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Original Article

Improving Artificial Neural Network Indoor Positioning System Accuracy using Hybrid Method

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Abstract *— The indoor positioning system is widely used nowadays, increasing the favors in indoor positioning systems significantly. The usefulness of the indoor positioning system in many aspects, such as security, item tracking, and many others, is why an indoor positioning system is widely used. Unlike the positioning system that uses satellite signals, indoor positioning systems have superiority in dealing with signal difficulties in closed environments, which is why indoor positioning systems are becoming increasingly popular. Much research looks at improving this indoor positioning system's accuracy by using trilateration, weighted k-nearest neighbor, and artificial neural networks. The artificial neural networks were chosen compared to the weighted k-nearest neighbor and a hybrid method that combines the neighbor of the weighted k-nearest neighbor algorithm results as data for the artificial neural network. This research shows that the weighted k-nearest neighbor and artificial neural network combined as the hybrid method can significantly increase the accuracy by 25%.*

Keywords — *Indoor Positioning System, Weighted K-Nearest Neighbor, Artificial Neural Network, Internet of Things, Indoor Localization*

I. INTRODUCTION

Nowadays, positioning and navigating industries are increasing rapidly [1]. This growth is only possible because of the benefit of positioning and navigating itself. Positioning and navigating through satellite signals – such as Global Positioning System (GPS), GLONASS, BeiDou, Galileo – already have great accuracy and reliability in an outdoor environment with good signal strength [2].

However, the satellite signal is hard to use in indoor[3]–[5] usage due to the signal inferences penetrating the building itself, such as concrete, metal, and other building material. There are many approaches to conquer these problems. One of them uses Radio Frequency Signal (RF) – such as Wi-Fi, Bluetooth [6]–[9], ZigBee, RFID [10]. Among all RF approaches, the Wi-Fi approach is the most attractive and promising candidate in the absence of the building satellite signal caused by the satellite signal stiffness to penetrate the structure. Wi-Fi has the pervasive penetration and characteristic that does not require line-of-sight measurement of access points (AP) [11].

Many algorithms and techniques for indoor positioning systems have been developed in the past few years [12]. Most of them use Received Signal Strength (RSS) as a medium to calculate the location. That is also the reason why we choose Wi-Fi instead of Bluetooth. By default, Wi-Fi has higher transmitted power and more robust multipath components than Bluetooth. Wi-Fi can make a more robust and more stable signal than Bluetooth [13].

The most developed algorithm for locating and navigating indoor is the Nearest Neighbor (NN). NN uses Euclidean distance to measure the nearest point in data collected in the offline phase with the cluster as its label. The NN algorithm results are the label on the point already inside the database with the minimum distance vector value [14]. The NN algorithm development can be improved using the k-NN algorithm, where *k* is the minimum distance valued neighbors need. The most taken label in *k* neighbors is the result of this algorithm [15]. However, we can improve these two algorithms by using weight in calculating the result or, in short, using a weighted *k*-NN algorithm. In the weighted *k*-NN algorithm, the calculation of the result uses the average of each label. The selected label with the minimum average value is the one matters in this algorithm. The label with the minimum average value is the result of this algorithm [16].

The result of the previous research above is already good but still can be improved. That is why this hybrid method comes to improves the result accuracy of the current method. This paper will use hybrid methods that combine the weighted k-nearest neighbor algorithm with the artificial neural network. The neighbor of each point that resulted from the weighted k-nearest neighbor will be used as training data in the artificial neural network.

II. RELATED WORKS

This section consists of a generally used algorithm that mostly utilizes RSS as its medium for locating and navigating indoor.

A. *Multilateration*

The intuition behind Trilateration is to calculate the distances between the mobile target and the measuring unit using the received RSSI. The object's position can be estimated with a minimum of 3 calculated distances called Trilateration. The distance can be estimated by using the Time of Arrival (ToA), Time Difference of Arrival (TDoA), or measured RSSI of the received signal [12].

