WLAN-BLE Based Indoor Positioning System using Machine Learning Cloud Services

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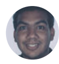

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WLAN-BLE Based Indoor Positioning System using Machine Learning Cloud Services

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***Abstract*—This paper presents the design and implementation of a system for micro-localization using Wireless Networking Technologies, such as WiFi and Bluetooth Low Energy (BLE) based on the Internet of Things (IoT) philosophy. The solution consists of an acquisition system of wireless signal parameters and the subsequent position system inference meanly cloud computing-based services. The proposed localization mechanism is based on a Machine Learning (ML) location algorithm stemming from the Signal-to-noise ratio (SNR) and Received Signal Strength (RSS) footprinting method, which allow us to detect the XY-position in a regression case o the reference zones in classification inside indoor environments. This paper reports a systematic description of the proposed IoT-based system and its connection to the Amazon Web Services (AWS) cloud computing services. An evaluation of different classification and regression algorithms was performed. The resulted model was deployed in the cloud, for an online and real-time inference following stage through the Internet. Real experiments were performed in order to assess the proposed system.**

***Keywords:*—Embedded System, Internet of Things, LBS, Micro-localization, WLAN, WiFi, BLE, Cloud Computing, AWS, KNN, SVM.**

1. Introduction

Thanks to the development of the ubiquitous computing, the increase in the processing capacity of embedded systems, mobile devices and the development of new wireless telecommunication networks, the microlocalization technology has aroused interest in researchers and developers in recent years. Nowadays, the applications that use location-based services (LBS) in different solutions and areas, such as security, the logistic, wearables, Smart-cities, etc. have increased in recent years. As well, location-based services are used in conjunction with other technologies such as Simultaneous localization and mapping (SLAM) [1], Internet of Things (IoT) [2], mobile services [3], among others.

The positioning systems according to their *location place*, are classified in outdoor and indoor environments. Each environment presents its characteristics associated with the infrastructure, in which the wireless signals suffer interaction and propagate. In the majority of cases, depending on the environment, exploitation of the positioning system becomes a complex task.

The localization task in indoor environments can become more difficult than in the outdoor cases because these spaces present complex infrastructures. The complexity of the space lies in the present composite structures, such as the objects inside, static and moving, the physical infrastructure variations of the emplacement, in addition to the openings inside the indoor environments, like the doors and windows. For LBS applications in indoor environments, it is complicated to find lines of sight for the signal propagation, not allowing to guarantee precision for methods based on times and angles measurement [4]. In closed environments, the *multipath* effect plays a relevant and negative role. Most wireless signals face this type of interference in structured environments, with many reflective and attenuating surfaces, such as walls and windows. For these reasons, the indoor environment positioning demands high levels of quality, which can only be guaranteed by efficient exploitation of the hardware, a high complexity, and robustness. In addition to this, cloud-based services have become popular, because they offer clean and abstract interfaces with high processing capacity. For this reason, it is possible that the terminal nodes, which usually have many limitations, require more simple hardware requirements [5].

This paper proposes the design and implementation of a system for micro-localization using Wireless Networking Technologies, such as WiFi and Bluetooth Low Energy (BLE) based on the Internet of Things (IoT) philosophy. The rest of the paper is organized as follows. In Section 2 a description of the existing indoor positioning techniques is presented. Section 3 presents a modular architecture solution for indoor positioning applications. Next, in Section 4 a description of machine learning algorithms and implementation are presented. A test-bed for validation is described. The experimental results and analysis are presented. Finally, the paper is concluded and we discuss some future guidelines to continue our work.

2. WLAN-based Indoor Positioning

Recently, there is a demand for indoor/outdoor precise positioning, using non-invasive infrastructure and wireless

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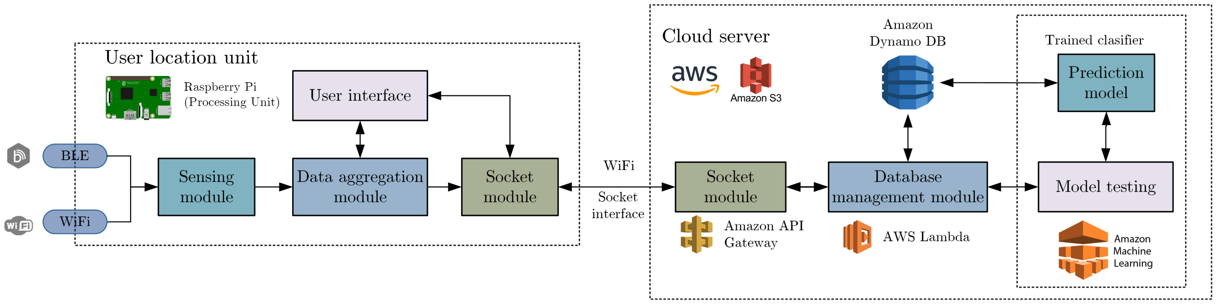

Figure 1. Proposed Indoor Positioning System architecture.

