UPF EDITORA
RBCA ISSN 2176-6649

Revista Brasileira de Computação Aplicada, November, 2023

DOI: 10.5335/rbca.v15i3.14592
Vol. 15, Nº 3, pp. 106–114
Homepage: seer.upf.br/index.php/rbca/index

ORIGINAL PAPER

Studies on indoor positioning algorithms using BLE Beacons

Felipe Carreiro Marchi [1] and André Leon S. Gradvohl [1]

[1]Faculdade de Tecnologia da Universidade Estadual de Campinas

*f196695@dac.unicamp.br; †gradvohl@unicamp.br

Received: 2023-04-05. **Revised:** 2023-10-30. **Accepted:** 2023-11-17.

Abstract

Global positioning systems have become very popular, helping locate people and objects. Currently, with greater specificity, indoor location services are gaining more relevance. Despite the recent developments, the technology for indoor localization is still incipient, demanding better accuracy, lower costs, and greater practicality. Therefore, this paper presents a study of a technique for indoor localization with Bluetooth low-energy beacons. In addition, we propose and perform experiments to implement a low-cost, low-power, BLE-enabled device-based indoor positioning system. With such devices, we calculate the distance between the emitters and the receiver using known techniques and determine the user's location. The results we obtained reduced the time and complexity of calibrating the offline phase of the systems. However, the accuracy of the localization is related to the accuracy of the distance estimation.

Keywords: Bluetooth Low Energy. Indoor Positioning System. Programming.

Resumo

Os sistemas de posicionamento global se tornaram muito populares, ajudando na localização de pessoas e até de objetos. Atualmente, com maior especificidade, os serviços de localização interna estão adquirindo mais relevância. Apesar dos desenvolvimentos recentes, a tecnologia para localização interna ainda é incipiente, demandando melhores precisões, menores custos e maior praticidade. Assim, com o objetivo de melhorar a qualidade dos sistemas de posicionamento interno, este artigo propõe uma estratégia de posicionamento dos beacons, um filtro para seleção de RSSI e um algoritmo de busca. A metodologia que utilizamos inclui experimentos com dois tipos de beacons e a técnica da trilateração. Os resultados que obtivemos reduziram o tempo e a complexidade de calibração da fase offline dos sistemas. No entanto, a exatidão da localização está relacionada à precisão da estimativa de distância. Por isso, verificamos que existem oportunidades de melhorias na precisão quando se decide utilizar a potência de sinal de beacons como a principal tecnologia de um sistema de posicionamento interno.

Palavras-Chave: Bluetooth de Baixa Energia. Programação. Sistema de Posicionamento Interno.

1 Introduction

Geographic positioning systems became widespread due to the free availability of the American Global Positioning System (GPS) service around the 2000s. Initially designed for military use, GPS is the most widely used outdoor orientation and location system for people or objects. However, these systems are ineffective indoors due to partial or total signal loss (Ho and Chan, 2020).

A mobile device industry consortium was founded in 2012 to promote the deployment of indoor location services. The consortium, called the InLocation Alliance, employed efforts to create easy-to-deploy solutions with high accuracy, mobility, usability, and low power consumption (indoo.rs, 2022).

In this context, there is a growing interest to locate, with reasonable accuracy, a device indoors (indoors) due to the various forms of application. Moreover, unlike GPS, indoor positioning can reveal, in addition to geographic coordinates, sectors, and environments representative of the device's location.

Therefore, using an indoor location system varies depending on the scenario deployed. In a shopping mall, for example, one could suggest offers of the products in that section that a user has been in for some time. In airports, these systems would help locate check-in and boarding procedures. As well as to find doctors, patients, or hospital equipment in emergencies.

In addition to the positioning mechanism, indoor location systems allow tracking, i. e., a strategy to trace the paths a device takes from its arrival in an enclosed environment to its departure. Tracking of this kind is interesting to determine users' most traveled paths and thus define marketing strategies.

Despite the opportunities for indoor localization, the indoor positioning system technology is still in its infancy. Factors such as high-cost infrastructure, the configuration complexity, and signal interference have hindered its large-scale adoption. Therefore, there is a field of study in this area to seek better accuracies, ease of deployment, and usability. In this field of study, using Bluetooth and other Wireless Personal Area Network (WPAN) have reduced infrastructure costs. Furthermore, Bluetooth Low Energy (BLE) (Spachos and Plataniotis, 2020) can be a potential component in developing indoor positioning systems, due to its passive connectivity.

According to Rezende and Ynoguti (2015), a major challenge for indoor localization systems is found in the physical space due to furniture, walls, or wireless devices that can interfere with the sensor network. Thus, the techniques and algorithms used in these systems are as relevant as the device used. Therefore, this paper presents a study of a technique for indoor positioning with beacons using BLE.

We organize the remainder of this paper as follows. Section 2 and 3 contain the survey of concepts and papers related to indoor positioning systems, their techniques, and algorithms. Section 4 presents the materials and methodology for the experiments developed in this research. Then, Section 5 analyzes and displays the data resulting from the experiments. Finally, we present the final considerations, summary, and future work in Section 6.

