# A Collaborative Approach Using Neural Networks for BLE-RSS Lateration-Based Indoor Positioning

Pavel Pascacio*,†, Joaquín Torres-Sospedra‡, Sven Casteleyn* and Elena Simona Lohan†

*Institute of New Imaging Technologies, Universitat Jaume I, Castellón, Spain
†Electrical Engineering Unit, Tampere University, Tampere, Finland
‡Algoritmi Research Centre, Universidade do Minho, Guimarães, Portugal

*Abstract*—In daily life, mobile and wearable devices with high computing power, together with anchors deployed in indoor environments, form a common solution for the increasing demands for indoor location-based services. Within the technologies and methods currently in use for indoor localization, the approaches that rely on Bluetooth Low Energy (BLE) anchors, Received Signal Strength (RSS), and lateration are among the most popular, mainly because of their cheap and easy deployment and accessible infrastructure by a variety of devices. Nevertheless, such BLE- and RSS-based indoor positioning systems are prone to inaccuracies, mostly due to signal fluctuations, poor quantity of anchors deployed in the environment, and/or inappropriate anchor distributions, as well as mobile device hardware variability. In this paper, we address these issues by using a collaborative indoor positioning approach, which exploits neighboring devices as additional anchors in an extended positioning network. The collaborating devices' information (i.e., estimated positions and BLE-RSS) is processed using a multilayer perceptron (MLP) neural network by taking into account the device specificity in order to estimate the relative distances. After this, the lateration is applied to collaboratively estimate the device position. Finally, the stand-alone and collaborative position estimates are combined, providing the final position estimate for each device. The experimental results demonstrate that the proposed collaborative approach outperforms the stand-alone lateration method in terms of positioning accuracy.

*Index Terms*—Collaborative Indoor Positioning, Multilayer Perceptron, Received Signal Strength, Bluetooth Low Energy

## I. Introduction

Nowadays, there is a growing demand for indoor location-based services (LBSs) which are able to ubiquitously and accurately provide a user's position relative to the surrounding environment in an inexpensive manner [1]. Examples of LBS include navigation and location-aware and tracking services [2]–[4]. To this end, the pervasiveness of mobile and wearable devices with high computing power, together with growing deployment of anchors in indoor environments, play an important role. Among the large variety of technologies and methods used, solutions relying on Bluetooth Low Energy (BLE) and Received Signal Strength (RSS) are very popular, as they provide a cheap and easy deployment [5]–[8].

Although the feasibility of using BLE–RSS anchors/devices for proximity detection applications has been demonstrated [9], [10], their implementation for accurate positioning applications is still an open issue. Due to their relatively straightforward implementation, lateration algorithms are one of the most explored solutions to enhance positioning accuracy. Unfortunately, they suffer from accuracy degradation mainly due to four factors:

1) Anchor deployment: a low quantity of anchors deployed in the environment and/or the inappropriate anchor distribution increase not only the chance of Non-line-of-sight (NLOS) conditions but also the locations inside the operational area with insufficient anchor coverage for reliable lateration, reducing the overall positioning accuracy dramatically.

2) Unstable BLE signal strength: RSS of Radio Frequency (RF) signals are prone to fluctuate due to environmental conditions (geometries, temperature, crowded environments), building materials and presence of obstacles or people between transmitter and receptor devices (NLOS conditions) [11]–[13]. Such dynamic fluctuations are often difficult to predict and compensate for, and cause position estimation errors when used for positioning. In fact, the BLE signal propagation in indoor environments has not been properly modeled yet in order to estimate the relative distance between transmitter and receiver using smartphones.

3) Hardware heterogeneity: the RSS signature depends on the transmitters and receivers involved [14]. The diversity of devices involved in localization – both anchors and smartphones – comes with variability in the hardware-specific parameters, such as antenna gains, and thus in the BLE received signal strength [13], [15]. Furthermore, the transmission power and transmission period preset in each device – either by the device owner or manufacturer – presents variations due to tolerance in the design of antennas or in the RF circuit components, even in similar devices.

4) Software limitations: the energy-saving modes and execution task priorities prescribed by the mobile devices' operating systems may alter the transmission/reception period of BLE signals, rendering these devices non-deterministic for the BLE broadcasting.

In this article, we aim to enhance the positioning accuracy of the stand-alone lateration method applied to an adverse indoor scenario that copes with the first, second, and third issues mentioned above, namely the lack of sufficient beacons or problematic beacon distribution with the associated presence of large NLOS areas, the lack of appropriate signal propagation models to deal with fluctuating signal strength in unpredictable indoor conditions, and the heterogeneity among mobile devices typically present in any scenario. We do so by proposing a collaborative indoor position system which exploits the neighboring mobile devices as additional anchors in an extended, ad-hoc positioning network. The collaborating devices' information (i.e., their stand-alone estimated position and BLE–RSS) is exchanged and processed using a neural network model (rather than the traditional path-loss models) to estimate relative distances, after which lateration is applied to estimate the device's collaborative position. Unlike the path-loss models, which estimate the distance primarily based on signal attenuation formulas, the neural network model aims to relate the distance to RSS patterns, pairwise device position, identification of devices (transmitter and receiver), and variation of RSS measurements due to the devices' hardware heterogeneity. The collaborative algorithm takes mobile device variations into account by considering, for each device, a BLE reference measurement at one meter. Finally, a midpoint line algorithm is used to combine the collaborative and the non-collaborative position estimates to provide the final position estimates of each collaborative device. The key contributions of this paper are summarized as follows:

- We present a collaborative indoor position approach using Multilayer Perceptron (MLP) Artificial Neural Network (ANN) to enhance BLE–RSS lateration-based indoor positioning.
- We present a MLP ANN model to estimate relative distances between collaborative devices in order to provide a most reliable distance estimation. The MLP model provides a better modeling of the NLOS and Line-of-sight (LOS) conditions of the environment with respect to path-loss-based models, as well as, the characteristic inherent of each receiving device. Additionally, the proposed model avoids setting the parameters needed in path-loss-based models.
- We experimentally demonstrate, using a scenario with a poor quantity and inappropriate distribution of anchors, and rich NLOS conditions, that our collaborative approach outperforms the stand-alone lateration approach with respect to positioning accuracy in such conditions.

