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Enhancing Wi-Fi based Indoor Positioning using Fingerprinting Methods by Implementing Neural Networks Algorithm in Real Environment

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Abstract: Global positioning systems have difficulties in finding positions inside buildings, since indoor positioning needs additional indoor infrastructures deployment. In this research, indoor positioning by using Wi-Fi access point is investigated as the main usage of Location Based Service (LBS) applications. We employed fingerprinting method to increase the accuracy of positioning. The study has been done in real environment in Universiti Teknologi Malaysia (UTM). Two models were designed by using Neural Network algorithm for indoor positioning. The fingerprinting dataset contains received signal strength from different numbers of existing Wi-Fi access points in the real environment. Accuracy rate and mean square error were calculated for the algorithm. Evaluations of models have been done by conducting experiments to compare both models. Analysis suggests that Neural Network method which achieved 71% of accuracy with number of neurons = 11 is the most precise model for indoor positioning in this project. In future, more features can be applied to this model in order to increase the accuracy. This approach has the potential to be implemented as a real mobile application for indoor environment.

Key words: Indoor positioning, fingerprinting, Wi-Fi, neural network, global positioning system, implemented

INTRODUCTION

Development of navigation systems need sophisticated methods in order to find the current location of a user or device with an adequate accuracy for a given context. Various technologies and methods are available for different type of application. Outdoor positioning system can be enhanced by combining the satellite positioning systems such as Global Positioning System (GPS) but for indoors environment, since we have buildings limitation such as walls or narrow corridors positioning has been a challenge these days. Therefore, the need for precise indoor positioning during a short time and at any specific position is forcing us to use efficient positioning systems (Belakbir *et al*., 2012).

Regarding the complexity of the indoor environment, large coverage techniques such as cellular base station for indoor localization technique are unreliable. Thus, the indoor positioning solution requires additional indoor infrastructure deployment. Unless, cheap and convenient techniques such as Wi-Fi can be developed and comprehensive indoor localization continues to be a challenge (Bao and Wong, 2013). According to Vathsangam *et al*. (2011), one of the suitable and cost effective candidate's techniques is using existing Wireless Received Signal Strength (RSS) based indoor positioning methods. Wi-Fi location determination consists of two primary methods, signal strength propagation models and fingerprinting techniques. Wi-Fi based indoor positioning is one of the most popular systems that have lots of pre-installed Wi-Fi access points. However, its accuracy is not good enough for indoor LBS. In comparison with outdoor environment, the accuracy of Wi-Fi based technology cannot satisfy the expectation of the indoor users because there are lots of Point of Interests (POIs) and narrow corridors which are hard to distinguish the position. Therefore, the indoor service requires more accurate positioning system than outdoor (Jeon *et al*., 2014).

Although, there is considerable amount of research, precise indoor positioning is still a long standing problem. The most common technique for indoor navigation is Wi-Fi based approaches, since GPS is not useful inside buildings. Besides by using Wi-Fi for indoor positioning there is no need for additional peripheral and almost all smart phones are equipped with Wi-Fi features. Despite the robustness of Wi-Fi localization method, there is a challenge for evaluation Wi-Fi signals because of their variety from time to time. The Wi-Fi signals hardly can get stable hence there is much complexities through

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indoor environment and it is difficult to get precise and flexible signal from wave propagations (Xu *et al*., 2013). There is a need to expand the range of Wi-Fi based positioning methods to be analyses and compared for achieving better insight on the efficient technologies to deploy. While the requirement of Location Based Services (LBS) in indoor places increases, there is a need for high accuracy positioning methods and it has been caused to development of finger printing based positioning approaches which use Wireless Local Area Network (WLAN). They used single finger printing algorithm with the integration of several methods (Xu and Sun, 2012).

MATERIALS AND METHODS

Proposed reseach: This project is aiming to develop a Wi-Fi based indoor positioning approach by using fingerprinting method for mobile users which has acceptable accuracy. This research will investigate prospect of Received Signal Strength Indication (RSSI) algorithms and the investigation and analysis among the fingerprinting method in real environment inside Universiti Teknologi Malaysia also simulation and testing will be done along with the result of designed model. Data collection which is Received Signal Strength (RSS) will be measure by existing mobile application on user smart phone in a selected place in Menara Razak (Systems Engineering Lab in level four). This research presents comprehensive details of indoor positioning using location fingerprinting algorithms such as Artificial Neural Network (ANN).

