accuracy [1]. There are two main methods: RSSI heat maps, that allow to visually describe the infrastructure, detects its weaknesses and use simpler algorithms than most others [1] and RSSI fingerprinting, that compare user values to a database of registered reference values.

2.1.10 Bluetooth

Bluetooth is as widely deployed as Wi-Fi and is even more prevalent in mobile devices such as smartphones, smartwatches, and wireless headphones. Numerous Bluetooth beacons are available on the market at a low cost [19], and their transmission range can be easily adjusted. Typical user devices have a range of 10 to 15 meters [12]. In real-world scenarios, Bluetooth positioning provides accuracy close to that of Wi-Fi, typically ranging from 2 to 3 meters [12] [19].

One key advantage of Bluetooth is its lower power consumption compared to Wi-Fi, thanks to its low power operating mode. Bluetooth Low Energy (BLE) further improves efficiency and privacy, as its beacons only transmit signals without listening [19]. The receiving device can process the data locally, reducing network dependency. The transmission frequency of BLE signals varies from every 20 milliseconds to 10 seconds, which significantly impacts battery life [19]. While battery-powered beacons are easy to deploy and can function for months using a coin cell, they are also more prone to failures, increasing the maintenance burden [19].

The accuracy of BLE localization depends on beacon density and placement. While the optimal density remains uncertain, research agrees that higher beacon density improves positioning accuracy and requires environment-specific testing [19] [17]. BLE beacons can reach distances of up to 60 meters, but this significantly increases power consumption. A typical transmission range of 2 to 20 meters is often preferred [19], though this may impact localization accuracy when users are not directly in front of reference points, such as artworks in museums.

Bluetooth does not interfere with wireless technologies like Wi-Fi, GPS, or FM signals. However, it may suffer from interference with other Bluetooth devices [19], which could be particularly problematic in environments like digital museums where visitors may be using Bluetooth for audio guides. In optimal conditions, the theoretical Received Signal Strength Indicator (RSSI) for BLE follows the equation 2.1, where the received signal strength depends logarithmically on distance. This relationship explains why accuracy decreases as the distance between the beacon and receiver increases [19].

As outlined by [3], BLE uses 5 different channels, and the channel has an impact on the received RSSI. Enforce the beacons to use only one channel can improve the precision.

$$RSSI = A - 10n \cdot \log_{10} d \tag{2.1}$$

2.1.11 Hybrid

More and more systems combine multiple methods to achieve the best possible accuracy [17]. Various device sensors, such as inertial sensors, accelerometers, and gyroscopes, can also be used to improve real-time precision between beacon emissions [1]. However, the availability of these technologies may be heterogeneous, depending on the devices and environments, which can introduce additional complexity and increase the maintenance burden for the infrastructure.

2.1.12 Summary

The Table 2.1 summarizes the various technologies discussed in the literature, highlighting the best values for each criterion. For indoor localization within a museum using smartphones, we prioritized the use of users' smartphones over specialized devices, favoured passive technologies over active ones, sought an accuracy of around one meter, and targeted a coverage of at least 20 meters for each device.

While no single technology meets all these requirements, some stand out more than others. Satellite navigation fulfils most requirements, explaining its widespread use; however, it suffers from poor accuracy indoors and is primarily designed for outdoor positioning. QR codes, RFID, and NFC are also widely available, but they necessitate user involvement and a high density of tags. Infrared, ultrasound, and ultra-wideband technologies perform well but require specialized devices and beacons, leading to higher costs. Vision-based systems are intriguing but demand substantial infrastructure to capture and analyse data in real time, which also raises privacy concerns.

Finally, both Wi-Fi and Bluetooth are widely accessible and do not require active user participation, but their accuracy typically ranges from 3 to 5 meters. This level of precision may suffice in a museum context when accompanied by adequate post-processing to enhance accuracy. Ultimately, Bluetooth was selected due to the low cost of its beacons, power efficiency, and the fact that BLE bands are less congested than Wi-Fi's.

Technology	**Device**	**Involvement**	**Accuracy**	**Cost**	**Coverage**
Satellite Navigation	**Smartphone**	**Passive**	$>$ 20m	**Low**	**Worldwide**
QR Code	**Smartphone**	Active	**$<$ 1m**	**Low**	~1m
RFID	**Smartphone**	Active	**$<$ 1m**	**Low**	$<$ 0.1m
NFC	**Smartphone**	Active	**$<$ 1m**	**Low**	$<$ 0.05m
Vision	**No**	**Passive**	**$<$ 1m**	High	~10m
Infrared	Specialized	**Passive**	$<$ 5m	High	~5m
Ultrasound	Specialized	**Passive**	**$<$ 1m**	High	~10m
Ultra Wide Band	Specialized	**Passive**	**$<$ 0.5m**	High	**~30m**
Wi-Fi	**Smartphone**	**Passive**	$<$ 3m	**Low**	**~30m**
Bluetooth	**Smartphone**	**Passive**	$<$ 3m	**Low**	**~30m**
Hybrid	Varies	Varies	Varies	High	Varies

Table 2.1: Comparison of Indoor Localization Technologies

2.2 Localization Methods

Determining an accurate position within an indoor environment presents unique challenges due to signal interference, obstacles, and dynamic layouts. Various localization techniques have been developed, each with distinct advantages and limitations. This section explores different approaches to indoor localization, including multi-lateration, RSSI-APIT, machine learning-based algorithms, fingerprinting, and range-free techniques. Each method is evaluated based on criteria such as accuracy, scalability, reliability, and ease of deployment. Given the specific constraints and requirements of a museum setting, where moderate accuracy, stability, and minimal pre-configuration are preferred, this analysis aims to identify the most suitable localization technique.

2.2.1 Multi-lateration

Multi-lateration is a widely used technique for device localization. It estimates the receiver's position based on calculated distances, which are derived from the Received Signal Strength Indicator (RSSI) using the formula in Equation 2.1. An example of multi-lateration with three beacons is shown in Figure 2.1. Assuming that the smartphone is located at (x, y), and three beacons are positioned at (x_1, y_1), (x_2, y_2) and (x_3, y_3) with distances r_1, r_2 and r_3 respectively, we can express their relationships as:

$$
\begin{aligned}
r_1^2 &= (x - x_1)^2 + (y - y_1)^2 \\
r_2^2 &= (x - x_2)^2 + (y - y_2)^2 \\
r_3^2 &= (x - x_3)^2 + (y - y_3)^2
\end{aligned}
\tag{2.2}
$$

By eliminating variables and reorganizing these equations, the estimated position (x, y) is given by:

$$
\begin{aligned}
x &= \frac{C_1E - BC_2}{AE - BD} \\
y &= \frac{AC_2 - C_1D}{AE - BD}
\end{aligned}
\tag{2.3}
$$

where:

$$
\begin{aligned}
A &= 2(x_1 - x_2), \quad B = 2(y_1 - y_2) \\
D &= 2(x_1 - x_3), \quad E = 2(y_1 - y_3) \\
C_1 &= (r_1^2 - r_2^2) + (x_2^2 + y_2^2 - x_1^2 - y_1^2) \\
C_2 &= (r_1^2 - r_3^2) + (x_3^2 + y_3^2 - x_1^2 - y_1^2)
\end{aligned}
\tag{2.4}
$$

To assess the accuracy of this method, considering RSSI-induced errors, the Mean Square Error (MSE) can be calculated [19]:

$$
MSE = \sqrt{(x_{est} - x_{real})^2 + (y_{est} - y_{real})^2}
\tag{2.5}
$$

2.2.2 RSSI-APIT Algorithm

Research has shown that the RSSI-APIT localization algorithm achieves an average accuracy of 1.55 meters, reducing localization error by 57% [18]. However, it relies on the APIT framework, which requires numerous anchor points for effective functioning. In Shen et al. [18], 20 anchors were used to achieve these results. They found that at least 15 anchors are needed to maintain an error below 5 meters, and 20 anchors are required to reduce it to approximately 2 meters. Beyond 25 anchors, further improvements become negligible.

