

# Indoor Positioning with floor determination in Multi Story Buildings

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**Abstract**—Floor determination is one of the challenges in indoor positioning research. To date indoor positioning solutions for floor determination have been mainly based on either Fingerprinting [2] or RF-IDs [3]. While these solutions have been able to locate persons or equipments accurately even in multi story buildings, they can not be considered as time and cost efficient solutions. Therefore, in this research we present new Wi-Fi based indoor positioning algorithms in order to accommodate the need for limited resources solution in terms of deployment time and cost. While finger-printing and RF-IDs based solutions have been targeting sub-meter position accuracy, this research focuses on floor determination only. In addition, in this research we have highlighted two possible approaches for using available Wi-Fi signals for floor determination.

**Keywords**— Indoor Positioning; Floor detection; Floor determination;

## I. INTRODUCTION

The recent growth of mobile computing devices has created new demands for more location-aware applications. Applications such as finding the nearest pharmacy, restaurant or cash machine require knowledge of the user's current position. Such applications are gradually expanding to indoor environments such as shopping centres, libraries or museums. In such type of buildings there is no feasibility of using GPS or similar GNSS solutions. Therefore, researchers have been actively looking at the possibility of using Wi-Fi signals in order to estimate user position. In addition, Wi-Fi is a mature and relatively cheap technology, and many mobile computing devices are already Wi-Fi capable.

While indoor positioning seems to be developing very quickly, floor determination is still a remaining question. In multi story buildings the two dimensional position is not always enough to describe the user location. Also many businesses and services are showing their interest in floor determination. All the above reasons have encouraged researchers to investigate the possibility of using wireless signal transmitters to fill this gap. Nevertheless, the currently available indoor positioning solutions for floor determination are either RF-IDs [3] or fingerprinting [2]. While these solutions have been able to locate persons or equipments accurately within sub-meter of

the actual position, they were unable to fully fill the needs for time and cost efficient solution.

## II. RESEARCH OVERVIEW

In this research we have designed two different models for using Wi-Fi signals to determine the floor number in multi-story building. The first model is "The Nearest Floor Algorithm" which is a simplified solution of "The K Nearest Neighbour Algorithm" used in finger printing. The second one is proprietary statistical model "The Group Variance Algorithm" which groups the Wi-Fi RSSIs depending on the level (floor number), and compare the Variance for each group to find the best match floor number. Each model assumes that a reference Database, associating every Wi-Fi Access point with its floor number, is available. Such Database could be available from the IT infrastructure documents relating to the particular buildings or sites. To avoid the process of obtaining such information from the IT department in our tests, we have used Loc8R from SATSIS ([www.satsis.com](http://www.satsis.com)) to determine the three dimensional location of the Access Points in the test site.

### 1. The Nearest Floor Algorithm:

This algorithm has been developed to simplify the well known fingerprinting algorithm "K Nearest Neighbour Algorithm".

*K-Nearest Neighbour Algorithm (KNN)* [4] is a training based algorithm where the result of new position query is classified based on finding the K-Nearest Neighbour references. The main part of this algorithm is the training samples. The training samples should be collected intensively during the calibration process of the area of interest. Each record of the training samples will contain a reference position along with a row of Wi-Fi access points information. The access points information stored with each row of data should contain pairs of MAC address and RSSI for each one.

Given a new position request, new pairs of MAC address and RSSI (online measurements) will be scanned from the unknown position. After that, we enquire the reference database to find the closest K number of training points (samples) to the query point. Equation (1) is used to calculate the distance between

the online measurements and the collected training data.

Let  $D$  be the calculated distance,  $Online\_SSi$  be the online measurement signal strength of an access point  $i$ ,  $Training\_SSi$  be the signal strength of an access point  $i$  in the training reference database and  $n$  be the maximum number of access points that found in working area.

$$D = \sqrt{\sum_{i=1}^n (Online\_SSi - Training\_SSi)^2} \tag{1}$$

By calculating the distance between the unknown position and each of the training data points, we should be able to choose the closest  $k$  points. Depending on the trials we do in the training area we should decide how far we go with the  $k$  parameter. Usually the recommended value of  $k$  parameter is between 3 and 5. After selecting the  $k$  closest points the only thing we need to do is to average the position of these points to calculate the user position.