Experimental setting: Our study area is the systems engineering lab which is located in level four of Menara Razak in Universiti Teknologi of Malaysia which contained furniture and equipment such as tables, chairs and computers. A set of data is required for this research. Data set was collected by measuring the RSSI values of the signals received from the four points. Each point has the dedicated label: a, b, c or d. Figure 1 shows a simple view of our research location area map.

For collecting data, an application called Light weight Wi-Fi Scanner (APScan) is used to collect signal strengths from Wi-Fi access points. APScan Version 2.3 is 431 k and can be installed on android mobile phones. We used a Sony mobile phone with android OS and APScan is a free and open source application. This application provides a Comma Separated Value (CSV) file containing information about signal strength it also saves the date and time of scanning. The structure of information is: BSSID, Power, Chanel and ESSID. In this

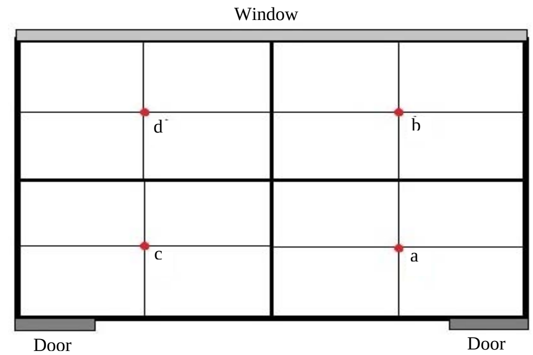

Fig. 1: Experiment layout

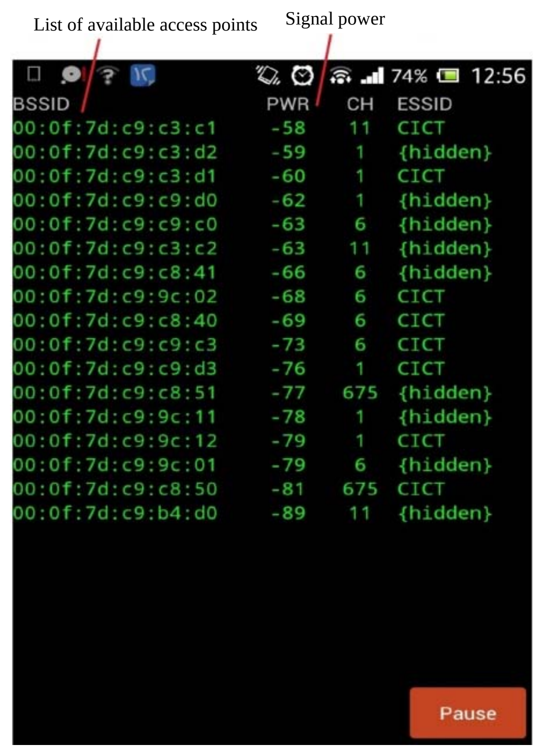

Fig. 2: Recording RSS using APScan

research, we just need BSSID which contains access points and Power of signal strength. Figure 2 shows an image of running APS can application interface.

Neural Network with four number of access points: We used Neural Network method to approximate position using signal strength data. In this project, we used multi layer perceptron of back propagation for implementing Neural Network structure. Neural Network will train the model for generalizing the prediction for positioning. In the input layer, we have received signal strength from access points and in the output layer the position of mobile user or labeled point will be generated in this research. In the hidden layer in Neural Network Model, new weight will be generated in the iterations till the acceptable result will gain. So, during process of training different weight and bias will be updated according to number of iterations. So, it is needed several trial in order to get general analysis in Neural Network Model and each trial may have different result which need to be analyzed. The following features used to develop the Neural Network Model:

- Algorithm: Artificial Neural Network
- Goal: prediction the position
- Input: received ssignal strength from 4 access points (RSS vector)
- Output: predicted position (can be a, b, c or d)
- Testing: 70% training set-30% testing set

Generally, Neural Network Model is to predict the output position. Basic back propagation algorithm has two aspects: forward propagation and error back propagation (Chen *et al*., 2014a, b). The output is calculated in the direction from input to output. Weight and threshold value is modified in the direction from output to input. Assume we have n number of input in input layer and then the forward propagation equation from input layer to hidden layer is (Eq. 1):

$$y_i = f\left(\sum_{j=1}^{n} w_{ij} R_j\right) \quad (1)$$

And if we have m number of neurons in hidden layer, the forward propagation equation from hidden layer to output layer is (Eq. 2):

$$O_k = f\left(\sum_{i=1}^{m} V_{ki} y_i\right) \quad (2)$$

For calculating error back propagation, the error of nerve cell in each layer is calculated layer by layer starting from the output layer then the weight of each layer is adjusted according to gradient descent method and the final output will be made by approximate expected value. Consider Tk is the expected output for each sample p, the error function is (Eq. 3):

$$E_p = \frac{1}{2}\sum_{k=1}^{2}\left(T_k - O_k\right)^2 \quad (3)$$

Then, the weight will be corrected and forward propagation will be started again, error will be calculated and result will be compared if the result is not satisfying then renew the weight is required and need train the network again until we reach to the level of accepted accuracy.

