Evaluation of artificial neural networks for indoor positioning using Bluetooth Beacons

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***Abstract*—Indoor positioning opens up opportunities for a wide range of applications, including active marketing, accessibility and security. Although GPS (Global Positioning System) is widely used for outdoor location, it is inaccurate and in some cases unavailable indoors. One of the solutions is to use Bluetooth Beacons to determine the distance between the device and the beacon indoors using the Received Signal Strength Indicator (RSSI). The location of the object in the environment can be determined using at least three beacons and methods such as trilateration. This work aims to evaluate the use of artificial neural networks (ANN) to determine the distance and location of the laptop in an indoor environment. A first experiment compares the Log Distance Path Loss (LDPL) model and the ANN to determine the distance between the beacon and a laptop. A second experiment compares which method is best to determine the position of the laptop in a room. The following methods were evaluated: a) trilateration with distance calculation using the LDPL method; b) trilateration with distance calculation using an ANN; and c) position determination using an ANN. The results show that RSSI values can vary due to obstacles and the position of the antenna between the beacon and the laptop.**

***Index Terms*—receive strength signal indicator, RSSI, distance estimation, trilateration, LDPL**

I. Introduction

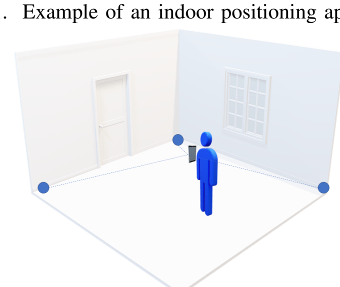
With the increasing use of smartphones, tablets and other devices, estimating their location indoors enables a variety of applications, such as, determining which area of a store an user is located, enabling active marketing or ensuring security, for example. In outdoor environments, the Global Positioning System (GPS) provides accurate target location and is widely used. However, this type of technology is more effective in outdoor environments and the error rate increases when trying to determine the location of the target indoors [1].

For this reason, various technologies and methods have been used to achieve better results, mainly infrared, Radio Frequency IDentification (RFID), ultrasound, Bluetooth, WiFi, and other wireless technologies.

Since Bluetooth version 4.0, the protocol has the Bluetooth Low Energy (BLE) profile and included the broadcast transmission mode, that allowed the development of small devices that can be powered by small batteries and thus have a lifetime of months or even years. Broadcast mode in BLE technology is used to transmit broadcast data without requiring a connection. This includes identifiers that can be received by devices with a Bluetooth interface, such as smartphones and smartwatches. In this mode, no connection needs to be established, resulting in fast interaction and low power consumption [2].

The Fig. 1 shows how the indoor localization is performed, where the blue dots represent the beacons, the user is the target whose position is to be determined (smartphone or other device with Bluetooth), and the line dots represent the distance between the beacon and the target. The distance is estimated using the Received Signal Strength Indicator (RSSI). One application example is guiding people with visual impairments in an art gallery, and as they approach a painting, an application previously installed on the user's smartphone would detect its position in the environment and describe the work where the user is [3], [4].

Fig. 1. Example of an indoor positioning application



This work aims to evaluate the accuracy of Bluetooth Beacons for determining the position of a laptop in a room. First, a preliminary evaluation of three beacons built with the HM -10 board was performed. Based on this initial study, the Log Distance Path Loss (LDPL) model was calibrated, which estimates distance using the RSSI value. Based on the initial model, the second step was to compare the LDPL model with the artificial neural network (ANN) to evaluate the accuracy of the distance estimation. The third step was to determine the position of the device in a room using the trilateration method, in which three beacons are positioned at different locations in a room. The trilateration method requires the distance between the beacon and the object. The LDPL and ANN methods were used to calculate the distance. A third method for position determination was also evaluated in this work. It consists of training a neural network to estimate the position of the object in space directly from the RSSI values obtained from the beacons.

This work is divided as follows. In Section II, the Bluetooth Beacons, the trilateration method and the LDPL model are discussed. Section III exposes the related work. Section IV presents the methodology. Section V discusses the results. Section VI concludes the paper and presents the future work.

II. Background

This section describes the information about Bluetooth Beacons, trilateration, and the LDPL model used to estimate indoor distance and location.