*How we approach KNN in this research?*

To avoid maintaining and searching the massive data of training points which usually used in KNN algorithm, we have designed the reference Database to hold only one position reference for each access point. Figure1 shows the structure of the database which has been designed for floor determination only.

Reference ID	MAC Address	Floor Number	Maximum RSSI
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Figure 1. Reference DB Record Structure

Either during the calibration or in the online phase, maintaining the reference point's data is essential. In our proposed algorithm we only maintain one value as the maximum seen RSSI for each access point in the reference database. Therefore, we have designed a new procedure for selecting the neighbour reference points based on the signals strength (RSSI) during the online phase.

Coming to the online phase, whenever there is a request for floor determination, we would use the reference Database to estimate the floor number. Similar to the KNN algorithm we need to pick up the best mach reference points. As we only have one RSSI measurement for each access point, so in this research we don't need to calculate any distance to select the closest points. Instead by comparing the RSSI readings in the online mode with the ones we keep in the reference Database, we should be able to select the closest  $k$  access points. After defining the search terms based on the RSSI value, the value of "k" usually define the search limits. In this research we have used  $k=3$  as a guide for matching the floor number with the reference database. Figure2 shows the pseudo-code of the nearest floor algorithm.

READ scanned wi-fi list  
SET available\_waps to empty list

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FOR each MAC in scanned wi-fi list DO
  R ← Call locate(MAC)
  IF R returns a valid position then
    Calculate R[SSi] = R[ref_rssi]-R[scanned_rssi]
    Move R to available_waps
  ELSE
    Do nothing
  END IF
END FOR
SORT available_waps by SSi value ascending
SET FloorEstimate1 to none
SET FloorEstimate2 to none
SET I to 0
FOR each Rec in available_waps
  IF FloorEstimate1 is none THEN
    SET FloorEstimate1 to Rec[Floor]
  ELSE
    IF Rec[Floor] = FloorEstimate1 THEN
      RETURN FloorEstimate1
    ELSE
      IF FloorEstimate2 is none THEN
        SET FloorEstimate2 to Rec[Floor]
      ELSE
        IF FloorEstimate2 t= Rec[Floor] THEN
          RETURN FloorEstimate2
        ELSE
          SET A to FloorEstimate1
          SET B to FloorEstimate2
          SET C to Rec[Floor]
          SET M to median(A,B,C)
          RETURN M
        ENF IF
      END IF
    END IF
  END IF
END FOR
    