2 Concepts and definitions

This section brings concepts relevant to the study of indoor positioning algorithms using BLE beacons.

2.1 Fixed Internal Positioning

According to Al Nuaimi and Kamel (2011), fixed indoor positioning is one of the types of Indoor Positioning System (IPS) that can be the solution when it comes to determining a person's location or an object within a limited physical space. To implement fixed IPS, three steps are necessary: the distribution of sensors over the area, the calibration of these devices, and the calculation of the location in real-time. In these situations, Radio Frequency (RF) is the cheapest wireless technology, with the broadest coverage and the most widely used.

In a fixed IPS, we can use several measurement attributes to determine a location, varying depending on the techniques and technologies used. Among the most common attributes are Received Signal Strength Indication (RSSI), Angle of Arrival (AoA) and Angle of Departure (AoD) (Kárník and Streit, 2016).

The RSSI is the power of the signal received from the sender. We typically use this attribute to estimate the distance between the sensors and the devices participating in the positioning system. In turn, the arrival and departure angles serve to know the direction of signal emission. These parameters are also present for reference in BLE beacons, a common technology in fixed IPS. We adopt BLE beacons as the object of study in this paper and detail them further in Section 2.2.

2.2 BLE Beacons

Beacons, like lighthouses in coastal areas, have the primary purpose of periodically emitting signals so that they can be recognized. BLE is the technology used by beacons to save power while they are not actively working on exchanging data packets.

Also known as Bluetooth Smart, BLE was developed for the Internet of Things (IoT) industry in 2010, along with the Bluetooth 4.0 (Yang et al., 2020) specification. Compared to earlier versions, such as Classic Bluetooth, BLE can be more efficient for low-complexity communications, such as controls and sensors, because they require no pairing, send few bits of data, and use little power.

A beacon comprises a BLE chip, a coin-type lithium-cell battery, and an antenna. The antenna facilitates wireless data transmission without an internet connection while saving energy during idle times. These features, coupled with the functionality of continuous transmission of a proprietary identifier, make it possible to apply localization methods on beacons to develop an indoor positioning system. Section 2.3 discusses some of these methods.

2.3 Internal Localization Methods

In an IPS, we need to determine the location of an object or user device through the analysis of parameters provided, in real-time, by sensors that compose the system. For this, the behavior applied in the algorithm of this type of system obeys the following steps: 1) capture the parameters; 2) preprocessing of the data; 3) calculation of the distance; and 4) calculation of the position (Davidson and Piché, 2017).

For instance, let us consider a mobile phone application that wants to locate itself in an environment with Wi-Fi networks. In the first phase, we will store the strength of the Wi-Fi signal received by the device, also known as RSSI, and use it as a parameter. By doing this with the various network points near the user, the values we have obtained will become part of a database that, at this point, is not yet reliable for operation. This situation happens because the RSSI is sensitive and suffers many oscillations, requiring the preprocessing of this data.

With this database with the location parameters, we calculate the distance between the emitters and the receiver using known techniques and determine the user's location. Taking the previous example as a basis, we can make adaptations for implementing an IPS. The Wi-Fi transmitters, for example, can be replaced by BLE beacons that also provide the parameter RSSI. The following action defines which technique to use for the distance calculation.

We can even combine different localization methods. These methods have various classifications among the authors. However, Al Nuaimi and Kamel (2011), and Rodrigues and Carvalho (2019) have classified two principles used in positioning systems – Triangulation and Trilateration – which we discuss next.

2.4 Triangulation and Trilateration

Triangulation is one of the main localization techniques. This technique applies the geometry of triangles to determine the position of a target object through three anchor points of known coordinates. We can achieve it by using either the measurement of angles or the measurement of distances between the points. This second approach is trilateration, the focus of this paper.

The precision of trilateration varies according to the accuracy in estimating the distances between the anchors and the target, represented by the radii of the circumferences (r_1, r_2, and r_3) in Fig. 1. In this way, the result of the target location may be spot on (P) when it is possible to determine the distances correctly, or it may lie within the area of the intersection of the circles (A, B, and C) when the sensor parameter readings suffer from interference. In this case, it is necessary to calculate the geometric center of the estimated area to find a solution for the target positioning.

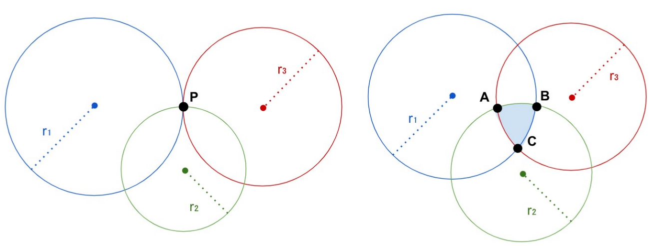


Figure 1: Cases in locating a point using trilateration. Adapted from Cipriano (2018).

This technique does not estimate the most accurate location, since the internal radio frequency propagation channel varies greatly. However, one of its advantages is that it requires no effort in the setup and calibration steps.

2.5 Refining techniques

After reading the sensors' parameters in the localization algorithm's first step, the next phase is data preprocessing. This phase is necessary to filter out some variations in the signals obtained.