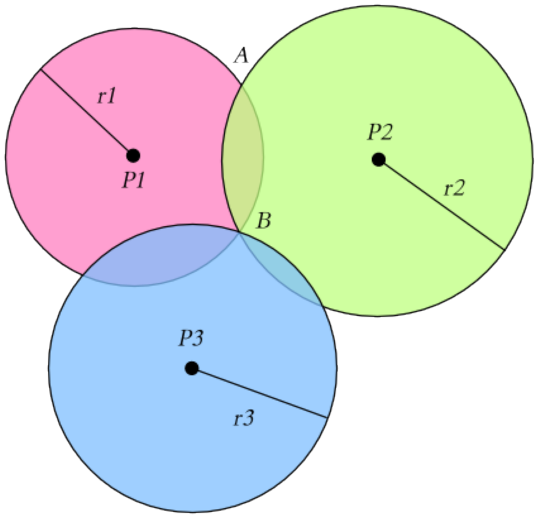


Figure 2.1: Example of trilateration

Additionally, this algorithm requires training an artificial neural network, which presents challenges such as high data and energy consumption, as well as the need for retraining in different environments. As a result, the added accuracy does not justify the high setup, operational, and maintenance costs.

2.2.3 Machine learning based algorithms

Significant research efforts aim to enhance Indoor Positioning System (IPS) accuracy using machine learning. However, surveys have failed to demonstrate clear advantages over traditional techniques. These methods remain limited in accuracy, reliability, scalability, and adaptability to diverse environments [13].

The main benefit of machine learning approaches is their ability to make predictions without requiring explicit mathematical modeling—relying solely on observed data [13].

2.2.4 Fingerprinting

Fingerprinting-based localization requires an initial offline training phase before being used online [13], making it less scalable and adaptive. Constructing a radio map for localization involves substantial effort, particularly in large or dynamically changing environments [13]. Furthermore, retraining is necessary when nodes are added or removed.

K-Nearest Neighbors (K-NN) is the simplest algorithm applied for localization based on fingerprints. Recent research suggests that machine learning-enhanced fingerprinting methods, such as FPFE, can achieve a precision up to one meter. However, data collection is time-consuming and intensive. For example, Jiang et al. [10] required 2 minutes per reference point and over 6 hours for the complete dataset. Furthermore, any changes in the environment necessitate retraining, which can be impractical in dynamic settings like museums.

2.2.5 Range-free localization techniques

Some studies explore range-free techniques that do not rely on RSSI. However, they only become reliable in large environments with numerous devices. Chen et al. [6] demonstrated this approach using 300 nodes across 40,000 square meters.

2.2.6 Summary

In a museum setting, localization requires a balance between accuracy, stability, and ease of deployment. While fingerprinting and machine learning-based methods offer higher precision, their reliance on extensive pre-data collection and frequent retraining makes them impractical for dynamic environments where room layouts may change. Similarly, range-free techniques, which perform well in large-scale deployments, are not suitable for the relatively small indoor spaces of museums.

Given these constraints, multi-lateration emerges as the most viable solution. Although it is an older technique, it remains a robust and resilient method that provides sufficient accuracy without the need for extensive calibration or high infrastructure costs. By relying on RSSI-based distance estimation from multiple beacons, multi-lateration offers a stable and cost-effective approach that aligns well with the requirements of a museum environment.

2.3 Application in museums

Only a few applications of Bluetooth Low Energy (BLE) in museums have been studied. For instance, [3] utilizes BLE beacons as proximity sensors, while [22] focuses on determining a visitor's location within a specific room rather than identifying individual art pieces, enabling the delivery of relevant content in a broader context.

In the realm of indoor localization, [19] employed Kalman filtering to enhance distance estimation, achieving an error of less than 3.5 meters for 95% of readings with raw data, and 3 meters with filtered data. This indicates that filtering uncertainties in raw data can significantly reduce average errors. The study found that when the receiver is within 50 centimeters of a beacon, the accuracy of the system is notably high, suggesting that positioning beacons close to Points of Interest (POIs) can enhance overall performance. Conversely, it is also noted that if beacons are spaced less than one meter apart, the accuracy may decrease.

2.4 Summary

This chapter has provided an overview of the main technologies and methods for indoor localization, with a particular focus on their applicability in museum environments. We compared the strengths and limitations of various approaches, including satellite navigation, QR codes, RFID, NFC, vision, infrared, ultrasound, ultra-wide band, Wi-Fi, Bluetooth, and hybrid systems. We also discussed key localization algorithms such as multi-lateration, RSSI-APIT, machine learning-based methods, fingerprinting, and range-free techniques.

While no single technology or method is perfect, Bluetooth Low Energy (BLE) combined with multi-lateration offers a practical balance between accuracy, cost, and ease of deployment for museums. The review of related work highlights that, although BLE has been applied in some museum contexts, the field remains relatively underexplored, leaving room for further research and innovation. This background sets the stage for the following chapters, which will detail the design, implementation, and evaluation of a BLE-based indoor localization system tailored to the needs of museums.

Chapter 3

Implementation

This chapter details the practical realization of the indoor localization system described in the previous sections. It covers the overall system architecture, the design and configuration of the ESP32 BLE beacons, the development of the smartphone application, and the integration of the MQTT broker for communication. Each component is discussed in terms of its role, implementation choices, and how they collectively contribute to a robust and scalable solution for museum environments.

3.1 System Architecture

The full system is composed of three different components, each playing a crucial role in its functionality. First, ESP32 devices are used as BLE beacons to broadcast their position. These devices operate by periodically transmitting Bluetooth Low Energy (BLE) signals, ensuring reliable communication with nearby devices. When network access is available, they upload their position data to an MQTT broker, enabling real-time updates across the system.

Second, a smartphone application is developed to receive and process these beacon signals. This application retrieves a list of authorized BLE beacon signatures and uses them to identify and locate nearby ESP32 devices. The application's design focuses on providing a seamless user experience, with clear and intuitive interfaces for displaying relevant information, and guiding visitors through the museum. It also includes features for audio explanations of areas and art pieces, enhancing the visitor experience by providing context and information about the exhibits.

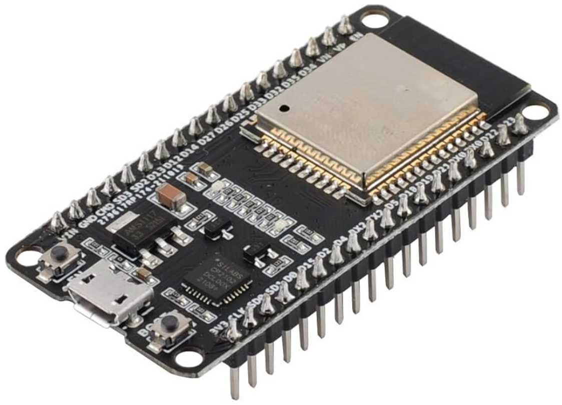


Figure 3.1: Photo of the ESP32

Third, a cloud MQTT broker facilitates communication between the ESP32 devices and the smartphone application. This decentralized approach eliminates the need for a central server, enhancing the system's scalability and reducing potential points of failure. Together, these components form a robust and efficient architecture suitable for applications like museum indoor positioning.

3.2 ESP32 Beacons

The ESP32 devices are low-cost, versatile microcontrollers that can be configured to function as BLE beacons. These devices are equipped with a custom firmware that enables them to broadcast their position periodically. When network access is available, they upload their position data to an MQTT broker; otherwise, they operate as standalone beacons, ensuring continuous functionality even in offline scenarios. An illustration of the ESP32 device is shown in Figure 3.1.

The firmware is built in C++, using the standard Arduino library and some popular and bullet-proven packages to handle dedicated critical features such as MQTT communication and BLE management. This choice ensure an efficient firmware while using proven technologies to ensure minimal power consumption and reliable operations even on edge cases. The beacons broadcast at the default frequency of 100ms[1].

A BLE beacon can be uniquely identified using three values: UUID, Major, and Minor. All the beacons used in the system are configured with the same UUID, `4bfde2c7-e489-47a9-965e-484dae07e8dd`, and major value, `100`, to ensure that

[1] `https://reference.arduino.cc/reference/en/libraries/arduinoble/ble.setadvertisinginterval/`

they are recognized as part of the same group. Those values have been arbitrarily chosen and are not relevant to the system's functionality. The minor value is used to differentiate between individual beacons, with each ESP32 device assigned a unique minor value ranging from 1 to n.

