Advanced Geomatics

http://publish.mersin.edu.tr/index.php/geomatics/index

e-ISSN: 2791-8637

Effect of Calibration Point Density on Indoor Positioning Accuracy: A Study Based on Wi-Fi Fingerprinting Method

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Keywords
Wi-Fi Positioning
Fingerprinting
IPS
WKNN

ABSTRACT

Indoor positioning refers to all methods used in areas(indoor) where GNSS signals are too weak or non-existent for position determination, using various signals (Signals of Opportunity) and various sensor data. The availability of these signals and sensors for general navigation use is an important factor in terms of cost and feasibility. Considering the diversity of smart mobile devices and the technologies they contain; it is clear that they are perfect candidates for this job. Signals of Opportunity (SoOP) are intended for purposes other than navigation and Wi-Fi is a great example for this. Since majority of mobile devices have built-in Wi-Fi hardware, many studies focused on Wi-Fi positioning. This study used the fingerprint approach, which is among the most successful methods of indoor positioning using this technology. The number of calibration points to be marked in the calibration phase, which is the first of the two stages of this method, affects both the position accuracy and the time and effort spent. In this study, location accuracy was studied using NN, KNN and WKNN algorithms on a radio map with low calibration point density and it was discovered that the NN method provides both simplicity and satisfactory results in all scenarios. It was determined that the mean errors were minimal at the 2-meter point density and better results were obtained with the weighted-KNN algorithm compared to the KNN.

1. INTRODUCTION

The growing usage of smart mobile devices has boosted the demand for indoor location determination significantly. Furthermore, given that individuals spend the majority of their time indoors, this need is growing by the day. Because GNSS signals have yet to fully address this issue, research has concentrated on the use of Signals of Opportunity (Kunhoth et al., 2020). FM waves, Wi-Fi, and Bluetooth are examples of signals whose primary purpose is not navigation. Some of these technologies, which are now accessible in nearly all mobile devices, can be used to determine position indoors. Wi-Fi technology is the most widely used. Several approaches are utilized for determining position using this wireless communication technology (He & Chan, 2016). These are similar to fingerprinting, trilateration, and triangulation. It is unavoidable that the approaches have benefits and drawbacks in comparison to one another. The fingerprint technique, on the other hand, stands out since it does not require any external hardware and can thus be used in any indoor space. (Torres-Sospedra et al., 2015; Wang et al., 2020). Furthermore, the fingerprint technique has gained popularity over signal propagation models since signal propagation is highly variable in an indoor space due to various solid objects and obstacles (Mautz, 2012).

The fingerprint technique relies on a pre-generated radio map of the interior environment, which is a significant drawback. In other words, it necessitates a preliminary investigation that takes time and effort. This pre-study step is known as the Calibration stage, and it is the first of two phases in the fingerprint technique. The other stage is known as the positioning stage. The signal strength information (RSS) received at various points within the building is gathered and saved in a database with the correct location coordinates in the first step. This database is referred to as the radio map described earlier. Each entry in this database is referred to as a fingerprint since it comprises the coordinate information of the point as well as the RSS vector collected from the nearby wireless access points. RSS measurements are performed multiple times at each calibration point due to signal fluctuations. The location is then determined by correlating and comparing RSS measures in this database

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Cite this article;

Özdemir B N & Ceylan A (2021). Effect of Calibration Point Density on Indoor Positioning Accuracy: A Study Based on Wi-Fi Fingerprinting Method. Advanced Geomatics, 1(1), 12-26

Research Article

Received: 09/09/2021; Accepted: 30/09/2021

with existing RSS measures. The calibration point with the shortest distance is simply obtained as the current position as a consequence of this procedure, which typically employs the Euclidean distance. While Euclidean signal distance is the most commonly used distance/similarity measure in this comparison, several other distance/similarity measures are also used (Cha, 2007; Torres-Sospedra et al., 2015).

KNN algorithms are employed when the number of calibration points used in this matching is greater than one. In this case, depending on the density of calibration points, the spatial distances and geometry of K selected neighboring points change and this affects the position accuracy. In this study, in order to examine the effect of this, location accuracy was investigated by using different radio maps created by calibration points placed at different densities.

2. METHOD

This study was carried out in the Faculty of Engineering and Natural Sciences building of Konya Technical University (Fig. 1). The wireless network infrastructure of the building consists of approximately 80 wireless access points broadcasting 2.4GHz and 5GHz signals.

