(Article begins on next page)

Assessing Material Impacts in NLOS UWB Ranging Errors: Characterization for Museum Environments

1st Angeliki Makellaraki
Dept. of Environment, Land and Infrastructure Engineering
Politecnico di Torino, Turin, Italy
angeliki.makellaraki@polito.it

2nd Vincenzo Di Pietra
Dept. of Environment, Land and Infrastructure Engineering
Politecnico di Torino, Turin, Italy
vincenzo.dipietra@polito.it

3rd Paolo Dabove
Dept. of Environment, Land and Infrastructure Engineering
Politecnico di Torino, Turin, Italy
paolo.dabove@polito.it

***Abstract*—Museums, with their intricate layouts and diverse materials, present unique challenges for accurate indoor positioning, especially in environments rich with glass and other reflective surfaces. These materials can interfere with many positioning technologies, complicating efforts to track visitor movement accurately for insights into visitor behavior, exhibit engagement, and space utilization. Indoor positioning technologies have become essential for understanding movement and interaction within enclosed spaces, especially in environments like museums, where optimizing visitor experience and curators exhibit management are key priorities. While several technologies have been applied in museums, Ultra-wideband (UWB) positioning has emerged as a standout solution due to its high accuracy and resilience in complex indoor environments. This study exploits low-cost UWB positioning devices to track and analyze visitor behavior within a museum characterized by extensive glass and reflective surfaces. Through a comprehensive measurement campaign with volunteer participants visiting a real exhibition, real-time data on visitor trajectories, engagement patterns, and interactions with exhibits were collected. The UWB raw data, acquired from actual visitor movements, allows us to post-process them and propose solutions to overcome challenges posed by the glassy and crowded environment. The results show the capability of the algorithm to enable robust and reliable tracking even in challenging spatial configurations. The study's findings highlight patterns in visitor flow, high-engagement zones, and preferred pathways, offering insights into optimizing exhibit layout and visitor satisfaction. This research underscores the potential of UWB positioning to generate actionable, data-driven insights in museum environments, supporting informed decisions in crowd management, exhibit arrangement, and personalized visitor experiences.**

***Index Terms*—Ultra-wideband (UWB), Indoor Positioning, Non-Line-of-Sight (NLOS), Ranging Errors, Signal Attenuation, Museum Environments**

META-MUSEUM [101132488 – META-MUSEUM 'Moving Emotions towards confidence in the Transformative Appropriation for a Meaningful Understanding of cultural heritage: a neuroScientific approach to EUropean Museums' – HORIZON-CL2-2023-HERITAGE-01] funded by the European Union.

I. Introduction

Improving the museum experience is an important goal in order to make visits more engaging and meaningful for visitors. To achieve this, museums are adopting technologies such as Augmented Reality (AR), 3D imaging, and multi-touch screens [1], which enable more engaging and innovative interaction with exhibits. However, understanding visitor behavior is the first step in enhancing this experience, which requires accurately tracking visitors' positions within museum spaces. Such data are crucial for analyzing their emotional responses, understanding how they interact with the spatial layout of rooms, and evaluating the effectiveness of exhibits in communicating their intended messages.

Many museum exhibits are located in enclosed environments, where tracking the positions of people and objects requires specialized systems known as Indoor Positioning Systems (IPS). Unlike Global Navigation Satellite Systems (GNSS), which rely on satellite-based signals to estimate positions, GNSS is ineffective indoors due to signal attenuation and multipath effects caused by walls, glass, or other structural elements [2]. IPSs are specifically designed to overcome these challenges, utilizing a range of advanced technologies. Some of the core technologies used in IPS include Ultra-Wideband (UWB), Bluetooth Low Energy, Wi-Fi, and Radio Frequency Identification (RFID) ([3], [4]). Among indoor positioning solutions, UWB stands out as one of the most effective due to its high accuracy, reaching centimeter-level precision [5], resilience to interference (as it operates across a wide frequency spectrum), and low power consumption.

UWB systems typically consist of two key components: the anchors (base stations) and the tags (small portable devices). The anchors emit and receive UWB signals to calculate the distance between themselves and the mobile tags. The accuracy and robustness of the system improve as more anchors are added. Tags receive signals from the anchors, and in some cases, they may also transmit signals back to assist in determining their position. Position estimation techniques can vary, including Time of Flight (ToF), Time Difference of Arrival (TDOA), Angle of Arrival (AoA), Phase Difference of Arrival (PDoA), Two-Way Ranging (TWR), as well as methods like multilateration, trilateration, and triangulation [3]. UWB is a real-time location system (RTLS), and it has gained significant attention across various domains such as manufacturing, healthcare, warehouses [6], and consumer applications, including smartwatches and smart home devices.

To better understand how UWB systems operate in indoor environments, we need to examine the conditions that affect signal propagation and accuracy. When a signal is emitted, there are two conditions to describe the path of the signal: the Line-Of-Sight (LOS) condition and the Non-Line-Of-Sight (NLOS) condition. Under LOS conditions, the signal travels directly to the receiver without interference. In NLOS scenarios, however, obstacles attenuate the signal, leading to inaccuracies in distance estimations [7]. This multipath effect is quite complex and varies significantly with material properties. Prior research has explored UWB performance in obstructed environments, offering insights into its behavior under such conditions [8]–[11]. Reference [12] provides an additional study on the characteristics of UWB signal propagation through various building materials, emphasizing the delay and attenuation effects observed.

This study evaluates the performance of a low-cost commercial UWB system in two distinct enclosed environments. In the first case study, the UWB device is used to quantify the effects of five common materials, plexiglass, wood, concrete, glass, and the human body, on signal propagation and ranging accuracy. A statistical analysis is conducted to characterize signal attenuation and estimate errors in range calculations, while also exploring potential correlations between distance, power, error estimation, and material type. The second case study examines the UWB system's accuracy in a real-case museum setting, where visitors move dynamically within the room. This experiment assesses the system's ability to track positions under kinematic conditions using only the filtering methods provided by the device's algorithm. The presence of glass exhibits introduces challenges such as multipath effects, making this an ideal scenario to evaluate the system's performance in realistic conditions.