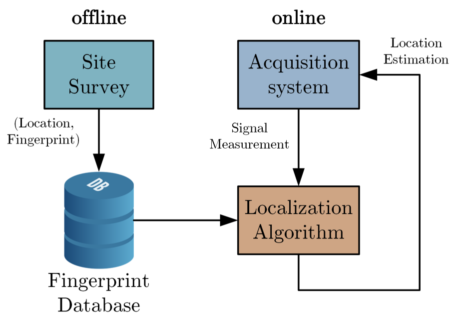

Figure 2. Flow diagram of the system based on footprinting. Adapted from [6].

signals and networks. Global Navigation Satellite System (GNSS) are used to provide location-based services in outdoor environments. GNSS in indoor environments, without a line of sight, loses precision and stops well working [7].

Currently, Radio-Frequency Identification (RFID) technology is used to provide localization in indoor environments. RFID technologies provide limited coverage (max. $2\,m$), does not have enough bandwidth and they are invasive in the infrastructure [8] [9].

Techniques that implement WiFi technology can achieve precision positioning if a proper initial calibration is performed. The radio parameters of a WiFi signal, radiated by a WAP, allow positioning. The techniques based on RSS, proximity and times are implemented using WiFi technology [4], [6]. The BLE technology has been implemented to mitigate the energy consumption problems of WiFi networks. Currently, the accuracy is slightly above 2 m, and depends mostly on the number of BLE anchors installed in the location space and on the environmental features [10].

Lately, the most adopted methods to perform LBS in indoor environments are the methods based on power footprinting measurements of the electromagnetic signals, like the Received signal strength indicator (RSSI) [11], [10]. These techniques are based on the attenuation that radio signals suffer as they propagate. There are three kinds of methods that use received power measurements: range methods, proximity methods, and fingerprinting based methods [12].

The RSS measurement by the positioning system can be calculated using the equation 1,

$$RSS^i_{d_k} = RSS^i_{d_0} + 10\alpha \log_{10}(d_k) + \eta_{\text{BLE}} + q_{\text{BLE}} \quad (1)$$

where, η_{BLE} is the noise due to the multipath effect, $\eta_{\text{BLE}} \sim \mathcal{N}(0, \sigma^2_{\text{BLE}})$. q_{BLE} is the quantization noise with uniform distribution, such the RSS in the BLE protocol handles only discrete values. $q_{\text{BLE}} \sim \frac{1}{\sqrt{12}}$LSB, where LSB is the quantizer least significant bit.

For a positioning system located in a 2D position, (x_k, y_k), the Euclidean distance to the i-the BLE beacon located at the coordinates (x^i, y^i) is found by,

$$d_k = 10^{\frac{RSS_{d_k} - RSS_0}{10\alpha}} \quad (2)$$

where RSS_0 is the received RSS at the $1\,m$ distance.

In the range methods, knowing the RSSI between two wireless devices, a transmitter, and its receiver, it is possible to find the relative position between both [4]. Through theoretical and empirical models, the power differences between the transmitted and received signals are measured. Then, the distances between transmitters and receivers are estimated (eq. 2).

The accuracy of the location systems using fingerprinting increases as the number of RSSI reference stations grows. The position estimation algorithms based on fingerprinting become more complex, because many interferences cause that the power measurements becomes a random variable, with a remarkable dispersion.

2.1. Fingerprinting based method

The fingerprinting based methods divide the indoor environment in a certain number of cells. Then, the received signal power or other radio-signal parameter is measured in each of cells, organized by data association in the form of a *radiomap*, like a characterization of the signal strength distribution. This stage is known as the *training phase*.