Figure 1. Aerial photograph of the building where the application was carried out

The methodology of the study was carried out in the following order.

I. Obtaining and coordinating the CAD plan of the building (Fig. 2)
II. Establishment of calibration points as routes along corridors at desired intervals
III. Conducting coordinated signal strength measurements at each calibration point on the routes prepared with the measurement setup and software (Fig. 4).
IV. Conducting coordinated signal strength measurements at random points to test positioning accuracy
V. Analyzing the collected data with the prepared software

The workflow applied in this study is shown in Fig. 3. Furthermore, the specifics of this procedure are summarized below.

I. Obtaining and coordinating the CAD plan of the building: In order to mark the correct coordinates on the CAD file of the building, it is necessary to make corrections such as scale and rotation of the drawing. This is done with the use of a total station instrument and a few basic typical terrestrial observations.

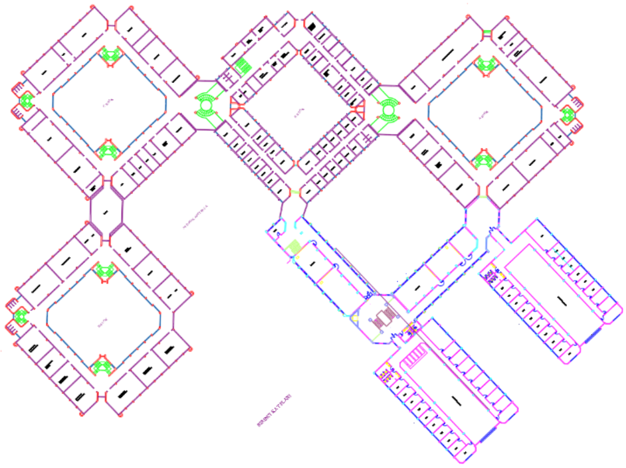

Figure 2. CAD plan of the building

II. Establishment of calibration points as routes along corridors at desired intervals: After the first step, every point to be marked on the CAD will have the actual coordinate. Taking advantage of this, points were placed at equal intervals on the routes created along the corridors. Thus, it has become possible to make high-accuracy calibration measurements by moving along the route from the starting point. With the method we have put forward, the measurement at the calibration points by following the routes has accelerated this stage.

III. Conducting coordinated signal strength measurements at each calibration point on the routes prepared with the measurement setup and software: The signal strength measurements were completed with the measurement setup by importing the coordinate list of these marked points into the mobile data collection software. With this software, information such as the number of measurements at the point where RSS measurement will be made, signal frequency (2.4GHz-5GHz), coarse GNSS coordinates can be recorded.

In this stage, the operator monitors the distance traveled along the route from the screen on the measuring wheel and starts the measurement from the mobile device when the relevant point is reached. The Δs correction between the axis on which the measuring tool makes the length measurement and the axis on which the mobile device makes the RSS measurement has been applied to all measurements (Fig. 4).