In ToA, the propagation time from the mobile target to the measuring unit is assumed to be proportional to the distance if the system's transmitters and receivers are perfectly synchronized. Meanwhile, TDoA estimates the distance by examining the difference when the signal arrives at multiple measuring units. As defined in the IEEE 802.11 standard, RSSI is the transmitter power ratio and the received power presented in dBm unit. It is well known that the RSSI will get weaker with increasing distance [9]. One of the signal propagation models is the Log-Distance Path Loss, as shown in [14] and described as:

$$RSSI_{dBm} = -10.\, n.\, log_{10}(d) + C \tag{1}$$

Where n is the signal propagation exponent, d is the distance between the transmitter and receivers, and C is the RSSI at a one-meter distance. With (1), the distance can be known by calculating:

$$d_m = 10^{\frac{RSSI-C}{-10.n}} \tag{2}$$

A method that combines RSSI measurement and trilateration technique (2) with acceptable accuracy were proposed [14]. Trilateration will return an exact and unique position, which is the intersection of three circles (Figure 1), if the distance calculation is very exact and precise. However, RSSI measurement will vary dramatically depending on the environment itself, the location of obstacles, etcetera. With noisy RSSI measurement, it is difficult to get the exact intersection of the three circles. They are more likely to not intersect at only one point (Figure 2), or they may even not intersect at all (Figure 3).

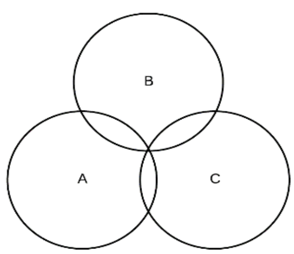

Figure 1. Trilateration with precise distance calculation

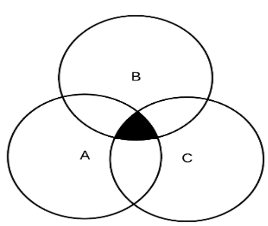

Figure 2. Trilateration with noisy distance calculation

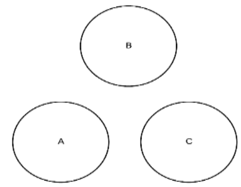

Figure 3. Trilateration that does not intersect at all

The inter Ring Localization Algorithm (iRingLA) was proposed to solve this problem[14]. Instead of drawing circles, iRingLA draws rings around the three transmitters. Each has an inner and outer radius that will be computed upon RSSI measurements already carried out during the ranging phase.

Based on the trilateration technique, Reference Point (RP) was introduced to improve the receiver's position in the environment where obstacles block the signal between the transmitter and receiver [14]. We can minimize the error rate by calculating distances between the receiver and every transmitter, then comparing it to the distances from the RP to each transmitter.

B. Fingerprinting

Because the RSSI measurement is very dependent on the indoor environment's characteristics, such as the location of obstacles, metal objects that cause the multipath effect, and fading, The fingerprinting technique is a reasonable approach that will examine the character of the indoor environment itself. Fingerprinting consists of an offline phase and an online phase. A site survey will be conducted in the offline phase to examine the character of the environment. A considerable amount of location was picked to explore the nature of the RSSI received in each location. The collected fingerprint will be stored in a database to be used later in the online phase. The object's position can be estimated by comparing the measured RSSI in the online phase with the stored RSSI fingerprint in the database using a particular algorithm.

In k-Nearest Neighbor (k-NN), the similarity between measured RSSI and stored RSSI fingerprint is determined using Euclidean distance [17]. The object location is predicted to be close to the cluster with the smallest distance [15]. In addition to Euclidean distance, several formulae can be used to calculate the distance between measured RSSI and stored RSSI fingerprint; for example, [14] use Jiffreys&Matusita distance instead of Euclidean.

However, in several cases, k-NN did not produce results as expected. If k is too small, k-NN could be very sensitive to outliers. On the contrary, the neighborhood may include too many neighbors from other clusters if k is too large. The k-NN algorithm most likely will choose the cluster with the majority vote; this can be a problem if the nearest cluster only consists of a few neighbors, while more neighbors from another cluster with further distance are detected. Therefore, Weighted k-Nearest Neighbor (Wk-NN) was proposed to solve this problem [18]. Wk-NN considers the cluster's overall distance and chooses the cluster with the smallest distance [19]. IPS with Wk-NN as its positioning algorithm is used in [14], [20]–[22]and results in better positioning accuracy than conventional k-NN.

