Graph-Based Semantic Indoor Localization Using Ultra-wide Band

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Abstract. This work presents an indoor localization system based on Ultra-Wide Band technology, enhanced with a semantic inference layer through graph-based modeling. These systems, focused on the person using them, have high applicability in the context of the Internet of Things and the Internet of Everything, as they provide not only precise location but also contextual information through reliable room identification. The proposed methodology models the monitored space as an undirected graph, where the nodes represent rooms defined by bounding boxes, and the edges indicate physically valid transitions. This improves spatial coherence and reduces erroneous room changes. The solution was validated in the SmartLab of the University of Jaén, achieving a 94.08% accuracy in room classification compared to the classic algorithm, while maintaining real-time performance on low-cost hardware. The results confirm its potential as a robust, scalable, and context-aware localization layer for intelligent environments.

Keywords: Internet of Everything · Indoor Location · Ultra-Wide Band · Graph-Based Modeling

1 Introduction

Indoor positioning is a growing and evolving field of research, with an increasing impact on applications linked to the Internet of Everything (IoE). In these environments, Indoor Positioning Systems (IPS) are essential, as they allow integrating sensory information related to people and connecting it with their immediate context. This interconnection capability is key for user-centered smart systems, especially when accurate real-time location data is required [1].

In contrast to Global Navigation Satellite Systems (GNSS) such as GPS, GLONASS, Galileo or BeiDou, which typically have an outdoor accuracy between 2 and 6 m, IPS employ alternative technologies capable of providing

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higher spatial resolution in indoor environments. These technologies can be classified according to the physical medium used: magnetic, optical, acoustic or radio frequency, the latter being the most widely used due to their good balance between accuracy, cost and energy efficiency [2].

In the radiofrequency field, technologies such as Wi-Fi, Bluetooth Low Energy (BLE) and Ultra-Wide Band (UWB) are particularly relevant as they achieve accuracies of the order of 0.1 to 0.3 m [3]. This level of detail allows its application in demanding contexts such as monitoring people within complex indoor spaces, as required by the IoE paradigm.

In order to estimate the location of a person or device, IPS systems employ geometric methods such as the trilateration [4,5], or triangulation [6,7]. These techniques, when combined with UWB sensors, enable high-precision localisation, even in indoor environments with obstacles and complex structures. Furthermore, the choice of the most suitable technology depends on a number of factors such as power consumption, deployment costs and the complexity of signal processing.

However, to transfer these technical capabilities into practical applications, it is necessary to complement the physical infrastructure with methodological approaches to interpret location within real and dynamic contexts. For example, determining the location of a person in a dining room, a living room or a bathroom is essential to make sense of location data, especially in systems oriented towards contextual and personalised monitoring.

Therefore, this research work presents an IPS system based on UWB technology, complemented with a novel graph-based localisation methodology [8]. This proposal aims to improve the contextual interpretation of position in indoor environments, integrating structural and semantic aspects of the monitored space.

This proposal presents the following novelties:

- High accuracy without the need for complex calibration processes.
- Incorporation of a graph-based semantic inference layer, which allows representing the logical structure of the space and limiting the changes of stay to physically possible transitions.
- Improved temporal consistency of localisation while maintaining real-time responsiveness. Easy editing of bounding rooms and reconfiguration of the environment.

This article is organised as follows: Sect. 2 reviews the work related to the proposal. Next, Sect. 3 describe the developed system, including the devices used, the general architecture and the graph-based methodology. Subsequently, Sect. 4 presents the experimentation carried out and the results obtained. Finally, Sect. 5 discusses the conclusions of the study and future work.

2 Background

Indoor localisation is a field that has been widely studied in recent years, due to the need to provide accurate tracking services in environments where GNSS systems are inaccurate [9]. As indicated in the previous section, signal-based solutions are among the most widely used technologies. In recent years, UWB technology has been widely used due to its high accuracy and low latency [10]. However, these systems often combine sensing technologies, positioning algorithms and communication devices to provide real-time locations with different levels of accuracy and cost [11].