The ESP32 have two phases of operation: the initialization phase and the running phase. During the initialization phase, the ESP32 device starts by identifying itself using its internal MAC address to determine its unique minor value and its localization. It then setups and starts its BLE advertising server that will asynchronously broadcast the beacon signal. Broadcasting so early in the setup ensure fast discoverability and efficiency even in case of a failure in another part of the setup as it is the more critical and important part of the system. The device then attempts to connect to a local Wi-Fi network using the credentials provided in the firmware. If the connection is successful, it connects to a predefined NTP server, `pool.ntp.org`, to retrieve the current time, which is used to timestamp the position data. The device then attempts to connect to the MQTT broker using the provided credentials.

Once the device is initialized, it enters the running phase, where it continues to broadcast BLE signals. The device also checks for network access every 5 seconds. If the connection is broken, the device will attempt to reconnect to the Wi-Fi network, the NTP server, and the MQTT broker. If the connection is successful, the device will upload its position data to the MQTT broker every 5 seconds. The ESP32 blue LED indicates the current status of the device: it blinks every 50 milliseconds when the device tries to connect to the Wi-Fi network and every 5 seconds when the device is working properly.

3.3 Smartphone Application

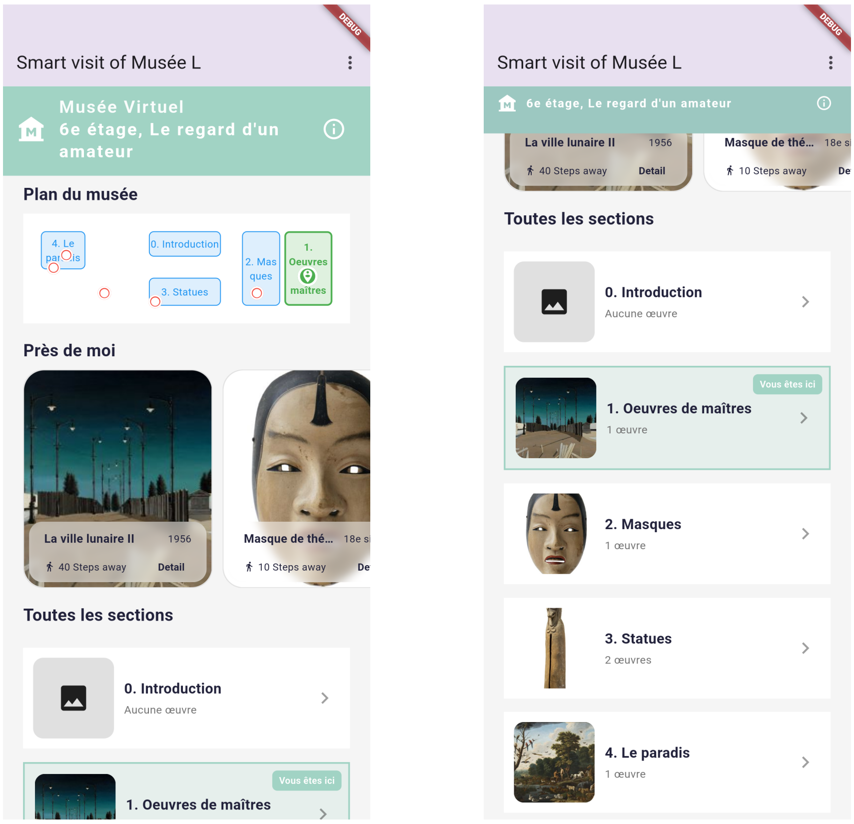
The smartphone application is a critical component of the system, responsible for displaying information to the visitor while collecting and processing BLE beacon signals in the background to enhance the visitor experience. It is built using the Flutter framework, which allows for cross-platform development and ensures compatibility with both Android and iOS devices. It also provides a huge collection of packages to handle low-level features of the application, such as BLE management, MQTT communication, data visualization, permissions and audio players, allowing to focus on the application logic and user experience.

The current version of the application contains only the 6th floor of the museum, which is the only one that has been equipped with ESP32 beacons and is analysed in this study. The application is designed to be user-friendly, with a simple and intuitive interface that allows users to easily navigate through the available features while not being forced to use any of them. The home page displays three different sections and is shown in Figure 3.2. The first one is a map of the floor, with the user's current location indicated by a green dot, the current area with a green background while the others are displayed with a blue background. Main art-pieces are marked with a red dot. The visitor can click on a specific section to access its content. The second section is a horizontal list of the closest art-pieces, shorted by distance, with current section art-pieces first. Each art-piece is represented by a card containing its name, realization date and rounded distance in steps. A button allows the visitor to access the art-piece page. The third section is a list of all the areas of the floor, with the current area highlighted. Each area is represented by a card containing its name, one of the art-pieces and the amount of art-pieces presents in the area. The user can click on a specific area to access its content.

The area page shown in Figure 3.3a displays the list of art-pieces in the area, with more information than the home page. It also provides an audio explanation of the area, which is played automatically when the visitor enters it. The visitor can always decide to stop the audio playback, or to listen to the audio explanation of another area. If the user move from an area to another during the audio playback, the audio will not be interrupted, but the audio of the new area will be played when the previous one is finished. The audio files are stored locally in the application. If the visitor is still in the area when the audio playback is finished, the audio will stop, and the user has the ability to play it again, or to listen to the audio of a specific art-piece for more information. The audio files are played using the native audio player of the smartphone, allowing the visitor to listen to them while navigating through the application or even with the device turned off. The area page also contains a button to access the home page.

The art-piece page shown in Figure 3.3b displays a picture of the art-piece and all the available information. If the art-piece contains an audio explanation, the user can listen to it by clicking on the play button. Art-piece specific audio will never be played automatically as the wish to get more information about an art-piece depends on the visitor. The audio file works the same way as the area audio file, allowing the visitor to listen to it while navigating through the application, or to change area without interrupting the audio playback. The art-piece page also contains a button to access the area page.

The current content of the application is limited to demonstration purposes, with only a few art-pieces available. The application is designed to be easily extensible, allowing for the addition of new content and features in the future. It also contains a top bar menu to access the debug and experiment pages. The debug page contains a map of the floor with the beacons' location, the estimated distance to each beacon, and the current location of the user. The experiment page allows recording data following the instructions provided in chapter 4.

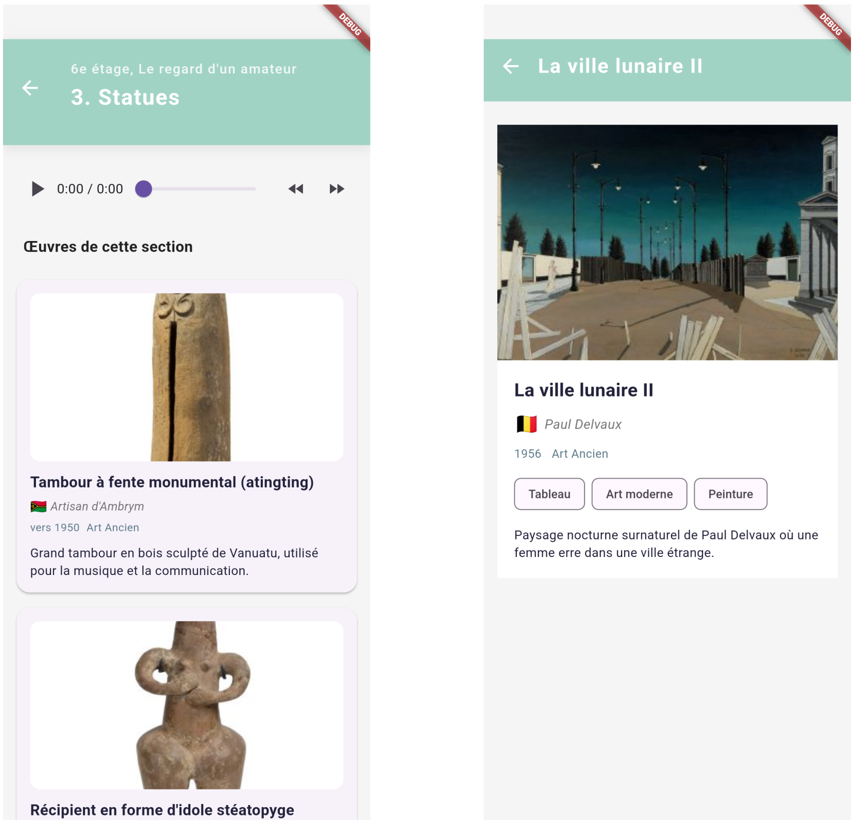


(a) Top of the home page (b) Bottom of the home page

Figure 3.2: Screenshots of the home page: top (left) and bottom (right).