We notice the high impact of noise when using RSSI for distance calculation. This situation occurs even in a static environment and position, where the signal strength can vary, causing inaccuracies or significant deviations in the location estimate.

These instabilities, also known as fading, are caused by the physical environment. Starting from the transmitter, a radio signal can vary randomly due to shadowing, i. e. signal obstruction by walls and furniture. Another negative effect is path loss, the natural reduction in power density during propagation. Multipath can also occur, a situation caused by the reflection of the signal by objects, water streams, or the atmosphere itself, causing the signal to reach the receiver through two or more paths. Therefore, to minimize the impact of these instabilities, low-pass filters or something similar should be applied. Examples are the Moving Average or the Kalman Filter (Bishop et al., 2006).

The Moving Average applies a simple average along with the movement of a data window. It allows us to calculate an average as values arrive by adjusting the window size. In turn, the goal of the Kalman filter is to remove noise. Therefore, we often use the Kalman filter in filtering RSSI for internal location (Li et al., 2020). The operation of this filter is based on an algorithm that estimates a value in a linear model from the history of noisy inputs.

3 Related work

In this section, we cover the related work. We divide the group between works with experiments, developments, and improvement proposals.

Initially, we highlight Tariq et al. (2018)'s work, which reviewed and categorized several techniques and technologies of non-GPS positioning systems. Furthermore, Tariq et al. listed some advantages and disadvantages of using the RSSI technique, as well as challenges and trends in indoor localization. The authors noticed that using beacon signal strength in an IPS provides scalability due to the simplicity of the hardware and the low cost. On the other hand, this technique still has points for improvement regarding accuracy, time, and calibration complexity in the system implementation phase compared to other techniques.

3.1 Works with experiments

The works with experimentation are those that compare, evaluate or test algorithms through simulations or field testing.

Cipriano (2018)'s work evaluated indoor localization techniques due to the growing commercial interest in such applications. To do so, he experimented with Triangulation and Fingerprinting methods to determine the indoor location of devices through BLE. In addition, the author pointed out the possibility of independently applying the localization algorithms while reading the beacon data. It occurs because we can save the data collected from RSSI beacons at different positions and apply different algorithms later to validate each position. Although satisfactory, the results of this work indicate that there are still important challenges before achieving full reliability, robustness, and accuracy in indoor location systems due to the high interference suffered by BLE technology.

Next, we detail the Fingerprinting method along with the Kalman filter applied by (Spachos and Plataniotis, 2020).

3.1.1 Fingerprinting

Fingerprint-based algorithms are classifiers. Their operation defines the user's position by comparing the current sensor readings to the pattern of readings of each system location preregistered in the offline phase. Among the various classifier algorithms, two of the most widespread and with the best results in recent studies were considered, the K-Nearest Neighbor (KNN) and the Multilayer Perceptron (MLP) neural network.

The KNN needs a criterion to define which preregistered points are the closest to the position to be measured, according to the variable k. Therefore, we used $k = 1$ to obtain the return of the first nearest neighbor of the rank.

Considering that each measured position generates a vector of n values of RSSI, being n the number of beacons in the system, the selection criterion adopted for the KNN algorithm was the absolute difference between the vectors of the training and search phase. Fig. 2 exemplifies the execution of the Fingerprinting technique.

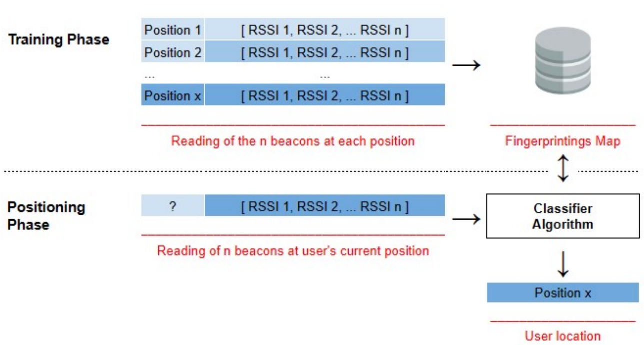


Figure 2: Fingerprinting operation for internal localization based on RSSI. Adapted from Davidson and Piché (2017).

As an alternative to the KNN algorithm, the MLP neural network used in the experiments applied the L-BFGS algorithm to solve the nonlinear problem, as this is known to determine parameters in machine learning. The L-BFGS is based on the Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm (Kelley, 1999). However, it uses a limited amount of memory.

For the internal localization experiments carried out by Cipriano (2018), the best configuration found for MLP was to use two layers of hidden neurons, with 150 and 25 neurons, with the parameter $\alpha = 1^{-5}$, which is the penalty term that controls the magnitude of adaptation by constraining the size of the network weights. Increasing α can correct for the high variance, encouraging smaller weights. However, decreasing α can correct for high bias, encouraging larger weights.

Although both Fingerprinting algorithms performed well, with hits above 90 %, a results comparison showed better performance for the MLP neural network.

3.1.2 Kalman Filter

The Kalman filter is one of the techniques used to process RSSI readings to reduce signal noise and consequently improve the accuracy of the distance estimate between the sensors and the system user. This technique uses measurements over time, which contribute to estimating results close to the real values.