II. Methods

Radiofrequency signal transmission typically requires a clear LOS between the transmitter and receiver to achieve accurate and precise time measurements, which are essential for range estimation. UWB positioning technology has garnered significant attention due to its capability to maintain high precision even in NLOS conditions. This is attributed to UWB's ability to penetrate various materials, including walls, making it a robust solution for indoor localization and positioning applications.

Understanding the ability of UWB signals to penetrate obstacles and analyzing signal obstruction caused by different materials are fundamental to developing compensation and correction algorithms for NLOS conditions. Our approach is centered on the statistical characterization of ranging errors and their dependence on key variables such as material properties, transmission distances, and received power levels. By systematically investigating these factors, we aim to enhance the accuracy of UWB-based localization systems in obstructed environments.

The proposed methodology is based on a well-structured testing framework conducted in a controlled environment, as described in detail in Section III-A. The primary objective of these experiments is to assess the impact of obstacles on UWB two-way ranging (TWR) measurements and develop an empirical correction model to mitigate range estimation errors in NLOS scenarios.

Additionally, the secondary objective of this study is to classify the type of material obstructing the UWB signals. Materials can be broadly categorized as insulators and conductors. Insulating materials such as wood, plastic, and glass exhibit high transparency to radio signals, resulting in minimal signal attenuation. Conversely, conductive materials such as metals and liquids significantly attenuate and distort UWB signals, leading to reduced accuracy and increased ranging errors. The properties of these materials influence penetration loss, signal reflections, and propagation speed, all of which directly impact the precision of UWB-based distance measurements. This study systematically examines these effects in a controlled experimental setup and presents a methodology for correcting NLOS-induced range errors.

A. *Experimental setup*

The experiment employed a controlled setup with a UWB transceiver pair operating in TWR mode. Measurements were conducted under both LOS and NLOS scenarios to capture the effect of different materials on signal strength and range errors. The setup consisted of a set of fixed reference distances between the transmitter and receiver. A schematic representation of the test configuration for each distance is shown in Figure 1. The distance between the material and the tag was kept constant at 0.5 m throughout all the experiments. Various materials, including glass, wood, and concrete, were introduced into the signal path to assess their impact on signal attenuation. Each material was tested using multiple samples to minimize random variations and ensure statistical robustness. The received signal strength (RSSI) and computed range estimates were recorded in decibels per milliwatt (dBm) and millimeters, respectively.

B. *Problem Definition and Data Processing*

This study aims to predict the range error in UWB measurements by analyzing the influence of material properties, distance, and received power under NLOS conditions. The range error is defined as the deviation between the estimated and actual distance, influenced by signal attenuation and multipath effects. In the proposed test, the range error (Δd) is given by:

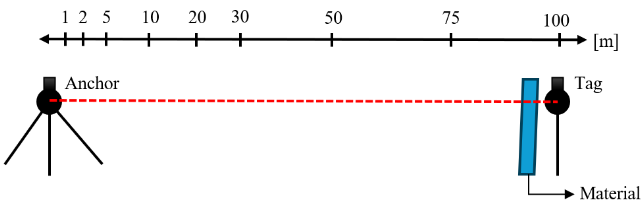

Fig. 1. Schematic representation of the UWB test setup.

$$\Delta d = d_{\text{meas}} - d_{\text{true}}, \tag{1}$$

where d_{meas} represents the estimated distance provided by the UWB transceiver, and d_{true} is the known reference distance.

To characterize the material impact on UWB signals, we first computed penetration loss, which measures the attenuation caused by different materials. The Penetration loss (PL) it is defined as the attenuation in signal strength caused by the material through which the signal propagates. For each material and distance test, we computed the mean received power as:

$$\overline{P}_{no-material} = \frac{1}{N}\sum_{i=1}^{N} P_{no-material,i} \tag{2}$$

$$\overline{P}_{material} = \frac{1}{M}\sum_{j=1}^{M} P_{material,j} \tag{3}$$

where:

- $\overline{P}_{\text{no-material}}$ is the mean received power measured in free-space conditions,
- $\overline{P}_{\text{material}}$ is the mean received power measured when the signal propagates through the material.

The penetration loss for each material was computed finally as:

$$PL_{\text{material}} = \overline{P}_{\text{no-material}} - \overline{P}_{\text{material}}, \tag{4}$$

The dataset was preprocessed to extract key predictive features:

- **Material Type** (Encoded as a categorical variable)
- **Distance (Range)** – The spatial separation between UWB transceivers
- **Received Power in NLOS Conditions** – Indicator of signal strength degradation
- **Penetration Loss** – Measures material-induced attenuation

C. Exploratory Statistical Analysis

Before selecting a predictive model, it is essential to understand the statistical properties of the range error distribution, which was initially unknown. Many standard regression techniques assume that errors follow a normal distribution. To verify these assumptions, we performed the Shapiro-Wilk (SW) test to assess normality.

If the range error was found to follow a Gaussian distribution, parametric models (e.g., linear regression) could be considered. However, if the test results indicated non-normality, alternative methods such as robust regression or non-parametric models would be evaluated.

D. Prediction Models

To establish a predictive model for range error correction, we initially considered parametric regression approaches:

- **Linear Regression**:

  $$\Delta d_{\text{predicted}} = \beta_0 + \beta_1 \cdot \text{PL} \tag{5}$$

  where β_0 and β_1 are regression coefficients estimated using the least-squares approach [13].
- **Polynomial Regression**:

  $$\Delta d_{\text{predicted}} = \beta_0 + \beta_1 \cdot \text{PL} + \beta_2 \cdot \text{PL}^2 \tag{6}$$

  to account for potential non-linear dependencies between Penetration Loss (PL) and range errors.