C. Artificial Neural Network

Artificial neural network nowadays is top-rated in solving most of the problem, one of which is this indoor positioning problem [23]. An artificial neural network is an algorithm inspired by how the human brain analyzes and processes information [24]. As Figure 4 shows, the artificial neural network is a collection of some units that connect one another to make one single unit, each unit is called a node, and each connection is called an edge. The artificial neural network comes with three main components in the artificial neural network: neurons, connections and weight, and propagation functions. Every neuron in an artificial neural network has a real number that acts as a signal on the human brain. Those real numbers start from the input neuron through all the hidden neurons, in which every neuron will update those real numbers with the calculation between those real numbers, weight, and bias until those numbers reach the output neuron.

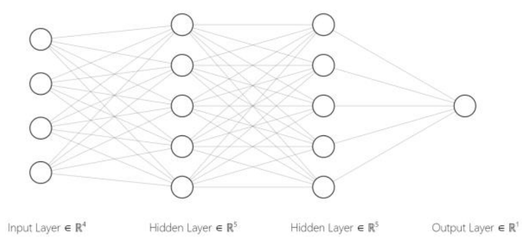

Figure 4. Artificial Neural Network Architecture Example

The weight in an artificial neural network is often called an activation—those weight updates based on the activation function, such as sigmoid, ReLu, Softmax, etcetera. That weight and bias are the main things that transform raw data from the input layer to the output layer. Raw data from the input layer will be multiplied by an assigned weight to be added with bias before passing it to the next layer until the data reach the output layer. For the last process, the output layer tunes the latest hidden layer's input to produce the desired numbers in the specific range of numbers.

In [25], Hamid Mehmood et al. use an artificial neural network with backpropagation to classify the point of location. [25] use forty training samples taken at 8x9 m space, and they thirty percent of error rate within 1 m.

III. PROPOSED METHOD

A hybrid method was proposed to improve the indoor positioning system's accuracy—this hybrid method combines the artificial neural network with a weighted k-nearest neighbor. This chapter will explain more about the hybrid method we use to improve the indoor positioning system.

A. Weighted k-Nearest Neighbor

The weighted k-nearest neighbor was used in the online stage of our indoor positioning system. The chosen algorithm to measure the distance from the RSSI at the online stage and our dataset at the database at the calculation in the weighted k-nearest neighbor algorithm is Euclidean distance.

$$d = \sqrt{\sum_{i=1}^{n}(q_i - p_i)^2} \qquad (3)$$

Where n is the number of receivers that collect RSSI data, q_i is the fingerprint RSSI measured by i^{th} receiver, and p_i is the RSSI measured in the online stage by i^{th} receiver.

The smaller the Euclidean distance, the closer the measured object to the cluster should be. k-Nearest Neighbor will be collected, and the object's position will be calculated using (4). In this research, the k was set to 50.

$$(x, y) = \frac{\sum_{i=1}^{k}(x_i, y_i)}{k} \qquad (4)$$

Using the formula above, the data will be sorted from the smallest to the largest distance from the calculations. The top twenty-five data will be gathered from the sorted data in ascending order to be summarized per cluster. The cluster with the least total distance will be taken to be processed in the next process.

Every detection result will be saved to a database using the MySQL engine to calculate and validate this algorithm's error rate. This error rate will be used in the next process as a percentage of the hybrid method.

B. Artificial Neural Network

An artificial neural network was also used in this research to measure the location in our indoor positioning system. The model was trained with the dataset before stepping into the online stage. The dataset was split into two, the training dataset, and the testing or validation dataset, with eighty percent for the training dataset and twenty percent for the testing or validation dataset.

As mentioned in [25], [26], backpropagation was also used to update each node's weight in the training process. Backpropagation is one of the most used and considered as useful in the neural network model, especially for with the data that contains many noise and non-linearity as in indoor positioning system's data [26]

The previously trained model will be used to predict the location in the online stage. In this artificial neural network model, the number of inputs used is the number of microcontrollers that have been predetermined. The resulting output is one, which is the label of the points used previously to train the data.

The processed data will be saved to a database using the MySQL engine, which in the future can be used for various things, such as monitoring, movement history, and etcetera. The data in the database will be used to calculate and validate the error rate for each method.

C. *Hybrid Method*

In the hybrid method, the two algorithms above were combined. All the neighbors' weight calculations were used for each testing row of data in the testing dataset as the artificial neural network training set.

Each point in testing data will have a total of *k* neighbors' weight for training model inputs, so each point's actual location in every testing data from the model we trained before can be predicted. Figure **4** below shows the flow of how the hybrid was made.