The background process retrieves the list of authorized BLE beacon signatures and use them to identify and locate nearby ESP32 devices. This process involves scanning for BLE signals, filtering out unauthorized beacons, and calculating the user's distance relative to the detected devices, and then use those data to determine the user's position. Finally, the change of user position is sent to the front-end to update the map, the list of closest art-pieces, and detect when the user changes area.

The core localization logic in the application is designed to robustly estimate the user's position using signals from multiple BLE beacons. For each beacon, the application maintains a filtered estimate of distance, leveraging a Kalman filter to



(a) Area page (b) Art piece page

Figure 3.3: Screenshots of the area page (left) and art piece page (right).

smooth out the inherent noise in RSSI measurements. At each update, the system selects up to six beacons with the lowest estimated distances, ensuring that only the most relevant and reliable signals are used for position calculation.

To determine the user's location, the algorithm considers all possible combinations of three beacons among the selected set. For each trio, it computes a weighted centroid, where the influence of each beacon is adjusted according to the relative distances. The quality of each triangle formed by the beacon positions is also assessed, favouring well-shaped, non-degenerate triangles to improve accuracy. The final estimated position is then calculated as a weighted average of all candidate positions, with higher-quality triangles contributing more to the result. This approach balances robustness and precision, allowing the application to provide real-time, reliable localization even in the presence of signal fluctuations and environmental noise.

3.4 MQTT Broker

The MQTT broker serves as the communication backbone of the system, enabling seamless data exchange between ESP32 devices and the smartphone application. ESP32 devices upload their position data to the broker whenever network access is available. This data is then relayed in real-time to the smartphone application, ensuring that users receive up-to-date information without noticeable delays. Those position data are published as retained message, ensuring that the smartphone application receives the last known position of the ESP32 devices even if they are not connected to the MQTT broker. The data are published on the topic `ibeacon/devices/<UUID>_<MAJOR>_<MINOR>`. A typical payload of the position data is shown in Listing 3.1.

Listing 3.1: Payload of the position data

```
{
  "device_id":"ESP32_1",
  "name":"ESP32-1",
  "uuid":"4bfde2c7-e489-47a9-965e-484dae07e8dd",
  "major":100,
  "minor":1,
  "txPower":-69,
  "X": 26.681,
  "Y": 0.252,
  "beacon_name":"ESP-B1",
  "timestamp":1743496190
}
```

The use of an MQTT broker offers several advantages. First, it eliminates the need for a centralized server, enhancing the system's scalability and reducing potential points of failure. Second, it supports asynchronous communication, allowing devices to operate independently while still sharing data efficiently. Finally, the broker's lightweight protocol is well-suited for low-power devices like the ESP32, ensuring minimal impact on battery life.

This decentralized approach not only improves system reliability but also simplifies maintenance and upgrades. By leveraging the MQTT broker, the system achieves a high level of flexibility and efficiency, making it suitable for a wide range of applications.

Chapter 4

Methodology

4.1 Objectives

The primary objective of this study is to evaluate the reliability of RSSI (Received Signal Strength Indicator) values from ESP32 Bluetooth Low Energy (BLE) beacons for determining smartphone positioning and detecting user proximity to predefined areas or points of interest (POIs) within a threshold of three meters or less. This validation is essential for ensuring that the proposed indoor localization system can accurately detect a user's presence near specific locations in museum environments.

In addition to the primary objective, the study addresses several secondary goals. First, the impact of environmental factors, such as signal interference, obstacles, and layout complexity, on localization accuracy will be assessed to ensure robustness in real-world settings. Second, the system's responsiveness to dynamic user movements will be evaluated, focusing on latency and stability during transitions between areas and POIs. Finally, the study will compare localization accuracy across different smartphone models to determine whether variations in hardware affect the system's reliability. These secondary objectives aim to provide a comprehensive evaluation of the system's feasibility and generalizability.

4.2 Considerations

4.2.1 Privacy and Ethical Considerations

Protecting visitor privacy in public cultural spaces such as museums is essential, both for museums and their audiences. From an institutional perspective, it enables compliance with strict and often complex European data protection regulations (such as the General Data Protection Regulation, GDPR), while from the visitor's perspective, it fosters trust and encourages acceptance of digital technologies within the museum environment.

Traditional indoor localization systems often rely on centralized servers for data processing, which may result in sensitive location data being stored or transferred externally. This introduces legal and ethical risks, particularly when data can potentially be linked to identifiable individuals or behavioral patterns. However, recent developments in privacy-focused computing demonstrate that it is feasible to maintain localization functionality without compromising user privacy [2, 19].

In this study, privacy protection is achieved through a local-only processing model. All position computations are performed directly on the visitor's smartphone. No user-identifiable data or location history is transmitted to external systems without the express user consent. The server only provides static configuration data (such as beacon identifiers and positions), ensuring that all tracking and decision-making remains strictly client-side. This design minimizes the risk of privacy breaches and aligns with best practices for responsible personal data processing [8].

4.2.2 Sustainability and Energy Efficiency

Sustainability is an increasingly critical responsibility across public institutions, and museums are no exception. Their role in promoting sustainability is twofold: on the one hand, museums, as any actor, must address their direct environmental impact through energy-efficient infrastructure, responsible material use, and sustainable operational practices. On the other hand, they also serve as cultural and educational institutions that can foster sustainable development indirectly, by raising public awareness, inspiring behavioural change, and supporting interdisciplinary research on sustainability and climate resilience.

As emphasized by the International Council of Museums (ICOM) [9], museums are "perfectly positioned to address and enhance sustainability" through collaboration with communities, knowledge creation, and the promotion of planetary and societal well-being. This vision aligns with a growing movement within museums to contribute to the fulfilment of the United Nations Sustainable Development Goals (SDGs) [14, 16].

Against this backdrop, technological solutions implemented within museum environments must be evaluated not only on performance metrics but also on their energy efficiency, environmental footprint, and alignment with institutional sustainability goals. The indoor localization system developed in this study is designed with such responsibilities in mind. Specifically, it uses ESP32-based Bluetooth Low Energy (BLE) beacons, which are known for their low power consumption and can operate for extended periods on minimal energy. Some variants may also harness solar energy, reducing battery replacement cycles and electronic waste [19].

By opting for a lightweight, low-maintenance infrastructure, this system helps minimize long-term environmental impact, while meeting technological requirements for real-time positioning. It reflects an intentional effort to align technical implementation with the broader sustainability goals increasingly embraced by cultural institutions worldwide.

4.2.3 User Experience and Engagement

Current research on indoor localization in cultural institutions has primarily focused on technical evaluation metrics such as accuracy and signal strength, with relatively few studies addressing user-centred outcomes. Visitor engagement, perception of usefulness, and interface design remain underexplored dimensions.

For example, in [2], personalization is introduced through a preliminary questionnaire, but systemic user feedback on the localization experience itself is largely absent. In this project, although full-scale user evaluation is beyond the scope, preliminary efforts were made to incorporate user-oriented features, such as real-time visual feedback on location and a simplified interface where the visitor can still choose to go deepen or against the automatic suggestions. Those behaviours as well as the popularity of the different areas are collected anonymously to assess both popularity and perceived added value.

4.3 Experimental Setup

4.3.1 Hardware and System Architecture

The experimental setup comprises up to four ESP32 devices running a custom firmware that enables them to operate as BLE beacons. A picture of an ESP32 is provided at Figure 3.1. These devices periodically broadcast BLE signals. When network access is available, they upload their position to an MQTT broker; otherwise, they function solely as standalone BLE beacons.