In a subsequent phase, the position inference is realized. Received power measurements are made again. Then, these obtained power measurements are related to the location information generated in the *training stage*, and by estimation and data association techniques, the position of the object is estimated. In figure 2 si shown the flowchart diagram of a positioning system based on power measurements. The *fingerprinting* method does not require distance calculates

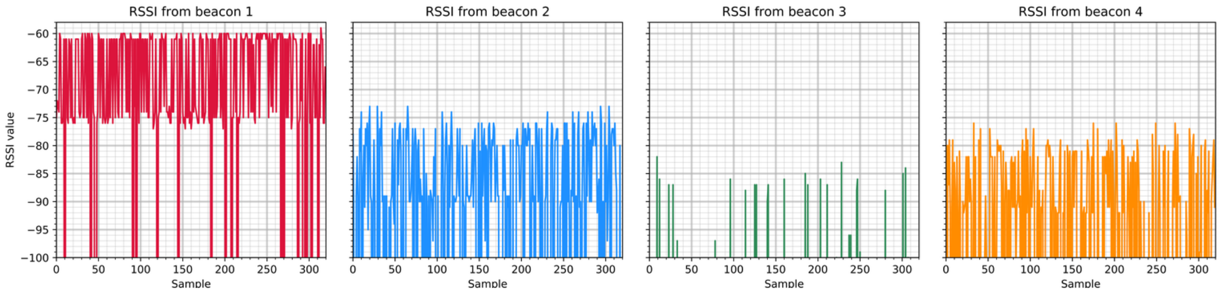

Figure 3. RSSI variations at the position 1 of the grid.

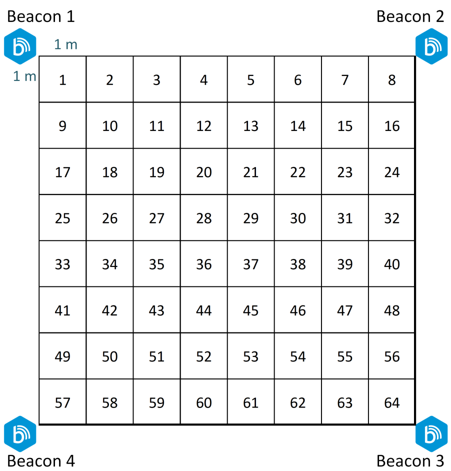

Figure 4. The layout of the location map, where the experiments were conducted.

and this method guarantees enough accuracy, although in too dense and dynamics environments the precision decreases [12].

The position estimation problem is a classical Bayesian problem, but lately, Machine Learning methods have become popular to solve it. Machine laerning methods, such as pattern recognition techniques, neural networks and *deep learning* [6].

3. IoT-based system solution

A general system architecture with two main systems was proposed: *User location unit* and *Cloud Server*. The User location system receives and stores the power signal measurements, through the WiFi and BLE Technologies, Then, the system performs pre-processing and data aggregation tasks on the measurements. After that, the sensed data is transmitted, via WiFi technology, to the Cloud Server system which implements a local storage database and a local web interface to display the raw and processed data stored in the database. During the training stage, the Cloud server system is in charge of executing the selected ML training algorithm.

In the inference stage, the Cloud server system executes the localization learned model, sending the estimated position to the user trough an Internet connection, and also storing the results in the database. After receiving the data frame trough AWS gateway and the AWS Lambda function, the Database (DB) management module stores the results in a cloud Dynamo database. The trained ML model runs using the Amazon Machine Learning services. The results of the inference of the position are sent to the user module [13].

In Figure 1 is shown a general block diagram of the proposed architecture.

4. Experiments and Results

In order to assess the performance of the proposed location systems, were performed several tests at the campus of the Universidad Sergio Arboleda, Bogotá, Colombia.

First, a training phase was performed, in which all the necessary measurements were obtained from the beacons and available APs. Then, and the ML models were trained. After that, was performed a functionality test of the location system.

4.1. Training stage

All the experiments were carried out in an area of interest covered approximately 64 m^2. The area was divided into grid squared cells, each of size 1 $m \times 1$ m as shown in Figure 4. Four BLE beacons (nRF51822 Nordic) were located at the corner of the square, at the points of $(0\,m,\ 0\,m)$, $(0\,m,\ 8\,m)$, $(8\,m,\ 0\,m)$, and $(8\,m,\ 8\,m)$. Each beacon was at the height of approximately $100\,cm$ from the floor. The five most strongest WiFi SNR signals at the campus were measurement too. The measurements were taken at the center of each grid cell. In total, were taken 15680 measurements with a sampling frequency of $1\,Hz$. The RSS of each BLE beacon and the SNR of each WiFi Access Point (AP) information were stored in the database. All the data acquisition process was made following the recommendations from [6].

Figure 3 is showen the RSSI variation for the position 1 of the grid for each $1\,Hz$ BLE beacon. The Figure shows that the power highest levels are registered from the nearest beacon, *beacon 1*. It can be observed that in position 1, the measurements of the farthest beacon, *beacon 2*, continually disappears from the register. The Table 1 shows the mean levels, the maximum values and the variance of the four received signals RSSI for each beacon in dB at the position 1.