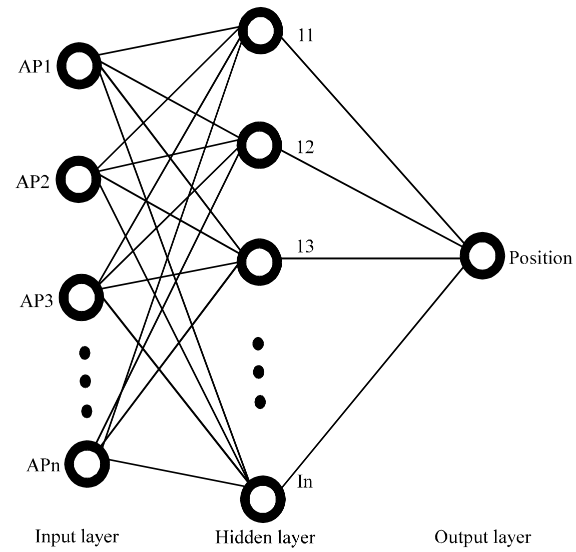

Fig. 3: Neural Network structure

During the training process, the difference between the actual output and the target output is calculated using the mentioned error function Ep. The error is then propagated backwardly to the network and the weight of each connection will be updated in order to reduce the value of the error (Chen *et al*., 2014a).

Number of neurons in hidden layer is one of main parameter which affects the accuracy rate in Neural Network Model. We changed the number of neurons and the result was compared. The network structure of our model is shown in Fig. 3.

In this research firstly, we used 4 number of access points, so we have 4 input as input layer. Then we increased the number of access points to 6 to get better accuracy so in that model we have 6 input as input layer. In this model of Neural Network we just have one hidden layer. Theoretically, a Neural Network with a single hidden layer can fit most of the hypothesis functions and there is almost no need to go for another hidden layer.

Various numbers of neurons was tested. For hidden layer = 4, 8, 10, 11, 12, 14, 16 the accuracy measured and the result is shown in Fig. 4. The most accurate result related to model with 4 and 14 numbers of hidden layers with the value of 0.5024 and 0.6862. For testing this method we separated the data into 30% for testing and 70% for training. The number of epochs was 40 and we just change the number of neurons in hidden layer. The weight and bias changed automatically during each iteration. Our experiment just focuses on accuracy rate in

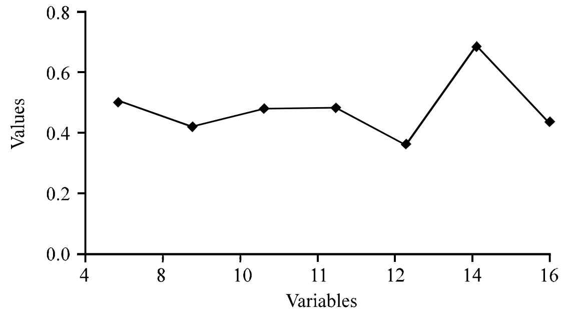

Fig. 4: Accuracy rate by various number of neurons

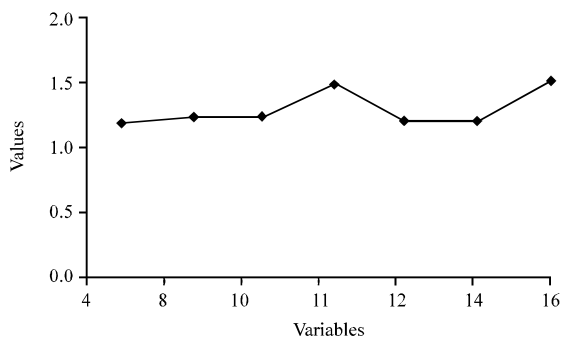

Fig. 5: Mean Square Error (MSE) by various number of neurons

this project. The Mean Squared Error (MSE) has been measure by neural network and result shown in Fig. 5.