## II. RELATED WORK

The design of reliable Indoor Positioning System (IPS), which provide a balance between position accuracy and low-cost and easy deployment, is one of the main concerns in the design of location-based services (LBSs) [1]. To meet this concern, diverse solutions have been proposed. In this section, we focus on those fields relevant for this work, namely lateration, artificial neural network, and collaborative IPS.

### A. Lateration

Lateration approaches estimated the target position by considering the distance between the target and multiple reference anchors (minimum three)[16]. The distance is the result of the conversion of RSS measured between reference anchors and target [16], [17]. Free space path, two-ray ground, and logarithmic path-loss are some of the most used models to convert RSS into distance [18]–[20].

In the context of indoor positioning, it has been shown in literature that having more (even redundant) anchors yield better positioning accuracy –independent of the lateration approach used– and least-square lateration performs better than traditional lateration. For example, Dag *et al.* [16] proposed an RSS-based lateration algorithm, which was implemented using a least-squares method and required redundant anchors deployment. The distances between anchors and target were estimated with the Logarithm Distance Path Loss (LDPL) model, whose parameters were computed statistically. The experiments were conducted in a $6\,\mathrm{m} \times 6\,\mathrm{m}$ area, considering 196 measurement points collected with a single device in complete LOS. The authors conclude that adding least-squares to lateration reduces the error by $67.6\%$ to $2.8\,\mathrm{m}$, and including redundant anchors reduces the error to $1.35\,\mathrm{m}$. Cengiz [17] also proposed a least-square lateration approach and performed an accuracy error analysis using simulated environments. The analysis included the level of Gaussian noise, number of anchors, and size of the area. The results were compared with a traditional lateration, concluding that increasing the density of anchors deployed improves positioning accuracy. The proposed method significantly improved lateration in scenarios with a strong noise component (high Gaussian noise, $\sigma = 5$), reducing the error from $4.5\,\mathrm{m}$ to $1.9\,\mathrm{m}$, $5.9\,\mathrm{m}$ to $3.9\,\mathrm{m}$ and $18\,\mathrm{m}$ to $7.5\,\mathrm{m}$ for $6 \times 6\,\mathrm{m}^2$, $12 \times 12\,\mathrm{m}^2$ and $24 \times 24\,\mathrm{m}^2$ test areas respectively.

In line with literature, our method uses least-square-based method for lateration. Moreover, our approach aims to increase the amount of anchors, yet in contrast to previous works that deploy additional fixed anchors in the environment, we dynamically extend the positioning network using the devices of the users in a collaborative setting.

### B. Artificial neural network

Artificial Neural Networks (ANNs) are commonly used to self-learn the relationship between data provided to resolve complex problems [21]. Specifically, in indoor positioning they are used to provide robustness against noise and interference that affect the positioning accuracy [22]. For example, Wu *et al.* [21] presented a path-loss model based on Multilayer Perceptron (MLP) neural networks for wireless communication networks. For that purpose they considered several models using input vectors with fifteen features of the environment. The authors conclude that the introduction of environment features in the MLP model input and adding two hidden layers (with 5 and 10 neurons) provide an accurate and efficient path-loss prediction. On the other hand, Elbes *et al.* [23] proposed an indoor localization approach based on

Wi-Fi fingerprinting and Long Short-Term Memory (LSTM) neural networks for position estimation. The experiments were carried out in $54 \times 32 \, \mathrm{m^2}$ test L-shape area with ad-hoc Wi-Fi anchors deployed and a single smartphone to scan the signals. The LSTM model consist of $42$ input features, $2$ outputs, $300$ neurons, learning rate $\lambda = 0.2$, drop error, and $250$ epochs. The results reported an average error of around $1 \, \mathrm{m}$.

In contrast to related work, our MLP architecture is intended for use with heterogeneous mobile devices to estimate the relative distance between neighboring devices in a collaborative approach. To this end, our MLP architecture exploits the usual short distance between neighboring devices to reduce the dimensionality of features and, consequently, obtain a lightweight neural network architecture that is feasible to implement on mobile devices. Specifically, the MLP architecture relates the distance to four main elements of BLE-RSS collaborative approaches. The elements used for the features of the architecture are the RSS patterns, pairwise device position, identification of devices (transmitter and receiver), and variation of RSS measurements due to devices' hardware heterogeneity.

### C. Collaborative indoor positioning systems

Collaborative IPSs aim to enhance positioning of devices/users by using wireless communication technologies, both for relative distance estimation and information exchange between them [24]. Within the collaborative IPSs, those relying on BLE-RSS for the non-collaborative and collaborative phase, as our approach, are scarce (for a comprehensive overview of collaborative IPSs, we refer to our recent systematic literature review [24]). One of the most representative ones is proposed by Qiu *et al.* [20], which presented a collaborative IPS based on inertial sensing, adaptive multi-lateration, and a mobile encountering approach. All these sources of data were combined using a particle-filter model to locate a target.

The author conclude that the accuracy improvements are approximately $28.19\%$ in LOS and $19.99\%$ in NLOS when using adaptive ranging device-specific parameter with respect to the none adaptive approach.

In contrast to what has been done in the literature, we do not rely on the LDPL model to estimate the relative distance between a receiver (RX) and a transmitter (TX). Instead, we use a neural network to process the RSS value depending on the transmitter and receiver location and receiver calibration.

### D. Overall summary

From the above-mentioned systems, we can summarize that the lateration methods considerably decrease the positioning accuracy as the density of anchors in the area decreases and the noise signal increases. ANNs can mitigate the effect of the environment on the position and distance estimation, as well as reduce the accuracy error. Additionally, the implementation of collaborative approaches can help to reduce the positioning error of individual estimations. To the best of our knowledge, this is the first BLE–RSS indoor positioning system that implements a collaborative approach based on ANNs.