Figure 5 shows the WiFi SNR variation for the position 25 of each AP. The mean levels, the maximum values and the

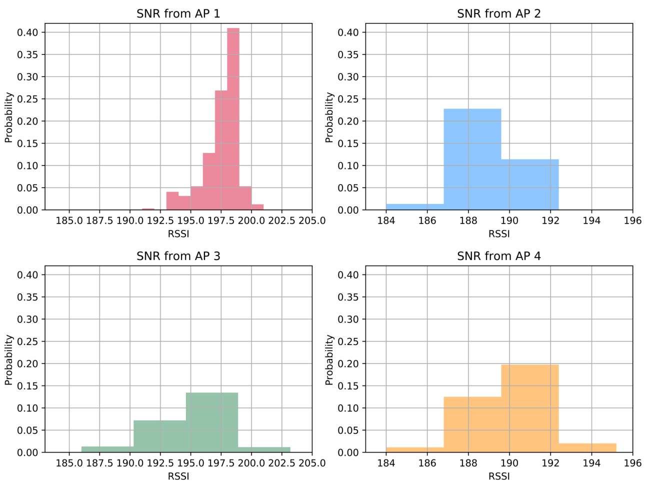

Figure 5. SNR variations histogram at the grid position 25.

variance of the five received WiFi SNR for each AP at the position 25 are shown in Table 2. It is possible to appreciate that AP number 5 did not generate any measurement at position 25.

Indoor position estimation from random RSS measurements should be regarded as a statistical problem. In many works, Machine learning algorithms have been considered as a non-deterministic solution to the position estimation problem [14]

To estimate the position of the receiver in each cell were implemented two different classification algorithms: k-Nearest Neighbours (k-NN) classifier [15] and Support Vector Machine (SVM) algorithm [16]. For each algorithm, the dataset was split into 10-folds of cross-validation of equal size by preserving stratified classes. A training partition of

beacon	**mean**, dB	**maximum**, dB	**minimum**, dB	σ, dB
1	-22.27	-15	-200	55.71
2	-34.89	-22	-200	55.15
3	-90.11	-42	-200	58.39
4	-50.04	-43	-200	55.47

Table 1. RSSI LEVEL CHARACTERISTICS FROM EVERY BEACON AT THE POSITION 1.

AP	**mean**	**maximum**	**minimum**	σ
1	197.05	201	191	1.464
2	189.07	212	184	2.273
3	195.38	229	186	3.487
4	190.1	212	184	2.632
5	-200	-200	-200	0

Table 2. SNR LEVEL CHARACTERISTICS FROM EVERY WIFI AP AT THE POSITION 25.

70% of the dataset was created. The remaining 30% of the dataset was used for the testing and validation realization.

For the k-NN classifier, a parameter estimation using a *gridsearch* with cross-validation was performed. Was determined that the number of possible neighbors was between 1 and 49. The possible values for weight function used in prediction were uniform weights and weight points by the inverse of their distance. ON the algorithm were tested four different power parameter for the *Minkowski* metric: the Manhattan distance, the Euclidean distance, the $L3$, and $L4$ distance.

Likewise, for the case of the SVM classifier a parameter estimation using grid-search with cross-validation was performed too. The kernel type used in the SVM algorithm was the Radial basis function (RBF) kernel. If RBF kernel is used, the adjustment of two hyper-parameters is usually required: the RBF kernel coefficient γ and the penalty parameter C. Both parameters were explored using a parameter grid (see Tab. 3) and their performance evaluated using 10-fold cross-validation.

4.2. Experimental results

In Table 4 is shown the best tuning parameters of the k-NN classifier for each used technology (Tech.): The best neighbor numbers, the distance metric, and the weights (Wgt.). Also, is shown its accuracy (Acc.), the F1 and the recall values.

he Figure 6 shows the accuracy that results from the cross validation to various k-neighbors values using WiFi technology, that got the best results. It can be seen in the Figure, that there is a maximum of accuracy for 4 neighbors. Then the precision decreases as the number of neighbors increases.

In Table 5 is shown the tuning parameters of the SVM classifier with the best results for each used technology: the RBF kernel coefficient γ and the penalty parameter C. The resulting accuracy, the F1 and the recall values are shown.