Spachos and Plataniotis (2020) performed experiments to examine the performance of a system that uses beacons to increase interaction in a museum. In the same work, we can observe promising results in the application of the Kalman filter to improve location estimates since: (i) the user's device can support the algorithm without an internet connection, (ii) the filter helped to minimize noise from different environments, and (iii) it showed clarity in improving the estimates, the overall result, and obtained a decrease in errors.

3.2 Works with development

Works with development present the entire development process of a system or application and serve as a direction for applying this research in practice.

In this category, we highlight the application developed by Menegotto (2015) that offered a spatial location for people, besides being a support tool for human resources and physical building managers. The app also features a voice interface that sends spoken prompts that assist visually impaired users.

Regarding the results of this work, Menegotto (2015) faced problems with fluctuations of the signals RSSI that did not correspond to the real distances. However, after applying two filters on the signal readings, the localization hit rates rose close to 90 %.

Another observed development was performed by Homayounvala et al. (2019), who used Gaussian Process Regression (GPR) to train a model to localize the internal position of a mobile phone application using the Fingerprinting technique. In practical terms, this work succeeded in developing a smartphone application with the ability to be trained and accurately detect the users' location. Moreover, the results were superior to conventional methods, such as KNN.

Despite the satisfactory results, we know that using the Fingerprinting technique promotes a high implementation cost in the offline phase. This technique demands time for data collection at each reference point distributed throughout the system's performance space. In addition, the technique requires time to train the algorithm, which in this case was minimized using the Gaussian process.

GPR is a new machine learning method based on Bayes' Theorem and statistical learning theory. When used in location problems, GPR predicts an unknown point from the database collected in the offline phase. It does this by using lazy learning[1] and a measure of similarity between these points (the kernel function).

3.3 Works with improvements proposals

The works identified with proposed improvements point to new solutions that optimize or increase the accuracy of a localization method and serve as a reference to advance the knowledge of this research.

Single anchor and dead reckoning techniques were used by Ye et al. (2019), who presented a single anchor solution to reduce deployment costs compared to traditional indoor positioning systems. To improve their results, the work designed a Kalman filter-based fusion algorithm to integrate their solution with the results obtained by a simplified Pedestrian Dead Reckoning (PDR) algorithm.

3.3.1 Single Anchor

For example, a single anchor-based indoor positioning can locate a device using only a known reference point or a BLE transmitter beacon.

To do this, Ye et al. (2019) used a relationship between the known coordinates, the estimated distance, and the angle formed between the transmitter and the device, as represented by Fig. 3.

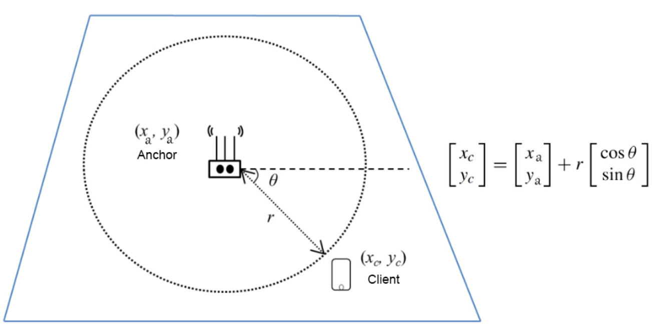


Figure 3: Single anchor-based positioning model. Adapted from Ye et al. (2019).

The estimated distance, represented by the polar radius *r*, is derived from the analysis of RSSI provided by BLE. While the angle, relative to the polar axis and represented by *theta*, is the AoA extracted from the BLE physical layer.

In addition to the single anchor solution presented, this work complemented its positioning system with three other procedures, evaluating the accuracy of estimates with each new implementation. The complementary methods proposed were: (i) use a high-precision module for distance estimation; (ii) use the inertial sensors of the device to apply the PDR algorithm; and, finally, (iii) use a fusion algorithm in the absolute and relative positioning to increase the accuracy of the user's location.

At the end of the propositions, we found that the single anchor solution performs well and that the fusion with the PDR algorithm increased the system's accuracy. On the other hand, as with other work in this area, the average error obtained was close to 1 meter. Regarding the distance parameter used, Ye et al. (2019) recommended using an accurate estimation module to replace unstable RSSI.

3.3.2 Pedestrian dead reckoning

The concept of dead reckoning refers to navigating and positioning an object loaded with inertial sensors. Starting from an initial position and an estimated speed, this process increments and updates the current position. Dead reckoning is also a technique used for maritime and air navigation.

However, we used the terminology PDR when it comes to human localization and carriers of sensor devices. Smartphones, for example, have an inertial measurement unit consisting of a triaxial gyroscope and accelerometer capable of detecting footsteps and estimating pedestrian actions. For most devices, a magnetometer is also essential to determine their orientation.

In practice, applying these concepts is based on the following process: 1) detection of a step; 2) estimation of the length of the step; and 3) estimation of the direction taken, thus structuring a PDR algorithm.

An indoor positioning system based on PDR alone is insufficient. This is due to the lower quality of the sensors selected for smartphones, external interferences from how the user manipulates the device, or different types of sensor measurement error, which makes it challenging to develop a generalized error correction.