In case of error deviation from Gaussianity, a Random Forest Regression model is proposed. Random Forest is a non-linear approach capable of capturing complex feature interactions and handling non-Gaussian distributions effectively [14].

To ensure model generalization, the dataset was randomly split into 80% training data and 20% test data. The model was trained using the selected features and evaluated based on:

- **Mean Absolute Error (MAE)** – Measures the average magnitude of prediction errors.
- **Root Mean Squared Error (RMSE)** – Evaluates overall error magnitude with emphasis on large deviations.

Additionally, we performed:

- **Actual vs. Predicted Error Analysis** – To visually assess model accuracy.

III. Case Studies

To achieve the goals of this paper, two distinct case studies were conducted. The first focused on a controlled environment, aiming to determine whether correlations exist between measured distances, materials, power, and errors. In this context, the objective was to estimate a mathematical function that could be used to correct the measured ranges in a real-case scenario, which is explored in the second case study.

A. First Case Study

In this section, we describe the setup and methodology of the first experiment. The primary objective of this study is to analyze the impact of material obstruction on signal attenuation and ranging accuracy at varying distances.

1) Test Setup: The test was conducted in a long corridor at Politecnico di Torino, Italy, a controlled environment chosen to minimize external interference. The experiment setup involved placing a single UWB anchor at a fixed position and measuring the signal received by a UWB tag positioned at predefined distances: 1 m, 2 m, 5 m, 10 m, 20 m, 30 m, 50 m, 75 m, and 100 m. To evaluate the effect of material obstruction, five different materials, Figure 2, were individually placed between the anchor and the tag at a fixed distance of 0.5 m from the tag. The selected materials were chosen to reflect common elements found in a museum environment:

- Plexiglass – commonly used in museum display cases.
- Wood – representing structural or decorative elements.
- Glass – simulating museum display cases.
- Concrete – representing walls and barriers in indoor spaces.
- Human body – accounting for visitor interference.

Additionally, a measurement was conducted without any obstructing material to provide a reference for comparison.

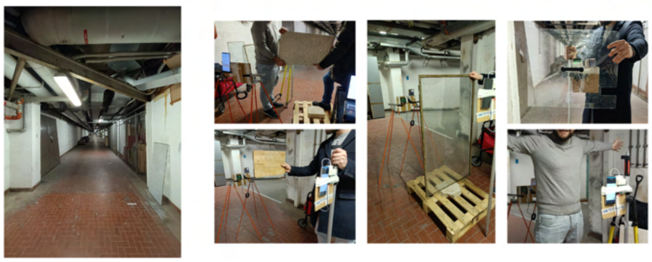

Fig. 2. The left image shows the corridor used for the acquisition, while the images on the right illustrate the five different materials tested for the experiment.

2) Hardware and Tools: The range values were acquired using the cost-effective commercial device Pozyx®, "Ready to Localize" development kit. This system consists of a network of radio frequency modules operating at 500 MHz, which allows centimetric-level precision [5]. The system was configured to use channel 5 (6.48 GHz bandwidth, 500 MHz wide) and relied on the TWR technique for range estimation. The key specifications of the device are detailed in Table I. For the experiment, we used a single UWB anchor and one UWB tag. The anchor was securely mounted on a tripod to ensure stability during the tests, while the UWB tag was attached to a pole, which functioned as a rover. This setup is illustrated in Figure 3.

Data acquisition was managed via a Python script provided by Pozyx®, which continuously recorded the range data during each experiment. Each test was conducted under static conditions for 2 minutes per material, ensuring sufficient data collection at each distance. To validate the positioning accuracy of the UWB system, it was necessary to establish a reference trajectory, commonly known as the ground truth, that is more accurate than the solution being evaluated. In our study, a laser distance device was used to measure the actual distance at the beginning of each test.

B. Second Case Study

In this section, we analyze the setup and methodology of the second experiment, which aims to evaluate the performance of the UWB device in a real-case indoor environment, a museum room. The primary objective of this study was to individually track the positions of seven visitors and assess the system's accuracy in a space filled with exhibit cases made of glass. Glass surfaces are known to affect UWB signal

TABLE I
SPECIFICATIONS OF THE POZYX® SYSTEM

Feature	Pozyx® Specification
Size	60 × 53 mm
Weight	12 grams
Band	3.5–6.5 GHz
Power	-41 dBm/MHz
Antenna	Onboard DW1000
Ranging	IR-UWB TWR
Rate	80 Hz

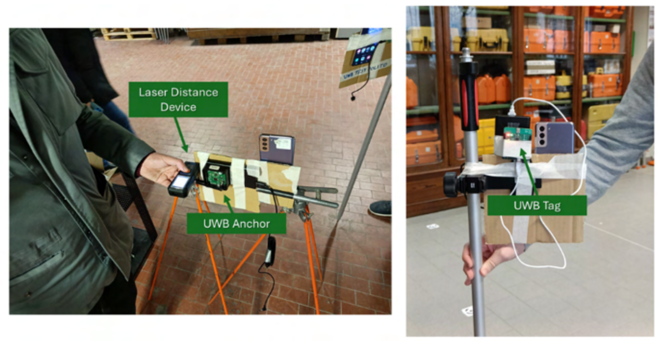

Fig. 3. Laser distance device used for ground truth measurements alongside the UWB anchor. The image on the right illustrates the mounted tag used for data acquisition.

propagation due to their reflective and refractive properties, making this scenario an excellent opportunity to test the device's performance in a practical, real-life setting, Figure 4.

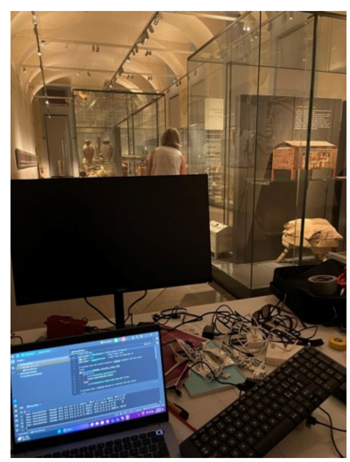

Fig. 4. Setup during the museum experiment: PCs used for real-time data acquisition.

