Using Received Strength Signal Indication for Indoor Mobile Localization Based on Machine Learning Technique

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Abstract

The techniques of triangulation in Euclidean geometry can be considered the base of a wide range of positioning techniques for sensor networks; where they deduced the sensor locations by using its geometrical characteristics. This work presents a completely different method based on machine learning, where the data is obtained directly from the natural coordinate systems through the readings provided by Bluetooth Low Energy Devices. The known locations of beacon nodes in the network and the Received Strength Signal Indication (RSSI) can be exploited to detect the current position on mobile device based on the Bluetooth technology.

Keywords

Neural Networks; Localization; iBeacon; Received Strength Signal Indication; Precision

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Introduction

In sophisticated spaces such as hospitals, schools, commercial centers, mines, public libraries and smart buildings, Indoor mobile localization is considered one of the most important problems. The variety of locales involves differing ambient environments, obstructions, architectures, and materials, which makes accurate localization difficult. In addition to the problem of localization, there are other challenges represented by the movement of people, furniture and equipment inside these buildings.

The importance of positioning is by finding applications that track people and equipment. Factory and warehouse automation through asset tracking and optimization analysis can serve to increase productivity by effectively scheduling resources and equipment (Langlois, Tiku, & Pasricha, 2017), and as shown in Figure 1.

Figure 1. An examples of using smart phone in indoor localization

Sensor's position is known through one of two ways, the former is based on GPS which is a device built-in, while the latter is by localization techniques. Depending on these methods every sensor recognizes its exact position (Frattasi, & Della Rosa, 2017).

Many approaches for detecting sensors' locations based on localization techniques, the straightforward one is gathering the information about the entire network such as (pair-wise distance measure, connectivity, where these gathered data are collected together into one place to be processed centrally (Cheng, et al., 2017).

The sensors nodes transmit the data which had been gathered from their environments, but all these gathered data would be useless unless the sensors' location precisely known. Furthermore, the availability of information about the sensor's location may enable a countless of applications (e.g., health monitoring, intrusion detection, road traffic monitoring, inventory management, and etc.) (Wu, Tan, & Xiong, 2016).

Inside the buildings, Radio signal transmission may be affected by the fluctuations resulted from the indoor obstacles. To solve this problem, several solutions that use learning approaches have been suggested. Artificial intelligence and machine learning have seen enormous growth in recent years. In machine learning, emphasis is placed on using data extracted by means of statistics and tools for making the system able to learn the rules and the models (Zhang, Patras, & Haddadi, 2019).

In the context of using RSSI with localization, the complex relationship between the parameter of RSSI and the position estimation is solved by employing the approaches of machine learning. In this paper a new method has been proposed based on machine learning approaches in general, more specifically k Nearest Neighbors (kNN).

Related Works

There is a lot of research presented in Indoor Localization in recent years here we summarized some of the literary works. Mohammadi and Al-Fuqaha (2018) suggested a semi-supervised learning model based on deep reinforcement. Their model aimed to evolve the learning agent by improving the accuracy and performance through making that model convenient for the applications of smart cities as it consumes both labeled and unlabeled data. They concentrate on smart buildings and based on BLE signal strength they apply their model to the problem of indoor localization. Indoor localization can be considered the main component of the services at the smart cities where populations spent most of their time in indoor environments.

The model learns the best action policies that lead to a close estimation of the target locations with an improvement of 23 percent in terms of distance to the target and at least 67 percent more received rewards compared to the supervised DRL model.

A K nearest neighbor (KNN) profiling-based localization method using RSSI has been proposed. It has been demonstrated that this method offers high estimation accuracy with low cost algorithm (Haque & Assi, 2013).

Wang et al. (2013) obtained their results based on BLE RSS reading. Where four of them were fixed in the corners of a classroom with dimensions 6*8.Three different methods were used to measure the accuracy of the experiment Centroid positioning, border positioning and Least Square Estimation (LSE), the last algorithm is more accurate than the other two methods.

There are new methods for the positioning process that started to appear. This method depends on Received Signal Strength (RSS) fingerprints containing data from a huge numbers of cellular base stations-up to the entire GSM band of over 500 channels; where new information was extracted from these stations by employing machine learning techniques in this field. Experimental results in a domestic and an office setting are presented; the data has been collected over a period of one month to ensure the results are reliable.