A. Bluetooth Beacons

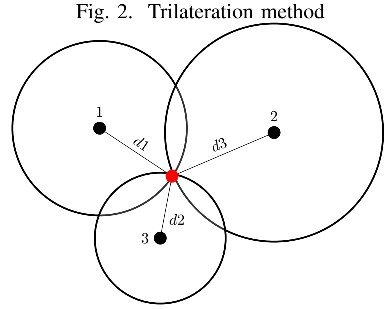
Beacons are small devices that use Bluetooth Low Energy (BLE) and send constant radio signals with small amounts of data. These signals have a range of 10 to 100 meters depending on the environment and their data can be received by another device with a Bluetooth interface, a smartphone for instance. Their price ranges from US$ 3-60 per beacon and can vary depending on functionality and size.

In this work, iBeacon solution is used. The iBeacon data packet consists of a Universally Unique IDentifier (UUID) with a size of 16 bytes used to represent a specific group or company. Additionally, the data packet includes also the Major and Minor identifiers, used to distinguish individual beacons [5].

B. Trilateration

Trilateration is a method for determining the position of a node in the environment. It requires at least three other reference nodes with known position and the distance between the target node and the anchor nodes. An example of a device that serves as an anchor node is Bluetooth Beacons, which can be used to locate the smartphone or tablet in an indoor environment. To determine the location of the target node, each anchor node is surrounded by a circle whose radius is equal to the distance between it and the target node. The location of the target node corresponds to the intersection of the three circles, as shown in Fig. 2 [6].

Fig. 2. Trilateration method



The Equations 1-9 calculate the intermediate variables A_1, A_2, A_3, B_1, B_2, B_3, C_1, C_2 e C_3, that are used in the Equation 10 to calculate the target node position (x_e, y_e). The coordinates $(x_1,\, y_1)$, $(x_2,\, y_2)$, $(x_3,\, y_3)$ are the position of the anchor nodes(beacons) 1, 2 and 3 in the room respectively.

$$A_1 = 2(x_2 - x_1) \tag{1}$$

$$A_2 = 2(x_3 - x_1) \tag{2}$$

$$A_3 = 2(x_3 - x_2) \tag{3}$$

$$B_1 = 2(y_2 - y_1) \tag{4}$$

$$B_2 = 2(y_3 - y_1) \tag{5}$$

$$B_3 = 2(y_3 - y_2) \tag{6}$$

$$C_1 = d_1^2 - d_2^2 + x_2^2 - x_1^2 + y_2^2 - y_1^2 \tag{7}$$

$$C_2 = d_1^2 - d_3^2 + x_3^2 - x_1^2 + y_3^2 - y_1^2 \tag{8}$$

$$C_3 = d_2^2 - d_3^2 + x_3^2 - x_2^2 + y_3^2 - y_2^2 \tag{9}$$

$$\begin{bmatrix} x_e \\ y_e \end{bmatrix} = \begin{bmatrix} A_1^2 + A_2^2 + A_3^2 & A_1B_1 + A_2B_2 + A_3B_3 \\ A_1B_1 + A_2B_2 + A_3B_3 & B_1^2 + B_2^2 + B_3^2 \end{bmatrix}^{-1} \times \begin{bmatrix} A_1C_1 + A_2C_2 + A_3C_3 \\ B_1C_1 + B_2C_2 + B_3C_3 \end{bmatrix} \tag{10}$$

The distance d_n between the beacon n and the target device must be determined. In this work, it is estimated converting the RSSI to distance using the LDPL or an artificial neural network.

C. Log Distance Path Loss Model (LDPL)

Before determining the position of the target node using the trilateration method, it is necessary to determine the distance between the beacons and the target node. This calculation is based on the RSSI values, since they vary depending on the distance, i.e., the greater the distance, the lower the RSSI value. Since RSSI is affected by obstacles in the environment, it is necessary to use a model that takes these disturbances into account. In this work, the Log Distance Path Loss Model, which is given in Equation 11 is used to determine the distance from the RSSI values [7].

$$RSSI = RSS_{d0} - 10n \times log_{10}\left(\frac{d}{d_0}\right) + X_\sigma \tag{11}$$

The parameter RSS_{d0} represents the value of RSSI at the given distance d_0, usually one meter. The parameter n represents the path loss exponent, which is the growth rate of path loss as a function of distance. The variable d is the actual distance and X_σ is the random mean variable with standard deviation used when there are large obstacles in the test environment to calculate the shadowing.