## III. SYSTEM OVERVIEW

Under simulations or in ideal testbed conditions, i.e. scenarios featuring a rich amount and well distributed anchors in the environment and LOS conditions, RSS-based lateration approaches have provided high accuracy with positioning errors within the range of $0.8 \, \mathrm{m}$ to $1.3 \, \mathrm{m}$ [16], [17]. Nevertheless, in real environments (e.g., offices, stores, libraries) the positioning accuracy decreases dramatically. Real environments are characterized by large NLOS areas and anchor deployments that may not be exclusively designed for positioning tasks. In addition, each environment requires a dedicated modeling of the RF signal propagation to compensate for environment-specific conditions and accurately convert RSS into distance.

In this work, we propose a collaborative IPS using ANNs to enhance BLE–RSS lateration-based methods. Our approach tackles three main sources of positioning inaccuracy: mitigating the inaccuracy due to NLOS areas and inadequate deployment of anchors; reducing the impact of a inappropriate signal propagation modeling; and minimizing the impact of device heterogeneity. Potential application scenarios of our approach is indoor positioning in buildings with a poor infrastructure deployment, but with a moderate amount of mobile devices (people) inside and where the latency for users/devices positioning is moderate (e.g., tracking library assistants in libraries, patients in hospitals, personnel in government offices, among others).

Our collaborative approach is divided in three phases which are described in this section. The first phase is devoted to registering devices used in the collaborative approach, the second phase consists of the stand-alone (non-collaborative) lateration algorithm for position estimation of each device/user, and the last phase is devoted to collaboratively enhance the position of the target device/user.

### A. Registering a device for collaborative positioning

The registration procedure aims to identify a mobile device and record an RSS reference value, to be used in the collaborative algorithm. To this end, a fixed reference anchor ($BX$) emitting BLE advertisements is placed at an entry point to the environment. Each new user is then asked to position himself at 1 meter from the anchor (marked on the floor) in LOS, and measure and record the RSS value (i.e., $RSS_{RX}^{1m}(BX)$). This lightweight calibration procedure is performed only once for each (new) device. To ease this procedure, the calibration could be integrated with the electronic locking system of the main doors, calibrating the device every time the user's smartphone is used to unlock a door.

### B. Stand-alone phase

The stand-alone phase is devoted to estimating each initial individual device/user's position considering the RSS and the Ground-Truth (GT) coordinates of BLE anchors deployed in the environment. For reference, in this article this position estimation is performed using a lateration method based on

the LDPL model, a minimization problem, and the Levenberg-Marquardt algorithm for weighted nonlinear least-squares to solve the minimization problem.

The LDPL model expresses the relation between RSS and distance, as described by Eq. (1) [25]:

$$RSS_{RX}^d(TX) = RSS_{RX}^{1m}(BX) - 10\,\eta\,log\left(\frac{d}{d_0}\right) \quad (1)$$

Where $RSS_{RX}^d(TX)$ is the RSS measured at a distance $d$ between transmitter $(TX)$, which can be a BLE beacon or a smartphone, and receiver $(RX)$; $RSS_{RX}^{1m}(BX)$ is the RSS measured at $1\,m$; and $\eta$ is the path-loss attenuation factor.

Mathematically, the lateration approach is expressed by Eq. (2) as a minimization of the sum of squared errors between the measured distances $(d_m)$ and hypothetical ones $(g_m(\underline{x}))$, based on the unknown target position, $g_m(\underline{x})$, which is denoted by Eq. (3) [26].

$$\min_{\underline{x}} \sum_{m=1}^{M} \left(g_m(\underline{x}) - d_m\right)^2 \quad (2)$$

$$g_m(\underline{x}) \triangleq \sqrt{(x - bx_m)^2 - (y - by_m)^2} \quad (3)$$

Where, $m = \{1, 2...M\}$ are the number of BLE anchors deployed; $\underline{x} = \{x, y\}$ are the device/user's unknown coordinates; and $\{bx_m, by_m\}$ the GT coordinates of BLE anchors.

Algorithm 1 shows the pseudo-code for the stand-alone lateration approach, whose workflow is summarized as follows:

- **1st step:** Collect the RSS from BLE anchors $(RSS_{RX}^d(TX))$ within a time window $(tw)$ of $60\,s$, by discarding those not belonging to the deployed scenario (input data for Algorithm 1);
- **2nd step:** Group the RSS readings by anchor removing the outlier values. We consider the values falling out of 25 and 75 percentiles (lines 1–2 in Algorithm 1) as outliers;
- **3rd step:** Apply the average operator to the RSS values of each anchor, in order to get one averaged RSS value per anchor (line 3 in Algorithm 1);
- **4rd step:** Select "strong reference BLE anchors", defined as the anchors with averaged RSS equal or greater than a predefined threshold (lines 4–8 in Algorithm 1);
- **5th step:** Estimate the relative distances of selected reference BLE anchors to the device/user's target position, by using the LDPL model, which is expressed by eq.(1), and their RSS values (line 9 in Algorithm 1);
- **6th step:** Estimate the device/user's position, $\hat{\mathbf{P}}^{Lat1}$, using the Levenberg-Marquardt Weighted Least Squares (L-MWLS) lateration method to fit the Euclidean Distance model. Henceforth, $Lat1$ will refer to the L-MWLS lateration method. The input data to fit the model are the distances estimated in the 5th step, the weights and the GT of the BLE anchors. The weight value for every BLE anchor is computed as the inverse of its distance square with respect to the device/user;
- **7th step:** Share the estimated position, $\hat{\mathbf{P}}^{Lat1}(RX) = [\hat{P}_x^{Lat1}(RX), \hat{P}_y^{Lat1}(RX)]$.

We set the $threshold$ value to $-83\,dBm$ and the path-loss attenuation factor to $\eta = 2.1$, as we previously used in [27] and which are in phase to values in literature [16]. Each device involved in the collaborative positioning model will have its own value for $RSS_{RX}^{1m}(BX)$ calculated from the data collected in the device registration phase (see Table II).