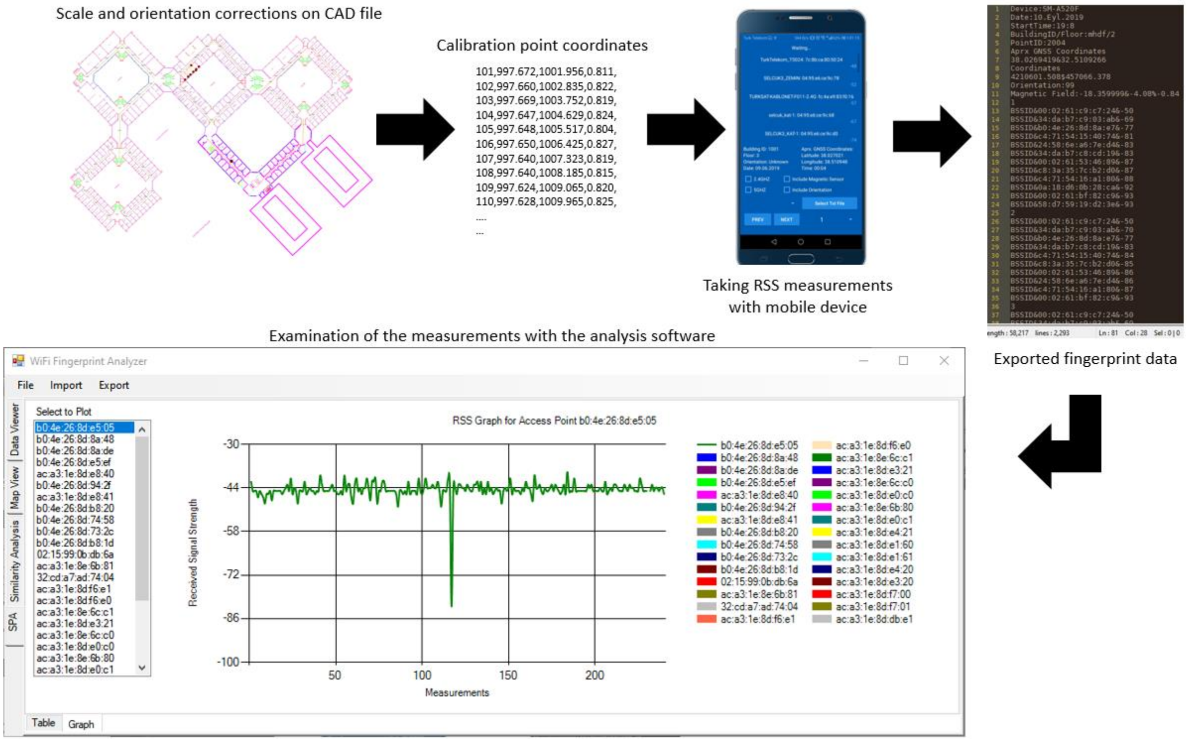

Figure 3. Workflow implemented in the study

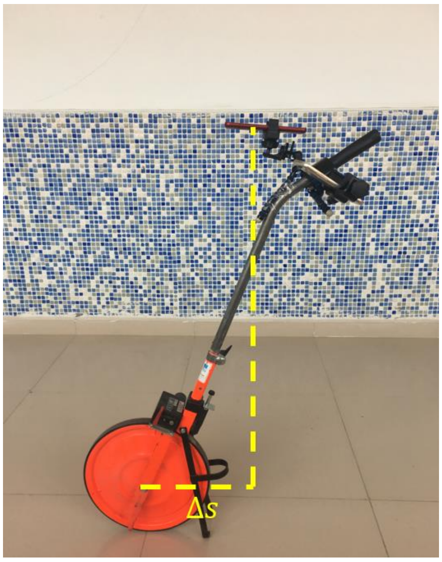

Figure 4. Measurement setup consisting a measuring wheel and a mobile data collection device

Wireless signals propagating indoors are subject to some fluctuation (Jooyoung Kim et al., 2016). This is due to both the hardware in the wireless access point emitting the signal, the hardware of the mobile device receiving these signals, and the variable indoor environmental conditions (Fig. 5). For this reason, in studies, multiple RSS measures are usually made at a calibration point and the average of these measures is used.

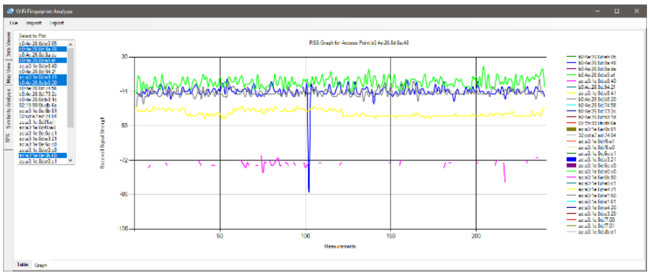

Figure 5. An example of signal fluctuation

Although there is no specific number in the studies on the subject, the number of measurements between 5-20 is generally preferred in terms of time-accuracy. We utilized a database of three observations at each calibration point in this work to decrease the influence of signal variations and experiment with a quicker calibration phase.

To determine the point positioning accuracy, measurements were taken at 237 test points and 1771 calibration points. In addition, the table below shows the number of calibration points for data arranged between 1 to 5 meters to investigate the effect of various neighbor numbers/calibration point density (Table 1).

Table 1. Point densities

Gap between two calibration points	Total Calibration Points
1 m	1771
2 m	907
3 m	606
4 m	471
5 m	366

IV. Conducting coordinated signal strength measurements at random points to test positioning accuracy: In order to test the location accuracy of the system, coordinated RSS measurements were also carried out at various random points.