Neural Network with six number of access points: The Neural Network method applied to new approach with 6 number of access points. The following features used to develop the Neural Network model:

- Algorithm: Artificial Neural Network
- Goal: prediction of position
- Input: Received Signal Strength from 6 access points (RSS vector)
- Output: predicted position (can be a, b, c or d)
- Testing: 70% training set-30% testing set

Various numbers of neurons was tested. For hidden layer = 4, 8, 10, 11, 12, 14, 16 the accuracy measured and the result is shown in Fig. 6. The most accurate result related to model with 11 and 14 numbers of hidden layers with the value of 0.7134 and 0.6589. Data set is separated to 30% for testing and 70% for training. The Mean Squared Error (MSE) has been measure by Neural Network and result shown in Fig. 7.

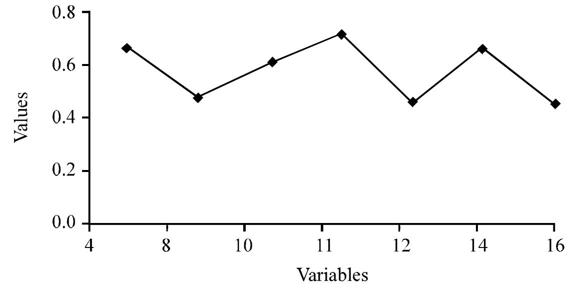

Fig. 6: Accuracy rate for Neural Network using 6 APs

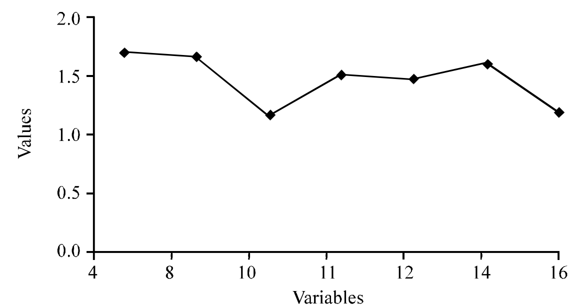

Fig. 7: Mean Square Error (MSE) for Neural Network using 6 APs

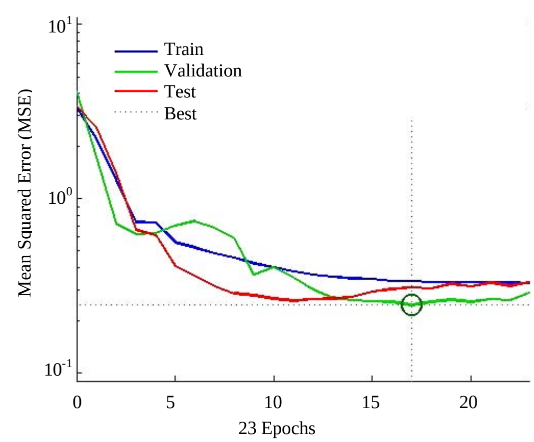

Fig. 8: Best validation performance for Neural Network using 6 APs

Since, Neural Network needs more time on trial and error to train the network in order to get better accuracy, beside usually Neural Network reaches to a good result while huge amount of data fed to the algorithm. The best validation performance diagram shows that MSE value is very high in Neural Network method. The best validation performance for 6 APs model with 14 numbers of neurons is shown in Fig. 8. The best value of performance reaches at epoch 17 while total number of epochs is 40.

Table 1: Cross validation result for Neural Network

Model	Features (AP)	Accuracy by cross validation (%)	Real calculated accuracy (%)
Neural Network	4	52	50
Neural Network	6	58	71

Cross validation for Neural Network: Cross validation test done for Neural Network model. In the model with 4 APs, the error rate range was between 0.48 and 0.49 it means that the correction of this algorithm was near 51-52%, this result is almost near to our real experiment result. In model with 6 APs, the test shows that error rate was between 0.42 and 0.44 so the accuracy in this model was almost near to 56-58%. It is also near to our real test result. We can see that in model with 6 APs the accuracy increased. Although, cross validation test is used to assess the result of algorithms, it might not be 100% accurate test because the result is the average of 10 fold data set which has been trained. Table 1 shows the cross validation result for all approaches we can see that the results are almost near to accuracy rate calculated by algorithm regarding training and testing sets.