For this reason, IPS systems often integrate PDR with some other positioning technique, as performed in the work of Ye et al. (2019). The authors chose to simplify the algorithm and apply only the estimated speed and heading information to their fusion algorithm.

The following section describes the materials and methods used in this research to perform experiments and evaluate localization techniques in practice.

4 Methods

BLE technology-based IPS are composed of mobile devices that scan and apply algorithms over the radio frequency signals emitted by BLE beacons distributed on-site. However, this work proposes using more affordable equipment to eliminate high acquisition costs. We describe below the set of materials and methods used in this research.

4.1 ESP32 development board

The ESP32 module is a low-cost and low-power device, also categorized as a system-on-a-chip, because it contains computer components on an integrated circuit. This board is further distinguished by incorporating a microcontroller and wireless communication components: Wi-Fi and Bluetooth. Thus, several programming languages and development environments can be used to program the ESP32 and create various applications in IoT, remote access, and web servers.

[1]In artificial intelligence, lazy learning, as opposed to eager learning, is a method in which the data generalization is made only when the system is asked to make a prediction.

The ESP32 board can be an alternative to mobile devices in indoor positioning experiments because it has the following features: Integrated BLE, which will perform the sensor readout; processing power to execute the positioning algorithms; and accessible communication with a computer to evaluate the results. In addition, there is no need to develop a graphical interface, which would be required if we used a mobile device. Table 1 presents the main specifications of this development board.

Table 1: ESP32 development board specifications for prototyping and proof of concept.

ESP32 development board	
Dimensions	5.5 cm × 2.8 cm
Processors	CPU: Xtensa Dual-Core 32-bit LX6; Ultra Low Power (ULP) co-processador;
Memory	ROM: 448 kB; RAM: 520 kB SRAM; Flash: 4 MB;
Wireless conectivity	Wi-Fi 2.4 GHz; Bluetooth: v4.2 BR/EDR e BLE;
Power	3.3 V CC.

4.2 iTag Device

The iTag is a small device designed to track objects using Bluetooth technology. Its portable format, similar to a keychain, helps its attachment to the user's objects. Thus, in case of loss, the device helps in the localization through the application indicated for iTag management.

As an alternative to beacons in indoor positioning experiments, we used iTags because they use Bluetooth Low Energy, emit a signal that reaches approximately 22 m in open locations, and have low cost and ease of purchase compared to beacons.

During the experiments, we used up to five trackers. They have a single central button that controls the on and off functions when pressed for a few seconds. Each tracker has a coin-type CR2032 lithium battery with approximately six months of charge life.

4.3 Integrated Development Environment

The first step in developing the experiments in this section was to prepare an environment for programming the system, as Table 2 describes.

Table 2: Step 1 – Digital environment specifications.

Tool	Specification
Arduino IDE	Software version: 1.8.16. Programming Language: C++. Library: *BLEDevice*. Resources installed on the board manager : *ESP32 Dev Module*.
GitHub	Repository available at `https://github.com/felipemarchi/ips-studies`.

We used the Arduino Integrated Development Environment (IDE) for programming the algorithms in this research. This IDE can send code to a microcontroller and interact with the ESP32 through serial communication.

GitHub was the code hosting and versioning platform chosen to make the products of this research available.

After preparing the digital environment for the experiments, we defined the physical environment – an experiment bench. Fig. 4 illustrates the bench with a stand for the board. We also placed three supports for iTags at distances of 1 m, 1.20 m, and 1.40 m. This scenario was mainly aimed at systematizing the calibration phase and studies on RSSI signal readings from the first experiment.

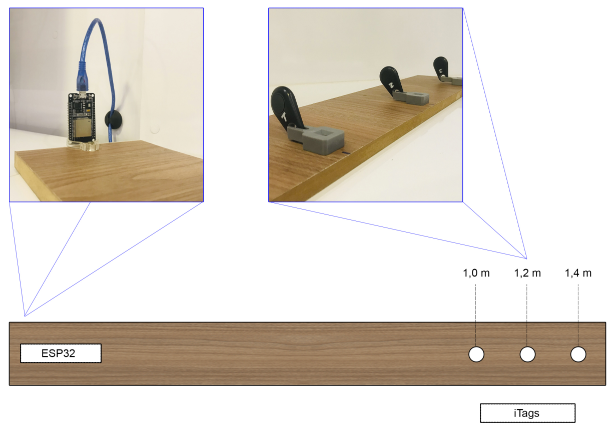


Figure 4: Step 2 – Experiment bench with ESP32 and iTags board holders.

The following section presents our experiments to develop an indoor positioning system incrementally.

4.4 Experiments

We developed all experiments using the Arduino IDE. The code used ESP32 compatible BLE functions derived from the `BLEDevice` library. Algorithm 1 shows the code we developed.

4.4.1 *Measurement Attribute*

We remind the reader that the RSSI is a value obtained through the BLE specification that indicates the strength of the radio frequency signal received from the beacons. To improve the precision of selecting these values that suffer some variation, we consider the value resulting from the mode of the same device's first five RSSIs. Thus, this attribute integrates the distance estimate between the devices.