V. Analyzing the collected data with the prepared software: A program based on .NET and coded in C# was used to quickly evaluate the data obtained in various scenarios. A summary of the features of the program is given in section 2.2.

2.1. Position Estimation

The performance of the fingerprinting varies depending on the number and density of calibration points. In addition, the positioning algorithm also affects the results. These factors should be taken into account and analyzed during the positioning phase. Therefore, we tested the performance of NN and k-NN algorithms at various calibration point densities.

The k-Nearest Neighbor rule compares a current sample to all the labelled samples from a database (Cover & Hart, 1967). It's a distance-based classifier that necessitates the creation of a database for comparisons in which all of the samples are appropriately labeled (Torres-Sospedra et al., 2015). Euclidean distance is often used as the base metric in these comparisons. The Euclidean distance which is used to determine similarity is calculated as (1), where P and Q are two signal vectors and j is the vector length.

$$d_{euclidean}(P,Q) = \sqrt{\sum_{i=1}^{j} |P_i - Q_i|^2} \qquad (1)$$

While the nearest neighbor algorithm selects the calibration point with the shortest Euclidean distance, the k-KNN algorithm chooses the K closest calibration points and calculates the position as the mean of their X and Y coordinates (2).

$$P(X,Y) = \frac{1}{K}\sum_{i=1}^{K}(x_i, y_i) \qquad (2)$$

Because the impact of each neighbor on the point is evaluated equally in this technique, a certain degree of inaccuracy is introduced (Fig. 6).

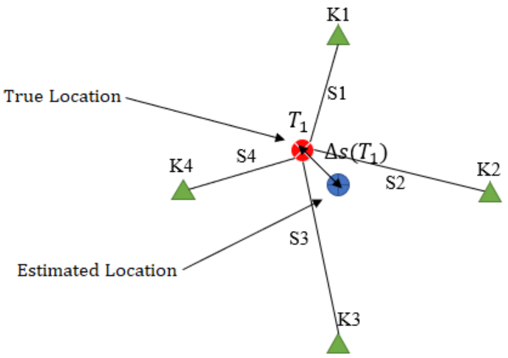

Figure 6. Error caused by means in the KNN algorithm

By prioritizing nearby points in accordance to their Euclidean distances, the WKNN algorithm mitigates the problem's impact (3).

$$w_i = \frac{1/D_i}{\sum_{j=1}^{k} 1/D_j} \quad i = 1,2,\dots,k \qquad (3)$$

2.2. Analysis Software

The results of the tests were evaluated using the Wi-Fi fingerprint location program that we created. The following are the program's main features:

- Thresholding to remove WAPs under certain signal strength
- Plotting signal strength changes over time
- Viewing calibration points on the map
- Interpolation module
- Position estimation with weighted measurements
- Analyzing with Euclidean, Manhattan, Minkowski L3-5 and Sørensen distances
- Different data representation schemes (dBm, Exponential Function and Powed (Torres-Sospedra et al., 2015), Positive, Normalized and Experimental Functions)

3. RESULTS and DISCUSSIONS

When the number of neighbors selected in the KNN algorithm rose beyond two, the average inaccuracy increased by up to six meters. As the reason for this, we can say that with the increasing number of neighbors, more irrelevant points have affected the location determination. In this case, the weighted KNN algorithm provides a reduction in maximum errors by distributing relative weights to distant points (Fig. 7). This is especially true in corridor-style interior areas. However, in hall-type interior environments where the number of relevant nearby calibration point counts is significantly larger, this situation might give quite different results (Shin et al., 2012).

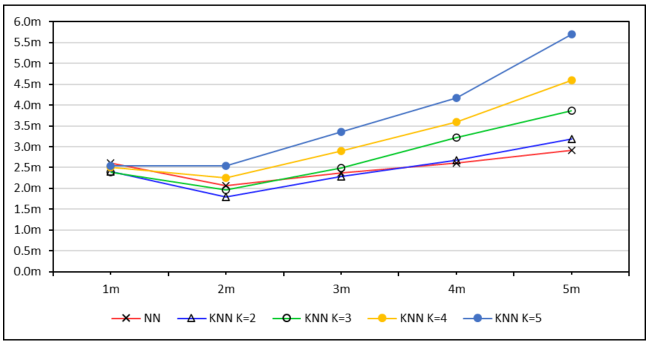

Figure 7. Mean errors of KNN with different neighbor numbers and calibration point gaps

The WKNN method, which has lower average errors, provides comparable results (Fig. 8). WKNN is more successful in this case since it reduces the impact of insignificant points on position estimation.