RESULTS AND DISCUSSION

A Back Propagation Neural Network algorithm has been used as a second method for indoor positioning in this project. The Neural Network structure tested with various numbers of neurons in hidden layer. In this experiment, we also applied two models using different features for Neural Network algorithm signal strength from different numbers of access point used as inputs for neural network algorithm. These two models described as:

- Using 4 numbers of access point
- Using 6 numbers of access point

Result for experiment 1-a; neural network using 4 APs: In this model, we used 4 number of access point as an input layer and the Neural Network algorithm train with various number of neurons in hidden layers. The most accurate result for this model is shown in Table 2.

Result for different number of neurons are different by increasing the neurons accuracy firstly increases and then it decrease we can see that the most accurate result is related to Neural Network with 14 neurons in hidden layer, however the MSE value is more than model with 4 neurons because by increasing the neurons more noises concern with the model so more error will caused.

Result for experiment 1-b; neural network using 6 APs: In this model, we increased the number of access point to 6 APs as an input for input layer, the algorithm tested again and the result were compared. The most accurate result for this model is shown in Table 3.

Table 2: Most accurate result for Neural Network using 4 APs

Neurons	Accuracy rate (%)	MSE (m)
4	50	1.19
11	48	1.48
14	68	1.22

Table 3: Most accurate result for Neural Network using 6 APs

Neurons	Accuracy rate (%)	MSE (m)
4	66	1.70
11	71	1.51
14	65	1.60

Table 4: The most precise result in Neural Network algorithm

Features (AP)	Number of neurons	Accuracy (%)
4	14	68
	4	50
6	11	71
	14	65

Result shows that by increasing the number of access points while the more input data fed to input layer, the more precise result will gain. In this model with 11 numbers of neurons in hidden layer we got the most accurate result which is 71% accuracy and the least MSE value 1.51 m. The interesting point is that Neural Network shows the most accurate result in same number of neurons in both model (4 and 6 APs) it means that increasing number of APs and input data has a good effect on Neural Network to get better accuracy but the number of neurons in hidden layer do not need to be changed. Moreover, most accurate result in model with 4 APs happen with 14 neurons but most precise result in model with 6 APs observed with 11 neurons this suggests that by increasing RSS vectors as an input, less number of neurons is needed to get accurate result.

Comparison of both models in Neural Network: Neural Network approach used for another positioning method in this project in one model we used 4 number of access point as an input and the result were compared then we increased the number of access points to 6 and we found that Neural Network has better accuracy with increased number of access points too and the more precise result gained. The most accurate result of this approach is shown in Table 4.

Neural Network algorithm tested for various numbers of neurons. The result shows that by increasing the number of access points, accuracy rate increased except at few numbers of neurons which has not efficient accuracy change. This result can be shown in Fig. 9. We can see in the accuracy plot that the fluctuation of accuracy remain the same in both approaches except in

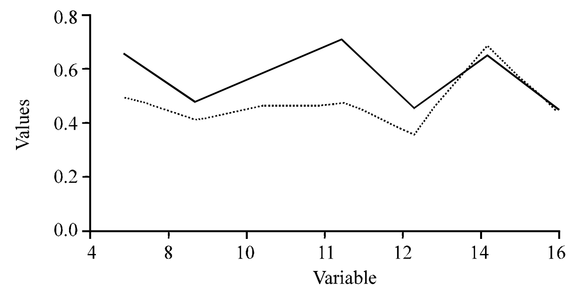

Fig. 9: Accuracy rate for Neural Network models

ending part while the number of neuron increases the accuracy of 4 AP Model and 6 AP Model reaches almost to same level, however with 14 number of neurons the accuracy of model with 6 AP is less than model with 4 access point.

CONCLUSION

In this study, the result of each models were summarized. In each experiment, increasing the number of access point has a goof effect on accuracy and we got better result by increasing the number of APs in these approaches. We used one the most commonly used and effective fingerprinting algorithm which most advanced researchers used in their researches. Our approaches were designed in different features and the result were compared and analyzed in many aspects to show the performance. The fingerprinting algorithm used in this project, does not need the coordinates of Wi-Fi access points in the positioning. So, this method is convenient for Wi-Fi based indoor positioning system for areas such as shopping malls where access point's positions are not possible to be determined precisely. In this project, we used Systems Engineering Lab as our experiment area, the data was collected in this area and our research is based on real environment which can be used in indoor positioning for this are in future development. Besides, we also applied additional features to our model in order to enhance the accuracy. These features can be used without using additional infrastructure and it can be used from existing Wi-Fi access point in the building. By increasing the number of neurons in hidden layer, more data involves in positioning and accordingly more error values rises but by employing the more access points signal strengths we enhanced the accuracy to get more precise result with less MSE value.

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