In general, IPS consists of two main phases to estimate the location of a person or device: signal measurement and position calculation using techniques such as trilateration [5], which is based on the calculation of distances to multiple reference points, or triangulation [6][7], which uses known angles or lines of sight to infer position. These techniques, when combined with UWB sensors, enable high-precision localisation, even in indoor environments with obstacles and complex structures. In addition, the choice of the most suitable technology depends on various factors such as power consumption, deployment costs and the complexity of signal processing. However, many of these systems focus solely on providing spatial coordinates of the device or user, without incorporating a contextual interpretation of the location to robustly identify the specific room or area within the environment.

Thus, an extensive state-of-the-art approach bases detection in zones on direct comparisons between the obtained coordinates and predefined areas, without taking into account the topology of the space. This approach, although simple to implement, tends to fail in real situations where small inaccuracies in the signal can lead to erratic changes in the location of the area [12]. Some work attempts to mitigate this problem by applying machine learning techniques to classify areas from sensor data, but such solutions tend to require expensive training processes, depend heavily on the environment in which they are trained, and do not guarantee interpretability and spatial consistency [13].

On the other hand, there are solutions that rely on mobile platforms or web interfaces to display location results, although these rarely offer the end-user the possibility to directly modify the monitored environment. Most systems require technical expertise or access to administration tools to redefine rooms, adjust zones or configure the system, which limits their versatility and scalability in changing environments [14].

3 Graph-Based Indoor Localization System

This section describes the proposed IPS system, which combines UWB technology with a graph-based semantic model. The system is composed of three essential pillars: the sensors and devices used to locate the mobile element, the communication architecture and the graph-based localisation methodology.

3.1 Sensors and Devices

Although several commercial UWB-based devices are available on the market, the Decawave MDEK1001 development kit, based on the DWM1001-DEV module, has been selected in this proposal due to its ability to implement real-time localisation systems with an accuracy of 10–30 centimetres, low power consumption and compatibility with scalable architectures [15].

The system defines three types of nodes (see Fig. 1):

- **Anchor**: fixed devices with known position, strategically distributed in the environment. These devices receive signals from the mobile node and allow estimating their location by trilateration. To ensure consistency in measurements, it synchronises with each other.
- **Tag**: mobile node emitting UWB signals. It is carried by the user and its position is estimated based on measured distances to the anchors. This is optimised to operate in low-power mode and can be integrated into objects or wearables.
- **Gateway**: node that acts as a link between the UWB network and the central processing unit. It collects the estimates generated by the anchors and transmits them via UART to a Raspberry Pi 3B+ for real-time analysis.

The three types of nodes are based on the same development module, the **DWM1001-DEV** which integrates the **DWM1001C** chip, operating in 3.5 to 6.5 GHz bands for initial configuration, pre-loaded firmware for bi-directional range measurements, and a USB port for power and debugging. It also incorporates Raspberry Pi-compatible GPIO connectors, as well as physical buttons for reset and Bluetooth activation [16].

Fig. 1. Encased development board (DWM1001-DEV).

In addition, the following components are incorporated for the global operation of the system:

- **Raspberry Pi 3B+**: works as an intermediate server between the physical sensor network and the high-level services. It is programmed to receive the data sent by the bridge node, process it and send it to the cloud layer for

storage in a MongoDB database. In addition, the data will be exposed in a REST API. This interface, although not aimed at the end user, allows to connect, integrate and extend IT systems in a structured way.
- **Smartphone**: allows the user to check in real time the location of the tag node through an Android application. This app communicates with the REST API to retrieve both the position and the estimated location of the user, using graph-based methodology.
- **Additional elements**: the system also requires microSD cards for local storage, individual power supplies for each node and a wireless network to facilitate communication between the different modules.

System modularity and portability allow it to be deployed in different environments without requiring a complex infrastructure. In addition, the selected hardware has a low power consumption, which favours continuous operation with minimal manual intervention.