1) Test Setup and Hardware: The test was conducted in a museum in Turin, Italy, within a room measuring approximately 30 m × 9 m, Figure 5. Within the room, there were installed 10 UWB anchors in strategic positions in order to ensure optimal coverage and minimize obstruction from exhibit cases, maintaining LOS conditions wherever possible. The room mostly contained glass surfaces, commonly found in exhibit cases, which introduced realistic multipath challenges due to signal attenuation and reflections from these materials. The participants have been given an UWB tag in their hand throughout the test that emitted signals to the anchors. To simplify data acquisition, each participant was tested individually, resulting in separate files for each of them containing range measurements, signal power, and x, y, and z coordinates.

As in the previous case study, we utilized the same low-cost commercial device, Pozyx®, configured with a Python-based script provided by the manufacturer. This script enabled real-time data collection and ensured consistent acquisition settings across the experiment. The position estimation was carried out using the same TWR technique as in the first case study.

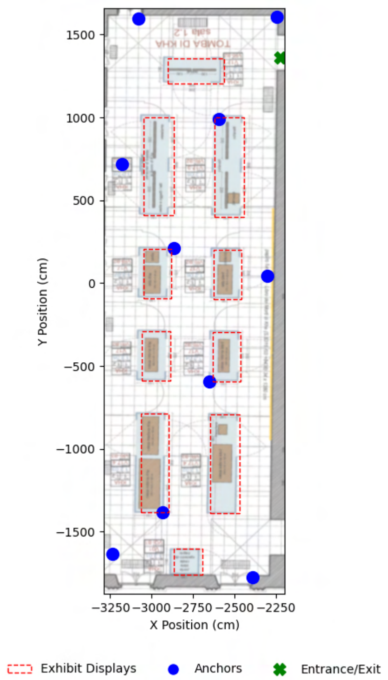

Fig. 5. Museum Room Layout

IV. Results

In this section, we describe the main analyses and results obtained considering the two test setups and data analyses made in this work.

A. Controlled environment test

1) Computation of Range Errors: To ensure that the analysis was based on stable data, we first pre-processed the dataset by removing the initial two seconds and the final two seconds of each acquisition period. This filtering step eliminated transient effects that might have skewed the results. Following the data filtering, we generated the error distributions for each material by comparing the UWB-measured distances with the corresponding ground truth values obtained from a laser distance device. To quantify the central tendency and dispersion of the error data, we utilized the Interquartile Range (IQR) method to compute both the mean error and the standard deviation. Figure 6 illustrates the error distributions under both LOS and NLOS conditions (Glass and Human Body). In certain cases, such as Glass at 100 m, and Human Body at 75 m and 100 m, the UWB device experienced significant measurement difficulties. Consequently, a large number of measurement errors were observed, leading to an insufficient amount of reliable data for the analysis. These tests were considered unsuccessful and were excluded from our study. For all the other valid observations, the normality check was performed by applying the Shapiro-Wilk (SW) test, which is common for small samples like in UWB ranging. As shown in Table II, all p-values are extremely small ($p < 0.05$), meaning all tests reject the null hypothesis that errors follow a normal distribution. In particular, it is possible to notice that also LOS measurements in case of no materials are not normally distributed. This deviation from normality suggests that parametric statistical models assuming Gaussian-distributed errors, such as Ordinary Least Squares (OLS) regression, may not be the most suitable approach for modeling the UWB ranging errors.

Instead, alternative approaches should be considered to better capture the underlying statistical properties of the data. Non-parametric methods, such as quantile regression or robust statistical estimators, could provide more reliable error correction models. Additionally, machine learning techniques, such as decision trees or neural networks, may be explored to model the complex relationships between range errors, material types, and received signal strength.

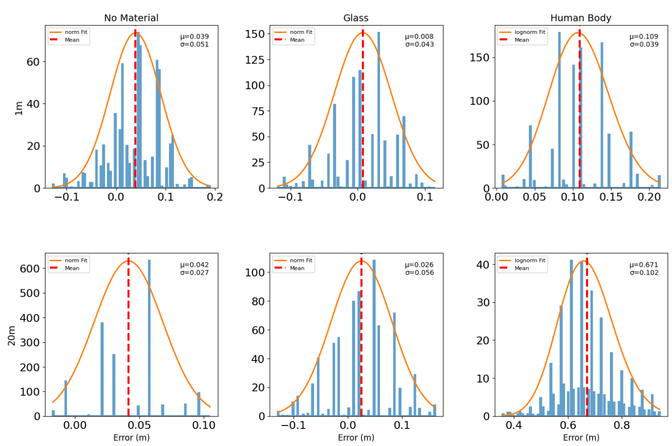

Fig. 6. Error distribution across all the materials.

TABLE II
Shapiro-Wilk Test Results for Different Materials

Material	Statistic	p-value
No Material	0.971951	1.106893e-29
Plexiglass	0.983311	1.892194e-21
Wood	0.986873	4.039059e-19
Glass	0.980028	8.628346e-11
Concrete	0.986879	2.941006e-11
Human Body	0.966726	8.739188e-81

In the next step of the analysis, the mean absolute error (MAE) and the root mean squared error (RMSE) are evaluated.

These metrics were calculated for each tested distance and for each material, providing an evaluation of the UWB system's accuracy. As illustrated in Figure 7, there was a noticeable increase in error values at the 50 m distance compared to other distances. Additionally, the number of valid measurements, those without error in estimations, decreased at this distance, demonstrating a poorer performance of the device.

Table III highlights materials that performed better, showing low MAE and RMSE values, while Table IV identifies those with the highest errors. In particular, the "Human Body" material caused the most significant disturbance in signal propagation.

