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# Wirelessly Indoor Positioning System based on RSS Signal

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*Abstract*—**Indoor positioning (IPS) detection is a research area, presently undergoing development, mainly due to its applicability in the construction of different system types. Because it is, the Smartphone has become an integrated part of human daily life with its capability of connecting to Wireless Fidelity (Wi-Fi) network, which can be used as a tool in positioning systems. The idea of the proposed system is to use the Wi-Fi access points, inside the building, together with a Smartphone Wi-Fi sensor for constructing an accurate and reliable indoor positioning system which lets the building administrator locate those carrying smartphones, wherever they exist inside the building. The proposed system uses fingerprinting technique it is consists of the two-stage the first is a testing phase (or preparation phase) and therefore, the second is the training phase (or positioning phase). Three types of intelligent classifier algorithms are used; these algorithms are K-Nearest Neighbor (K-NN), Multilayer Perceptron neural network (MLP), and Support Vector Machine (SVM). The performance results of the suggested classifiers based on the detection of the location of the target demonstrate that the detection accuracy for MLP is 94.38% and SVM is 90.91%. The best success rate is obtained when using KNN classifiers, which is 96.8595% and the mean error rate (m) is 1.2m when used KNN classifier.**

***Keywords— Indoor Localization, positioning, WiFi, Received signal strength (RSS), wireless.***

## I. INTRODUCTION

In recent years, Internet networks have been speedily developed were many alternative extended services have shown up. the widespread deployment of mobile devices networks has led to increased demand for indoor positioning systems that have been prevailing all around the world [1]. In general, one is able to divide the positioning technologies into outdoor positioning and indoor positioning systems. In outdoor environments, they have been widely used for navigation Global Navigation Satellite System (GNSS), (e.g. Global Positioning System (GPS)). However, in indoor environments, the wireless system has been widely used (e.g. Wi-Fi Positioning System) for navigation. Due to that, Wi-Fi is operated to be used for indoor navigation because nowadays it is being used everywhere to provide access to the Internet [2]. The proliferation use of mobile phones and the Internet led to a recent survey by Pew Research Center's Internet Project found that 74% of adult smartphone owners, aged 18 and older, use their phone to get directions or other information based on their current location [3]. IPS technology, for user and device, has wide-scale applications in the health sector, building management, industry; police the investigation, disaster management, and a variety of assorted different sectors, as shown in Fig 1. It can also benefit several novel systems, like the Internet of Things (IoT) [4], and smart architectures.

In general, many different types of signals are used for indoor positioning. Indoor positioning technologies often use Wi-Fi, Bluetooth Low Energy (BLE), RFID, ZigBee, and Image. Some of these technologies are not widely used due to the main disadvantage of these methods which is the demand for special equipment to obtain the location, such as ZigBee Sensor Node and RFID Tag and other less accessible equipment; because it is more expensive [1]. For many of these applications, time response and accuracy are key necessities [5]. Indoor positioning services have widely used Wi-Fi, many companies and customers have begun to pay attention to their related applications. So, in the installation and maintenance of shopping malls and large stores, Wi-Fi positioning and navigation have an absolute advantage [6]. Wi-Fi-based indoor positioning environments, there are many measuring approaches in which the parameter is positioning dependent, such as, received signal strength (RSS) which can be obtained from the WiFi access points, being the most commonly used approach in the positioning based parameter. They are usually reported as a number in (dB and dBm) by wireless device drivers. RSS measures the typical signal power at the receiver and depends on the transmission power at the sender and also the attenuation within the channel [7], [8].