In practice, the devices themselves exhibit variations that ultimately affect the value of n, that are cause by the environment [7] [2]. Therefore, it is possible to calculate the specific n for each environment/device using the Equation 12 and averaging n at different distances.

$$n = \left(\frac{RSS_{d0} - RSSI}{10 \times log_{10}(d)} \right) \tag{12}$$

III. Related work

In [7], the authors performed experiments to collect and analyze RSSI values in Bluetooth Beacons using the log distance path loss model with a calibrated n. They also performed the trilateration calculation with three beacons to determine the location of the smartphone. After testing, they found that the error rate in determining the location of the target was high due to RSSI variations caused by interference, such as the direction of the antenna and objects in the transmission path, such as the human body. For this reason, they applied three filters to obtain better results: Mean, Median and Kalman. The Kalman's filter showed the smallest errors. Finally, they concluded that the RSSI values are more accurate at distances less than or equal to 4 meters and that the deviation increases with distance and consequently the inaccuracy.

In [8], the author used a ANN to calculate the location of the target within a laboratory. The wireless technology used was Wifi and an ESP8266 board as the target node to collect RSSI values. A Feed Forward Multilayer Perceptron neural network was used in a 4-4-2 configuration, where 4 input neurons are the RSSI values related to each of the 4 Wifi points used, and 2 output neurons representing the target coordinates. A database was created by collecting RSSI values at different locations in the environment to train the neural network. The authors describe that determining the position of the target was not very accurate due to fluctuations in RSSI values caused by disturbances in the environment. They obtained an estimate of the target position with errors of 20.93% for distances up to 0.5 meters and 34.88% for distances between 0.5 and 1 meters.

In [9], the authors compared determining the location of an Android smartphone using ANN and the Centroid Localization (CL) method. They used 4 HC-06 Bluetooth cards connected to the MSP430 microcontroller and positioned in the four corners of the room where the experiment was conducted. The structure of ANN contains 3 layers, 6 input neurons with RSSI values and their respective identifiers, a hidden layer, and 2 output neurons with the target coordinates. The RSSI of the three sensors with the highest value were used as input. During the localization step, after training the ANN, the authors found that the ANN was more accurate. They obtained a total error of 33.26m for the ANN and 108.15m for the CL algorithm.

In [10], the authors evaluated 4 smartwatches of 2 different types and brands, one type with Broadcom BCM4334 Bluetooth chip and another with Broadcom BCM4341 and 10 omnidirectional Bluetooth Beacons on the same Bluetooth chip. The first experiment consisted of using a smartwatch to capture RSSI values from a distance of 1 to 7 meters. In this experiment, the authors found that RSSI values from smartwatches equipped with the same Bluetooth chip were different, even when they were placed in the same locations. Another experiment was used to test the angle of arrival of the signal. To begin, one of the smartwatches was positioned in the center of a circle with a diameter of 1m and 2m, and 8 beacons were placed at the edges of this circle. Based on the average value of the RSSI, the 2 beacons that received the best signal were positioned perpendicular to the Bluetooth antenna of the watch. In the second part of the experiment, the smartwatch was attached to a human arm and placed in a box containing 8 beacons. In this experiment, it was found that the beacon that was under the arm became the second beacon with the worst signal, a result that was different from the one obtained in the first part of the experiment. Finally, they concluded that the arrival angle of the signal caused greater interference, about 13dBm, compared to the distance, about 8dBm for the distance of 7m, and that the different brands of devices showed variations in RSSI values, with an average variation of 5.02dBm for smartwatches and 2.8dBm for beacons.

Unlike the proposal in [8], which uses Wifi to capture RSSI, this work uses Bluetooth Beacon, a solution focused on low-power consumption. In [9], the authors also use Bluetooth Beacons and ANN to determine the location. In this work, were tested two different ANN usage scenarios, one to estimate the distance used in the trilateration method and the second similar to applied in [8] to estimate the location of the laptop in the room.

IV. Methodology

To determine internal location with Bluetooth Beacons, were used three HM-10 boards [11] powered by Li-ion batteries as anchors, and an application developed in Python using the Bleak library [12] to collect RSSI values.

The work was divided into three steps. The first step was to calibrate the value of n used in the LDPL equation shown in Section II-C. The second step was to compare the LDPL model with the use of artificial neural networks to evaluate which method is more accurate for estimating the distance between the beacon and the laptop. The final step is to determine the position of the laptop in a room with three Beacons as anchors.

