École polytechnique de Louvain

Indoor Localization for Smarter 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.

Acknowledgments

I would like to express my deepest gratitude to my supervisors, Professor Ramin Sadre and Professor Christel Pelsser, for their guidance, expertise, and support throughout the development of this thesis. Their insightful feedback, constructive critiques, and encouragement have been instrumental in shaping the direction and quality of this research.

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We acknowledge the use of Generative AI (GAI) tools to assist in rephrasing and correcting grammar and linguistic errors in this thesis, in compliance with the guidelines set by the Université Catholique de Louvain (UCLouvain) [**?**] and the École Polytechnique de Louvain (EPL) [**?**]. These tools were used solely to enhance the clarity and readability of the text, and all ideas, analyses, and conclusions remain entirely my own.

Contents

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 [?]. 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 [?].

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 [?]. 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 [?]. 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 [?]. Each approach involves trade-offs in terms of accuracy, hardware requirements, and environmental impact, an often-overlooked factor despite its potential significance [?].

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 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 3, and the implementation details will be explained in **??**.

The system's performance will be evaluated through technical and user-based assessments, analyzing visitor movement patterns and engagement. The results and their implications, including limitations, will be discussed in chapter 5. Finally, conclusions and future research directions will be provided in chapter 6. This study aims to create an effective and sustainable indoor localization solution for 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 [?].

2.1.2 QR code

QR codes are a widely used method for providing information to visitors. However, as a passive 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 [?].

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 a large number of inexpensive tags. It also works without direct LoS [?]. It's a nice alternative to QR-code, and allow a bit more interaction. However, it is also a passive method, that as the same issues than discussed before. It short range make it also more efficient to determine if a user is near the tag rather than having a precise indoor localization [?].

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 [?].

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 [?].

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 [?]. Additionally, it is highly sensitive to environmental factors such as heat sources and ambient lighting, which can interfere with signal accuracy [?]. 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 [?]. It uses the technique of the Time Of Flight and can have an accuracy up to the centimeters, 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 [?] [?].

2.1.8 Ultra Wide Band

Ultra wide band can provide a very accurate localization, based on the Time-Of-Arrival 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 [?] and is expensive [?].

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 [?] and do not require extensive knowledge for users or maintainers [?]. 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 [?]. It doesn't require a direct LoS [?], even if the environment may have a huge impact on the precision, range and multi-path effect [?]. Most used techniques are Cell of Origin method, triangulation and RSS-based fingerprinting. It can achieve a theoretical precision of a few centimeters in a dense, errorless and open environment but usually achieve a precision of a few meters for more realistic ones [?].

More specifically, RSSI is the current mainstream system but is prone to noise and interfaces in a dense area [?]. The precision can be adjusted based on the density [?]. It offer a proper balance between efforts and accuracy [?]. There is two main methods: RSSI heat maps, that allow to visually describe the infrastructure, detects it's weaknesses and use simpler algorithms than most others [?] 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. A large number of Bluetooth beacons are available on the market at a low cost [?], and their transmission range can be easily adjusted. Typical user devices have a range of 10 to 15 meters [?]. In real-world scenarios, Bluetooth positioning provides accuracy close to that of Wi-Fi, typically ranging from 2 to 3 meters [?] [?].

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 [?]. The receiving device can processes 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 [?]. 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 [?].

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 [?] [?]. BLE beacons can reach distances of up to 60 meters, but this significantly increases power consumption. A typical transmission range of 2 to 5 meters is often preferred [?], 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 [?], 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 [?].

As outlined by [?], 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 [?]. Various device sensors, such as inertial sensors, accelerometers, and gyroscopes, can also be used to improve real-time precision between beacon emissions [?]. 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, favored 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 fulfills 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 analyze 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**	$<$ 5m	**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 trilateration 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 [**?**]:

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

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% [**?**]. However, it relies on the APIT framework, which requires a large number of anchor points for effective functioning. In Shen et al. [**?**], 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.

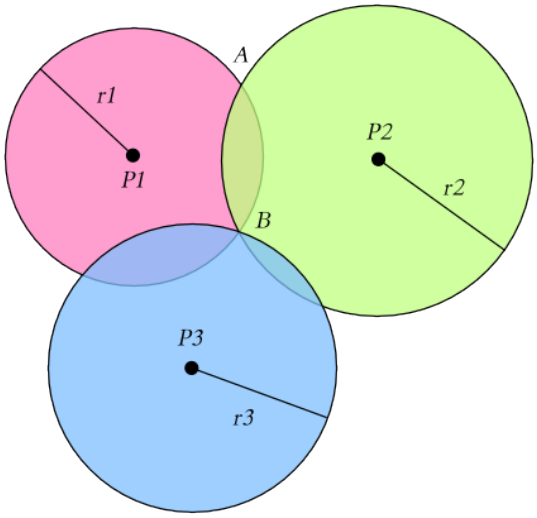

Figure 2.1: Example of trilateration

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 [**?**].