## II. LITERATURE REVIEW

No particular way exists that can be considered as a global guide to indoor positioning. Several studies have been conducted in the field of indoor positioning. Some of these studies, in this section, will only be those that researchers have focused on and that have reasonable accuracy. Yungeun K., et al, 2012 [9] proposed an internal pedestrian tracking system based on the smartphone; it also investigated a different aspect of the RSS variation problem when using smartphones. The proposed system is accurate but has a low incidence problem. They have compensated by integrating the system with the PDR. The test environment was an office building, which was 50 m by 50 m and had 19 APs marked with circles. To evaluate the performance of the proposed system (PWF+PDR), the system was compared with three different systems: (KNN+PDR), (KNN-MC+PDR), and (HLF + PDR). PDR provided good results compared with other algorithms. The average error distance of PWF+PDR is 2.4 m. Manikanta K., et al, 2015 [10] presented the design and implementation of SpotFi, an accurate indoor localization system that can be deployed on commodity Wi-Fi infrastructure. This system was used in an indoor office environment with an area of roughly 15 × 10 sq.m and deployed six APs to span the area. The SpotFi achieves a median accuracy of 40 cm and is robust to indoor hindrances, such as obstacles and multipath. Youngsam K. and Soohyung K., 2017 [11] proposed the AR-WFL system including an update phase that can reflect environmental change periodically and prevent performance degradation. They developed an android application that uses the getScanResult method in the WiFi Manager class. The device used for data collection is the Samsung Galaxy S4. The office has 8 rooms. Room 1, 2, 3, 4, 5, 6 are about 3x5 meters, room 7 is about 6x5 meters, and room 8 is about 8x6 meters. Positioning accuracy according to the number of active queries is 94.38%. Moustafa A. et al, 2019 [12] presented WiDeep, a deep learning-based indoor localization technique on a neural network. It is implemented and deployed WiDeep on different Android phones and evaluated its performance in two different testbeds: a 629m2 university building and a 65m2 residential apartment. They leverage the RSS of pre-installed WiFi APs in the building or overheard from nearby floors/buildings (university floor has an overall of 122 APs whereas the apartment has 59 APs). The results showed that WiDeep can achieve a consistent mean accuracy of 2.64m and 1.21m in the two testbeds respectively under different scenarios.

## III. Applications of Indoor Positioning System

Indoor positioning technology has recently witnessed a major increase in usage around the world. IPS technology, for user and device, has wide-scale applications in the health sector, building management, industry; police the investigation, disaster management, and a variety of assorted different sectors, as shown in Fig. 1. It can also benefit several novel systems, like the Internet of Things (IoT) [4], smart architectures. marketing and customer assistance [13], health sector [14] [15], and security[16].

Fig. 1. Application of Indoor Positioning.

This section presents a concise description of the system implementation technologies and environments. The first step of the system design is the collection of appropriate data to detect person positioning which is the RSS data that collected data from the third floor of the electrical engineering department at the University of Technology. In the second step, various classification algorithms are suggested, such as KNN, MLP, and SVM, finally these classifiers are tested in the same training dataset.

## IV. Main Parts of the Proposed System

The essential part of the IPS is the positioning task which is the process of locating the user at a certain place inside the building. Before thoroughly discussing and analyzing the proposed system mechanism, an overview of the required components is first presented. Fig. 2 shows the main components that participate in the overall system design. Meanwhile, each component and its function flow related to the others are briefly explained as follows:

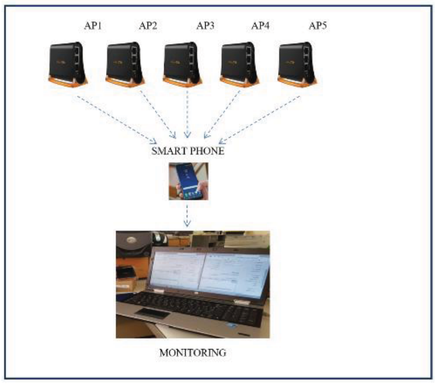


Fig. 2. Main System Components

- Wi-Fi APs: The positioning task of the proposed system adopted the Wi-Fi fingerprint mechanism to determine the user position in the building. In this work, we use Mikrotik hap mini as a WiFi access point, as illustrated in Fig. 3.

Fig. 3. Mikrotik hap mini used as a WiFi access point

- Smartphone: Smartphone: The smartphone is carried by the user who is subjected to indoor positioning.
- Controlling and Monitor screen: The screen allows the administrator to monitor, the user positioning inside the building in real-time. also, is used to detect and read the APs Wi-Fi RSS values for the purpose of finding user location as shown in Fig. 4, this shows the program interface for two routers, and this is done through monitoring the target signal.

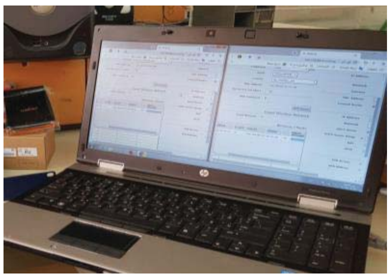

Fig. 4. Positioning detection for target from two routers.