A. Calibration of the parameter n in the LDPL equation

To calibrate the value of n, each HM-10 board was configured as a Beacon and then the RSSI values were collected in a straight line using the developed Python application. There were 24 RSSI values collected every 0.5 meters up to a distance of 6 meters. Then, the collected RSSI values were ordered and averaged, discarding the two highest and two lowest values for each distance with the purpose of eliminate the values of RSSI that don't corresponds to the actual distance. This average was used to calculate the n value for each beacon using the Equation 12, where RSS_{d0} is the RSSI value at a distance of one meter. The calibrated n value for each beacon is calculated as the average of the n values for the different distances.

B. Distance estimation

The second step was to determine the distance based on the collected RSSI using the LDPL equation and compare it to a artificial neural network-based model. To train the ANN, 1000 RSSI values per distance, from 0.5 to 6 meters, were collected with each beacon. The dataset was randomly split into 80% for training and 20% for testing using the random_split function from the pytorch.utils.data [13] library. Three neural networks were created, one for each Beacon.

For neural network training, some hyper-parameters were set to reduce the search space: the Adam optimizer, MSE as a loss function, a batch size of 32 and a number of epochs as 1000. Table I shows the hyper-parameters tested to determine the rest of the neural network configuration. Fig. 3, shows an example of what the structure of each neural network would look like, which has as input the 10 RSSI values read in sequence, and as output the distance between the laptop and the Beacon.

Fig. 3. Example of ANN for distance estimation

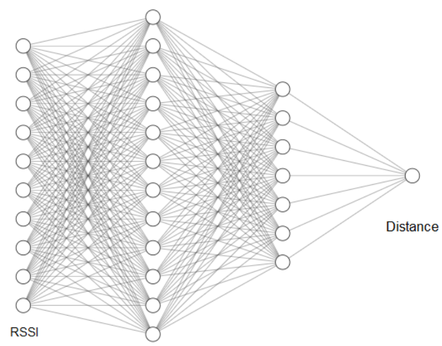


TABLE I
ANN CONFIGURATIONS EVALUATED

Parameter	Values
First Hidden Layer	10, 30, 50, .., 150
Second Hidden Layer	10, 30, 50, .., 130
Activation Function	Tahn, ReLu, Sigmoid
Learning Rate	0.1, 0.3, 0.01, 0.03, 0.001, 0.003

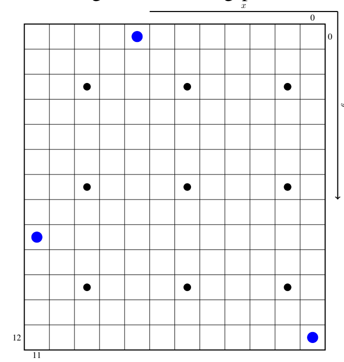
C. Indoor location

A third method evaluated is the use of a neural network to estimate the location of the laptop in space. The experiment was conducted in a 5.4 x 4.9 meter laboratory room with tables and chairs. To do this, it was collected 1000 RSSI values at specific points in the room, and these points were considered as points x and y in a 2D room space.

The room was discretized and the coordinates were determined using the floor tiles of the room with a size of 45x45cm, i.e., each tile was considered as a coordinate point x and y.

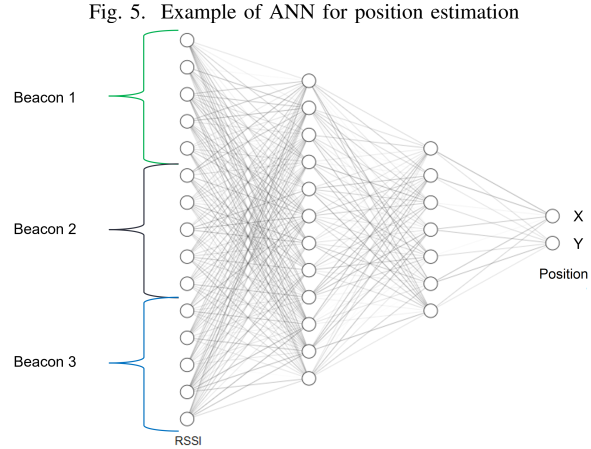
Fig. 4 shows the collection space, where the blue dots are the coordinates where the beacons were placed, and the black dots are where the laptop was placed to collect the RSSI values of the three Beacons simultaneously.

Fig. 4. Collecting points



For artificial neural network training, a split of 80% of the samples was used for training and 20% for testing. To find the best configuration, the same hyper-parameters listed in Table I were used. For neural network training, as used in the former experiment, some hyper-parameters were set to reduce the search space: the Adam optimizer, MSE as a loss function, a batch size of 32 and a number of epochs as 1000. Fig. 5 shows an example of the structure of the ANN used, with 15 input neurons for the RSSI of each beacon and two output neurons for the x and y positions.