A 100 percent efficiency is achieved when classifying based on room level using Support Vector Machines in one-versus-one and one-versus-all configurations. And when a semi-supervised learning techniques used ... there were amazing results, which through this technique was used a few parts of the training data are required to have a room label, are also presented while indoor RSS localization using WiFi (Oussar, Ahriz, Denby, & Dreyfus, 2011).

Background

A ***beacon*** is a small Bluetooth device, works for transmitting the radios' waves, powered by batteries (Inoue, Sashima, & Kurumatani, 2009). The function for both beacons and lighthouse is similar. The signals are transmitted constantly without stopping in a way of Bluetooth-Low-Energy(BLE), where unlike classical Bluetooth which transmits to long range and requires high power, BLE transmits signals carrying a small amount of data periodically for a short distance with much less power consumed. ***iBeacon*** is the protocol or a way for transmitting (only transmitting) signals in a way enable smartphones for scanning the signals of beacons in known ranges and displaying its contents after detect it (Inoue, Sashima, & Kurumatani, 2009). Figure 1 show the iBeacon's work.

Received Strength Signal Indication (RSSI) is a value which used for measuring the received signal. The value that represents RSSI at each one-meter distance known as *measured power* which is an extra byte of data broadcasted by iBeacons. The unit using for measuring $(RSSI)$ is known as decibel mill watts(dBm). dBm indicates the measured beacon's signal strength and the low distance the low of the dBm value (Inoue, Sashima, & Kurumatani, 2009; Jianyong, Haiyong, Zili, & Zhaohui, 2014).

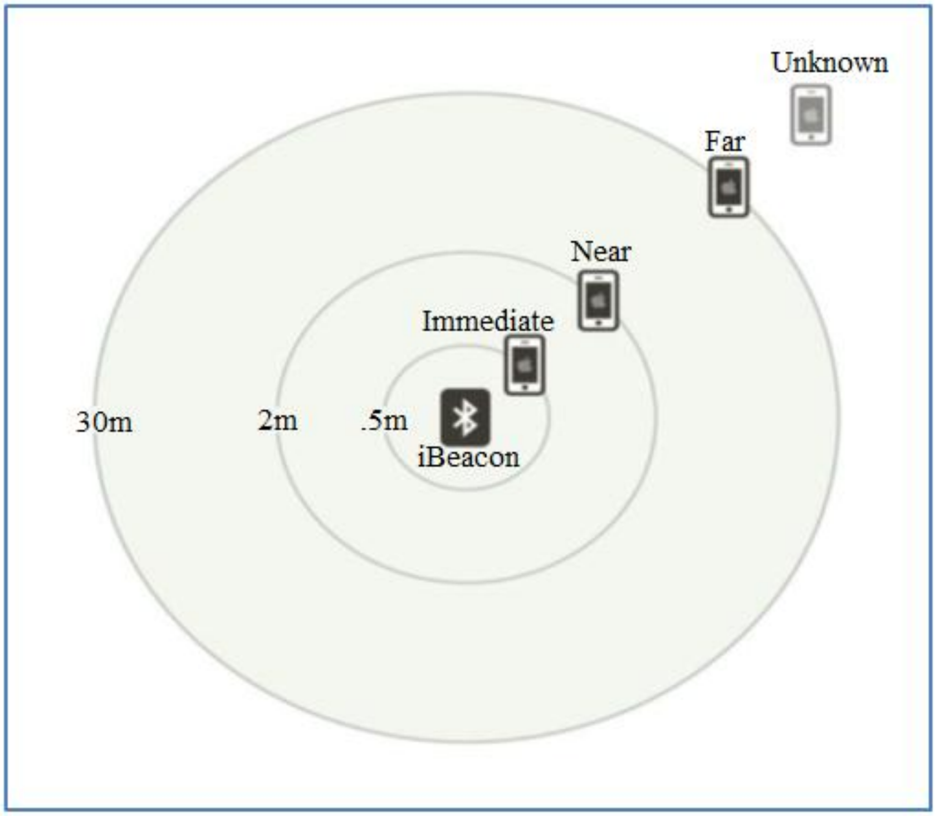

Figure 2. iBeacon's work

Indoor positioning system

Indoor positioning system (IPS) is a modern technology that has become a very interest in industrial, scientific and academic aspects due to the great results of locating robots, people or objects, precisely in indoor environments. The process of objects location is accomplished based on communications and sensors technologies through using radio waves, lights and acoustic signal (Jianyong, Haiyong, Zili, & Zhaohui, 2014). Four main categories under IPS technologies, these are proximity, fingerprinting, trilateration and motion, each one either used alone or combined for providing better accuracy performance.