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**Algorithm 1** Stand-alone Lateration

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**Input:** Deployed anchors information collected within a time window $tw$: $RSS_{RX}^d(TX)$ values and GT
**Input:** LDPL: $\eta = 2.1$ and $RSS_{RX}^{1m}(BX)$
**Input:** $threshold$
**Output:** Estimated device/user position $\hat{\mathbf{P}}^{Lat1}(RX)$
1: Group the $RSS_{RX}^d(TX)$ values by beacon
2: Remove $RSS_{RX}^d(TX)$ outliers values of each group
3: Average $RSS_{RX}^d(TX)$ values of each group : $\overline{RSS_{RX}^d(TX)}$
4: **for** $i \leftarrow 1$ **to** number of $\overline{SS_{RX}^d(TX)}(i)$ **do**
5:    **if** $(\overline{SS_{RX}^d(TX)}(i) \geq treshold)$ **then**
6:       Include $i$-th anchors to reference anchors set $(ref_{anchorset})$
7:    **end if**
8: **end for**
9: Estimate the distances between anchors of $ref_{anchorset}$ and the device/user position using Eq.1, $\eta$ and $RSS_{RX}^{1m}(BX)$
10: Estimate the device/user position $(\hat{\mathbf{P}}^{Lat1}(RX))$ using the Levenberg-Marquardt Weighted Least Squares method
11:   **Share the estimated device/user position** $(\hat{\mathbf{P}}^{Lat1}(RX) = [\hat{P}_x^{Lat1}(RX), \hat{P}_y^{Lat1}(RX)])$

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### C. Collaborative phase

The collaborative phase uses the neighboring mobile devices' information, which include the measured BLE-RSSs, the estimated positions for the receiver and transmitter devices, and the RSS at $1\,m$ of the receiver to collaboratively estimate the device/user's position, and ultimately provide the final position estimate based on the combined collaborative and stand-alone estimates, aiming to improve the latter. Each device/user, which exchanges information and collaborates with others, acts as an additional anchor, creating an extended ad-hoc positioning network, hereby improving the coverage of the original anchor network.

The collaborative phase relies on four main elements: 1) information exchanged between devices; 2) estimation of relative distances using a Multilayer Perceptron (MLP) neural network; 3) a lateration algorithm to collaboratively estimate the target device/user's position; and 4) a method to combine the stand-alone and collaborative position estimations.

*1) Information exchanged between devices/users:* Currently, the operating systems of mobile and wearable devices permit broadcasting BLE advertisements. This feature allows them to act as BLE anchors and share information, enabling the development of collaborative positioning systems [28]. The information used in our collaborative positioning system includes: the RSS received at receiver from transmitter $(RSS_{RX}(TX))$, the RSS at $1\,m$ $(RSS_{RX}^{1m}(BX))$ of the receiver obtained after registering the device and the position of each collaborative device/user estimated by the stand-alone lateration $(\hat{P}_x^{Lat_1}(TX), \hat{P}_y^{Lat_1}(TX), \hat{P}_x^{Lat_1}(RX), \hat{P}_y^{Lat_1}(RX))$.

All these collected data are used as inputs for the neural network presented in next subsection and the collaborative algorithm presented in Algorithm 2.

*2) Multilayer Perceptron (MLP) neural network and relative distances:* The MLP neural network model's architecture used to estimated the relative distances is presented in Figure 1. Its architecture consists of 6 input layers, 1 hidden layer with 3 neurons, and one output layer. The activation function used is the hyperbolic tangent. In the training, the scaled conjugate gradient back propagation was used as training function and 50 epochs were considered. Further information about the selection of hyperparameters of the MLP neural network is provided in Section IV.

The 6 inputs that feed the MLP neural network model correspond to the exchanged information between each pair (target device–neighbor device) and the output is the estimated distance of that specific pair. The input are: the $RSS_{RX}(TX)$, which corresponds to the RSS of the BLE advertisement sent by the transmitter $TX$ and measured at the receiver $RX$; the $x$ and $y$ coordinates of the transmitter (neighbor device/user) position estimated by the stand-alone lateration algorithm $(\hat{P}_x^{Lat_1}(TX),\hat{P}_y^{Lat_1}(TX))$; and the $x$ and $y$ coordinates of the receiver (target device/user) position estimated by the stand-alone lateration algorithm $(\hat{P}_x^{Lat_1}(RX),\hat{P}_y^{Lat_1}(RX))$.

Finally, the $RSS_{RX}^{1m}(BX)$ is the RSS value measured at $1\,\mathrm{m}$ of distance between transmitter and receiver assigned at each mobile device by phase one (see Table II).
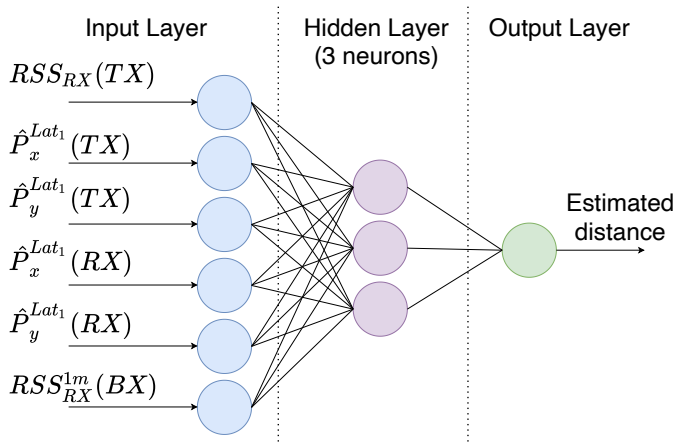


Fig. 1: MLP neural network model architecture. Used to estimate relative pairwise distance between target and neighboring devices/users.

*3) Collaborative lateration algorithm:* The lateration algorithm used in the collaborative phase is the same algorithm used in the stand-alone phase (see Section III-B). The main two differences are within the data used to perform the lateration.