Fig. 5. Example of ANN for position estimation



V. RESULTS

This section presents the results of the tests performed according to the methodology described in Section IV.

A. Preliminary tests and calibration of the LDPL equation

When the RSSI values were collected to perform the experiments, it was found that they were very unstable, as the values fluctuated even when the laptop was completely static in the same position. It was detected that the signal emitted by the Beacon was strongly disturbed by the environment, both by objects in the room and by the signals from other Bluetooth devices, which was observed on different days. It was found that the data obtained had greater fluctuations when there were multiple devices in the room.

B. Distance estimation

After evaluating the various ANN configurations, it was possible to determine the best configuration for each Beacon, as shown in the Table II, where LR is the *learning rate*. All ANN have 10 inputs for the RSSI and an output layer of size one, representing the estimated distance. It is important to note that a different configuration of ANN was obtained for each beacon.

TABLE II
ANN CONFIGURATIONS

Beacon	1st Hidden Layer	2nd Hidden layer	Function	LR
1	130	30	ReLu	0.001
2	40	50	ReLu	0.003
3	130	10	Sigmoid	0.001

Table III shows the comparison between the LDPL model and ANN for distance estimation. The MSE is the mean standard error and MAE is the mean absolute error. For the three beacons, ANN outperformed the LDPL model in estimating the distance between the beacon and the laptop. The maximum and minimum errors represent the error in meters between the actual position and the position estimated by the two methods. The errors of the LDPL model are due to the fluctuations and noise of the RSSI readings and indicate the need to filter the values or use a more robust method such as the artificial neural network proposed in this work.

TABLE III
DISTANCE ESTIMATION COMPARISON BETWEEN THE LDPL AND ANN

Metric	**LDPL Model**	**ANN**
Beacon 1		
Minimun error	-69.627	-3.932
Maximum error	357.738	2.659
MSE	4,765.239	1.011
MAE	53.286	0.762
Beacon 2		
Minimun error	-63.245	-2.573
Maximum error	184.840	2.374
MSE	2,914.055	0.866
MAE	41.461	0.701
Beacon 3		
Minimun error	-66.672	-2.977
Maximum error	43.175	1.859
MSE	1,562.070	0.734
MAE	34.603	0.641

C. Indoor location

After evaluating the various parameters, the best configuration was found for ANN with a first hidden layer of 100 neurons, a second hidden layer of 110 neurons, a Sigmoid activation function, a learning rate of 0.001, the Adam optimizer, MSE as a loss function, a batch size of 32 and a number of epochs of 1000. The input layer consists of 15 neurons containing the 5 RSSI inputs of each beacon, and the output layer consists of 2 neurons estimating the X and Y coordinates in space, similar to the architecture presented in the Figure 5. In the trilateration method, the distances were calculated using the models obtained from the distance estimation in the previous subsection.

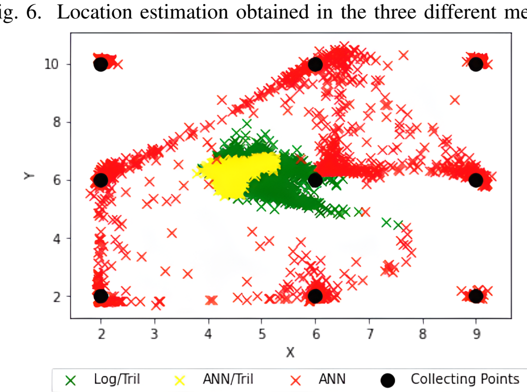
The errors in determining the location of the laptop are shown in Table IV. Among the methods used, ANN, which estimates the location directly from the RSSI values, was the one with the lowest errors. This is due to the collecting data considering the different positions of each beacon in the room and the adaptability of the neural network in detecting the RSSI behavior in the environment.

TABLE IV
ERRORS OBTAINED IN THE POSITIONING METHODS

	LDPL and trilateration	ANN and trilateration	ANN
X minimum error	-3.980	-2.830	-4.020
X maximum error	4.760	4.820	4.136
Y minimum error	-4.300	-4.340	-6.574
Y maximum error	4.200	4.060	4.280
MSE	8.379	9.113	0.503
MAE	2.591	2.669	0.347

Fig. 6 shows a scatter plot of the coordinates obtained with each of the 3 methods used. Most of the points estimated by the trilateration method are concentrated in the center of the space. Analyzing the distances calculated by the LDPL and ANN, it was found that most of them do not form intersections, and in this case the trilateration method yields points in the center of the space.