Proximity does not give the absolute position, but provide a proximity between a receiver and a device. RSSI used in proximity for locating the position of mobile device, where the distance among mobile devices or mobile devices and beacons are proximately estimated to obtain the position information for those devices. Also, proximity is applied in systems by using Bluetooth, IR, and RFID (Brena, et al., 2017).

IBeacon localization

The problem of localization can as be modeled as it with a classification one. The initial two stages are as per the following:

1. **Class definition:** In this stage, a set of classes $\{C1, C2, ...\}$ are defined, where each one (Ci) represents a geographical location at the building.
2. **Training data:** The region of each Beacon is known, so for each class (Ci) all Beacon nodes membership are known. The strength of signal $(signal - strength)$ for each beacon node is written as a vector, where each vector represents a feature vector for that beacon node. The information of both the membership and feature vector are introduced as the training data which are provided to the classification process on each class Ci.

```
array([[-200, -200, -200, ..., -200, -200, -200],
       [-200, -200, -200, ..., -200, -200, -200],
       [-200, -200, -200, ..., -200, -200, -200],
       ...,
       [ -72, -200, -200, ..., -200, -200, -200],
       [ -67, -200, -200, ..., -200, -200, -200],
       [ -79, -200, -200, ..., -200, -200, -200]],
```

Figure 3. The classification of nodes

By implementing the classification procedure, we get the prediction model as a result for this process. The resulted model is used for estimating the class Ci based on the $signal - strength$ (SS) of each beacon node and the membership of S in that class Ci. (Brena, et al., 2017).

Neural Network for Position Determination K-nearest neighbor's algorithm

In the area of pattern recognition, the algorithm of K-nearest neighbors which considers a non-parametric approach has been used for classification and regression. The input composes the k nearest training samples in the feature space for both classification and regression. The results are based on whether the K-nearest neighbor's algorithm is employed for classification or regression (Ponraj & Kathiravan, 2019).

The output is a class that is a member of a group that has the same features in the case of K-NN classification. The classification process of K-NN is achieved by using the technique of majority voting with the point being allocated to the class most popular among its K-NNs. in case of k = 1, then the point is simply allocated to the class of that individual nearest neighbor. In the case of k-NN regression, the output presents the property value for the point in space. This value is the mean of the values of its k nearest neighbors (Ponraj & Kathiravan, 2019; Amiri, et al., 2016).

Materials and Methods

There are many pattern recognition techniques used for localization systems by support a lot of location positioning algorithms. The implementation of these techniques falls into two stages. The first one called the training stage, at this stage the processes of collecting data and delivering it to the classifier are achieved, where these delivered data are used for building a model for classifying and predicting data properties. The second stage, which named the testing stage, tests the built model at the first stage (training stage) with new data. Several algorithms of machine learning can be used for regressions or classification. In regression, the machine-learning algorithm learns the prediction of a continuous variable by learning from the training data, while the classification learns classification of the data in different classes by using the machine-learning algorithm.

Dataset

The set of data was collected in a Waldo Library, Western Michigan Universityon the first floor of it by collecting 13 iBeacons readings where a iPhone 6s device was used to collect it, the dataset is available for free on the internet (Mohammadi & Al-Fuqaha, 2017).

Two sub-groups are grouped into the composition of the data set used in this researchone of them is formatted of 1420 samples which is label one and the other is consist of 5191 unlabeled samples. The process of collecting data was done in a library hall during working hours where 13 iBeacons were distributed in a specific order and as shown in the Figure 4. The input data were in the form of columns including the beacons sites, the time stamp and the RSSI reading.

Negative numerical values that were used to represent the RSSI readings, So that the bigger the value of the reading, the closest the distance for the bacon. For example, if the reading is -50, it means a smaller distance, then if the reading is -75 in relation to the bacon. The value -200 for RSSI was used to denote that the measurement is outside the iBacon range. The locations related to RSSI readings are integrated into one column containing a letter for the column and a number for the row of the position.