## V. The Proposed Indoor Positioning System

The mechanism of this work illustrates in Fig. 5. This figure described the proposed system consists of two phases: the testing phase and the training phase.

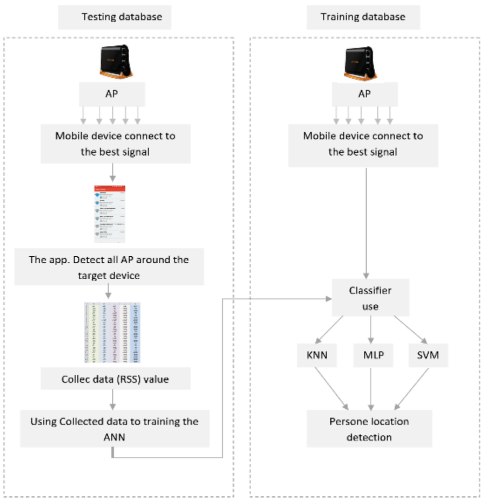


Fig. 5. Block diagram of the proposed indoor positioning system.

### A. Testing Stage

The proposed system uses Wi-Fi fingerprinting technique for locating the user position, in this work used the third floor as the experiment area. This technique requires creating a database that contains RSS of detected Wi-Fi APs at each position on the third floor.

- The third floor is equipped with multiple access points, in order to ensure that we have sufficient signal throughout the floor.
- The first stage of the system design is a distribution of routers in the required places from the experimental area, five MikroTik Access Points (AP) are distributed on the third floor of electrical and electronic engineering buildings, as illustrated in Fig. 6.

Fig. 6. Distribution of the Router in the third Floor Map.

- The second stage is data collecting, use an application that uses to scan the Wi-Fi in the Wi-Fi-manager class this app is a Wi-Fi switcher and uses the mac address of the mobile of a user as a target.
- The administrator based on smartphone passes through the whole third floor regions, the wireless signal strength is measured from the Access Points used as a feature. Each Access Point has a distinct MAC address and features only one wireless ID. The fundamental factors for processing data include SSID name, MAC address, RSSI value, recording the MAC addresses of the building APs and excluding all the APs that are detected and do not belong to the building.

The specifications of the UOT indoor positioning database which is used in this work are demonstrated in TABLE I.

TABLE I. UOT Indoor Positioning Database Specifications.

| Database Acquisition Specifications | |
|---|---|
| The total area used in the experiment | 3170 m |
| Total number of the routers used | 5 |
| Number of position detection | 14 |
| Number of RSS for one position | 26-130 |
| Total number of the RSS used | 1199 |

### B. Training Phase Detection and Classification

This is the most important phase of the system which is the last stage is positioning the person (Classification) which is used to locate the person based on RSS extracted from the previous stage. Three different types of classification are suggested to do this task as an individual: K-Nearest Neighborhood (KNN), and Multilayer Perceptron neural network (MLP), Support Vector Machine (SVM). These classifiers are tested in the same training datasets. The algorithm calculates the position based on the distance between the reference fingerprint and the fingerprints in the database. Various formulas can be used for distance calculation, e.g.: Manhattan distance or Euclidean Distance. It finds the K best matching fingerprints based on their mutual distance and calculates the position as the average of the positions of these K fingerprints We will further elaborate on the KNN classifier due to having the highest detection accuracy results.

### C. K-Nearest Neighbor Algorithm (KNN)

K- Nearest Neighbor (KNN) algorithm is one of the most common methods. It is a simple classifier and having a better accuracy when compared to other classification techniques. To understand the working of this algorithm, let's consider a two-class problem. Each class most likely has a similar sample. For an unknown test sample, the decision of the KNN classifier depends on the closest distance between the unknown input sample and each nearest sample per class using common distance calculation methods, like Euclidean and Manhattan. Then the unknown sample will be assigned to the class of the sample that given the closest distance, as shown in Fig. 7.

Equation (1) can be given for the Euclidean distance calculation method [17].

$$d = \sqrt{\sum_{i=1}^{n} (p_i - q_i)^2} \qquad (1)$$

Where:
$p_i = (p_1, p_2, \ldots, p_n)$ Stands for the unknown test sample.
$q_i = (q_1, q_2, \ldots, q_n)$ Stands for any sample within the training dataset.
n: stands for the feature size.