- First, rather than fixed BLE beacons in the environment with well-known position, the anchors considered in the collaborative lateration algorithm are the neighboring devices/users, of which only the position estimated by the stand-alone lateration is known.

- Second, the relative distances between the target device/user and the neighboring devices/users is computed using a MLP neural network model instead of the LDPL model.

*4) Combining stand-alone and collaborative estimated positions:* Once the position of the target device is collaboratively estimated using neighbor devices/users as anchors, it is combined with the stand-alone estimation to come to a final estimated position. In this article, we used a midpoint line algorithm, as described in Eq. (4).

$$\hat{\hat{P}}_x(RX) = \frac{\hat{P}_x^{lat_1}(RX) + \hat{P}_x^{lat_2}(RX)}{2} \qquad (4)$$

$$\hat{\hat{P}}_y(RX) = \frac{\hat{P}_y^{lat_1}(RX) + \hat{P}_y^{lat_2}(RX)}{2} \qquad (5)$$

Where $\hat{\hat{\mathbf{P}}} = [\hat{\hat{P}}_x(RX), \hat{\hat{P}}_y(RX)]$ represents the final estimated position, with $x$ and $y$ coordinates, of device/user $RX$, with $RX = \{1, 2....N\}$ and $N$ the number of devices. $\hat{P}_x^{lat_2}(RX)$ and $\hat{P}_y^{lat_2}(RX)$ are the position estimated, $x$ and $y$ coordinates, with the collaborative lateration and $\hat{P}_x^{lat_1}(RX)$ and $\hat{P}_y^{lat_1}(RX)$ are the position estimated, $x$ and $y$ coordinates, with the stand-alone lateration, both for device/user $RX$.

*5) Full collaborative workflow:* Finally, algorithm 2 shows the pseudo-code for the collaborative positioning algorithm. The algorithm inputs are the shared information exchange by each collaborative device/user within a time window ($wt$) of $60\,\mathrm{s}$ and correspond to the RSS transmitted by each collaborative device/user ($RSS_{RX}(TX)$), position of each collaborative device/user estimated by the stand-alone lateration ($\hat{P}_x^{Lat_1}(TX),\hat{P}_y^{Lat_1}(TX),\hat{P}_x^{Lat_1}(RX),\hat{P}_y^{Lat_1}(RX)$), and the RSS at $1\,\mathrm{m}$ ($RSS_{RX}^{1m}(BX)$). The algorithm workflow is summarized as follows:

- **1ⁿᵈ step:** Group the RSS readings by device and remove outlier values. We consider those values falling out of 25 and 75 percentiles (lines 1–2 in Algorithm 2) as outliers;

- **2ʳᵈ step:** Apply the average to the RSS values of each device/user, getting one averaged RSS value per device/user (line 3 in Algorithm 2);

- **3ᵗʰ step:** Estimate the relative distances of neighboring devices/users to the target device/user, using the MLP model, which structure is depicted in Figure 1. The inputs of ANN model are:$RSS_{RX}(TX)$, $(\hat{P}_x^{Lat_1}(TX),\hat{P}_y^{Lat_1}(TX),\hat{P}_x^{Lat_1}(RX),\hat{P}_y^{Lat_1}(RX))$, $RSS_{RX}^{1m}(BX)$ and (input values in Algorithm 2);

- **4ᵗʰ step:** Estimate the device/user's position ($\hat{\mathbf{P}}^{Lat2}(RX)$) using the Levenberg-Marquardt Weighted Least Squares (L-MWLS) lateration method to fit the Euclidean Distance model. The input data to fit the model are the relative distances estimated by the MLP neural network model (step 3), the weights and the estimated positions ($\hat{\mathbf{P}}^{Lat1}$) of the neighboring devices/users. As in the stand-alone algorithm, the weight value for every BLE anchor is computed as the inverse of its distance square with respect to the device/user;

- **5th step:** Compute the final estimated device/user's position ($\hat{\mathbf{P}}(RX)$) based in the formula expressed in eq.(4), using the estimated standalone position $\hat{\mathbf{P}}^{lat_1}(RX)$ and collaborative estimated position $\hat{\mathbf{P}}^{lat_2}(RX)$, where $(RX)$ is the identifier of the device/user to estimate its position.

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**Algorithm 2** Collaborative module

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**Input:** Collaborative devices information collected within a time window $tw$: $RSS_{RX}(TX)$, $\hat{P}_x^{Lat_1}(TX), \hat{P}_y^{Lat_1}(TX), \hat{P}_x^{Lat_1}(RX), \hat{P}_y^{Lat_1}(RX)$, and $RSS_{RX}^{1m}(BX)$

**Output:** Improved estimated device/user position ($\hat{\hat{\mathbf{P}}}_{dev}(n)$)
1: Group the $RSS_{RX}(TX)$ values by device
2: Remove $RSS_{RX}(TX)$ outliers values of each group
3: Average $RSS_{RX}(TX)$ values of each group: $\overline{RSS}_{dev}(i)$
4: Estimate the relative distance between the target device and the near collaborative devices using the trained ANN model
5: Estimate the device/user's position ($\hat{\mathbf{P}}^{Lat_2}(RX)$) using the Levenberg-Marquardt Weighted Least Squares (L-MWLS) Lateration method
6: Compute the final estimated device/user's position ($\hat{\hat{\mathbf{P}}}(RX)$) using the midpoint line algorithm of eq.(4)

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## IV. EXPERIMENTS AND RESULTS

### A. Objectives and Experimental setup

The principal goal of our experiments is to assess the feasibility and benefits of our collaborative approach with respect to a traditional BLE-RSS lateration baseline to mitigate inadequate deployment of BLE anchors and increased NLOS conditions. Specifically, we evaluate and compare the positioning accuracy of both in a realistic environment.