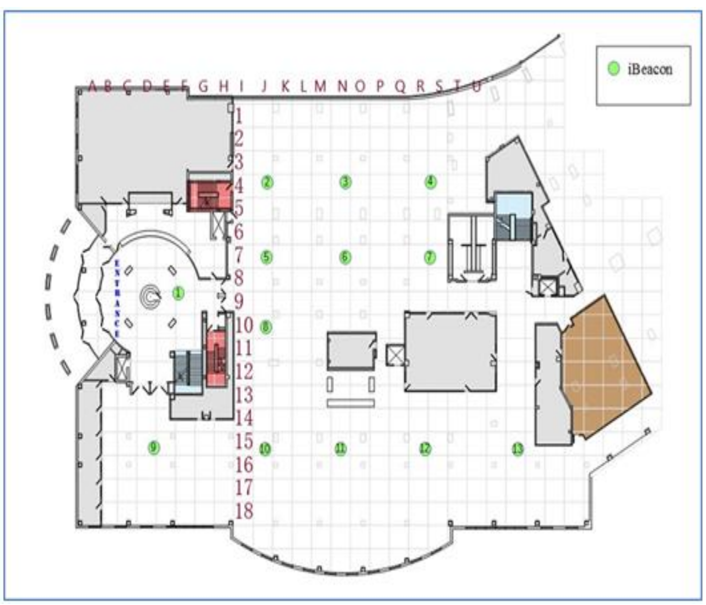

Figure 4. iBeacons distribution over the place

Evaluation Metrics

In our proposed method we evaluate the result by measuring the following listed below metrics during training and testing stage to see if the system can recognize the point that train on it:

1. support
2. f1-score
3. recall
4. precision

Results

In this section we will discuss our result in the two stages, training and testing depend on the four parameters to show our technique reliability.

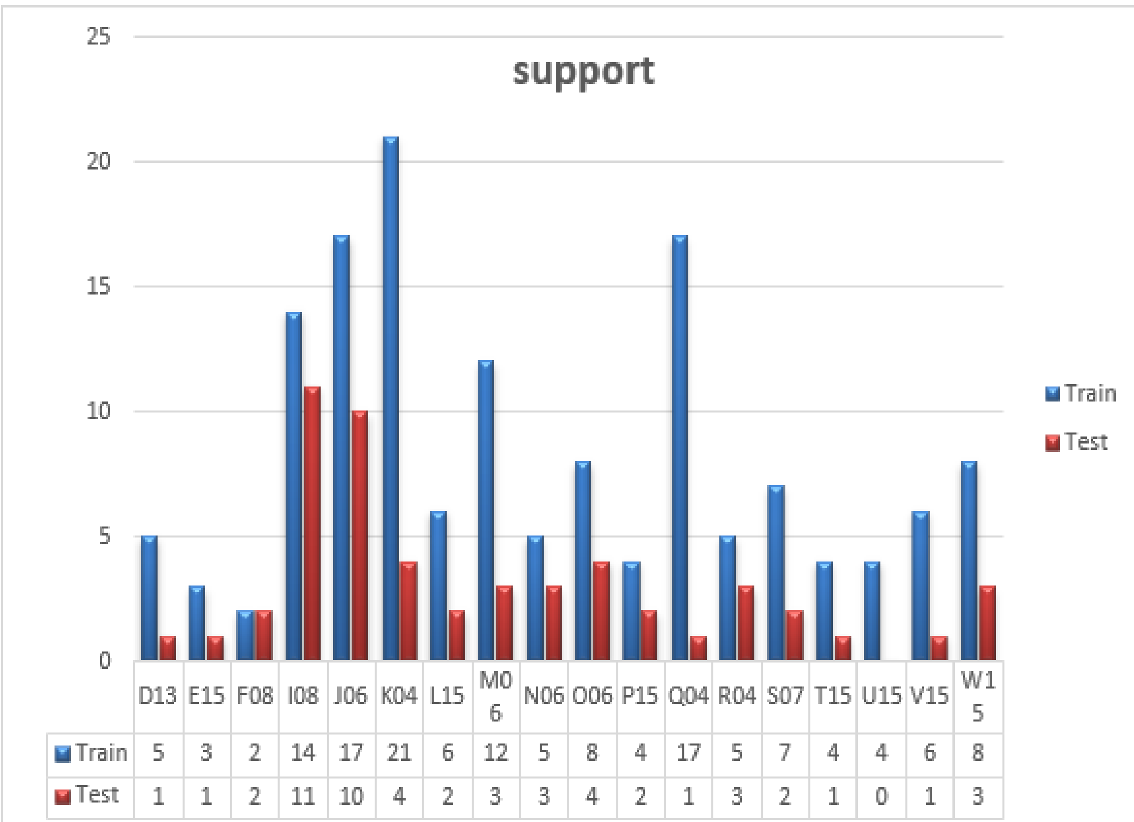

Figure 3. Support Measurement.