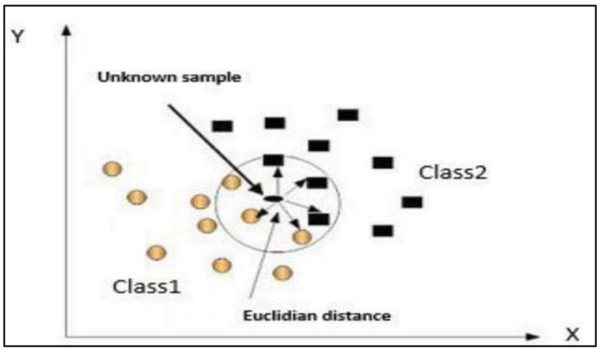


Fig. 7. An example of using the KNN algorithm with two classes [18]

*D. Positioning System Based on K - Nearest Neighbor (KNN) Classifier*

K-Nearest Neighbors is a best-suited method that can be used as indoor positioning detection since it is a simple and lesser time execution for classifying an unknown target's position based on the distance to the k nearest neighbor. In this work, the KNN classifier used to detect target location in fourteen positions based on the received signal strength that was taken from five routers. The training set of the K-NN classifier contains 594feature vectors that represent values of the RSS of the five routers at each test point. In the training phase, all features vectors and their classes are stored and distributed as individual classes.

In the test phase, the test set consists of 605vectors; each feature vector contains 5 features. The total number of the features represented a testing set is 605× 5 features. The unknown person's location is classed according to the minimum distance that fined by the KNN classifier. The minimum Manhattan distance of the class is represented as a target class in the indoor positioning classification.

A MATLAB program was written to evaluate the performance of the correct classification location for the indoor positioning KNN classifier. Based on these calculated distances and chose the k minimum distances the classifier can identify the class of the input feature vector. In this work, k=1 is chosen this mean KNN classifier to choose one minimum distance to make a decision. The highest detection rate was achieved when using K-NN classifier. The overall success rate of the indoor detection system using K-NN into fourteen-class classification is 96.86%, according to the formula in "( 2)".

$$\text{Success rate} = \frac{\text{total number of correctly classified sample}}{\text{total number of testing sample}} 100\% \qquad \text{s}(2)$$

The overall mean error rate of the indoor detection system using K-NN into fourteen-class classification is 1.2m, according to the formula in "(3)".

$$Mean\ \text{error rate} = \frac{100 - \text{Success rate of correctly classifiedposition}}{100} \times \text{Area of the position} \qquad (3)$$

*E. Positioning System Based on Multilayer Perceptron Network (MLP)*

The Multilayer Perceptron neural network is adopted as a classifier to classify indoor positioning into fourteen locations. The MLP is a feedforward neural network as shown in Fig. 8. The structure of the proposed neural network includes three layers: an input layer, a hidden layer, and output layer[19]. Moreover, the overall detection percentage of the indoor positioning system based on the MLP network is 94.38% and the mean error rate is 3.06m when used MLP classifier.

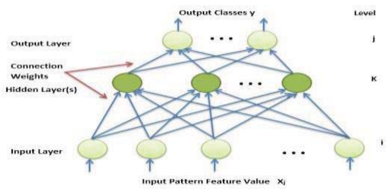


Fig. 8. Structure of a multilayer perceptron network [20].

*F. Positioning System Based on Support Vector Machine ( SVM )*

The application of SVM in the detection of the indoor positioning is investigated in this work, SVM is one of the classification algorithm used to classify two class based on the linearly separable hyperplane. The hyperplane is constructed in the dimensional space that is divided into two classes, which maximize thedistance between itself, and close the training samples, as shown in Fig 9. This hyperplane is used as a basis to classify vectors of unknown objects (test objects) [21].

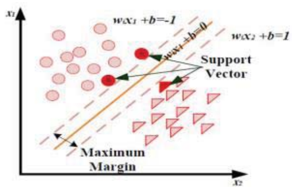


Fig. 9. optimal separating hyperplane between two classes [22].

The OVA-SVM has been adopting to determine the class of the test data with the most significant margin. Moreover, the overall detection percentage of the indoor positioning system based on the SVM network is 90.909% and the mean error rate is 5.08m when used SVM classifier.