3.2 System Architecture

Communication between the different nodes of the system is provided by the Decawave MDEK1001 development kit, which allows the sending and receiving of location messages via UWB technology.

In the proposed system, the tag node, carried by the user, emits periodic UWB signals that are captured by the anchor nodes, strategically distributed in the environment. From this information, the system calculates the relative position of the mobile node using trilateration techniques.

The bridge node centralises the information generated in the UWB network and transmits the data to a Raspberry Pi 3B+, which constitutes the system's edge layer. This unit performs the local processing of the positions, temporarily stores the data and obtains the location of the user. This edge layer enables real-time response and operational autonomy even in the absence of cloud connectivity.

In parallel, the processed data is transmitted to a cloud layer, where it is stored persistently in a MongoDB database and can be integrated with analytics, advanced visualisation or machine learning services.

All devices are configured according to the manufacturer's guidelines, ensuring stable and continuous communication. In addition, the included configuration software allows monitoring the UWB network, verifying the positioning of the nodes and facilitating their deployment.

The final architecture (see Fig. 2) is designed as a modular, scalable and distributed solution, composed of a UWB network (physical layer), an edge layer for local processing and a cloud layer for persistence, analysis and remote access to location data.

The system also includes a mobile application developed in Android (see Fig. 3), which allows the user to access the real-time location of the tag node. This application uses the data provided by the REST API, allowing not only to visualise the exact position, but also the defined rooms, modify them or consult

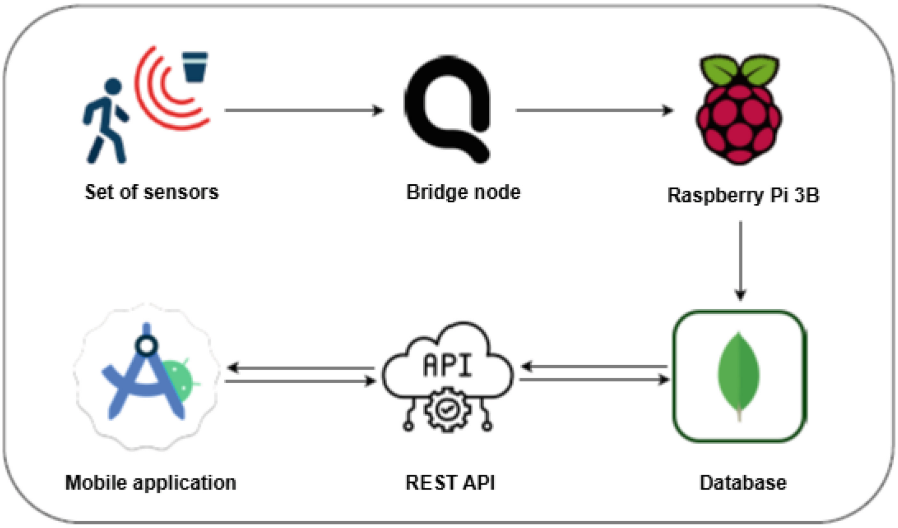

Fig. 2. System architecture.

their configuration. For this purpose, an intuitive interface has been designed, aimed at an easy interpretation of the results.

Finally, to summarise, it is possible to identify the main functional components of the system according to their role within the distributed architecture:

- **Edge layer**:
  - **UWB physical nodes** (anchor, tag and bridge): responsible for generating and sending location data using UWB technology.
  - **Local processing device** (Raspberry Pi 3B+): performs initial data processing, temporary storage and sending data to the cloud.
- **Cloud layer**:
  - **MongoDB database**: persistently stores location information and spatial configuration of the environment.
- **Client**:
  - **Smartphone application**: Android client that consults and visualises the user's position and location in real time.

This design allows the system to be easily configurable and adaptable to different physical environments. The modularity of its components facilitates scalability towards larger and more complex spaces, simply by incorporating new nodes and adjusting the definition of the rooms according to the needs of the scenario.