Figure 5 clearly shows that the system was able to identify the vast majority of the points it was trained depending on support measurement, while in many other points the accuracy of the testing phase was much higher in the training phase.

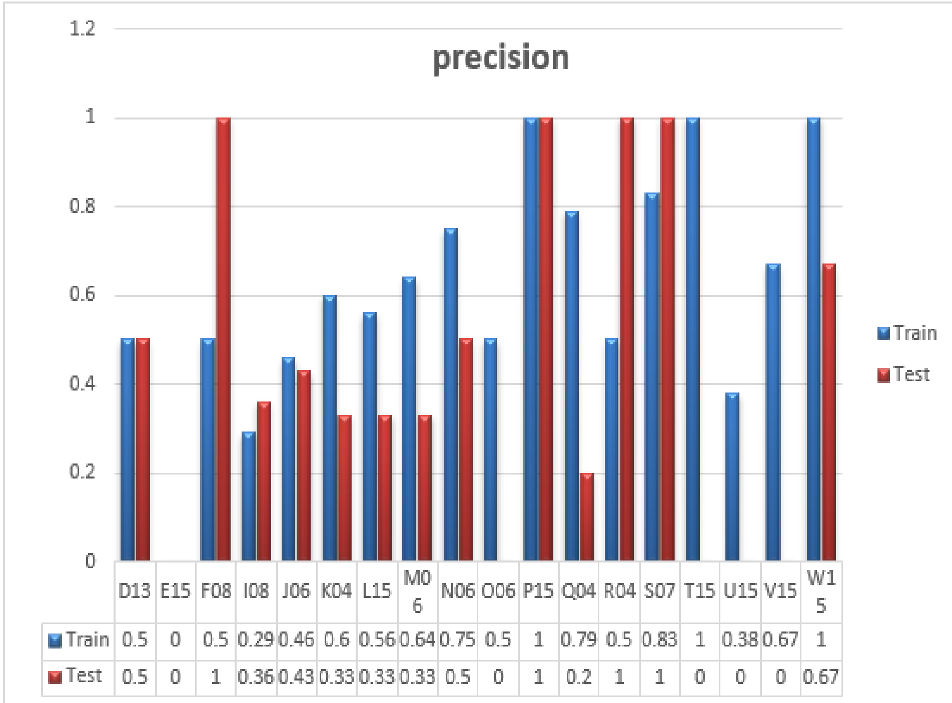

Figure 4. Precision Measurement

As is very clear in Figure 6, the convergence of results in both phases for most points by using precision metric, taking into account that there are some points the values could not be identified by the system in the training phase, but at the testing stage proved satisfactory results.