We performed the experiments in a real office scenario. The office covers an approximate area of $10.8 \times 16.7 \, \text{m}^2$ and contains seven deployed BLE beacons (anchors), with a transmission power and period of $-4 \, \text{dBm}$ and $250 \, \text{ms}$ respectively. Figure 2 shows the complete scenario through a 3D representation, which allows us to illustrate the complexity of the environment. The NLOS conditions are mainly created by the furniture, which includes chairs, desks, desktop computers, bookshelves, and the concrete metal-reinforced pillars.
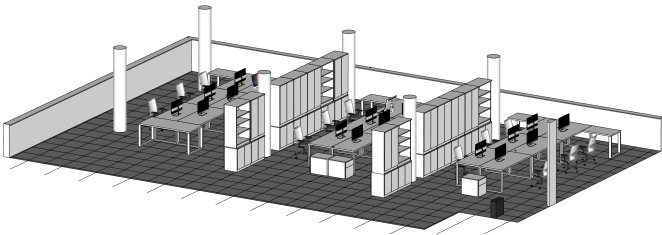


Fig. 2: 3D Office Scenario representation

In this office scenario, a comprehensive data collection was conducted. First, the five collaborative devices were registered during the registration phase (see Section III-A) and their $RSS_{RX}^{1m}$ was measured using a fixed BLE beacon from the environment. Table II summarizes the five devices that were

used in the experiment, and their corresponding $RSS_{RX}^{1m}$ value, which depend on the smartphone model and range from $-78.79 \, \text{dBm}$ to $-62.39 \, \text{dBm}$.

Then, seven different collaborative distributions (called configurations in this paper) made up of these five devices were considered. In each configuration, the five devices simultaneously broadcast and save the information of surrounding devices, including the BLE anchors, for 2 hours. Devices broadcast every 100 ms in accordance with the low latency mode supported by Android devices [29]. However, as mobile devices are not ad-hoc positioning devices, the broadcast period is affected mainly by the priority of executing tasks and power saving modes implemented by operating systems. The data collection for each configuration was performed independently, at a different time. As already mentioned, for the lateration approach based on the Logarithm Distance Path Loss (LDPL), the path-loss factor was determined to be $\eta = 2.1$ for all the five devices. Figure 3 and Figure 4 show the distribution of the devices in each configuration and the BLE anchors in the scenario, and Table I summarizes the GT coordinates of them.
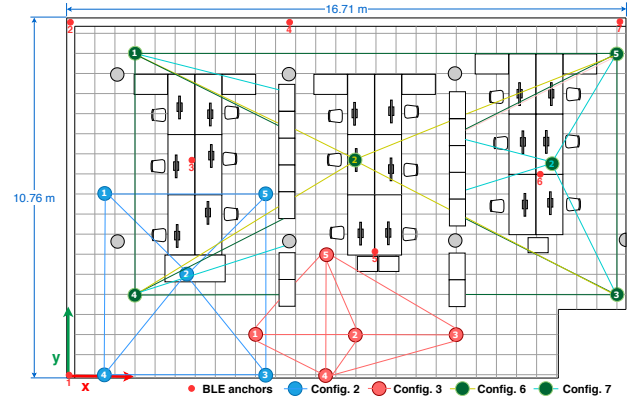


Fig. 3: Distribution of the configuration 2, 3, 6, and 7 used in the training & validation and distribution of the BLE anchors
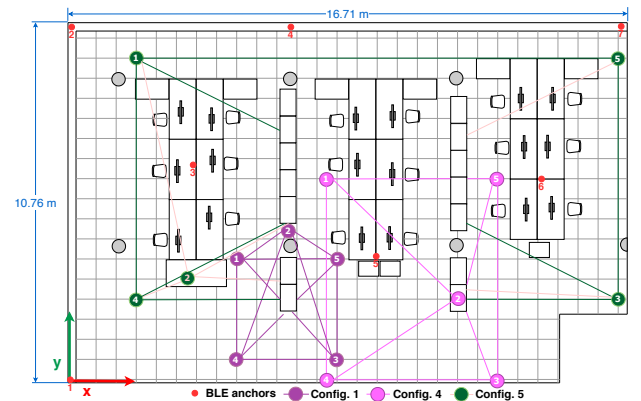


Fig. 4: Distribution of the configuration 1, 4, and 5 used in the testing and distribution of the BLE anchors

TABLE I: Position of the anchors, BLE beacons and collaborative devices in the 7 configurations

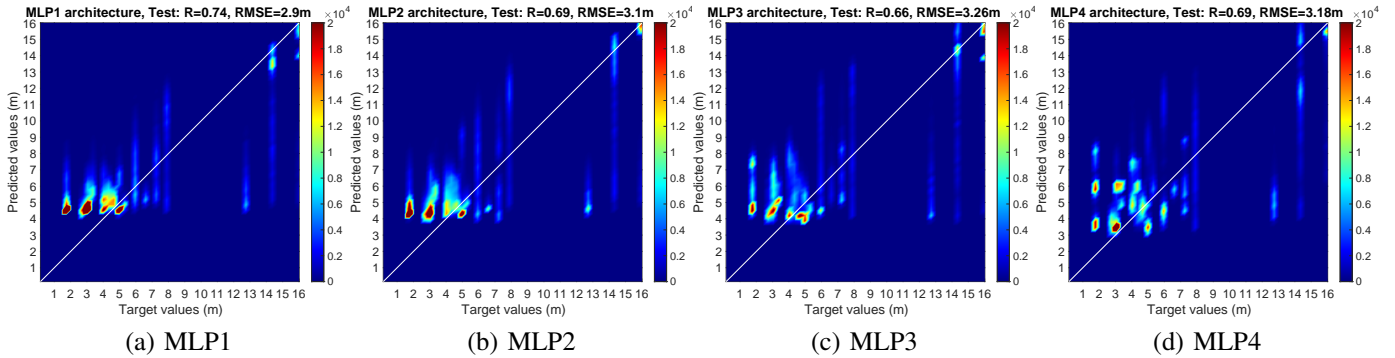| | BLE anchors | | Config. 1 | | Config. 2 | | Config. 3 | | Config. 4 | | Config. 5 | | Config. 6 | | Config. 7 | |
| $n$ | x | y | x | y | x | y | x | y | x | y | x | y | x | y | x | y |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 0 | 5.05 | 3.7 | 1.33 | 6.1 | 6.93 | 1.3 | 7.75 | 6.1 | 2.05 | 9.7 | 2.05 | 9.7 | 2.05 | 9.7 |
| 2 | 0 | 10.68 | 6.55 | 4.55 | 4.49 | 3.05 | 9.93 | 1.3 | 11.75 | 2.75 | 3.6 | 3.3 | 8.7 | 6.4 | 14.66 | 6.45 |
| 3 | 3.78 | 6.51 | 8.05 | 0.7 | 7.66 | 0.1 | 12.93 | 1.3 | 12.75 | 0.1 | 16.45 | 2.5 | 16.45 | 2.5 | 16.45 | 2.5 |
| 4 | 6.68 | 10.64 | 5.05 | 0.7 | 1.33 | 0.1 | 9.03 | 0.1 | 7.75 | 0.1 | 2.05 | 2.5 | 2.05 | 2.5 | 2.05 | 2.5 |
| 5 | 9.2 | 3.7 | 8.05 | 3.7 | 7.66 | 6.1 | 9.03 | 3.7 | 12.75 | 6.1 | 16.45 | 9.7 | 16.45 | 9.7 | 16.4 | 9.7 |
| 6 | 14.2 | 6.05 | - | - | - | - | - | - | - | - | - | - | - | - | - | - |
| 7 | 16.65 | 10.65 | - | - | - | - | - | - | - | - | - | - | - | - | - | - |