3.3 Graph-Based Semantic Localization Methodology

One of the main challenges in indoor location systems is not only to provide accurate spatial coordinates (x and y axes), but also to reliably identify the

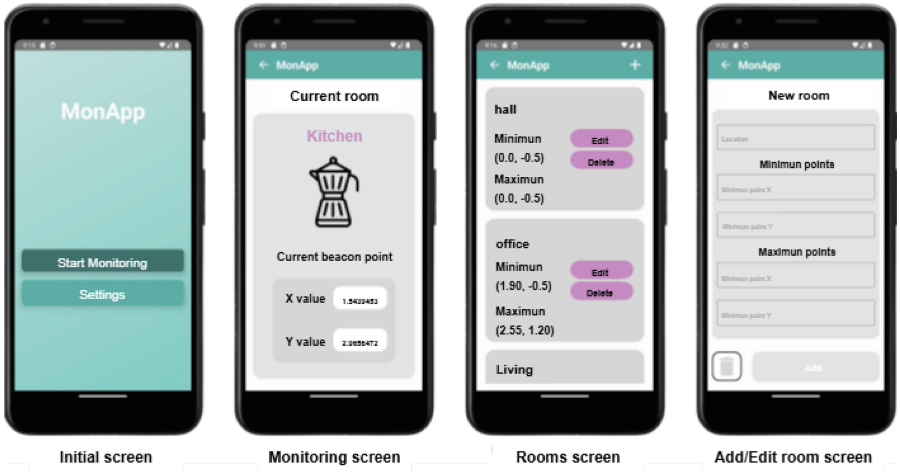

Fig. 3. Different views of the Android application.

room in which the user is located. This capability is especially critical in applications where spatial contextualisation is as relevant as exact location, such as in healthcare, industrial or home automation environments.

A commonly adopted approach is to assign rooms by verifying whether the user's current position is within the predefined boundaries of a given area or Bounding Box (BB). A BB is a rectangular region of space representing a room, defined by its minimum and maximum coordinates on the x e y axes. Formally, a BB can be represented as:

$$BB = \left\{(x, y) \in \mathbb{R}^2 \mid x_{\min} \leq x \leq x_{\max},\ y_{\min} \leq y \leq y_{\max}\right\}$$

where $(x_{\min}, y_{\min})$ y $(x_{\max}, y_{\max})$ define the opposite corners of the rectangle and (x, y) the estimated position of the person being monitored.

However, this method has significant limitations. It is highly sensitive to small variations in the coordinates, which can lead to incorrect assignments even with minimal movement or noise in the signal. Furthermore, it does not take into account the topology of the environment, which makes it impossible to restrict transitions to physically plausible routes. As a consequence, the user may be mislocalised in adjacent rooms, generating erratic changes that do not reflect their actual movement, especially in scenarios with some instability in the measurements.

To overcome these limitations, a graph-based inference methodology is proposed, in which the monitored physical environment is represented by a logical structure that incorporates both the geometry of the rooms and their spatial relationships. In this model, each room is defined as a node of an undirected graph, and the physically possible transitions between them are represented as edges. In addition, each node stores the geometric information associated with the corresponding room, i.e. the minimum and maximum values of the coordinates on the x e y axes, which allows its boundaries to be identified within the map of the environment.

This algorithm aims to infer the current location of the user from the estimated positions (x, y). Instead of assigning locations solely based on coordinates, the algorithm restricts the possible transitions according to the logical structure of the environment, represented by an undirected graph $G = (V, E)$, where each node represents a location and each edge indicates a physically possible connection between them.

General operation of the algorithm is as follows:

1. The new position (x, y) is checked to ensure that it is within the BB of the current location R_{prev}. Otherwise, the location is kept unchanged.
2. If the position is outside the bounds of R_{prev}, the adjacent rooms are queried through the network, obtaining the set of nodes directly connected to R_{prev}.
3. The new position (x, y) is checked if it belongs to the BB of any of the neighbouring locations. If there is a match, the current location R_{current} is updated.
4. If no valid transition is detected, R_{prev} is preserved, assuming that the change is the product of a minor oscillation or noise in the signal.