A smartphone application is responsible for collecting and processing the beacon signals. This application retrieves a list of authorized BLE beacon signatures from the MQTT broker and continuously scans for nearby devices that match these known signatures. No user data is transmitted from the smartphone to the server, ensuring privacy for both the user and other individuals within the area.

4.3.2 Application Features and Localization Logic

The smartphone application provides a real-time graphical interface that visualizes the current estimated localization for the visitor on a map. The map also shows the different areas and POIs, which are defined by the museum. The application is designed to be user-friendly and intuitive, allowing visitors to navigate the museum with ease.

While the application is mainly thought for the visitor, it can also provide debugging and in-depth real-time analysis of the localization process for the purpose of this study. The debug map displays the static positions of the beacons, circle estimating the distance from the smartphone, a dot indicates the estimated visitor position, and finally crosses mark to show the predefined points of interest. Other graphs displays the raw RSSI, the raw distance and the filtered distance for each beacon in range.

Localization is based on RSSI-based multi-lateration. A phone is considered to be within an area when it has been detected at least twice within. Conversely, the phone is considered to have exited the area if it is subsequently detected twice at a location beyond one meter of the area. This difference between the entry and exit thresholds is implemented to prevent unstable state changes between being inside and outside an area. These threshold values have been determined based on preliminary evaluations and may be adjusted for different experimental conditions, depending on beacon placement, artwork density, and the complexity of the indoor environment.

4.4 Experimental Procedure

To systematically evaluate the performance of the system, and it's value within a museum, four distinct experiments will be conducted. These experiments focus on evaluating localization accuracy, differences in smartphone models, impact of museum layouts and its operations within a museum.

4.4.1 Experimental layout

The first experiment will take place in a designated corridor within the university, while the others are directly on a floor of the museum. A picture of that floor is

Figure 4.1: Photo of the 6th floor of Musée L

provided in Figure 4.1. ESP32 beacons will be installed at predefined locations to provide adequate coverage of all POIs. The POIs correspond to specific reference points where localization should occur accurately. Participants performing the tests will execute a predefined sequence of movements, ensuring uniformity in data collection and minimizing variability caused by human movement patterns.

Localization data, including timestamps for detected entries, exits, and continuous tracking points, will be logged during all experiments. Additionally, manual records will be kept to compare the system's performance with a ground truth reference, ensuring accurate evaluation.

4.4.2 Experiment 1: Localization Accuracy

The first experiment focus on the beacons' data directly. It aims to calibrate the meta-parameters and analyses the precision of the distance estimation between the phone and the beacons. The experiment take place in a corridor, with no obstacle and a direct Line of Sight (LoS) between the phone and the sensors. The sensor is placed at 1.5 meters from the ground and measurements are taken at every meter, starting at "0" (L_0), with the phone touching the sensor, and up to 15 meters away from it (L_{15}). At each step, the phone take measurements for 20 seconds. Each sensor is tested with no other sensor active at the same time to minimize interferences.

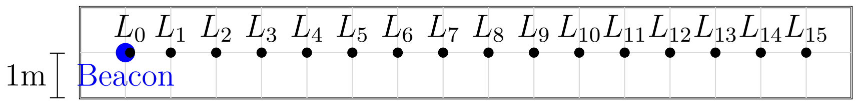


Figure 4.2: Experimental setup for the first experiment showing one beacon and all the references distances.

4.4.3 Experiment 2: Impact of Museum Layout and User Experience

The second experiment combines the evaluation of the impact of the museum layout on localization results with the assessment of user experience and the system's ability to detect user presence in specific areas and provide meaningful data.

This experiment takes place directly inside the museum on the floor used for this study. All ESP32 devices are installed close to the floor, and the user keeps the smartphone in hand, in front of him. The user follows a predefined path across several locations ($L_0 \rightarrow L_1 \rightarrow \ \dots\ \rightarrow L_7$), pausing for 20 seconds at each location before moving at a walking pace to the next.

During the experiment, the application provides two layers of information to the user: an overview by section (with general information about the sections and their main art pieces), and a list of art pieces in the current section and those close to the visitor. The visitor can choose to get more information on specific pieces by interacting with the application, or simply follow the suggested path without interaction. The exact time the visitor is detected in each area is recorded alongside the classical localization data, allowing for the evaluation of both technical performance and user engagement.

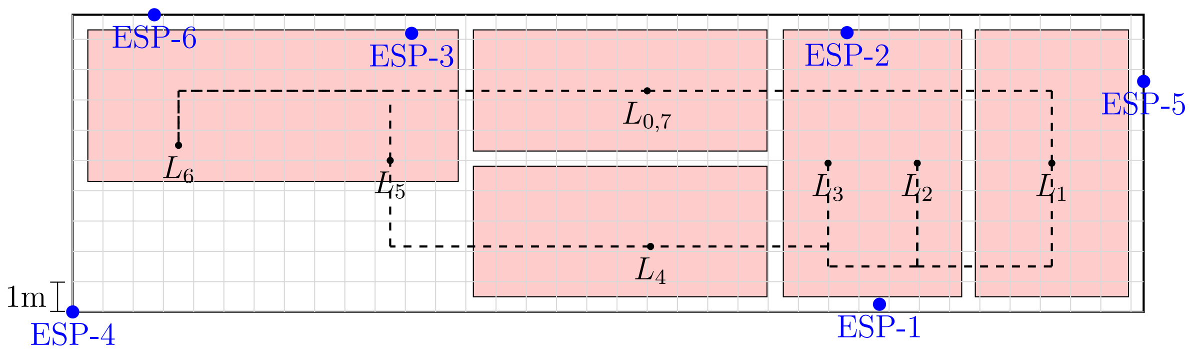


Figure 4.3: Experimental setup for the second experiment showing the beacons, reference points, and POI areas.

4.4.4 Experiment 3: Repeat with other phones

The third and last experiment aim to ensure the precision of the system with multiple other phones. The exact same steps as experiment 2 are repeated, but with different phones.

Chapter 5

Experimental Results

5.1 Calibration

The distance estimation from the Received Signal Strength Indicator (RSSI) is computed using Equation 2.1, which includes two meta-parameters. The first parameter, tx_{power}, represents the RSSI at a distance of one meter. The second parameter, the environmental factor (N), accounts for signal propagation characteristics that depend on the surroundings.

5.1.1 RSSI at One Meter (tx_{power})

Results from the first experiment in subsection 4.4.2 are displayed in Figure 5.1. These results indicate that although the RSSI distribution shows some variability, it remains centered around the mean. The optimal tx_{power} values can be obtained by averaging the RSSI values for each beacon.

Empirical results are consistent with the expected theoretical value of -69. The first two beacons yield values very close to this reference, while the third beacon reports a slightly higher RSSI of -63. The broader distribution for this beacon may suggest environmental influences affecting signal strength.

5.1.2 Environmental Factor (N)

The environmental factor N typically ranges from 2 in ideal conditions to 4 in highly obstructed or chaotic environments. Experimental results shown in Figure 5.2 support this range. The plots illustrate the Mean Squared Error (MSE) between measured distances and those calculated using various values of N (from 2 to 4),

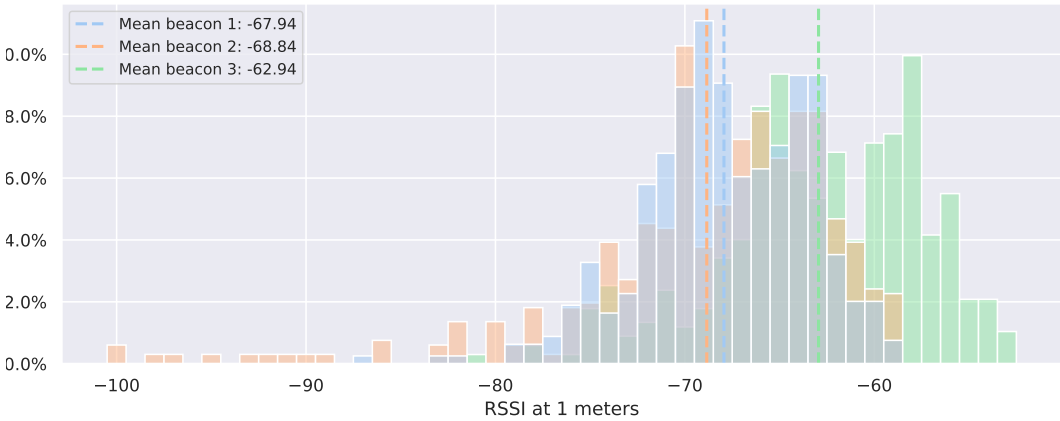


Figure 5.1: Experimental RSSI values at 1 meter

applied to measurements taken from both Experiment 1 (corridor) and Experiment 2 (museum).