4.4.2 *Distance estimation*

Measuring the distance the beacons are from the mobile device is important in internal localization by trilateration. Therefore, to convert from RSSI (in decibels) to distance (in meters), we use Eq. (1).

Algorithm 1 Pseudocode of the developed IPS

```
loop
    Clean the beacons list.
                                          ▷ Acumute RSSIs()
    for i=1 to 5 (mode set quantity) do
        Scan the surrounding known beacons.
        Store the signal strength of each beacon.
    end for
                                          ▷ DefineValues()
    for each beacon found do
        Set the mode through accumulated RSSI.
        Estimate their distance through the mode of the RSSIs.
    end for
                                          ▷ ElectBeacons()
    Select the three beacons with the smallest distances.
    Set their positions in the triangle (left, right, or top).
                                          ▷ ShowResults()
    Calculate the (x, y) position of the user by trilaterating the chosen beacons.
    Display as location information.
end loop
```

$$d = 10^{\frac{(A-\mathrm{RSSI})}{(10\times n)}} \quad (1)$$

Variable A is the value of RSSI positioned one meter away. The variable n is a correction factor for power loss. The precise value of n must be determined experimentally, but generally varies between 2 and 6, depending on the environment in which it is inserted.

Eq. (1) describes the Path Loss model, commonly applied in this context. We use this model to describe the power loss of a transmitted wave as it propagates through a medium. In wireless communication systems, the Path Loss model is used to predict the signal strength at a given position, considering the distance between the transmitter and receiver and the characteristics of the propagation medium. Shang et al. (2014) also use this model.

Even after calibrating the values of A and n, they can vary due to even humidity in the air. Therefore, we propose an hourly autocalibration routine in which an ESP32 board of a known location relative to a beacon would reset these parameters for the entire system. This process consists of the system resetting the correction factor according to the expected distance and takes about five seconds.

4.4.3 Positioning the beacons

Aiming at minimizing the step of configuring and mapping the position of each beacon, we use a positioning strategy by grouping them five by five in a configurable side square, as illustrated in Fig. 5. This way, the actual distance between the beacons is known and we can apply trilateration on the three beacons closest to the mobile device.

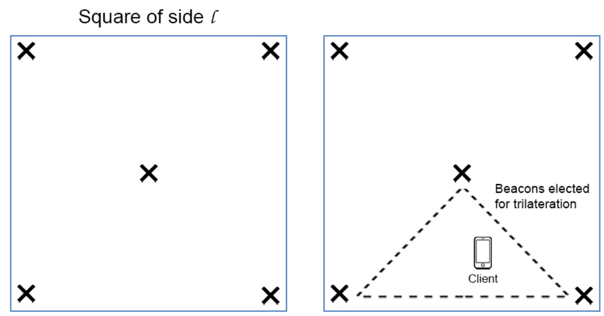


Figure 5: Proposed beacon placement strategy for an indoor location system.

4.4.4 Trilateration

With the described environment, our algorithm can find the closest beacons, convert RSSIs into distances, and apply the trilateration technique. This process, synthesized in Algorithm 1, has as a return the coordinates (x, y) in meters, referring to the user's positioning within the chosen triangle, defined through Eqs. (2) and (3) (Sadowski and Spachos, 2018). We adapted these equations for our positioning of five beacons.

$$x = \frac{(d_1^2 - d_2^2 + l^2)}{(2 \times l)} \quad (2)$$

$$y = \frac{(d_1^2 - d_3^2 + m^2 + m^2)}{2 \times m} - x \quad (3)$$

The variables d_1, d_2, and d_3 are the distances between the mobile device and the beacons on the left, right, and top of the triangle. The variable l is the size of the base of the square, and the variable m corresponds to half of this base $(\frac{l}{2})$ or half of the sides if the environment is rectangular.

5 Results

After executing the proposed project, we observed and tested the results from the perspective of two main points: the trilateration method and the use of BLE beacons in an indoor positioning system.

By applying the trilateration method, we proved that this technique is feasible even in a three-dimensional environment, where the user's mobile device is at a different height than the sensors distributed on the ceiling, as illustrated in Fig. 6.

In addition to the trilateration equations, we used the beacon positioning strategy that favored the calculations since we know and standardize the distance between the sensors. It is also possible to fix the beacons at various distances along the environment by informing the dimensions of their square for the system.

On the other hand, the accuracy of the results computed by the trilateration depends directly on the precision of the

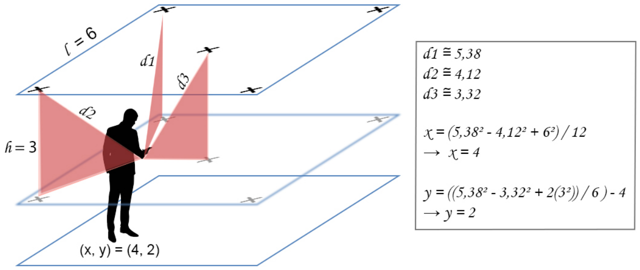


Figure 6: Trilateration applied to a three-dimensional environment.

estimated distance between the sensors and the device to be located. When using BLE technology, we observe some factors that influence distance estimation by RSSI, such as beacon direction, signal power selection, and calibration of the constants of the distance formula, but mainly the hardware used.