Below is shown the code corresponding to the Algorithm 1.

Algorithm 1. Location inference based on topological coherence

```
Input: $(x, y)$, $R_{\text{prev}}$, $G = (V, E)$
Output: $R_{\text{current}}$
if $(x, y) \in \text{BoundingBox}(R_{\text{prev}})$ then
    $R_{\text{current}} \leftarrow R_{\text{prev}}$
else
    $\mathcal{N} = \text{Neighbors}(G, R_{\text{prev}})$
    for all $R_i \in \mathcal{N}$ do
        if $(x, y) \in \text{BoundingBox}(R_i)$ then
            $R_{\text{current}} \leftarrow R_i$
            break
        end if
    end for
    if no match found then
        $R_{\text{current}} \leftarrow R_{\text{prev}}$
    end if
end if
return $R_{\text{current}}$
```

4 Experimentation and Results

In order to validate the proposed architecture and methodology, experiments were conducted in a controlled environment, adapted with the necessary devices.

This space simulates a closed environment with delimited spaces, and allowed us to evaluate the accuracy of real-time localisation and spatial coherence in location inference.

4.1 Case Study

The experiments were performed in the Smart Laboratory of the Centre for Advanced Studies in Information and Communication Technologies, located at the University of Jaén. This space, with a surface area of 25 m^2, has been used in several studies to emulate real situations [17]. As shown in Fig. 4, the environment was divided into six different locations. The experimental deployment included four anchor nodes, one in each corner, a tag node associated with the user and a bridge node connected to the pins of the Raspberry Pi.

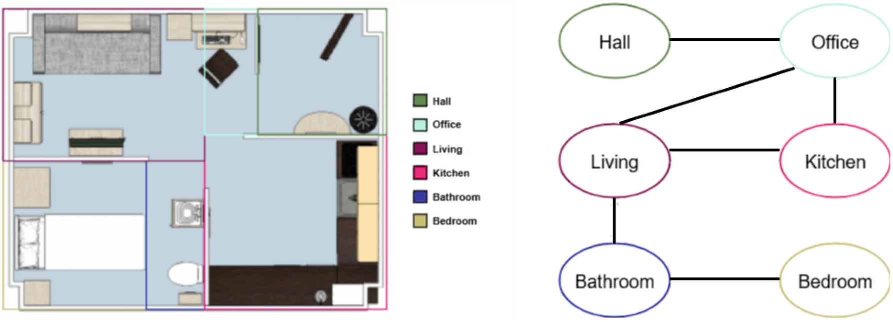

Fig. 4. On the left, a plan of the experimental environment divided into six distinct locations. On the right, undirected graph representing the physically possible transitions between locations.

For the experiment, a total of 17114 samples were collected, evenly distributed among the different locations. Routes included natural movements within the environment, smooth room changes and stops in bordering areas. During data collection, entry and exit times were recorded for each location in order to generate the ground truth of the dataset.

During the data collection process, the sensor network was configured according to the default parameters of the DWM1001 model. The anchor nodes transmitted in a repetitive superframe of 100 ms, corresponding to a sampling rate of 10 Hz. Meanwhile, the tag node periodically woke up every 500 ms to receive synchronization messages, equivalent to an effective listening frequency of 2 Hz.

On the other hand, a graph was defined consisting of six nodes, each associated with one of the locations in the experimental environment. The edges represent the physically possible transitions between adjacent locations. For example, from the Hall it is possible to directly access the Office or the Living room, but not the Bathroom or the Bedroom. The complete network structure is shown in Fig. 4.