In the corridor environment, which features line-of-sight (LoS) conditions and minimal interference, the optimal environmental factor is approximately 2.07. In contrast, measurements taken in the museum, with by complex layouts and significant obstructions, produce a higher MSE across all values of N. The lowest error occurs with $N = 2.83$, reflecting the increased signal attenuation due to environmental factors.

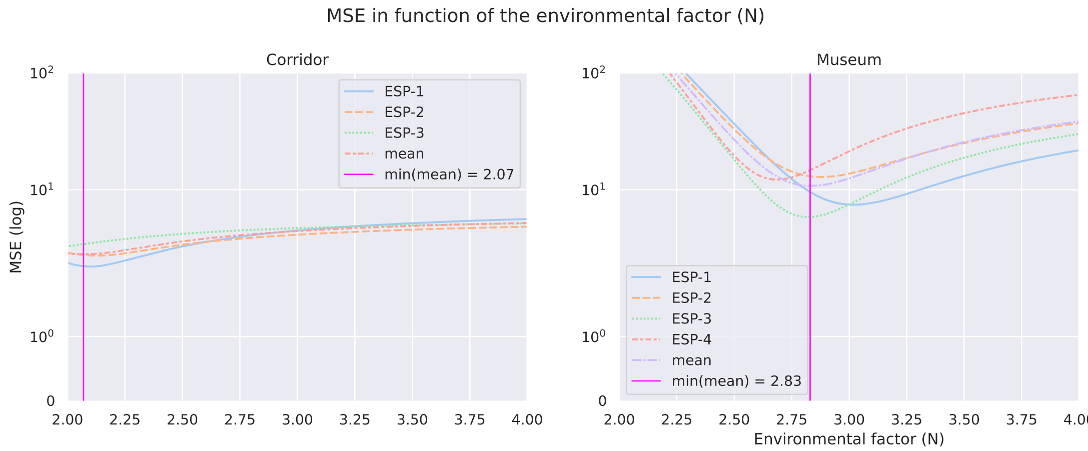


Figure 5.2: Comparison of environmental factors (N) in both test environments

5.1.3 Summary of Calibration Findings

These findings confirm that the theoretical value of $tx_{power} = -69$ is robust and does not require adjustment based on environment. In contrast, the environmental factor N must be calibrated for each new environment. Nevertheless, once determined, the same N can be applied uniformly across all beacons, thus simplifying the setup process.

5.2 Distance to Beacons

Experimental data from Experiment 1, as shown in Figure 5.3, confirm the findings reported by [19], which highlight a correlation between ranging precision and beacon distance. Specifically, beacons located within a few meters provide highly accurate distance estimates with minimal error spread.

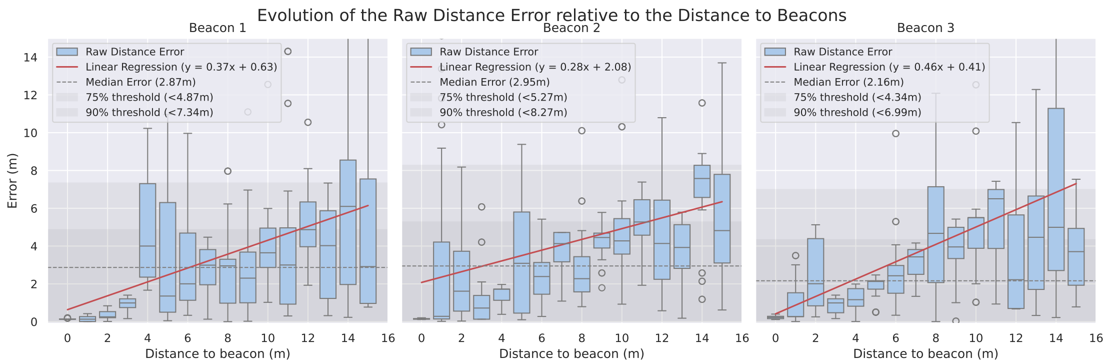


Figure 5.3: Raw distance error variation relative to distance from beacons

Analysis of the raw distance errors shows that the median error typically lies between 2 and 3 meters. Moreover, 75% of distance errors are below 5 meters, and 90% fall below 8 meters.

After applying a Kalman filter to the data, as presented in Figure 5.4, error margins are significantly reduced. The median error decreases to between 1.5 and 2.5 meters, with 75% of errors below 4 meters. However, the 90% threshold remains around 8 meters, indicating that although the filter reduces overall noise, extreme conditions still lead to larger errors.

5.3 Multi-lateration precision

The multi-lateration algorithm was evaluated based on its ability to estimate the position of the smartphone relative to the BLE beacons. The results demonstrate

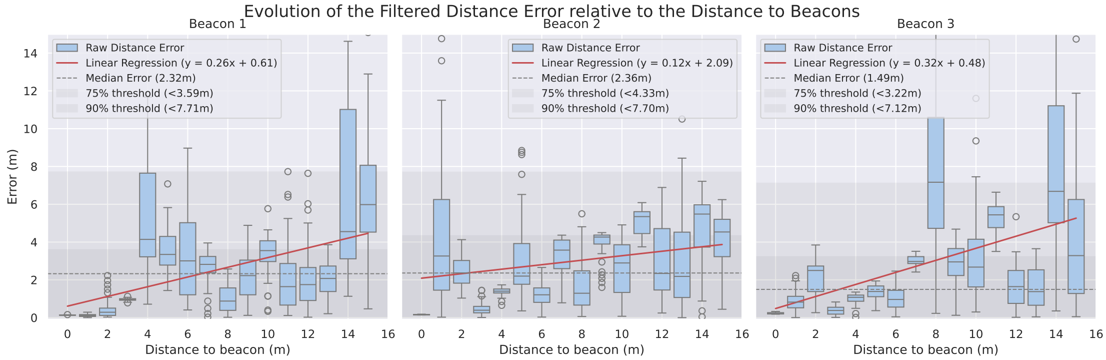


Figure 5.4: Filtered distance error variation relative to distance from beacons

that the system achieves a median localization error of 2.8 meters, as show by Figure 5.5), indicating that, in typical conditions, the estimated position is within 2.8 meters of the actual location. Furthermore, the distribution of errors shows that 75% of the position estimates fall within 3.86 meters, and 90% are within 5.81 meters. These results highlight the robustness of the multi-lateration approach in the tested environment, even in the presence of signal fluctuations and environmental noise.

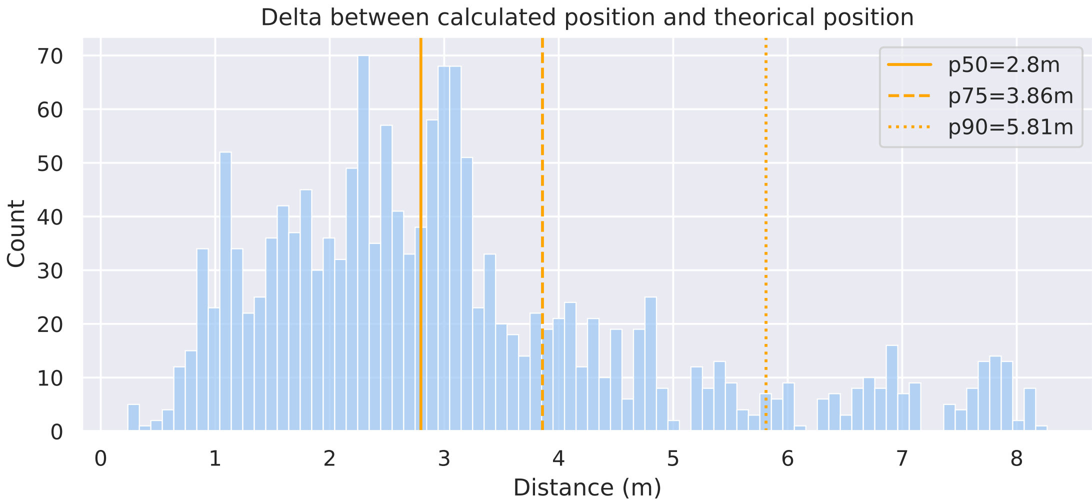


Figure 5.5: Multi-lateration error in the museum environment

It is important to note that in 9% of the measurements, the system was unable to compute a position estimate. This was primarily due to insufficient data, such as a lack of simultaneous beacon signals required for multi-lateration.