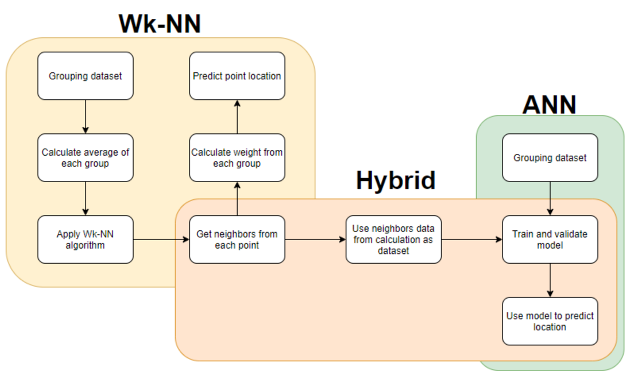

Figure 4. Hybrid method

VI. EXPERIMENTAL RESULT

A. *Data Collection*

In this paper, an online repository from the IndoorLoc Platform from University Jaume I, Castellón, Spain. Institute of New Imaging Technologies was chosen.

The dataset consisted of 670 records for the offline phase or training data and 405 for the online phase or testing data. Each record consists of 154 attributes; each attribute contains 152 RSS data from each WAP and the last two attributes for longitude and latitude in meters.

B. *Experiment Scenario*

The process of determining the actual location of each point are listed below:

i. Grouping each training dataset per longitude and latitude
ii. Calculate the average of each WAP in each group that was created before.
iii. Apply the weighted k-nearest neighbor algorithm to create a k training set for each point in the testing dataset. In this paper, 16 k was used as the neighbor we take for each point. 16 was chosen because the error rate of 16 k is the smallest among all the possibilities.
iv. The list of the neighbors was stored for each point in the MySQL database.
v. Train and validate the artificial neural network model with the training dataset in MySQL. The detail of the architecture can be seen in Figure 5
vi. Calculate the error rate of the prediction

The overall process of the experiment is shown in Figure 6.

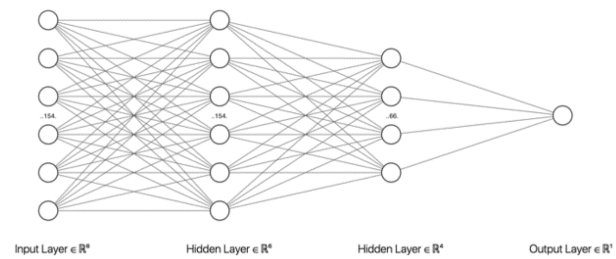

Figure 5. Artificial neural network architecture

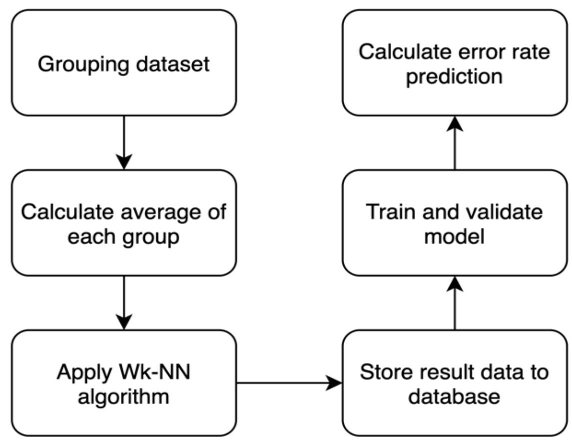

Figure 6. Experimental steps

C. *Error Rate Calculation*

The accuracy of every point in the testing dataset was calculated using (4).

$$E = \sqrt{(x - x_e)^2 + (y - y_e)^2} \tag{4}$$

Where x and y is the real position of the data point and x_e and y_e Is the predicted position of the data point. Then, the average positioning error for both scenarios was taken using a hybrid method and artificial neural network only. The result is shown in

Table **1**.

Table 1. Average error rate result table

Error Rate		
Wk-NN	**ANN**	**Hybrid Method**
11.86	6.17	5.89

VII. CONCLUSION

Three approaches in this research were created: a weighted k-nearest neighbor, an artificial neural network, and a hybrid artificial neural network. In the hybrid method, we use 16 as the total *k* at the weighted k-nearest neighbor phase. We can conclude that we can increase up to 25% of the prediction accuracy with the hybrid method from the result.

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