4.2 Results

With the graph-based methodology activated, the system's performance significantly improved. The algorithm avoided unnecessary changes of location, providing a more coherent spatial continuity. In trajectories where the user stopped near space boundaries, the system correctly maintained the previous location if there was no topologically valid transition, due to the verification of connections defined in the graph. This approach reduced false positives on location changes and significantly improved the stability of the system. These results can be seen in Fig. 5.

In quantitative terms, the succes rate increased from 89.25% (basic algorithm) to 94.08% with the graph-based algorithm, confirming its effectiveness in contextual spatial interpretation (see Table 1).

Table 1. Comparison of results.

Experiments	Successes	Failures	Accuracy
Basic algorithm	15275	1839	89.25%
Graph algorithm	16100	1014	94.08%

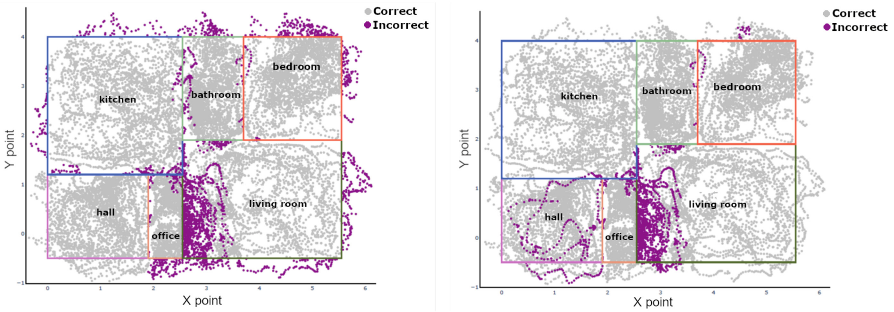

Fig. 5. Visual comparison between the results of the basic algorithm (left) and the graph-based algorithm (right).

In terms of performance, the system was able to process the positions in real time, confirming the feasibility of the solution on low-cost hardware. Moreover, the visualisation through the mobile application was instantaneous and correctly reflected both the estimated position and the active occupancy at any given moment.

Overall, the results obtained during the experimentation phase validate both the localisation architecture and the graph-based methodology. It demonstrates a substantial improvement in the contextual interpretation of the positioning, without compromising the performance of the system. It is thus presented as an effective alternative to increase the reliability of indoor localisation systems, especially in applications where the semantic tracking of the user is more relevant than the absolute accuracy of their position.

5 Conclusions and Future Work

This paper presents the development and implementation of a complete indoor localisation system based on UWB technology, which combines accuracy, low cost and deployment facility. In addition to providing the Cartesian position of the user, the system incorporates a contextual interpretation layer using a graph-based inference methodology designed to more reliably identify the location of the user. The proposal has been experimentally validated in the SmartLab of the University of Jaén, configured with six different spaces and a complete deployment of the system. The results obtained confirm the effectiveness of the approach, reaching a succes rate of 94.08%, which demonstrates its ability to improve spatial coherence and reduce errors in scenarios representative of real use.

The scalability of the system to larger and more complex environments, such as multi-floor buildings, is feasible since each floor can be modeled as a subgraph linked by nodes representing vertical transitions. Nevertheless, this entails added challenges such as synchronization between nodes, interference in dense areas, and increased deployment costs.

Another relevant aspect is the evaluation of the mobile app's usability. Although it already provides real-time visualization and room configuration, no formal study with end users has been conducted. Basic usability tests, such as questionnaires or pilot sessions, would help identify interface strengths and areas for improvement.

However, the proposed system has a limitation related to the tag node, because the currently used device requires a physical adaptation to facilitate its portability and comfort for the user. Addressing this aspect will be key in future developments, especially in applications where the discrete and ergonomic integration of the system is essential, such as in the monitoring of elderly people.

In terms of future work, the system offers several possibilities for improvement. These include the integration of complementary sources of information, such as inertial sensors or environmental data, which could enrich positioning and improve decision-making. Likewise, the possibility of incorporating time windows that allow the recent history of the trajectory to be considered, promoting a more robust and continuous inference of the user's spatial behaviour is also being considered.

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