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

2.2.4 Fingerprinting

Fingerprinting-based localization requires an initial offline training phase before being used online [**?**], making it less scalable and adaptive. Constructing a radio map for localization involves substantial effort, particularly in large or dynamically changing environments [**?**]. 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 of 0.7 meters. However, data collection is time-consuming and intensive. For example, Jiang et al. [?] required 2 minutes per reference point and over 6 hours for the complete dataset.

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. [?] 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, trilateration 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, trilateration offers a stable and cost-effective approach that aligns well with the requirements of a museum environment.

2.3 Application in museums

Bluetooth Low Energy (BLE) has been extensively studied in relation to the unique layouts of museums. For instance, [?] utilizes BLE beacons as proximity sensors, while [?] 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, [?] 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.

Chapter 3

Methodology

3.1 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.

3.2 Considerations

3.2.1 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 [**?**, **?**].

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 [**?**].

3.2.2 Sustainability and energy efficiency

Sustainability is crucial for museums as they aim to minimize their environmental impact and meet the expectations of eco-conscious visitors. By adopting sustainable practices, museums enhance their reputation and contribute positively to their communities. This commitment extends to the technologies they employ, including IT-enhanced solutions like indoor localization.

Integrating technologies such as Bluetooth Low Energy (BLE) beacons aligns well with sustainability goals. BLE beacons are known for their energy efficiency, often functioning for months or years on a single battery or even designed to operate using solar cells [**?**], which reduces electronic waste and lowers the carbon footprint.

3.2.3 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 behavioral change, and supporting interdisciplinary research on sustainability and climate resilience.

As emphasized by the International Council of Museums (ICOM) [?], 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 fulfillment of the United Nations Sustainable Development Goals (SDGs) [?, ?].

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 [?].

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.

3.2.4 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-centered outcomes. Visitor engagement, perception of usefulness, and interface design remain underexplored dimensions.

For example, in [?], 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 behaviors as well as the popularity of the different areas are collected anonymously to assess both popularity and perceived added value.

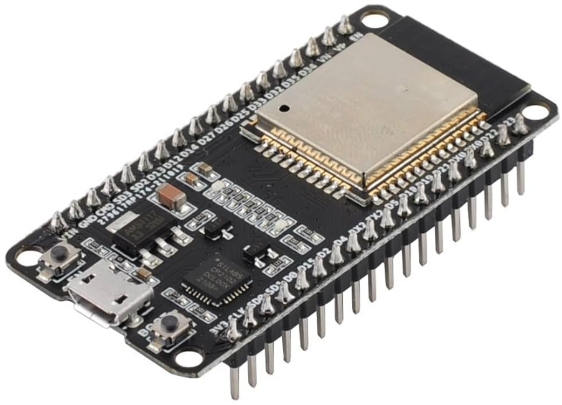

Figure 3.1: Photo of the ESP32

3.3 Experimental Setup

3.3.1 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.

3.3.2 Application Features and Localization Logic

The smartphone application provides a real-time graphical interface that visualizes the localization process, primarily for debugging and in-depth analysis. A map displays the static positions of the beacons, with each beacon represented by a circle corresponding to the estimated distance from the phone. Additionally, a dot indicates the estimated position of the smartphone, while crosses mark are the predefined points of interest.

Localization is based on RSSI-based triangulation. A phone is considered to be within a POI when it has been detected at least twice within a three-meter radius. Conversely, the phone is considered to have exited the POI if it is subsequently detected twice at a location beyond five meters. This difference between the entry and exit thresholds is implemented to prevent unstable state changes between being inside and outside a POI. 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.

3.4 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.

3.4.1 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 provided in Figure 3.2. 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.

3.4.2 Experiment 1: Localization Accuracy

The first experiment focus on the beacons data directly. It aims to calibrate the meta-parameters and analyzes 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 inteferences.

Figure 3.2: Photo of the 6th floor of Musée L

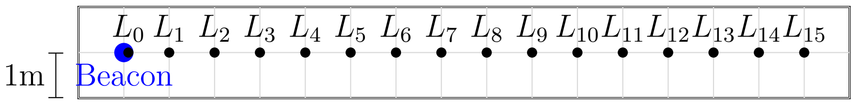

Figure 3.3: Experimental setup for the first experiment showing one beacon and all the references distances.