(a) MLP1    (b) MLP2    (c) MLP3    (d) MLP4

Fig. 5: Target vs Predicted distances from the test dataset estimated with MLP1–MLP4 architectures

TABLE II: $RSS_{RX}^{1m}(BX)$ values by device

| $RX$ | Device | $RSS_{RX}^{1m}(BX)$ values (dBm) |
|---|---|---|
| 1 | Galaxy S8 | -68.88 |
| 2 | Lenovo Yoga Book | -74.75 |
| 3 | Galaxy A7 Duos | -62.39 |
| 4 | Galaxy S6 | -62.99 |
| 5 | Galaxy A5 | -78.79 |

The data collected in the seven configurations were split into two datasets, where the devices cover different areas, and the distances among devices, and between devices and anchors, varies. Each dataset is used for different purposes: configurations 2, 3, 6, and 7 (see Fig. 3) were used to train the model and configurations 1, 4, and 5 (see Fig. 4) were used for evaluation. In order to tune the MLP neural network, the first dataset was randomly split into training (70%) and validation (30%) with 968798 and 242199 samples respectively. The testing dataset contains 936103 samples and it was used to test the MLP ANN for relative distances, and implement the BLE-RSS lateration baseline and collaborative approach.

The selected scenario is challenging and covers an area with low Geometric Dilution of Precision (GDOP) and strong heterogeneous NLOS conditions (diversity in obstacles): only 7 BLE beacons provide positioning, and there is device diversity in the collaborative phase. The proposed collaborative model targets dynamically extending the anchor coverage by using the collaborative user's devices, replacing the traditional LDPL model with a MLP ANN that processes the RSS considering the receiver and emitter location and the calibration of RSS (at 1 m) to minimise the device diversity effect.

## B. Multilayer Perceptron (MLP) neural network tuning

We tested four Multilayer Perceptron (MLP) neural network architectures in order to determine the best architecture and set of hyperparameters of our model. As hyperparameters, we considered different numbers of hidden layers (1 and 2) and neurons, as well as two types of activation functions, the Hyperbolic tangent sigmoid (tansig) and Log-sigmoid (logsig). Table III summarizes the hyperparameters configured in the proposed architectures.

TABLE III: Tested MLP architectures and hyper parameters

| Parameters | MLP1 | MLP2 | MLP3 | MLP4 |
|---|---|---|---|---|
| No. Input layers | 6 | 6 | 6 | 6 |
| No. Hidden layers (HLs) | 1 | 1 | 2 | 2 |
| No. Output Layer | 1 | 1 | 1 | 1 |
| No. Neurons HL1 | 3 | 3 | 6 | 12 |
| No. Neurons HL2 | - | - | 3 | 6 |
| Training function | | trainscg | | |
| Activation function | tansig | logsic | tansig | tansig |
| Performance Function | | Mean Square error | | |

Before presenting the main positioning results of the proposed collaborative approach and the lateration baseline, we present the results of evaluating the four proposed MLP architectures with the training dataset in order to determine which of them provides a more accurate estimation of relative distances. Figure 5 shows the density scatter plots of the real distance against estimated distance by each MLP neural network architecture. Also, the Root Mean Square Error (RMSE) and correlation coefficient (R) values are indicated in each of them.

From those values and density scatter plots, we can notice that the Multilayer Perceptron (MLP) architectures with one hidden layer (MLP1 and MLP2) present a RMSE lower than the architectures with two hidden layers (MLP3 and MLP4), as well as a greater correlation coefficient (0.74 and 0.69 for MLP1 and MLP2 respectively). Therefore, architectures with a single hidden layer are able to estimate the distance more accurately. In specific, MLP1, which use an hyperbolic tangent sigmoid activation function (tansig), presents a higher density of predicted values closer to the real values in comparison with the MLP2, which use a Log-sigmoid activation function, as can be observed in the density scatter plots of Figure 5 (a) and (b). Additionally, we notice that the density increases for the range between $3\,\text{m}$ to $6\,\text{m}$ and around $15\,\text{m}$. The results of high density values around the short distance demonstrate the potential of the MLP architecture to improve the accuracy of position estimations in collaborative IPS in scenarios with a high density of collaborating mobile devices (i.e., when the distance between neighboring devices is short).

As a result of assessing different MLP architectures, the MLP1 with one hidden layer (3 neurons), a scaled conjugate gradient backpropagation training function, and a hyperbolic tangent sigmoid activation function was selected to estimate relative distances with BLE–RSS data.