Cheaper devices, such as iTags, besides varying their signals with higher frequency and intensity, each device returns a different value of RSSI for the same distance. For a distance of one meter, for example, the five iTags in the experiment achieved a standard error of 1.86 dBm. Therefore, we solved the first case by selecting the mode of the first five RSSI readings of each iTag. Then, we evaluated the results using a table that calculated the mode and standard deviation for every 100 signal readings, illustrated in Fig. 7.

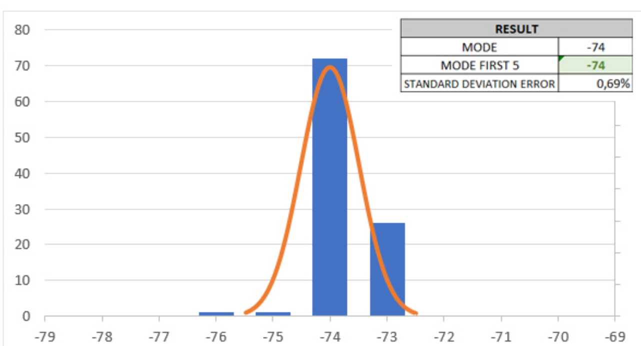
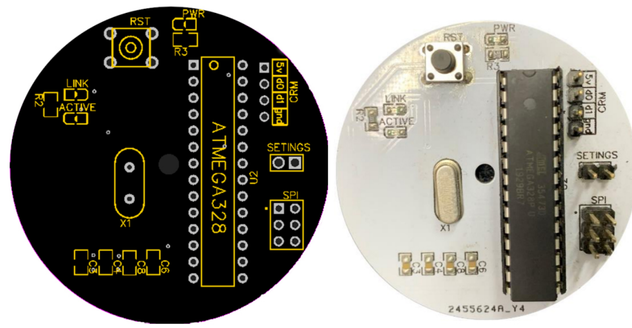


Figure 7: Analysis of the readings, calculation of a beacon's mode and standard deviation at a 1-meter distance.

Searching for better results, we used a Bluetooth reader provided by FRE[2] and specified in Fig. 8. At first, this beacon proved more stable, reducing the standard deviation error of the readings from 1.29 % to 0.67 %, compared to the iTags. We inserted this device into the test environment, calibrated the equation variables, and estimated its distance properly. However, we noticed that, as with the iTags, each device returned a different value of RSSI for the same distance from the reader. This condition eliminated our proposed single beacon-based calibration routine.



Power supply	5.0 Vcc
Operating power	0.3 W
Standby power	0.04W
Reading distance	Up to 30 meters
Maximum cable size	Up to 5 meters
Interface	Serial TTL 232
Reading time	< 0.5 s
Operating temperature	-10°C to 50°C
Ambient humidity	5% to 95%
Protection	IP 54
Protection box	ABS-3D
Dimensions	55 x 55 x 30 mm
Gross weight	60g

Figure 8: Technical specifications of the Bluetooth Reader BLE FREAccess.

At this point, considering the difference in values between the beacons, the influence according to their direction, and the different signal reflections from each place they were fixed, we experimented with combining them with an antenna. Using an aluminum foil, we constructed a parabola-shaped antenna and positioned it behind the beacons, which were the parabola's focus. As a result, the standard deviation error of readings at longer distances, such as 2.4 m, dropped from 2.11 % to 0.90 %. However, the accuracy of the distance conversion technique still does not support a trilateration indoor positioning system since small approximations at each elected sensor hinder the final result.

6 Conclusions

In this paper, we address systems for indoor localization, presenting the concepts of indoor positioning with BLE beacons and their related work. In addition, we propose and perform experiments to implement a low-cost, low-power, BLE-enabled device-based IPS.

The works we mentioned in Section 3 reported that indoor positioning systems, besides requiring costly calibration and configuration, still need improvements to address inaccuracies. Therefore, they demand a considerable amount of time and a combination of complex algorithms. On the other hand, our research was motivated by the search for more straightforward

[2]Partner company, located in Boituva-SP, which develops and manufactures electronic security products (software and hardware)

solutions that could meet a Bluetooth IPS, thus intensifying the development of these systems.

Thus, we propose fixing the beacons in a predefined positioning. With this procedure, we reduce the time and complexity of calibrating the offline phase of the systems. However, we have encountered challenges in achieving complete reliability and accuracy in indoor localization systems due to the high interference suffered by BLE technology. We highlight that our proposal is consistent with the results of the other studies, which also pointed out the difficulties of working with RSSI and suggested abandoning this technique.

To achieve accurate positioning through our system, it is crucial to improve the accuracy of distance estimation via RSSI. Therefore, we suggest, as a future work, to search for beacons of the same configuration that emit signals uniformly, at least 180°, considering their signal strength. Furthermore, thoroughly revising the path loss formula may improve the conversion process, making the model more suitable for indoor localization with BLE beacons.