3.4.3 Experiment 2: Impact of museum layout

The second experiment focus on the impact of the museum layout on the results. It takes places directly inside the museum on the floor used for this experimentation. All the devices are on the floor, and the user keep the smartphone in hand, in front of him. The user follow the path across the 8 locations, following the order $L_0 \rightarrow L_1 \rightarrow \ldots \rightarrow L_8$. Only the data at the different locations are considered, so the path between them has no impact on the results. Points $L_{0,1,2,4,5,8}$ are inside the covered area while $L_{3,6,7}$ are outside of it, in order to analyze the behavior in this edge case. The direct Lines of Sight (LoS) are never guaranteed between the beacons and the phone.

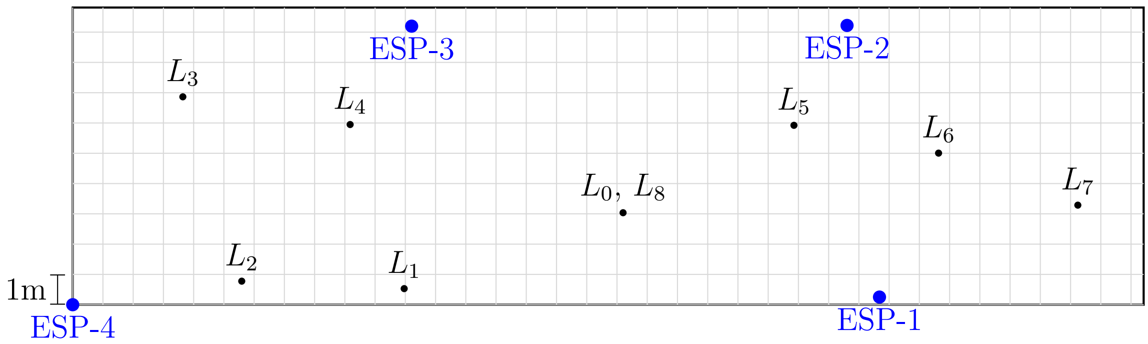

Figure 3.4: Experimental setup for the second experiment showing the beacons and some reference points.

3.4.4 Experiment 3: Detecting POI and providing meaningful data

The third experiment focus on the user experience within the exhibition. It has been chosen here to provide to the user two layers of information trough it's visit. First, an overview by section, to provide general information about the sections and their main art pieces, then the application provide the list of the art pieces of the section and close to the visitor, and he has to ability to chose to get more information on them by interacting with the application. This way, the visitor can follow the whole floor without having to interact with the application, but only by moving around areas, but can chose to move by it's own or to get more information on the sections he wants to.

The user follow the path across the 8 locations, following the order $L_0 \rightarrow L_1 \rightarrow \ ... \ \rightarrow L_8$. The user stay still for 20 seconds in each location, then move at a walk pace to the next one. The exact path is shown by dashed lines on the Figure 3.5. The exact time the visitor is detected in each area is recorded alongside the classical data.

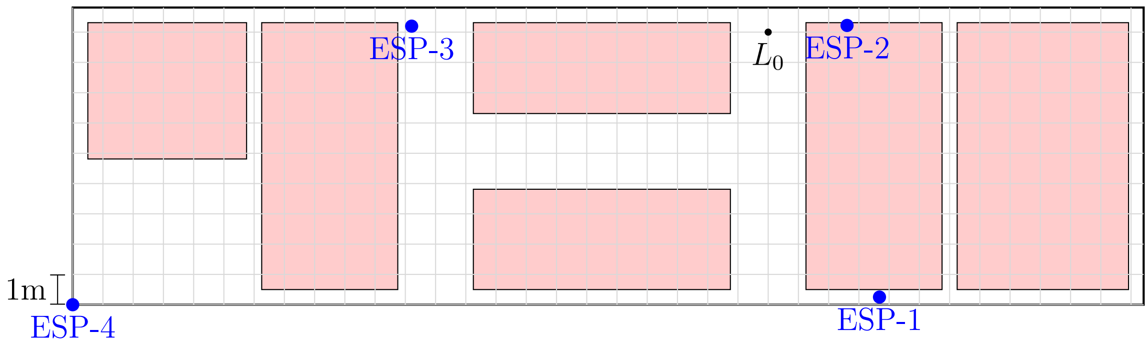

Figure 3.5: Experimental setup for the third experiment showing The beacons and the POI areas.