While this represents a small fraction of the total measurements, it underscores the importance of beacon placement and signal coverage in ensuring continuous localization. Overall, the multi-lateration method provided reliable and reasonably accurate position estimates for the majority of the experiment duration.

5.4 Area detection

As shown in Figure 5.6, the correct area is detected in more than 80% of cases. However, the detection accuracy varies significantly depending on the specific area. Side areas (steps 1, 2, 3, 5, and 6) achieve near-perfect detection rates, ranging from 93% to 100%. In contrast, central areas (steps 0 and 4) are correctly identified in only 27% and 57% of the cases, respectively.

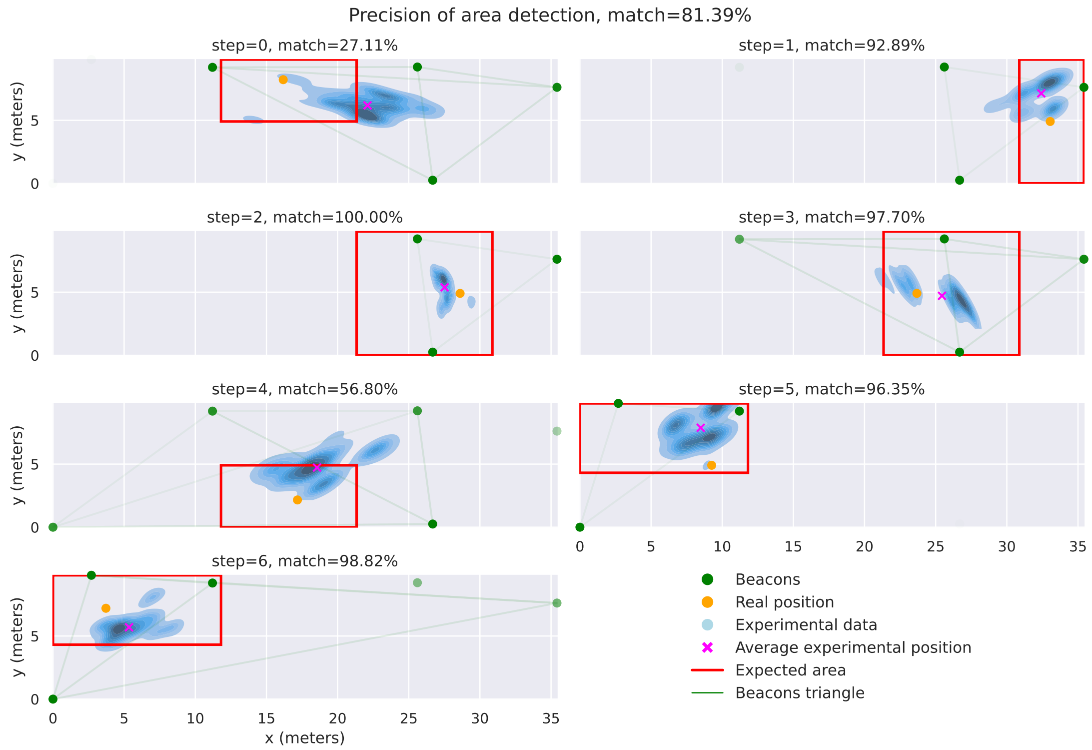


Figure 5.6: Area detection in the museum environment

Several factors, including the museum's layout and the placement of beacons, may explain these discrepancies. While most of the museum floor is an open space, the central areas are divided by large stairwell walls, which can obstruct signal transmission. Moreover, as illustrated in Figure 5.6, the placement of the beacons is not ideal for these central zones.

Beacon locations are marked by green dots, with their transparency indicating the frequency of signal detection. Green triangles denote groups of three beacons used in multilateration, which are selected only if all three beacons were detected simultaneously at least 50% of the time. In the worst-performing case (step 0), the relevant beacons are heavily off-centered from the target area, likely contributing to the low accuracy. At step 4, although up to five beacons are detected, only four are stable enough to be consistently utilized, and they typically form large, asymmetrical triangles. In contrast, better-performing steps benefit from small, well-balanced beacon triangles, which likely facilitate more accurate localization.

5.5 Summary

This chapter presented a comprehensive evaluation of the BLE-based indoor localization system. Calibration experiments confirmed that the theoretical transmission power parameter (tx_{power}) is robust across environments, while the environmental factor (N) requires context-specific adjustment but can be applied uniformly to all beacons within a given space. Distance estimation experiments demonstrated that, after filtering, median errors in near-perfect environment can be reduced to 1.5–2.5 meters, though occasional outliers persist due to environmental noise. Multi-lateration yielded a median localization error of 2.8 meters, with the majority of position estimates falling below 4 meters of the true location, highlighting the method's reliability under typical conditions. Area detection accuracy exceeded 80% overall, with side areas achieving near-perfect results, while central areas were more challenging due to suboptimal beacon placement and architectural obstructions. These findings underscore the importance of careful calibration and beacon deployment in achieving robust and accurate indoor localization.

Chapter 6

Discussion and Limitations

This chapter provides a comprehensive evaluation of the proposed localization system for museum environments, combining experimental insights with a candid acknowledgment of the study's limitations. By analyzing the system's performance, scalability, privacy measures, and sustainability, we aim to contextualize its potential within the broader landscape of indoor localization technologies and it's application in the specific context of museums. Additionally, we explore the constraints imposed by hardware, environmental factors, and user behavior, offering a balanced perspective on the system's strengths and areas for improvement.

6.1 Localization Accuracy

The localization accuracy of the system was mainly evaluated within a single museum environment, yielding median errors of 2.8 meters after applying a Kalman filter. This precision allows the system to be used for general proximity tracking but is not sufficient for application requiring relatively precise localization, limiting its applications. The final design of the mobile application had to take those challenges into account. The usage choice for the application to detect in which area of the museum the user is, and provide a by-row audio general explanation while following a recommended visit order is a good application of such constraints, while a per-art piece detection and audio description would probably not, and thus have not been chosen.

At the same time, while out of scope of the current study, there is no guarantee that the visitor would especially prefer a by-art piece experience, looking at the way most visitors visits museums. Many IT systems in museums fail to convince the visitor or to improve the user experience due to inadequacy between system and most visitors expectations.

Another important aspect is the precision and limitations of area detection. Experimental results showed that the system correctly identified the user's area in over 80% of cases. A near-perfect accuracy was observed in areas where beacon placement allowed for small and well-balanced triangulation and for minimal architectural interference. In contrast, detection performance declined in more complex spaces, with off-centered beacons and physical obstructions. These findings highlight that the effectiveness of area detection is closely tied to the spatial configuration of the environment and the quality of beacon deployment, suggesting that improvements in these domains are essential for achieving consistently high precision throughout the entire space.

6.2 System Responsiveness

System responsiveness was another critical factor, as delays in updating visitor positions or delivering information could negatively impact the user experience. Initial tests suggested that the system performs adequately in real-time scenarios, but further optimization is needed to ensure consistency, especially in environments with high signal interference.

A key challenge encountered during development was the trade-off between real-time responsiveness and localization precision. Achieving higher precision often requires more extensive data aggregation, which can introduce latency and reduce the immediacy of position updates. Conversely, prioritizing real-time updates may necessitate using less data or simpler algorithms, potentially reducing accuracy. In this system, a balance was sought to ensure that position updates were timely enough to be useful for guiding visitors, while still maintaining acceptable localization accuracy. This trade-off influenced both the choice of filtering techniques and the design of the user experience, favouring general area detection and timely feedback over fine-grained, but potentially delayed, localization.

