# Wi-Fi Based Indoor Positioning

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## Abstract

*In this paper we introduce Wi-Fi Based Indoor Positioning Systems that is detect the position of user or device. The detection of positions are determined by RSSI (Received Signal Strength Indicator) signals known as Wi-Fi fingerprints. We use UJIIndoorLoc dataset with 19937 training records and 1111 test records. We aim to predict location points with supervised machine learning algorithms such as K-Nearest Neighbor, Random Forest and Support Vector Machine and we plan to use the model with the highest accuracy in the rest of the progress.*

## 1. Introduction

Global Positioning System (GPS), which uses satellites, is the most popular outdoor positioning system, however its signals can be easily blocked by various structures and factors then it becomes useless for indoor environment because of signal loss. Unlike the GPS, Indoor Positioning Systems aims to detect the position of user or device by using Access Points signal also called Wi-Fi fingerprint. One challenge to this approach is that the received signal strength can vary based on the phone brand and model, and the position of the phone.

With the advancing technology and spread of wireless networks, Indoor Positioning Systems become even more important place in the fields of augmented reality, social networking, personal tracking, guiding blind people, tracking small children or elderly individuals and location-based advertising etc.

In this study we propose a supervised machine learning model.

## 2. Related Work

There are many designing options based on numerous technologies such as infrared (IR), ultrasound, radio-frequency identification (RFID), wireless local area network (WLAN), Bluetooth, sensor networks, ultra-wideband (UWB), magnetic signals, vision analysis and audible sounds for Indoor Positioning Systems. Some articles (15), (6), (7) have given an overview of various available technology options for the design of an Indoor Positioning Systems. Each system has advantages of using a particular positioning technology(or combining many of these technologies) and also has disadvantages of limitations of these technologies.(17)

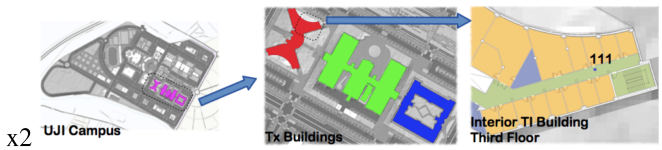


*Figure 1.* Source (14) Left: map of UJI campus and Tx buildings. Middle: red indicates ESTCE - Tx building. Right: example of a reference point.

This paper is related to the Indoor Positioning System based on RSSI (Received Signal Strength Indicator) fingerprint positioning using wireless local area network (WLAN) signals and effective machine learning methods for this system.

There are many different indoor positioning methods for wireless network such as time-based positioning(3), angle-based positioning(2), received signal strength indicator(RSSI) based modeling positioning(11) and RSSI-based fingerprint positioning[(8),(10),(9),(13)]. The references presented in the [(8),(10),(9)] are the researches that use k-nearest neighbor algorithm and Euclidean Distance to find nearest points. In the reference (13) , RSSI-similarity degree which was used as weight factors to estimate the coordinates of measured points is introduced as a different point of view.

## 3. The Approach

### 3.1. k-Nearest Neighbour

The k-Nearest Neighbour (kNN 3-NN) algorithm was used to search for K-neighbor closest between classes of training database and measure RSSI point based on Euclidean distance(4).

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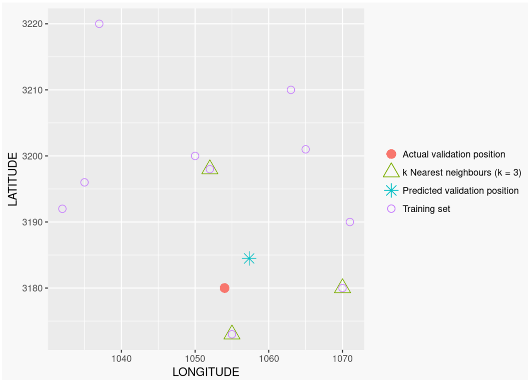


*Figure 2.* Source (12) This plot shows the predicted position, as well as the location of the k nearest neighbours.

1- Calculation of the Euclidean Distance of the current fingerprint with respect to the fingerprints in the training set.

2- If there are 3 point with the shortest distance.

a) The location of the current fingerprint corresponds to the location of the Euclideans closest training fingerprints.