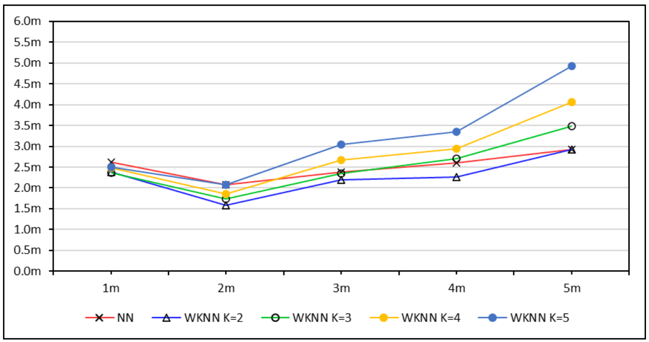

Figure 8. Mean errors of WKNN with different neighbor numbers and calibration point gaps

When each case is examined separately to determine the optimal point spacing, the 2-meter distribution has the lowest mean errors. Distributions of 1- and 3-meter intervals produced the best outcomes in second place (Fig. 9-10-11-12). As seen in Figures 9 and 10, all three methods up to three neighbors produced fairly similar results. It is also evident that the NN algorithm provides reasonable results in all ranges, particularly those greater than 3 meters.

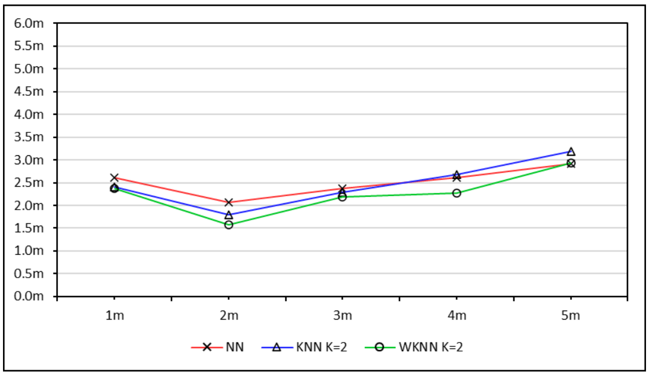

Figure 9. Mean errors of different neighbor numbers for each algorithm, K=2

The total number of test points and their placements are obviously related to the performance of the NN algorithm, which yields comparable average errors at intervals bigger than 3 meters. Because the distance between consecutive calibration points is large in a corridor type indoor environment, we can claim that the nearest calibration point to a location in that corridor will be equal to or closer to the specified interval.

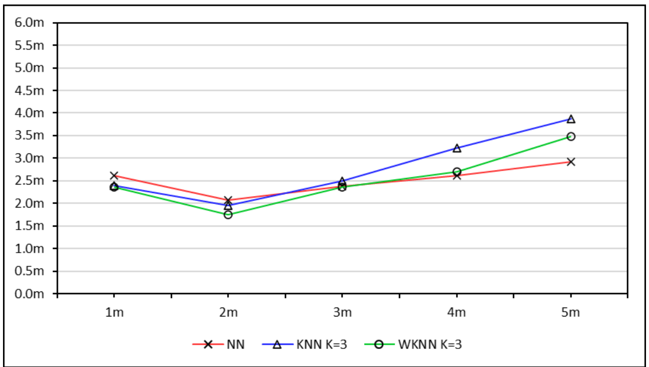

Figure 10. Mean errors of different neighbor numbers for each algorithm, K=3

When the number of neighbors exceeds 3, it is seen that the difference between KNN and WKNN widens, which is an expected result (Fig. 11-12).