6.3 Experimental Constraints

The study was conducted on a single floor of the museum, with a limited number of plug sockets available for beacon deployment. This constraint restricted the density and placement of beacons, potentially affecting localization accuracy. The experimental results tend to indicate that the beacon density was just sufficient to have interesting results, but that a higher density would significantly improve the results and the opportunities for the system. However, such a density was not feasible within the study's environment.

Additionally, the controlled environment of a single museum limits the generalizability of the results. Testing in diverse settings, such as on multiple floors, would provide a more comprehensive evaluation but was beyond the scope of this study.

6.4 Hardware and Software Limitations

The system relied exclusively on ESP32 devices as beacons, which, while cost-effective and energy-efficient, may not represent the full range of hardware options available. Different beacon types could yield different results in terms of accuracy and range.

The application was developed using Flutter, a framework designed for cross-platform compatibility. However, testing was limited to Android devices due to hardware availability, leaving unexplored the potential challenges of iOS or other platforms. Additionally, the system's reliance on pre-packaged art piece data ensures offline functionality but requires users to download updates for exhibit changes, which could hinder usability over time. Relying on the visitor phone may lead to performance variability due to differences in hardware and software configurations.

Finally, both Android and iOS impose strict limitations on the frequency and duration of Bluetooth scans, primarily for privacy protection and energy efficiency. These operating system-level restrictions are a major constraint for any real-time localization system relying on Bluetooth, as they directly limit how often the application can detect nearby beacons and update the user's position. On Android, background scan intervals are throttled and may be delayed or batched, while on iOS, scanning is even more restricted, especially when the app is not in the foreground. This means that, regardless of hardware or algorithmic improvements, the achievable update rate and thus the responsiveness of the system are fundamentally capped by these policies.

As a result, these limitations have a significant impact on the overall performance and user experience of the system, and must be considered a primary factor in the design and evaluation of any Bluetooth-based indoor localization solution. In contrast, using dedicated devices for localization, rather than relying on visitor smartphones, could bypass these restrictions, allowing for much higher scan frequencies and more precise, real-time localization. This would enable substantial improvements in both accuracy and responsiveness, but would come at the cost of increased hardware deployment and maintenance requirements.

6.5 Environmental Factors

The dense arrangement of art pieces on the museum floor introduced significant signal obstructions, challenging the system's ability to maintain consistent accuracy. While this environment provided valuable insights into the system's robustness, it also highlighted the need for adaptive strategies, such as advanced signal processing techniques, to mitigate the impact of environmental factors and raised the limitation of using beacons that require a plug rather than battery-based beacons.

6.6 Scalability and Management

The system was designed with scalability in mind, allowing for the potential expansion of the beacon fleet as needed. However, managing many beacons could become logistically challenging, particularly in terms of installation, maintenance, and synchronization. Implementing a dedicated management system, such as a centralized control platform for beacon configuration and monitoring, could address these challenges, though it was not explored in this study.

6.7 Ethical and Privacy Considerations

Privacy and ethical concerns were addressed through anonymized data collection and visitor consent protocols. Compliance with GDPR regulations was ensured by avoiding the use of Personally Identifiable Information (PII). While these measures are essential for maintaining visitor trust and legal adherence, they may limit the system's ability to offer personalized experiences. Future work could explore privacy-preserving technologies to balance data utility with user privacy.

6.8 Sustainability Impact

The system's sustainability was evaluated across both hardware and software dimensions. The use of small, energy-efficient beacons and visitor smartphones reduced the need for dedicated devices, minimizing resource consumption. Local computation on the smartphone further enhanced energy efficiency by eliminating the need for cloud-based processing. However, a detailed lifecycle analysis, including measurements of the power usage of the different devices and infrastructures, was beyond the scope of this study. Future evaluations could incorporate metrics such as carbon footprint and material recyclability to provide a more holistic understanding of the system's environmental impact.

6.9 User Interaction Variability

The system was designed to predict and accommodate visitor behaviour, but deviations from predefined patterns may limit its effectiveness. For example, visitors who choose to explore the museum in non-linear or unpredictable ways may not fully benefit from the system's features. Despite this, the design ensures that visitors can explore freely without interference, preserving the core museum experience. Future iterations could incorporate more adaptive user interaction models to better accommodate diverse visitor behaviours.

6.10 Implication for the Museums

Implementing an indoor localization system in museums introduces several practical constraints that must be addressed. Infrastructure challenges, such as limited power outlets or dense exhibit layouts, can hinder beacon deployment and signal coverage. Older or historically significant buildings may lack the necessary infrastructure, while multi-floor or complex spaces amplify these difficulties. Additionally, managing a large fleet of beacons can strain museum resources, requiring ongoing maintenance and synchronization. Financial constraints may further limit adoption, particularly for smaller institutions with limited budgets. Finally, ensuring compliance with privacy regulations and addressing visitor concerns about data use are essential for building trust. These constraints highlight the need for careful planning and resource allocation to ensure the system's feasibility and effectiveness in real museum environments.

Chapter 7

Conclusion and Future Work

7.1 Conclusion

This study explored the design, implementation, and evaluation of an indoor localization system tailored for museum environments, specifically deployed on the sixth floor of Musée L. The system demonstrated its potential to improve visitor navigation and engagement by offering contextual and spatially aware content through a user-friendly mobile application.

Key technical findings include a median localization error of 2.8 meters, with over 75% of estimates falling within 3.86 meters, sufficient for room-level accuracy. Signal filtering methods such as Kalman filtering contributed to stabilizing noisy signal data and improved the consistency of location estimates. Area detection accuracy exceeded 80%, validating the system's ability to correctly assign visitors to specific sections. Nonetheless, occasional signal dropouts underscore the critical role of optimized beacon coverage and signal quality in complex indoor settings.

The system was designed to be energy-efficient by leveraging visitors' smartphones and lightweight ESP32 beacons. Data privacy was respected through anonymized data handling, aligning with ethical standards for digital installations in public cultural spaces.

The study also confirmed the viability of Bluetooth-based solutions for indoor localization in museum contexts, while acknowledging inherent limitations, such as variability in signal propagation and hardware constraints related to power supply deployment. Additionally, user experience remains a critical dimension, as passive guidance systems must accommodate diverse visitor expectations and behaviours.

Overall, the system provides a foundational step toward more engaging, accessible, and intelligent museum visits. It shows the feasibility of scalable integration of indoor positioning technologies, with promising avenues for enhancement.

7.2 Future Work

Future research could expand the current system's capabilities by incorporating data fusion techniques, integrating signals from multiple sources such as Wi-Fi, cellular networks, and inertial sensors. By leveraging the complementary strengths of these technologies, the system could achieve increased localization accuracy and resilience, particularly in challenging environments with dense exhibit layouts or significant signal interference. Such multimodal integration would enable more consistent tracking experiences across a broader spectrum of visitor devices and movement patterns.

Another promising research direction is the adoption of Bluetooth 5.1 features, specifically Angle of Arrival (AoA) and Angle of Departure (AoD). These technologies introduce directional information into the localization process, substantially enhancing spatial resolution and reducing ambiguity caused by signal reflections or multipath effects. Implementing AoA/AoD could make the system more robust in architecturally complex or compartmentalized museum settings, enabling more precise content triggering and visitor guidance.

In addition, extending the system to support three-dimensional (3D) localization would significantly improve applicability in multi-floor or vertically layered exhibition spaces. This would necessitate accounting for floor structures, vertical signal attenuation, and non-uniform ceiling heights, but would greatly enrich the tracking experience and facilitate new kinds of spatial interactions with content.

To improve sustainability and deployment scalability, future work should also examine intelligent beacon management and energy-efficient hardware strategies. Solutions may include centralized platforms for monitoring and updating beacon networks, dynamic transmission scheduling, or the use of self-sustained beacon hardware such as solar-powered modules. These innovations could reduce maintenance overhead and support long-term integration into museum infrastructures.

Altogether, these future directions offer critical pathways to enhance the technical performance, adaptability, and long-term sustainability of indoor localization systems, and could position them as essential tools in the evolution of intelligent and inclusive museum experiences.

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