```

Figure 2. The Nearest Floor Algorithm

At the end the nearest floor algorithm has been designed to perform in any random distribution of the Wi-Fi access points. Although this algorithm might show better results if the Wi-Fi access points have been installed, especially the positioning system (for example if different access points maintain a strong Wi-Fi signal in each floor), Our initial test demonstrates a good performance even when the access points have been installed in a vertically aligned manner. Therefore, we conclude that the nearest floor algorithm does not require any vertical alignment but it will benefit from distributing the access points horizontally in each floor to maintain a strong Wi-Fi coverage.

2. Group Variance Algorithm:

The research limitation of the nearest floor algorithm has encouraged us to explore another possible solution based on statistical observations. The novelty of this algorithm comes from considering the distribution of RSSI values in each floor. Whenever there is a request for floor determination, the system will scan the air for Wi-Fi beacons and use the reference database to pair each one with a floor number. After that the Group Variance algorithm will group the pairs by the floor number so we can apply our statistical model on each floor separately. This model will use three parameters which are the range, the variance and the availability in the floor determination.

The sample variance,  $S^2$  as shown on (2) and (3), of the RSSI values in each floor will help the model to identify the floor with optimum signals distribution. In addition, the samples range,  $R$  as shown on (4), and signals availability ( $A\%$ ) could support the variance and correct the possible misleading.

$$\bar{x} = \frac{\sum x_i}{n} \tag{2}$$

$$s^2 = \frac{1}{n-1} \sum (x_i - \bar{x})^2 \tag{3}$$

$$R = | \max(\text{RSSI}) - \min(\text{RSSI}) | \tag{4}$$

The values of these three parameters will reflect signals distribution pattern for each floor. This should enable us to estimate which floor we are on. Depending on the structure and the building materials used in multi-story buildings, Wi-Fi signals will never spread equally in all directions. Therefore, in such buildings the horizontal and vertical signals distributions will certainly be different. This fact has given us the clue to estimate the floor number depending on the received signals characteristics.

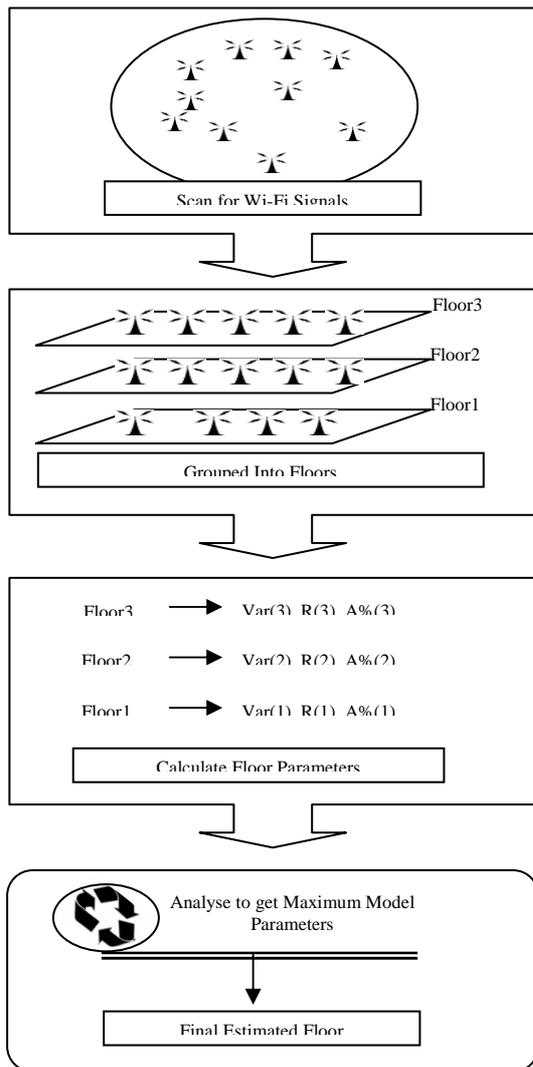


Figure 3. Group Variance Algorithm

*How we analyse the Model parameters?*

In order to estimate the floor number from signals distribution, this model works on selecting the floor that has the maximum values for variance, range and availability. We have noticed that it's not always as straight as getting the three parameters indicating to the same floor. Therefore, we have added a weight value to each parameter and combined the three values in floor points procedure. To select a particular weight for each parameter, we went through the test site running this solution on ten different locations for each floor. Each time we ran the solution we monitored the floor estimation of each parameter separately. Then the weight value for each parameter was calculated from the number of correct estimations.

The following process describes how this solution calculates the floor points during the analysis.

- 1- Adding five points to the floor with maximum Variance.
- 2- Adding three points to the floor with maximum Range.
- 3- Adding three points to the floor with maximum Availability.