### C. Results of the collaborative model

Table IV presents the main results of the lateration baseline and our collaborative approach using various evaluation metrics (i.e., RMSE, mean, median, 70th and 90th percentile), and also indicates the relative difference between them.

TABLE IV: Main results metrics provided by the Lateration baseline and our proposed collaborative approach

| | Lateration baseline | Collaborative approach | |
|---|---|---|---|
| Eval. metric | Error (m) | Error (m) | Diff. |
| RMSE | 5.76 | 5.22 | ↓ 9.37% |
| Mean | 5.36 | 4.55 | ↓15.11% |
| Median | 5.54 | 4.84 | ↓12.63% |
| $75^{th}$ percentile | 7.08 | 6.68 | ↓ 5.64% |
| $90^{th}$ percentile | 8.08 | 8.08 | 0 % |

As reported in Table IV, our collaborative approach outperforms the lateration baseline in four of the five evaluation metrics, with a maximum of $15.11\%$ of difference for the "mean" metric.

Figure 6 introduces the Empirical Cumulative Distribution Function (ECDF) of the lateration baseline (black dotted line) and our proposed approach (red line). For the first 40% of cases, our collaborative model significantly outperforms the baseline, for the next $50\%$ of cases, the improvement is moderate, being quite close for the last $10\%$ of cases.

It should be noted that the positioning accuracy of the lateration baseline was significantly degraded, compared to BLE-RSS approaches reported in the literature ($2\,\text{m}$ to $3\,\text{m}$ error [27], [30]), due to the adverse test scenario conditions, namely poor quantity and inappropriate distribution of anchors, unstable signal strength and hardware heterogeneity.

However, the magnitude of the errors is in line with scenarios that consider the low-density anchor deployment issue. For example, Cengiz [17] reported a mean error accuracy of $7.5\,\text{m}$ in their lateration algorithm, which was tested on a $24 \times 24\,\text{m}^2$ area with 8 anchors.
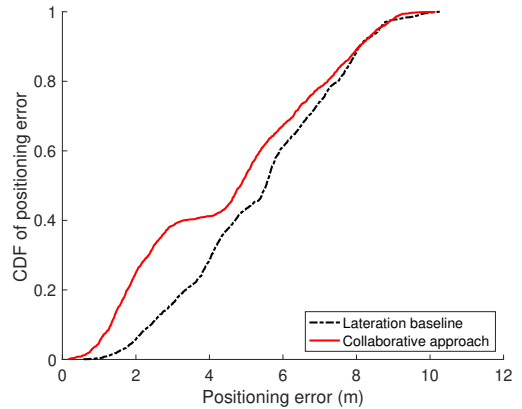


Fig. 6: Empirical CDF provided by the Lateration baseline and our Collaborative approach

Figure 7 provides a more detail representation of the individual positioning errors of the laterations used in the stand-alone phase and the collaborative phase.
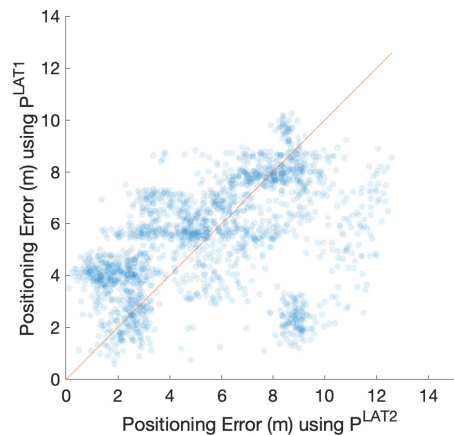


Fig. 7: Comparison of individual errors provide by the Lateration baseline and our Collaborative lateration approach

From the scatter plot, we can deduce that the lateration used in the calibration phase is providing better positioning results than the one based on the few beacons deployed in the environment. However, for a few cases the behavior is just the contrary as the accuracy is a few meters worse than the baseline. Nevertheless, the strongest feature of the proposed collaborative model is the combination of the lateration results from both phases, providing an ensembled output. According to the ensemble theory, the combination of estimators improves the accuracy of any of the individuals involved.

## V. Conclusion and Future Work

In this paper, we presented a collaborative indoor positioning system using Multilayer Perceptron (MLP) Artificial Neural Networks (ANNs) to enhance the accuracy of the models based on BLE and RSS lateration, in typical adverse conditions, namely poor quantity and inappropriate distribution of anchors, unstable signal strength and hardware heterogeneity. The proposed approach is divided in three phases. The first phase is devoted to registering devices used in the collaborative approach and establishing an RSS baseline measurement at $1\,\mathrm{m}$, the second phase consists of the stand-alone (non-collaborative) lateration algorithm for position estimation of each device/user, and the last phase is devoted to collaboratively estimate the position of the target device/user and combine it with the non-collaborative position estimate.

We evaluated our collaborative system in an indoor scenario (Office) and compared it with a lateration baseline. Our indoor scenario presents the aforementioned typical adverse conditions: an inadequate deployment of BLE anchors, rich NLOS conditions and heterogeneity among mobile devices used, causing a considerably reduction of positioning accuracy in RSS-based approaches. Experimental results show the feasibility and benefits of our proposed collaborative approach to outperform the positioning accuracy of the traditional lateration baseline under these adverse conditions. Particularly, our approach decreases, with respect to the lateration baseline, the mean, median, RMSE and $75^{th}$ percentile positioning error metrics with $15.11\%$, $12.63\%$, $9.37\%$ and $5.64\%$ respectively.

Furthermore, the results highlighted the usefulness of an MLP neural network model to model the signal propagation at short distance considering the inherent characteristic of each receiving device and in NLOS conditions, which is essential for estimating the distance between (heterogeneous) collaborative devices in real-world conditions.

As future work, we plan to use robust baseline approaches, which are able to provide a better positioning accuracy. We will consider more complex algorithms to combine independent collaborative estimates and reduce the overall positioning error. Additionally, we will enhance the neural network tuning, testing it in diverse and complex scenarios.

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