Figure 7 shows the accuracy that results from the cross-validation to various k-neighbors values using WiFi technology, that got the best results. It is possible to appreciate that the best values of γ and C are found in the lower left corner, that correspond to the lowest values. The classifier that showed the best results was the k-NN of 4 nearest neighbors, showing an accuracy of 75% with a resolution of $1\,m$, combining WiFi and BLE technologies.

5. Conclusions

This paper reports the design, implementation, and evaluation of an Internet of Thing (IoT)-based system for micro-localization using Wireless Networking Technologies. The

C	2^{-6}, 2^{-5}, 2^{-4}, 2^{-3}, 2^{-2}, 0.5, 1, 2, 4, 8, 16
γ	2^{-6}, 2^{-5}, 2^{-4}, 2^{-3}, 2^{-2}, 0.5, 1, 2, 4, 8, 16

Table 3. HYPER-PARAMETER VALUES FOR SVM GRID-SEARCH.

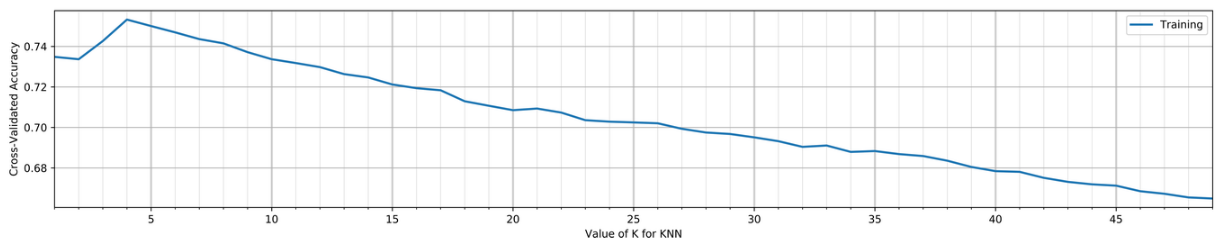

Figure 6. Cross-validation accuracy to k-neighbors values using WiFi/BLE technology.

Table 4. BEST TUNING PARAMETERS, ACCURACY, F1 AND RECALL VALUES FOR THE K-NN CLASSIFIER.

Tech.	k	Distance	Wgt.	Acc.	Error	F1	Recall
BLE	9	Manhattan	distance	0.68	0.31	0.67	0.68
WiFi	12	Manhattan	uniform	0.73	0.27	0.73	0.73
BLE/WiFi	4	Manhattan	distance	0.75	0.25	0.75	0.75

Table 5. BEST TUNING PARAMETERS, ACCURACY, F1 AND RECALL VALUES FOR THE SVM CLASSIFIER.

Tech.	C	γ	Accuracy	Error	F1	Recall
BLE	2	0.125	0.603	0.409	0.607	0.607
WiFi	2	0.0625	0.737	0.266	0.732	0.733
BLE/WiFi	4	0.015625	0.686	0.313	0.695	0.686

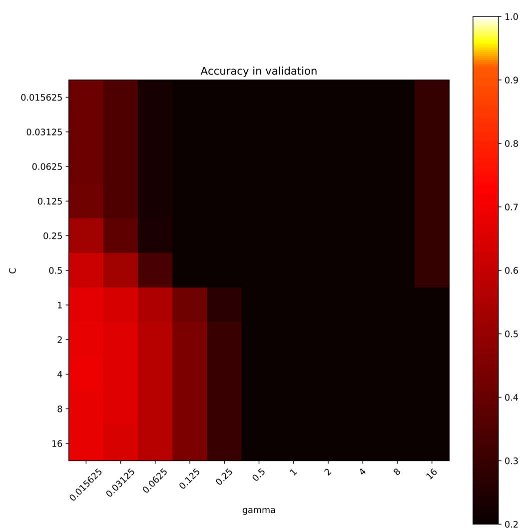

Figure 7. Cross-validation accuracy to the C and γ hyperparameters using WiFi technology.

general architecture proposed was composed by a data User position system, in charge of identifying and transferring of sensed data to a Cloud server for further computation, via the Internet.

This paper reports a systematic description of the proposed IoT-based system and its connection to the Amazon Web Services (AWS) cloud computing services. An evaluation of different classification and regression algorithms was performed. The resulted model was deployed in the cloud, for an online and real-time inference following stage through the Internet.

Real experiments were performed in order to assess the proposed system. A k-NN classifier of 4 nearest neighbors using presented the best results, with an accuracy of 75% with a resolution of $1\,m$.

As future work, the implementation of more robust localization algorithms in a real scenario, e.g., an office hall is proposed. One topic interesting is the implementation of heterogeneous information fusion, from inertial sensors and geomagnetic location.

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