## VI. The Proposed Indoor Positioning System Performance Comparisons

The previous section discusses the performance of the three proposed IPS system classifiers using data-based. The highest detection rate was achieved when using the K-NN classifier. The lowest indoor position detection rate was found when OVA-SVM classifier is used. The reduction in the performance of indoor positions for this classifier occurs because of the nonlinearity of the Support Vector Machine in the multiclass problem. In order to compare the performances of the three proposed identifiers, the probability of correct classification for each position in addition to the overall success rate is evaluated as shown in TABLE II.

TABLE II. The Overall Success Rate For The Proposed Classifiers

| | KNN | MLP | SVM |
|---|---|---|---|
| Overall Pcc | 96.8595% | 94.3802% | 90.9091% |
| Mean error rate (m) | 1.2 | 3.06 | 5.8 |

## VII. Comparison of the Proposed Indoor Positioning System Performance with Previous Approaches

It is very difficult to make a reliable comparison with other systems when these measurements are not done in exactly the same circumstances. Although based on published results from research papers, an approach of the accuracy comparison can be made. Table II, shows this overview, displaying the mean error for the algorithm and Probability of correct classification (Pcc). Their experiment involves localization at 14 unknown locations. The proposed IPS detection is an improvement in accuracy under a naturalistic environment. The features are used as the input of the different classifiers to identify the position of the person or device. The highest recognition rate of the position was obtained when the indoor positioning is identified using the K-NN classifier. Compared to the performance of the IPS using K-NN classifier with other positioning systems investigated by other researchers is shown in Table II. Therefore; the comparison will be based on the overall performance of the positioning system. The specific parameters used in this comparison are the number of the access points, number of RSS used at the adopted database by each approach, size of the locations, type of the classifier, and the number of classified positions classes as demonstrated in Table III. The proposed classifier in this work has a higher success rate than other classifiers in previous research. Knowing that the number of training and testing sets used in the suggested IPS systems are greater than other data sets used by previous approaches. Moreover, the proposed indoor positioning system is less complex and easy to implement in hardware.

TABLE III. The Summary of Previous Works

| Reff.No | No.Position | No. Routers | Area $m^2$ | No. Data | Classifier type | Pcc % |
|---|---|---|---|---|---|---|
| [2] | 1 | 6 | 115 | 30 | WKNN | 98.25 % |
| [10] | 1 | 6 | 16×10 | | MUSIC-AoA algorithm. | 99% |
| [23] | 1 | 4 | 20×20 | 2000 | OS-ELM | 97.47 % |
| [24] | 3 | 3 | 15×10 | 450 | Trilateration algorithm | 86.91 % |
| [25] | 2 | 1 | 4×7<br>6×9 | 500<br>1000 | Greedy Learning Algorithm | 89.8 %<br>81.15 % |
| (2)<br>[11] | 8 | 8 | 6(3×5)<br>6×5<br>8×6 | 7695 | KNN | 94.38 % |
| [12] | 2 | 122<br>59 | 37×17<br>14.5×4 | 7200<br>2000 | Greedy layer-wise | 96.51 %<br>92.06 % |
| Proposed system | 14 | 5 | total area | 1199 | KNN | 96.85 95% |
| | 8 × 9, 7.5 × 3.6. 3 × 8.4, 7.5 × 8, 8.4 × 15, 7.5 × 3.8. 3.55 × 7.5<br>7.5 ×3.8. 3.5 ×2.5. 6 ×9. 8.8 ×16. 3.5 ×4.5. 8 × 5. 81.8 ×1.5 | | | | | |

## VIII. Conclusions

In this work, the focus lies on the development of a WiFi-based on fingerprint technique indoor positioning system, should obtain information from nearby access points with the mobile device via a WiFi scan, and create a new database to test the performance of the proposed IPS technique, then measure the accuracy of indoor positioning of the suggested classifiers via MATLAB 2014a software depending on the collected database, finally evaluation of the performance of the proposed indoor positioning technique by comparing it with performances of the other systems in previous work. The main aim of the proposed system efficiently detects the location of the target relying only on analyzing the Wi-Fi fingerprinting. fourteen locations are considered in the experiment area were selected as the most important locations where people are heavily present. The proposed system efficiently detects the location of the target of the fourteen locations relying only on analyzing the Wi-Fi fingerprinting. A created new database is sufficient to enhance and evaluate the proposed system performance. This database is collected from 14 locations in the different areas of space with five routers that are distributed in places where people are frequently present. The proposed system can be worked on more than one location based on the Wi-Fi fingerprinting of this location.

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