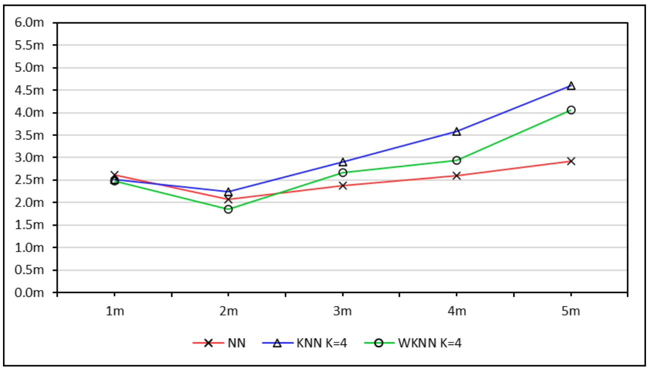

Figure 11. Mean errors of different neighbor numbers for each algorithm, K=4

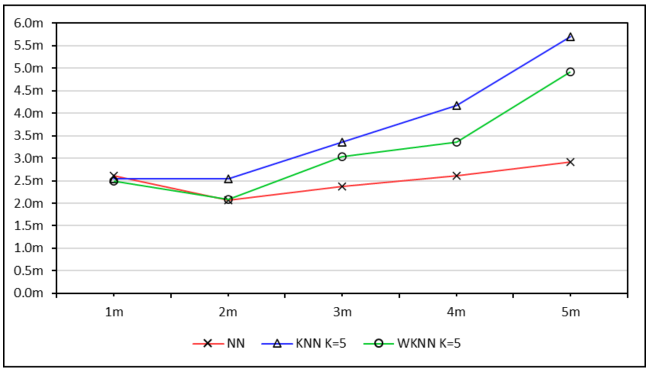

Figure 12. Mean errors of different neighbor numbers for each algorithm, K=5

Tables 1 and 2 also show the standard deviations generated from each scenario. In the NN-KNN comparison, the lowest standard deviation was obtained at K=2 and K=3 cases, while in WKNN this situation was realized at K=3 and K=5 cases.

Table 2. Standard deviations of NN and KNN algorithms

Gap between two calibration point	NN	KNN K=2	KNN K=3	KNN K=4	KNN K=5
1 m	2.45	2.33	2.22	2.34	2.29
2 m	2.38	1.79	1.70	1.80	1.87
3 m	2.16	2.05	1.70	2.17	2.27
4 m	2.71	2.20	2.40	2.61	2.85
5 m	2.42	2.76	2.65	3.11	3.52

Table 3. Standard deviations of NN and WKNN algorithms

Gap between two calibration point	NN	WKNN K=2	WKNN K=3	WKNN K=4	WKNN K=5
1 m	2.45	2.32	2.21	2.31	2.25
2 m	2.38	1.81	1.65	1.81	1.79
3 m	2.16	2.01	1.64	1.99	2.09
4 m	2.71	2.19	2.23	2.40	2.53
5 m	2.42	2.62	2.39	2.75	3.18

4. CONCLUSION

We offered a comparative analysis of fingerprint matching methods for Wi-Fi RSS signal-based indoor localization systems in this work. In terms of localization errors, the proposed study compares the performance of the NN, KNN, and WKNN fingerprint matching algorithms. The experiment was carried out in a real indoor environment, and the experimental results showed that the three positioning algorithms produced different results in different scenarios. Although the NN algorithm produced stable results for each scenario in terms of location accuracy compared to the other two, it is seen that its success is lower when the standard deviations are examined.

Creating a radio map requires careful planning, but determining an appropriate grid density is difficult. It is very important to find the optimum calibration point density as the time and effort spent will increase as the point density increases. It also has an effect on position accuracy. In our study area, the best density was determined as 2 meters. Since this parameter depends on the floor plan and the locations and number of available APs, it needs to be analyzed separately for different indoor spaces.

In addition, it has been observed that the location accuracy decreases as the number of selected neighbors increases. Although this is connected to the geometry of the interior area (Corridor-Type) and a fixed K-value(Bi et al., 2018), dynamic K-value algorithms can offer superior outcomes in a variety of circumstances. This will be the first topic we test in our next research.

Moreover, it would be interesting to investigate the effect of the number of access points and the number of RSS measurements made at each point on location accuracy.

ACKNOWLEDGEMENT

This study was produced from the doctoral thesis named "RSS Based Indoor Positioning Approach in Indoor Environments: Implementation of Fingerprinting Method and Its Performance Analysis" and is an expanded version of the paper presented orally at the " 2nd Intercontinental Geoinformation Days (IGD)" conference.

Author contributions

Behlül Numan Özdemir: Conceptualization, Methodology, Software, Data curation, Writing-Original draft preparation, Software, Validation
Ayhan Ceylan: Visualization, Investigation, Writing-Reviewing and Editing.

Conflicts of interest

The authors declare no conflicts of interest.

Statement of Research and Publication Ethics

The authors declare that this study complies with Research and Publication Ethics

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