3.4.5 Experiment 4: Repeat with other phones

The fourth and last experiment aim to ensure the precision of the system with multiple other phones.

Chapter 4

Experimental Results

4.1 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.

4.1.1 RSSI at One Meter (tx_{power})

Results from the first experiment in subsection 3.4.2 are displayed in Figure 4.1. 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.

4.1.2 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 4.2 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),

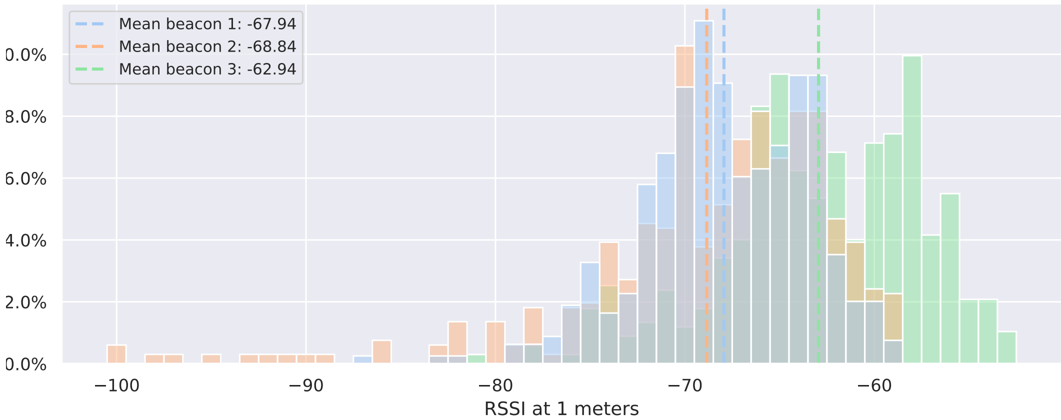

Figure 4.1: Experimental RSSI values at 1 meter

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.

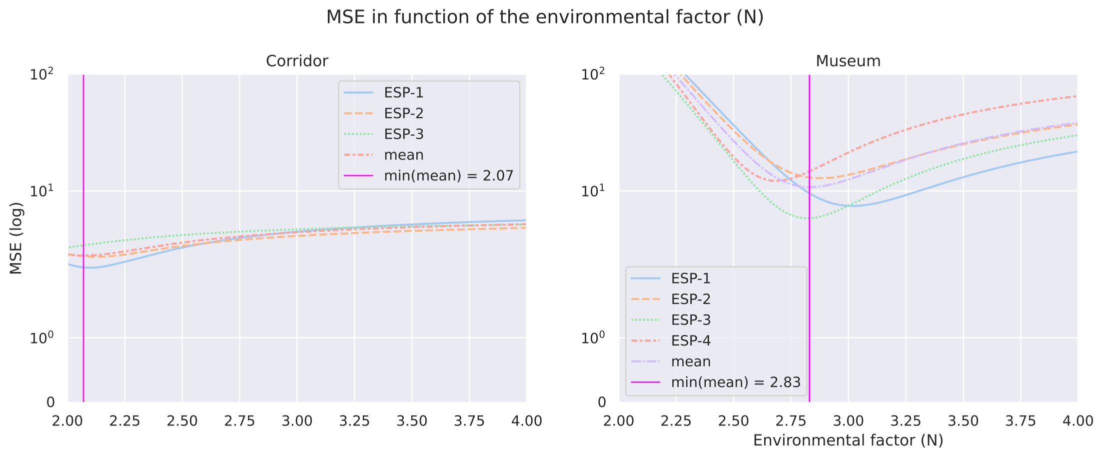

Figure 4.2: Comparison of environmental factors (N) in both test environments

4.1.3 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.

4.2 Distance to Beacons

Experimental data from Experiment 1, as shown in Figure 4.3, confirm the findings reported by [?], 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.

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 4.4, 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.