TABLE III
SMALLEST MAE AND RMSE VALUES ACROSS MATERIALS FOR DIFFERENT TEST DISTANCES.

Test Distance	MAE Material	RMSE Material
1m	Glass	Glass
2m	Plexiglass	No Material
5m	Concrete	Concrete
10m	No Material	No Material
20m	Wood	No Material
30m	Glass	Glass
50m	Wood	Wood
75m	Glass	Glass
100m	No Material	No Material

TABLE IV
HIGHEST MAE AND RMSE VALUES ACROSS MATERIALS FOR DIFFERENT TEST DISTANCES.

Test Distance	MAE Material	RMSE Material
1m	Human Body	Human Body
2m	Human Body	Human Body
5m	Human Body	Human Body
10m	Human Body	Human Body
20m	Human Body	Human Body
30m	Wood	Wood
50m	Human Body	Human Body
75m	No Material	No Material
100m	Concrete	Concrete

Figure 8 presents the error box plots for each material in the distances tested, providing an overview of the precision and accuracy of the UWB system. For shorter distances, most of the materials exhibit smaller error distributions with medians closer to zero, indicating both high precision and accuracy. The "Human Body" material introduces more significant errors and variability, with the error box deviating significantly from zero, especially at 2m, indicating low precision. In the case of medium distances, materials like Glass and Concrete show relatively stable distributions, but the Human Body continues to cause larger deviations and less consistent results. At 50 m, the "Human Body" material stands out for producing significantly higher errors compared to the other materials. Since the estimated ranges for this material resulted in errors at longer distances, the tests involving the Human Body were concluded at 50 m.

Previous analyses have demonstrated the impact of different materials on range measurement errors. However, two additional factors that strongly influence these errors are the relative distance between the transmitter and receiver and the received signal strength.

Regarding distance, Figure 9 illustrates the mean range error across different distance steps for all tested materials. While most materials exhibit relatively low errors across all distances, the "Human Body" material shows a significant error drop at 50 meters, with almost no recorded measurements beyond this point.

If range errors were purely dependent on distance, we would expect a steady increase in error as distance increases. However, the plot reveals fluctuations, suggesting that range errors are influenced by additional factors beyond distance alone.

From Figure 10, it is possible to analyze the dependency between range errors and received signal strength. There is a weak negative correlation between RSSI and error variance, meaning that weaker signals cause larger errors. Again, no steady relation is visible, and all the materials show several fluctuations around the zero.