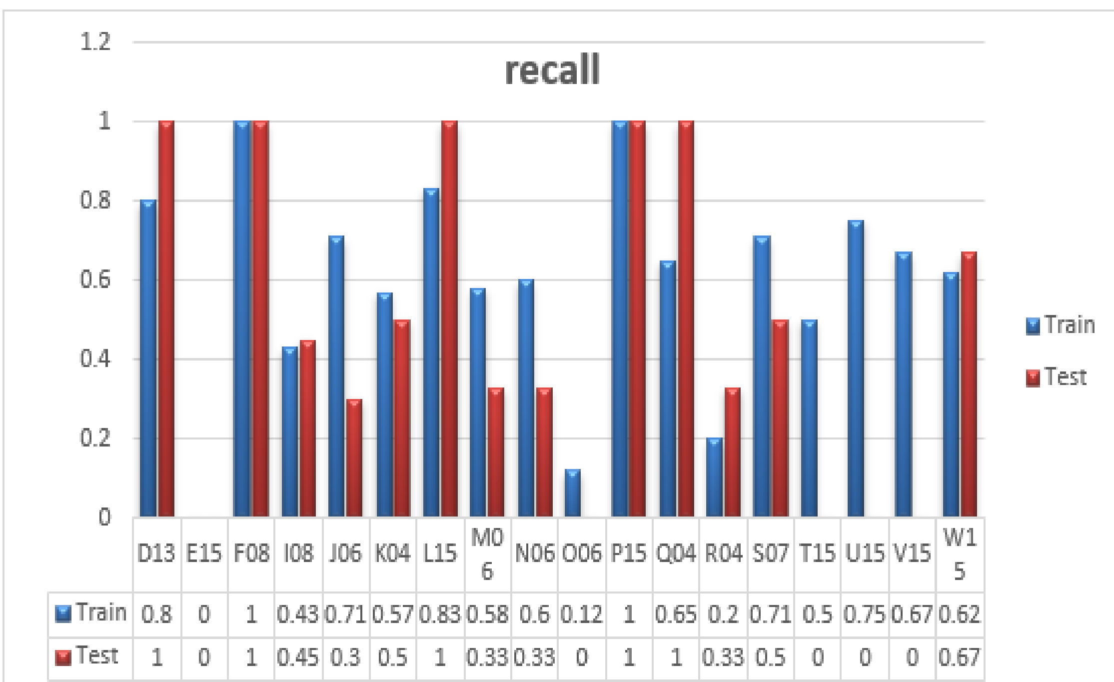

Figure 5. Recall Measurement

Using the recall measurement in Figure 7, the system showed fairly modest performance in its ability to identify some of points, in other points, the values of the metrics were equal, and in others the system was able to recognize the points well.

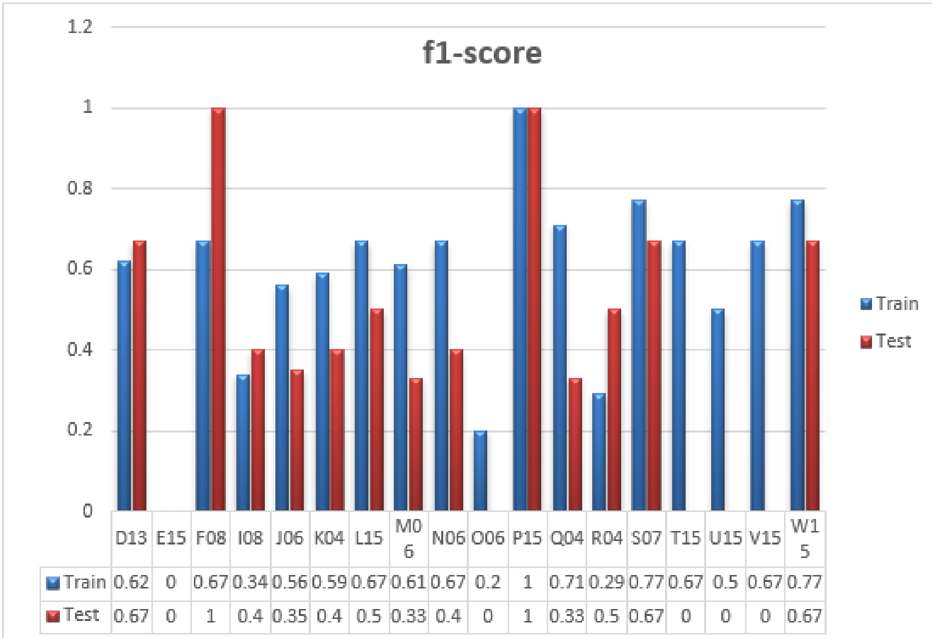

Figure 6. f1-score Measurement

Figure 8 shows the results depending on the F1-score measurement where it is possible to see clearly the system performed very well where it could recognize most of the points very well Except two points (F08 and D13) and This is not bad considered to Recognition ratio of other points.