References

Al Nuaimi, K. and Kamel, H. (2011). A survey of indoor positioning systems and algorithms, *2011 International Conference on Innovations in Information Technology*, IEEE, pp. 185–190. http://doi.org/10.1109/INNOVATIONS.2011.5893813.

Bishop, G., Welch, G. et al. (2006). An introduction to the kalman filter, *Proc of SIGGRAPH Course* **8**(27599-23175): 41. https://dl.acm.org/doi/book/10.5555/897831.

Cipriano, W. (2018). *Localização Indoor Baseada em Tecnologia Bluetooth de Baixa Energia*, Dissertação de mestrado, Centro Federal de Educação Tecnológica de Minas Gerais. https://sig.cefetmg.br/sigaa/verArquivo?idArquivo=2203988&key=275b23e6bc0120b16548418c13905623.

Davidson, P. and Piché, R. (2017). A survey of selected indoor positioning methods for smartphones, *IEEE Communications Surveys Tutorials* **19**(2): 1347–1370. http://doi.org/10.1109/COMST.2016.2637663.

Ho, Y. H. and Chan, H. C. B. (2020). Decentralized adaptive indoor positioning protocol using Bluetooth Low Energy, *Computer Communications* **159**: 231–244. http://doi.org/10.1016/j.comcom.2020.04.041.

Homayounvala, E., Nabati, M., Shahbazian, R., Ghorashi, S. A. and Moghtadaiee, V. (2019). A novel smartphone application for indoor positioning of users based on machine learning, *Adjunct Proceedings of the 2019 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2019 ACM International Symposium on Wearable Computers*, UbiComp/ISWC '19 Adjunct, ACM, New York, NY, USA, pp. 430–437. http://doi.org/10.1145/3341162.3349300.

indoo.rs (2022). InLocation alliance.
URL: *https://indoo.rs/partner/inlocation-alliance*

Kelley, C. T. (1999). *Iterative Methods for Optimization*, Frontiers in applied mathematics, SIAM, Philadelphia.

Kárník, J. and Streit, J. (2016). Summary of available indoor location techniques, *IFAC-PapersOnLine* **49**(25): 311–317. http://doi.org/10.1016/j.ifacol.2016.12.055.

Li, C. T., Cheng, J. C. P. and Chen, K. (2020). Top 10 technologies for indoor positioning on construction sites, *Automation in Construction* **118**: 103309. http://doi.org/10.1016/j.autcon.2020.103309.

Menegotto, J. L. (2015). Sensoriamento da edificação: um sistema de localização baseado em beacons BLE, *Anais do VII Encontro de Tecnologia de Informação e Comunicação na Construção – Edificações, Infra-estrutura e Cidade: Do BIM ao CIM*, pp. 264 – 274. http://doi.org/10.5151/engpro-tic2015-024.

Rezende, E. M. and Ynoguti, C. A. (2015). Tecnologias para localização interna, *II RST - Seminário de Redes e Sistemas de Telecomunicações, INATEL, BR*. https://www.inatel.br/biblioteca/todo-docman/pos-seminarios/seminario-de-redes-e-sistemas-de-telecomunicacoes/iii-srst/9458-tecnologias-para-localizacao-interna-indoor-location.

Rodrigues, M. S. and Carvalho, S. T. (2019). Sistemas de localização indoor utilizando Bluetooth Low Energy: Uma revisão sistemática, *Anais Estendidos do Simpósio Brasileiro de Sistemas de Informação (SBSI)*, SBC, Aracajú, pp. 5–8. http://doi.org/10.5753/sbsi.2019.7428.

Sadowski, S. and Spachos, P. (2018). RSSI-Based Indoor Localization with the Internet of Things, *IEEE Access* **6**: 30149–30161. http://doi.org/10.1109/ACCESS.2018.2843325.

Shang, F., Su, W., Wang, Q., Gao, H. and Fu, Q. (2014). A location estimation algorithm based on rssi vector similarity degree, *International Journal of Distributed Sensor Networks* **10**(8): 371350. http://doi.org/10.1155/2014/371350.

Spachos, P. and Plataniotis, K. N. (2020). BLE beacons for indoor positioning at an interactive IoT-based smart museum, *IEEE Systems Journal* **14**(3): 3483–3493. http://doi.org/10.1109/JSYST.2020.2969088.

Tariq, Z. B., Cheema, D. M., Kamran, M. Z. and Naqvi, I. H. (2018). Non-GPS Positioning Systems: A Survey, *ACM Computing Surveys* **50**(4): 1–34. http://doi.org/10.1145/3098207.

Yang, J., Poellabauer, C., Mitra, P. and Neubecker, C. (2020). Beyond beaconing: Emerging applications and challenges of BLE, *Ad Hoc Networks* **97**: 102015. http://doi.org/10.1016/j.adhoc.2019.102015.

Ye, F., Chen, R., Guo, G., Peng, X., Liu, Z. and Huang, L. (2019). A low-cost single-anchor solution for indoor positioning using BLE and inertial sensor data, *IEEE Access* **7**: 162439–162453. http://doi.org/10.1109/ACCESS.2019.2951281.