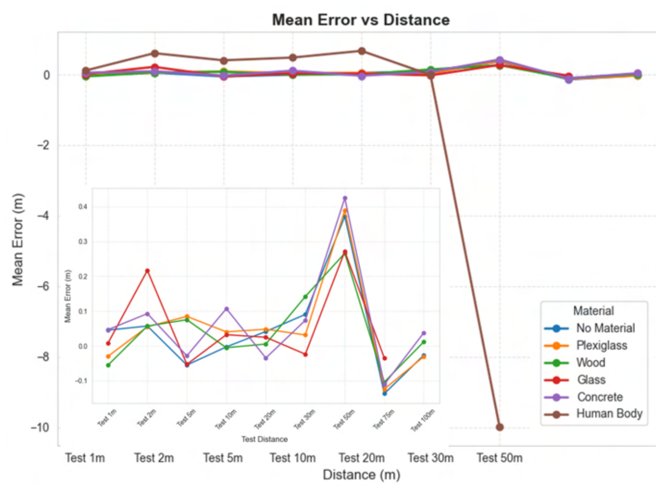

Fig. 9. Mean Range Error Across Different Distances for Various Materials

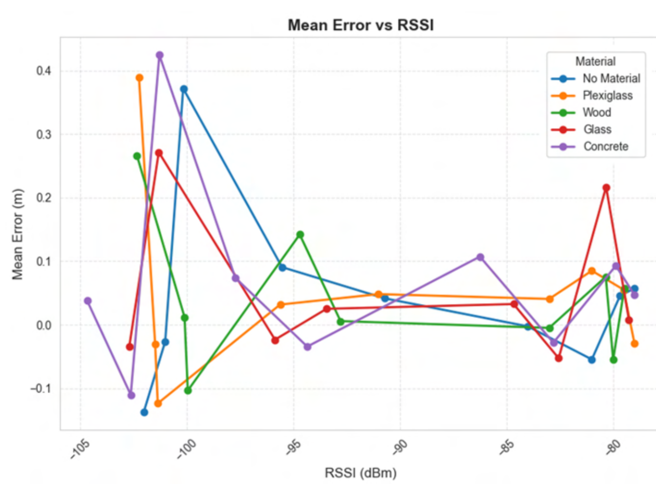

Fig. 10. Mean Range Error for Various Materials vs RSSI

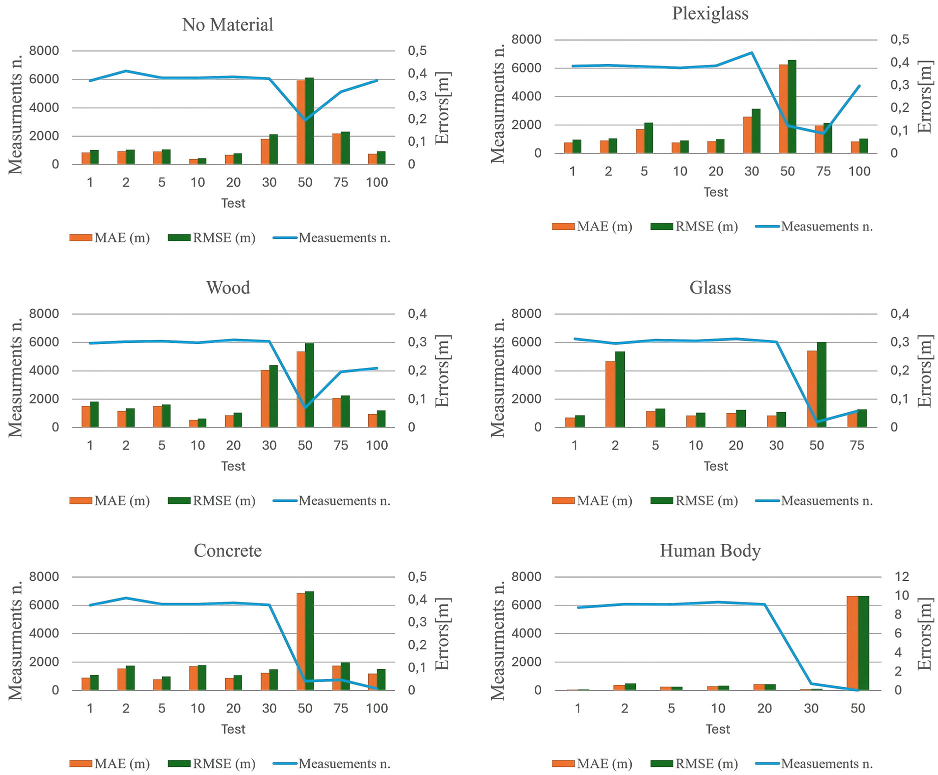

Fig. 7. Graphs with MAE, RMSE values and the number of processed valid measurements.

2) Penetration Loss: The penetration loss analysis of different materials was performed by comparing the received signal power in an LOS scenario with NLOS scenarios. The results indicate that different materials exhibit distinct penetration loss characteristics, which allowed for clustering based on their attenuation properties. Using K-Means clustering, materials were grouped into three distinct clusters based on their average penetration loss. The clustering results suggest the following trends:

- **Cluster 0 (Low Penetration Loss)**: This cluster includes materials such as *Plexiglass* and *Wood*, which exhibit the least attenuation. These materials are more transparent to radio waves, making them suitable for environments where minimal signal degradation is desired.
- **Cluster 1 (Moderate Penetration Loss)**: This cluster consists of materials like *Glass* and *Human Body*, which introduce moderate attenuation. Glass is often found in buildings and vehicles, and its moderate penetration loss suggests that radio signals can still propagate through it, though with some reduction in power.
- **Cluster 2 (High Penetration Loss)**: *Concrete* was placed in this cluster, indicating the highest attenuation among the tested materials. This is expected, as concrete is known to significantly weaken radio signals, making it a critical factor in indoor communication environments.

The findings from the controlled environment experiment provide critical insights into how different materials affect UWB signal propagation, particularly in NLOS conditions. Given that materials such as concrete and glass introduce significant attenuation and multipath effects, their impact extends beyond static range error measurements to real-world tracking scenarios.

TABLE V
MATERIAL CLUSTERING BASED ON PENETRATION LOSS

Material	Penetration_Loss [dBm]	Cluster
Concrete	0.95	2
Glass	0.70	1
Human Body	0.64	1
Plexiglass	0.32	0
Wood	0.28	0

In a museum environment, where exhibit cases, walls, and human presence create a complex propagation medium, understanding material-induced signal degradation is essential for improving positioning accuracy. The second case study applies the knowledge gained from material penetration analysis to evaluate UWB-based visitor tracking in a museum setting, where these signal distortions are naturally present. By correlating positioning errors with material presence and multipath effects, this study aims to assess the feasibility of using UWB technology for real-time visitor monitoring in environments with reflective surfaces and obstacles.

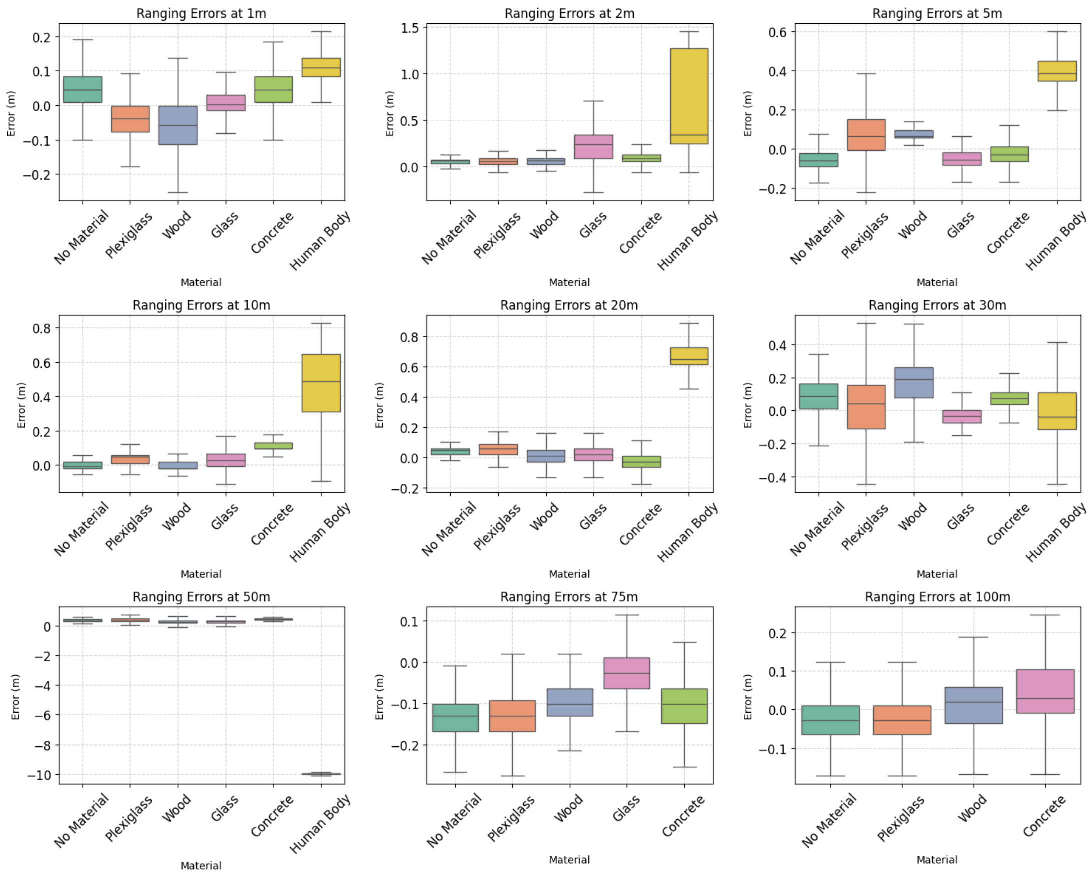

Fig. 8. Box Plot of error distributions across all distances and materials.