- 4- Compare the Points on each floor and pick up the floor number with maximum number of points.

These figures give priority to the variance if the three parameters estimate three different floors. Also any two parameters refer to the same floor will select this floor as our estimation.

III. TESTS AND RESULTS

As a test site we have used the Alrick Building at the School of Engineering buildings in the University of Edinburgh located within the Kings Buildings campus ([www.see.ed.ac.uk](http://www.see.ed.ac.uk)). All measurements are based on 50 different test points distributed over four levels of the school building.

The following platforms were used during the tests:

- Different mobile phones (Nokia 5800 XpressMusic and HTC WildFire) as a Wi-Fi client.
- SATSIS Wi-Fi Positioning Engine, Loc8R.
- SATSIS Web Reference APs Database.

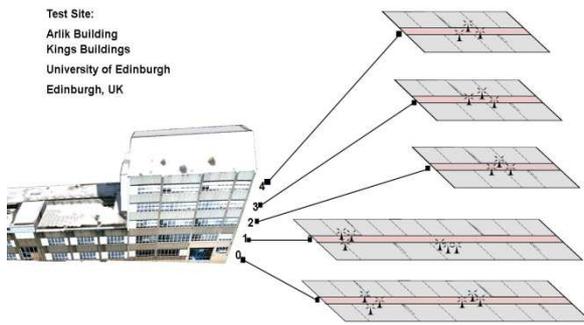


Figure 4. Test Site Floor Plan Details

The first phase of this test involves monitoring the performance of the designed algorithms. The unreliability of Wi-Fi signal strength, RSSI, has greatly affected the performance of both algorithms. The results for this test are compiled in Figure 5.

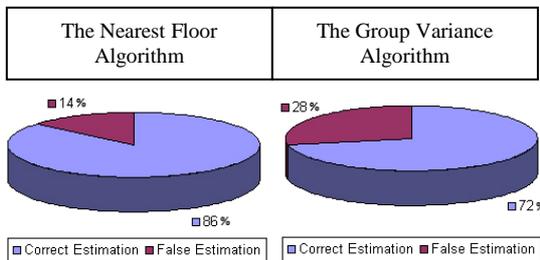


Figure 5. Algorithm Tests Results (based on 50 readings)

Figure 5 clearly shows that the nearest floor algorithm has performed better than the group variance algorithm. On the other hand the group variance algorithm has been more reliable in parts of the building where a strong Wi-Fi coverage is not expected. For example the test points in the washrooms, building edges and rooms far from any Wi-Fi access points, were failure points for the nearest floor algorithm. As a result we can say that while the nearest floor algorithm has shown better overall results, the group variance algorithm has shown better site coverage.

These results have encouraged us to look into the possibility of improving the group variance algorithm. Therefore, in the second phase of this test we have focused on the group variance algorithm performance. In addition, as we mentioned earlier the group variance algorithm is based on the floor estimation of three different parameters. For this reason we would expect an improved performance if we analyse the results of each parameter separately.

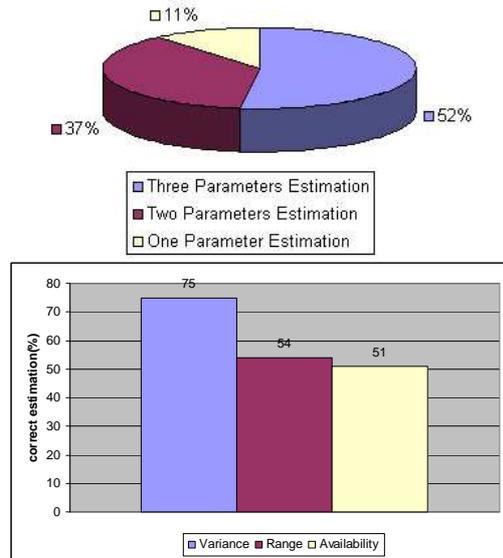


Figure 6. The Group Variance Algorithm (parameters contributions)

Figure 6 shows how each parameter has contributed to the group variance algorithm. These figures have also highlighted that the variance, if used alone, was able to provide better performance than combining all the three parameters. On the other hand, the range and the availability have shown reasonable results that should not be ignored in the proposed solution.

#### IV. CONCLUSION

In this paper we have shown the possibility of using Wi-Fi RSSI measurements in order to determine the floor number in a multi-floor building environment. The determination methods that we have presented in this research have focused on simplifying the implementation and reducing the time and cost that are usually associated with the learning phase. The novelty of this research compared to traditional fingerprinting based approaches are reflected in the implementation.

The possibility of combining the group variance algorithm and the nearest floor algorithm used in the proposed implementation remains an open question for future research.

#### V. REFERENCES

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