Fig. 6. Location estimation obtained in the three different methods



The neural network showed the best result in determining the location. Figures 7, 8 and 9 show the detailed estimated positions for each point of the room using the ANN method. Each collection point has a specific color and the position estimated by the neural network has the same color as the actual point. It is important to note that although the neural network is more accurate, it still has errors because in some cases the estimated positions are far from the actual position.

Another detail noticed is that in Fig. 8, the central points (D, E and F) have a lower accuracy than the others. This is probably due to the fact that the signal from the beacon in the central positions is disturbed by obstacles and the position of the antenna.

In the Figures 7 and 9, it is noticeable that the neural network achieves better accuracy at the corner points (A, C, G and I) of the space.

Fig. 7. Estimated positions for the points A, B and C

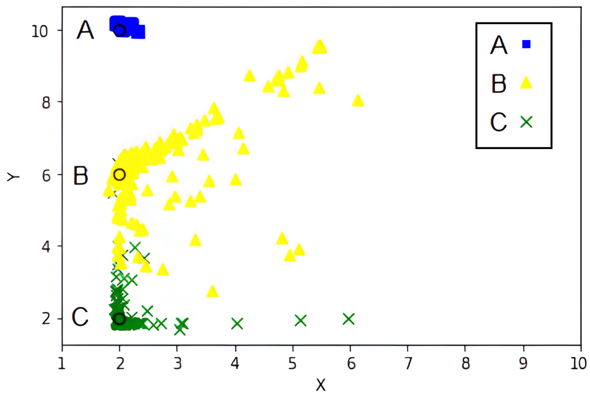


Fig. 8. Estimated positions for the points D, E and F

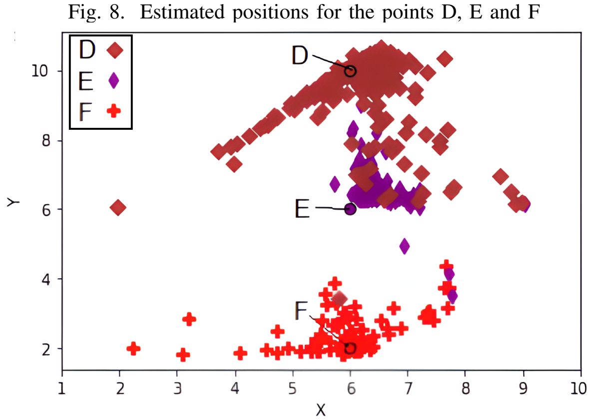
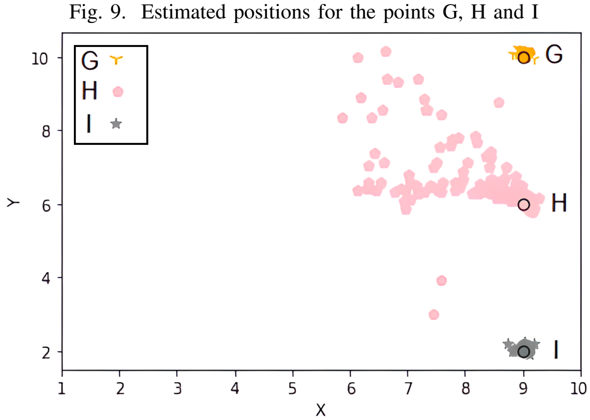


Fig. 9. Estimated positions for the points G, H and I



VI. Conclusions and Future Work

In this work, we investigated the use of Bluetooth Beacons to determine the distance between the device and the beacon indoors using the Received Signal Strength Indicator (RSSI). The results obtained show that the RSSI values vary greatly because they are very sensitive to interference from objects and devices, including other beacons. Therefore, one way to improve the accuracy of RSSI values would be to apply filters such as those presented by [7]. Another important factor was that the position of the receiver's antenna also affects the RSSI values, which was also observed by [10].

In the experiments analyzing the performance of the different methods, the artificial neural network gave the best results, both in estimating distance and position. With this level of precision, it could already be used indoors, for example in large stores, to check which area is most visited by customers and for active marketing.

Future work includes evaluating the accuracy when the target is in motion and checking the time that it takes to stabilize the position. Another future task is testing with more beacons to evaluate the impact on accuracy and applying filters to the data before it is used. In terms of estimation methods, we propose as future work the evaluation of other regression methods, such as random forest and multiple regression.

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