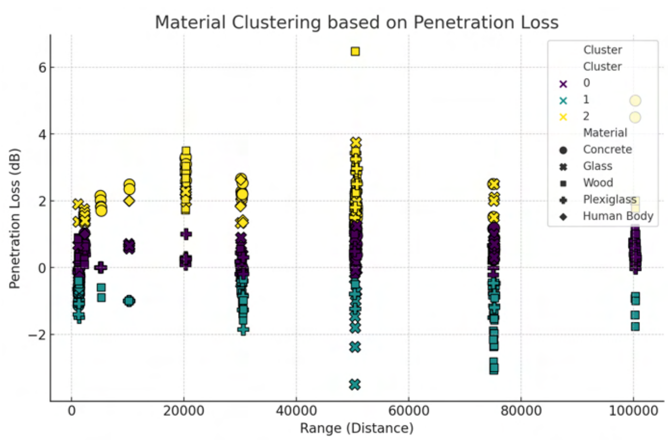

Fig. 11. Penetration Loss at different distances and materials clusterization.

B. Model Performance

The Random Forest Regression model demonstrated strong predictive capability in estimating range errors. The final performance metrics obtained were:

- **MAE:** 0.0117
- **RMSE:** 0.0367

These values indicate that the model provides highly accurate predictions of UWB range errors, reinforcing the suitability of non-linear approaches for NLOS error correction.

Figure 12 presents the scatter plot of actual vs. predicted range errors. The alignment of points along the ideal $y = x$ line suggests that the model successfully captures the underlying data distribution.

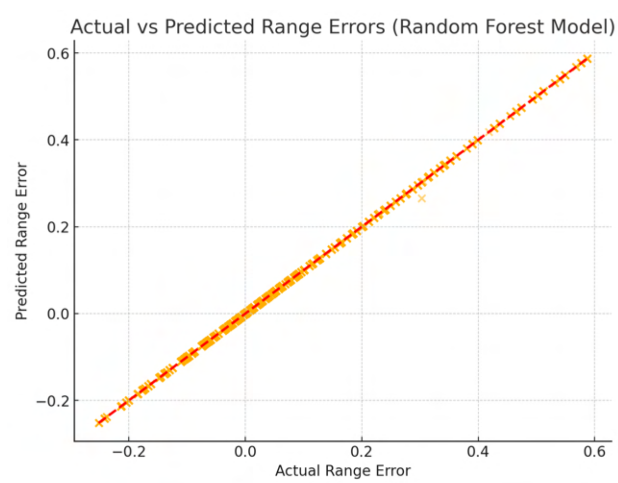

Fig. 12. Actual vs. Predicted Range Errors

C. Second case study

The position estimations obtained during the museum experiment provided a first overview of the trajectories followed by each participant. These estimations were recorded without any post-processing or additional data filtering, so they reflect the raw output from the UWB device. Figure 13 illustrates the estimated coordinates of three different participants. It is evident that there are moments where the estimated positions fall within the exhibit cases or even outside the area of the room, highlighting the system's limitations in accuracy. These infeasible solutions are likely the result of multipath effects caused by reflections from glass surfaces or even the participants' bodies, leading to incorrect range calculations.

Given that it wasn't possible to obtain a correlation between range values and materials, the estimations from the museum environment could not be improved. The discrepancies observed in this case demonstrate the need for future advancements to address the limitations of current indoor positioning systems. A future work will involve the development of a dedicated positioning algorithm capable of mitigating multipath effects by accounting for the types of materials present in the environment.

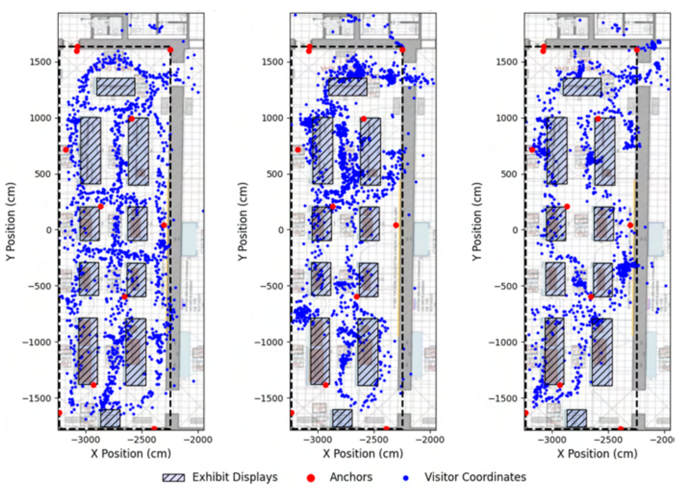

Fig. 13. Estimated coordinates of three different visitors.

V. Conclusions

This study aimed to evaluate the performance of a low-cost UWB device in two case studies: in a controlled environment and in a real museum setting. In the controlled environment, the experiment focused on understanding the impact of material type and distance on the UWB signal propagation. To address this, the ranging error distribution has been analyzed for each material used in the controlled environment. Both the visual plot and SW test show that UWB ranging errors deviate from the normality condition. Given these findings, the choice of correction model should take into account the skewed and heavy-tailed nature of the error distribution, which can impact the accuracy of positioning corrections in real-world applications. Future research should further investigate how different distribution-based models compare in reducing UWB-ranging errors in NLOS conditions. The analysis of Penetration Loss performed on the measurements acquired during the controlled environment test provided the following considerations:

- Buildings with high concrete content will require signal repeaters or alternative transmission strategies to maintain network performance.
- Materials in Cluster 1 (such as glass) can allow partial signal transmission, making them a viable medium for certain propagation paths.
- Materials in Cluster 0 are favorable for radio signal propagation and should be preferred in environments where high signal penetration is required.