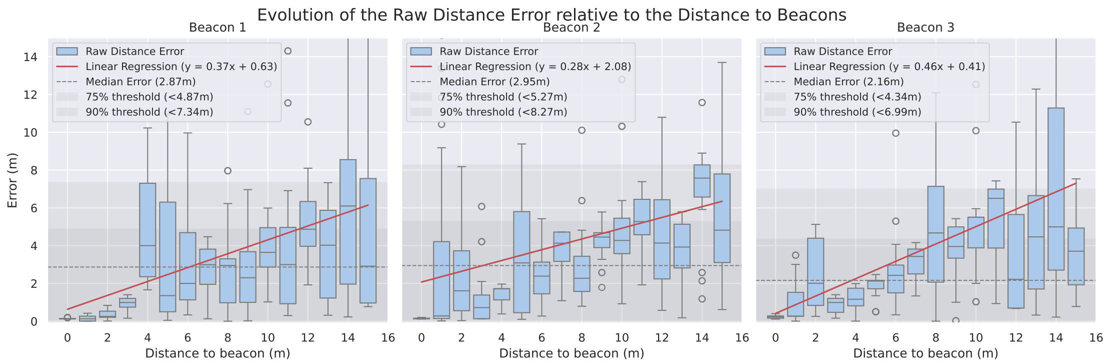

Figure 4.3: Raw distance error variation relative to distance from beacons

4.3 Trilateration precision

4.4 Area detection

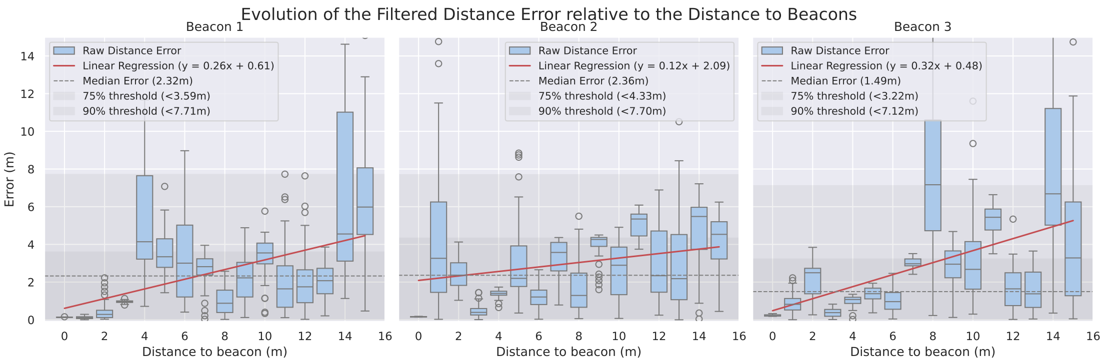

Figure 4.4: Filtered distance error variation relative to distance from beacons

Chapter 5

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.

5.1 Localization Accuracy and System Responsiveness

The localization accuracy of the system was evaluated within a single museum environment, yielding median errors of 1.5 to 2.5 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 the user 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 user or to improve the user experience due to inadequacy between system and most visitor expectations. **SOURCE NEEDED**.

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

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

5.3 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.

5.4 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.

5.5 Scalability and Management

The system was designed with scalability in mind, allowing for the potential expansion of the beacon fleet as needed. However, managing a large number of 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.

5.6 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.

5.7 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.

5.8 User Interaction Variability

The system was designed to predict and accommodate visitor behavior, 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 behaviors.

5.9 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 6

Conclusion and Future Work

6.1 Conclusion

This study explored the development and evaluation of an indoor localization system tailored for museum environments. The system demonstrated its potential to enhance visitor experiences by providing seamless navigation and contextual information through a mobile application. Key findings include the system's ability to achieve median localization errors of 1.5 to 2.5 meters, its energy-efficient design leveraging visitor smartphones and small beacons, and its compliance with privacy regulations through anonymized data collection. While challenges remain, such as signal obstructions in dense exhibit layouts and the need for scalable beacon management, the system represents a promising solution for museums seeking to integrate advanced technologies into their visitor engagement strategies.

6.2 Future Work

Future research could explore data fusion techniques to integrate information from multiple sources, such as Wi-Fi, cellular signals, and inertial sensors. This approach could significantly improve localization accuracy and robustness, particularly in environments with high signal interference or dense exhibits. By combining complementary data streams, the system could achieve more reliable and precise tracking.

Another promising direction is the adoption of Bluetooth 5.1's Angle of Arrival (AoA) and Angle of Departure (AoD) features. These technologies enable the use of directional information to enhance indoor positioning precision, reducing errors caused by signal reflections or obstructions. Implementing AoA/AoD could make the system more adaptable to the architectural complexities of museums, such as multi-room layouts or spaces with reflective surfaces.

Extending the system to support three-dimensional localization would further expand its applicability. This capability would allow for precise tracking in multi-floor museum environments, addressing a significant limitation of current two-dimensional approaches.

Finally, scalable beacon management and energy optimization strategies could enhance the system's feasibility for broader adoption. Developing centralized management platforms or exploring alternative hardware solutions, such as solar-powered beacons, could reduce operational challenges and improve sustainability. These future directions aim to address current limitations and unlock the system's full potential in museum settings.

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