3- If there are more than 3 candidate with the shortest distance.

b) The location corresponds to the average of the Euclideans training fingerprints on the winning building and floor.

### 3.2. Random Forest

Let (1)Ntrees be the number of trees to build for each of Ntrees iterations

1. Select a new bootstrap sample from training set
2. Grow an un-pruned tree on this bootstrap.
3. At each internal node, randomly select try predictors and determine the best split using only these predictors.
4. Do not perform cost complexity pruning. Save tree as is, along side those built thus far.

Output overall prediction as the average response (regression) or majority vote (classification) from all individually trained trees

### 3.3. Decision Tree

Decision Tree learning is one of the most widely used and practical methods for inductive inference over supervised data. A decision decision tree represents represents a procedure procedure for classifying classifying categorical data based on their attributes.

ID3 algorithm(16):

Decide which attribute (splittingpoint) to test at node N by determining the best way to separate or partition the tuples in D into individual classes

## 4. Experimental Results

The machine learning method that is the basis of the project is Random Forest according to the data we obtained related works and our experimental results.

We use ensemble methods from the scikit-learn library to build a random forest classifier and random forest regressor and MinMaxScaler to normalize the data values. Then we create our model, fit the training dataset. Our result are as follows:

*Table 1.* Random Forest experiment results

| MODEL | DISTANCE | MIN. | MEAN | MAX. |
|---|---|---|---|---|
| RF | METER | 0.17 | 15.2 | 80.2 |

## 5. Conclusions

We tried different machine learning methods such as K-Nearest Neighbor Algorithm, Random Forest Algorithm and Decision Tree to find the most effective one. According to accuracy of each algorithm, we discovered that random forest algorithm is the most effective one.

Our future goal is to make the system applicable to be used in real life. It is still a problem how to integrate the system in real life and more improvements and research are needed. As a future work, by using techniques like backtracking we can increase the accuracy of the system. This will avoid choosing between two close measurements. Main reason for backtracking is, the algorithm will go back to user's previous location then compare which might be the user's next location between the candidate locations. On the other side, using other signal source like Bluetooth and other wireless technologies will be our next improvement. The more the signal sources we have, the more the increase in accuracy of system.

### 5.1. Figures

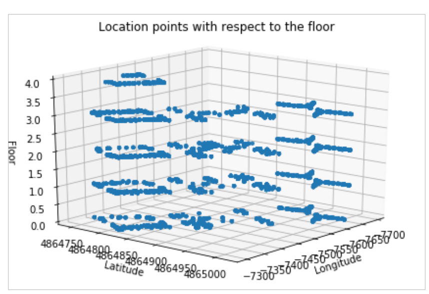


*Figure 3.* Floors inside the building

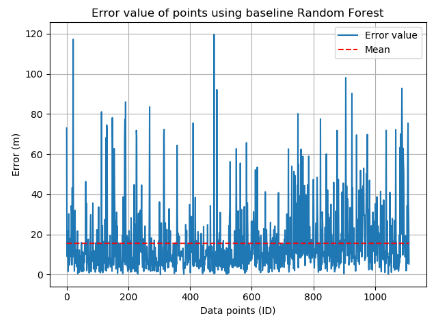


*Figure 4.* Random forest error values

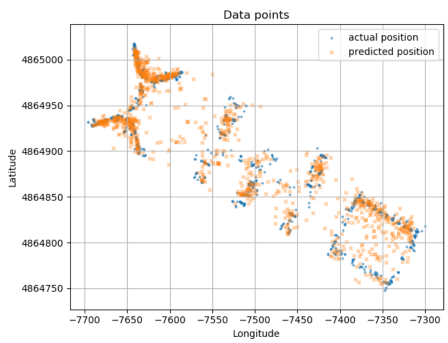


*Figure 5.* Location points representation

### 5.2. Tables

We can analogize the results of our predictive models by using three different methods which k-Nearest Neighbor, Random Forest, Decision Tree.

*Table 2.* Classification accuracies for kNN, RF, Decision Tree

| MODEL | ACCURACY | BETTER? |
|---|---|---|
| KNN | 77.3 | × |
| RF | 86.0 | √ |
| DECISIONTREE | 81.5 | × |

We can see that the Random Forest model outshout k-NN model and Decision Tree model. (5)

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