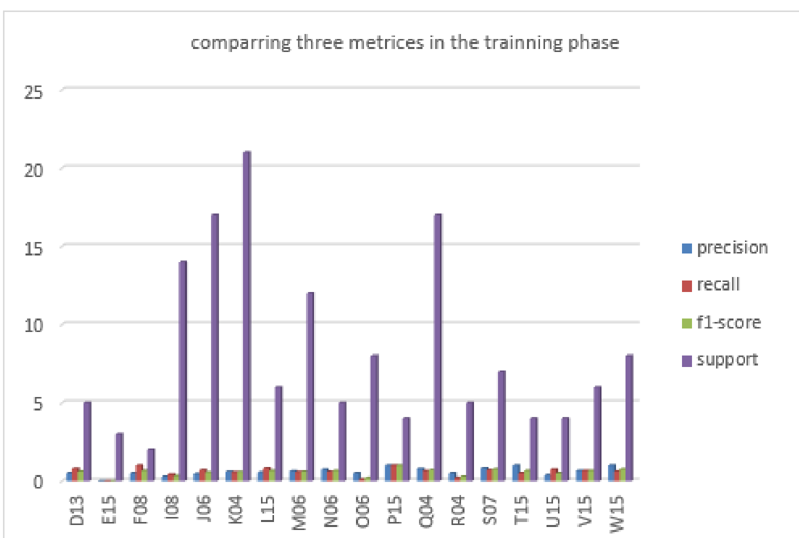

Figure 7. Comparing three metrics in the training phase

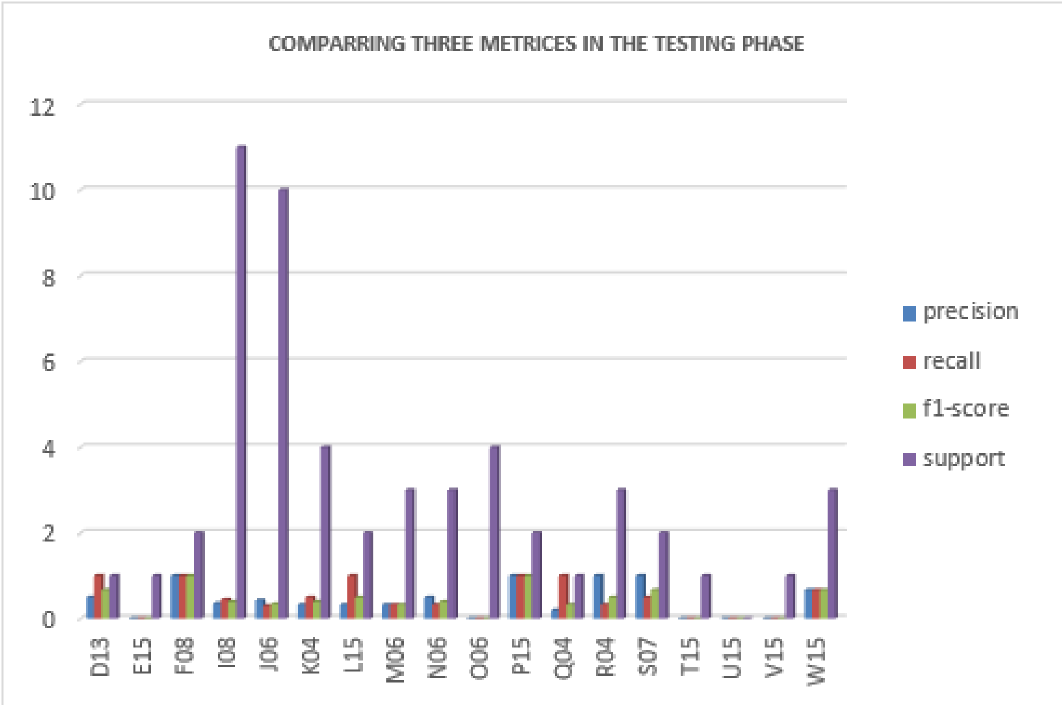

Figure 8. Comparing three metrics in the testing phase

Finally, Figures 9 and 10 comparing all four the criteria used to measure the performance of the system in both phases (training stage and identification stage) we can see that the system was able to achieve good results especially in values of support measurement, this is considered it can adopt system results. Table 1 shows the results of the performance evaluation metrics when n-*neighbors* equal to 1.

Table 1. The performance evaluation metrics of 1-NN

	precision	recall	f1-score	support
D13	0.5	1	0.67	1
D14	0	0	0	1
D15	0.33	0.5	0.4	2
E15	0	0	0	1
F08	1	1	1	2
I01	0	0	0	1
I02	0	0	0	2
I03	0	0	0	7
I04	0	0	0	5

Table 2 shows the results of the performance evaluation metrics when n-*neighbors* equal to 5.

Table 2. The performance evaluation metrics of 5-NN

	precision	recall	f1-score	support
D13	0.5	0.8	0.62	5
D14	1	0.67	0.8	3
D15	0.7	0.78	0.74	9
E15	0	0	0	3
F08	0.5	1	0.67	2
G15	0.67	1	0.8	2
I01	0.15	0.8	0.25	10
I02	0.19	0.45	0.27	11
I03	0.38	0.55	0.44	11

Conclusion

Depending on the results obtained, noted that the accuracy to determine the position using RSSI signal increased if the mobile device is closer to IBCON and that will be more accurate according to the evaluation metrics that were used to measure the efficiency of the system. A proposed method is introduced in this paper to enhance the performance of the indoor localization system Based on Machine Learning Technique, in the system simulation; we depend on the initial readings of the sensors that we obtained from a free database on the Internet (Brena, et al., 2017). We compared the system performance on two stages depending on evaluation metrics measurement. Simulation results show that the proposed system was able to identify the points on which it was trained.