This study has successfully categorized materials based on their penetration loss characteristics using clustering techniques. The results provide valuable information for UWB signal interaction behavior with the most common materials present in museum environments. In this regard, future studies can extend this analysis by incorporating more materials and different frequencies to understand frequency-dependent penetration losses. Additionally, testing in real-world environments with varying humidity and temperature conditions can provide a more comprehensive understanding of signal attenuation characteristics.

Acknowledgment

This paper is part of the research conducted in the framework of META-MUSEUM [101132488 – META-MUSEUM 'Moving Emotions towards confidence in the Transformative Appropriation for a Meaningful Understanding of cultural heritage: a neuroScientific approach to EUropean Museums' – HORIZON-CL2-2023-HERITAGE-01] funded by the European Union. Views and opinions expressed are however those of the authors and do not necessarily reflect those of the European Union or European Research Executive Agency (REA). Neither the European Union nor the granting authority can be held responsible for them.

References

[1] G. Karayılanoğlu and B. C. Arabacıoğlu, "Digital interactive experiences in contemporary art museums," *Turkish Online Journal of Design Art and Communication*, vol. 10, no. 4, pp. 423–440, 2020, Deniz YENGİN.

[2] P. Pascacio, S. Casteleyn, J. Torres-Sospedra, E. S. Lohan, and J. Nurmi, "Collaborative indoor positioning systems: A systematic review," *Sensors*, vol. 21, no. 3, pp. 1002, 2021, MDPI.

[3] M. F. R. Al-Okby, S. Junginger, T. Roddelkopf, and K. Thurow, "UWB-Based Real-Time Indoor Positioning Systems: A Comprehensive Review," *Applied Sciences*, vol. 14, no. 23, article 11005, 2024. DOI: 10.3390/app142311005.

[4] V. Minucciani, M. Benente, P. Dabove, et al., "Technology as a tool to study visitor behaviour in museums: positioning and neuropsychological detection to identify physical & cognitive barriers," in *Design for Inclusion. Proceedings of the 14th International Conference on Applied Human Factors and Ergonomics (AHFE 2023) and the Affiliated Conferences*, vol. 75, pp. 114–121, 2023, AHFE.

[5] V. Di Pietra, P. Dabove, M. Piras, A. Lingua, et al., "Evaluation of positioning and ranging errors for UWB indoor applications," in *IPIN (Short Papers/Work-in-Progress Papers)*, pp. 227–234, 2019.

[6] D. Gnaś, D. Majerek, M. Styła, P. Adamkiewicz, S. Skowron, M. Sak-Skowron, O. Ivashko, J. Stokłosa, and R. Pietrzyk, "Enhanced Indoor Positioning System Using Ultra-Wideband Technology and Machine Learning Algorithms for Energy-Efficient Warehouse Management," *Energies*, vol. 17, no. 16, article 4125, 2024. DOI: 10.3390/en17164125.

[7] F. Che, Q. Z. Ahmed, P. I. Lazaridis, P. Sureephong, and T. Alade, "Indoor Positioning System (IPS) Using Ultra-Wide Bandwidth (UWB)—For Industrial Internet of Things (IIoT)," *Sensors*, vol. 23, no. 12, article 5710, 2023. DOI: 10.3390/s23125710.

[8] D. Uzunidis, P. Kasnesis, E. Margaritis, M. Feidakis, C. Z. Patrikakis, and S. A. Mitilineos, "Real-Time Human Detection Behind Obstacles Based on a low-cost UWB Radar Sensor," in *2022 IEEE 8th World Forum on Internet of Things (WF-IoT)*, pp. 1–6, 2022. DOI: 10.1109/WF-IoT54382.2022.10152170.

[9] D. Uzunidis, E. Margaritis, C. Chatzigeorgiou, C. Z. Patrikakis, and S. A. Mitilineos, "A Dataset for Aftermath Victim Detection Behind Walls or Obstacles Using an UWB Radar Sensor," in *2023 12th International Conference on Modern Circuits and Systems Technologies (MOCAST)*, pp. 1–5, 2023. DOI: 10.1109/MOCAST57943.2023.10176448.

[10] H. Bardareh and O. Moselhi, "An Integrated RFID–UWB Method for Indoor Localization of Materials in Construction," *Journal of Information Technology in Construction*, vol. 27, 2022.

[11] M. Dong, Y. Qi, X. Wang, and Y. Liu, "A Non-Line-of-Sight Mitigation Method for Indoor Ultra-Wideband Localization With Multiple Walls," *IEEE Transactions on Industrial Informatics*, vol. 19, no. 7, pp. 8183–8195, 2023. DOI: 10.1109/TII.2022.3217533.

[12] P. Jaturatussanai, M. Chamchoy, and S. Promwong, "Characteristics of UWB propagation through building materials," in *IEEE International Symposium on Communications and Information Technology, 2005 (ISCIT 2005)*, vol. 2, pp. 987–990, 2005. DOI: 10.1109/ISCIT.2005.1567033.

[13] G. James, D. Witten, T. Hastie, R. Tibshirani, and J. Taylor, "Linear regression," in *An Introduction to Statistical Learning: With Applications in Python*. Springer, 2023, pp. 69–134.

[14] S. Adusumilli, D. Bhatt, H. Wang, P. Bhattacharya, and V. Devabhaktuni, "A low-cost INS/GPS integration methodology based on random forest regression," *Expert Syst. Appl.*, vol. 40, no. 11, pp. 4653–4659, 2013. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0957417413001164. [Accessed: Feb. 19, 2025].