References

Amiri, M., Amnieh, H. B., Hasanipanah, M., & Khanli, L. M. (2016). A new combination of artificial neural network and K-nearest neighbors models to predict blast-induced ground vibration and air-overpressure. *Engineering with Computers*, *32*(4), 631-644.

Brena, R. F., García-Vázquez, J. P., Galván-Tejada, C. E., Muñoz-Rodriguez, D., Vargas-Rosales, C., & Fangmeyer, J. (2017). Evolution of indoor positioning technologies: A survey. *Journal of Sensors*, Article ID 2630413. Retrieved January 3, 2020, from https://www.hindawi.com/journals/js/2017/2630413/

Cheng, R., Roth, H. R., Lay, N. S., Lu, L., Turkbey, B., Gandler, W., ... & McAuliffe, M. J. (2017). Automatic magnetic resonance prostate segmentation by deep learning with holistically nested networks. *Journal of Medical Imaging*, *4*(4), 041302. DOI: 10.1117/1.JMI.4.4.041302.

Frattasi, S., & Della Rosa, F. (2017). *Mobile positioning and tracking: from conventional to cooperative techniques*. John Wiley & Sons.

Haque, I. T., & Assi, C. (2013). Profiling-based indoor localization schemes. IEEE Systems Journal, 9(1), 76-85.

Inoue, Y., Sashima, A., & Kurumatani, K. (2009, July). Indoor positioning system using beacon devices for practical pedestrian navigation on mobile phone. In *International conference on ubiquitous intelligence and computing* (pp. 251-265). Springer, Berlin, Heidelberg.

Jianyong, Z., Haiyong, L., Zili, C., & Zhaohui, L. (2014, October). RSSI based Bluetooth low energy indoor positioning. In *2014 International Conference on Indoor Positioning and Indoor Navigation (IPIN)* (pp. 526-533). IEEE.

Langlois, C., Tiku, S., & Pasricha, S. (2017). Indoor Localization with Smartphones: Harnessing the Sensor Suite in Your Pocket. IEEE Consumer Electronics Magazine, 6(4), 70–80.

Mohammadi, M., & Al-Fuqaha, A. (2017). BLE RSSI Dataset for Indoor localization and Navigation Data Set. Retrieved January 3, 2020, from https://archive.ics.uci.edu/ml/datasets/BLE+RSSI+Dataset+for+Indoor+localization+and+Navigation

Mohammadi, M., & Al-Fuqaha, A. (2018). Enabling cognitive smart cities using big data and machine learning: Approaches and challenges. *IEEE Communications Magazine*, *56*(2), 94-101.

Oussar, Y., Ahriz, I., Denby, B., & Dreyfus, G. (2011). Indoor localization based on cellular telephony RSSI fingerprints containing very large numbers of carriers. *EURASIP Journal on Wireless Communications and Networking*, *2011*(1), 81.

Ponraj, A., & Kathiravan, K. (2019). Distributed Admission Control using Fast Adaptive Neural Network Classifier to assure Quality of Service in MANET. *International Journal of Applied Engineering Research*, *14*(11), 2757-2772.

Wu, M., Tan, L., & Xiong, N. (2016). Data prediction, compression, and recovery in clustered wireless sensor networks for environmental monitoring applications. *Information Sciences*, *329*, 800-818.

Wang, Y., Yang, X., Zhao, Y., Liu, Y., & Cuthbert, L. (2013, January). Bluetooth positioning using RSSI and triangulation methods. In *2013 IEEE 10th Consumer Communications and Networking Conference (CCNC)*, (pp. 837-842). IEEE.

Zhang, C., Patras, P., & Haddadi, H. (2019). Deep learning in mobile and wireless networking: A survey. *IEEE Communications Surveys & Tutorials*.

Zhang, S., Li, X., Zong, M., Zhu, X., & Wang, R. (2017). Efficient knn classification with different numbers of nearest neighbors. *IEEE transactions on neural networks and learning systems*, *29*(5), 1774-1785.

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