Wireless Indoor Localization Problem with Artificial Neural Network

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***Abstract*—Positioning in indoor application is a challenging problem with GPS signals. Because the obstacles such as doors and walls weaken the GPS signal amplitudes, indoor positioning results are not satisfying with global positioning system. Indoor positioning may be critical for a variety of applications such as, detecting number of people, locating criminals in bounded regions, and obtaining the number of users in a special area. The Wi-Fi signal strength may be a key point to solve this problem. With several routers, the received Wi-Fi signal power information may use to determine the indoor localization with using the information of routers location. In this work, Multi-Layer Perceptron (MLP) neural network method is proposed that can be implemented in monitoring and tracking devices. In the end the theoretical background and simulation results are shared. Both k-fold cross validation and hidden neuron numbers are changed in the simulation then the results are compared.**

Keywords*—Indoor positioning/localization, multi-Layer perceptron, positioning with Wi-Fi signals, user localization, neural network, MLP.

I. Introduction

Global Positioning System (GPS) is a very common application for localization. It is very effective in outdoor localization. There are several satellites in space to serve devices and receiving signals from more satellites improves position resolution. However, GPS indoor positioning has some limitations due to the signal strength affected by the doors, walls or as in underground places such as metro stations.

There are variety of solutions to solve the problem and in many applications additional devices are integrated to the system. The most common technologies are GPS, bluetooth and Wi-Fi. Bulusu et al. [1] used GPS methods for user localization, but the signal strength and the number of accessing satellites affect the resolution or precision of the localization. In [2] an indoor application is implemented and accuracy is equal 4.5-8 meters. In [3] a Wi-Fi GPS hybrid system is proposed in indoor-outdoor transitions. In [4] an adaptive filter is used for indoor positioning with previous state estimation value as the reference volume, in this solution the RMS error is up to 0.2 meters. In [5] additional outdoor pseudolities are used to improve indoor positioning with using BeiDou. The average positioning error is about 2 meters.

The applications with using additional equipment to solve the indoor positioning requires additional infrastructure cost even they have effective results. In [6] LIDAR based implementation is applied. The cumulative error is about 90% up to 1 meter error. In [7] optical camera is used and KNN algorithm is implemented. The position error is less than 0.2 meters. In [8] the positioning work is based on geo-magnetism which is available in smart phones but not available in all devices such as robots, autonomous vehicles. In [9] a depth camera, speed sensors, lighting systems, a motor driver and microcontrollers are added to the electric-powered wheelchair. In [10] the work is based on Frequency Modulated Continuous Wave radar is implemented to the system and error is about 0.6974 meters.

Bluetooth technology may be used in very small places and close ranges. Also, it depends on the device that must have Bluetooth connection without any connection failed.

Another unique solution without any additional hardware required is Wi-Fi localization. This method's another advantage is all Wi-Fi routers are in the building or facility and the positions are known. With this by using the Wi-Fi access points various signals are determined and may be used to solve indoor localization. Also, this method is easy to implement internet of things applications, smart homes and factories, hotels and conference rooms to orient people and to avoid congestion. In [11] magnetic field strength and cellular signal strength is used with Wi-Fi signals. The average position error is 1.30 meters after 20 seconds. In [12] two different Wi-Fi frequency bands are used for indoor positioning and weighted K-Nearest Neighbor algorithm is implemented. The error is about 2 meters. In [13], an improved fuzzy hybrid of particle swarm optimization & gravitational search algorithm (FPSOGSA) is proposed then the neural network is trained. To improve the algorithm the mass and acceleration of particles are included and the results are 95.16% correct.

In this paper we use the same data set with [13] and obtain similar results. While in [13] FPSOGSA is implemented, our solution is based on MLP back-propagation algorithm which is simpler and easier to implement.

II. Methodology

MLP is developed to solve nonlinearly separable input patterns. This is the difference between a single perceptron and MLP. It consists of an input layer, a hidden layer and an output layer and each layer has several neurons. These neurons have an activation function that maps the inputs to the outputs of each neuron [14].

All neurons are connected in a layer basis in the forward direction. These connections have synaptic weights that are optimized to solve a specific problem. Also, each neuron has a bias value to determine the effect of activation function.

The MLP with several inputs, one hidden layer and 3 outputs is shown in Figure 1.

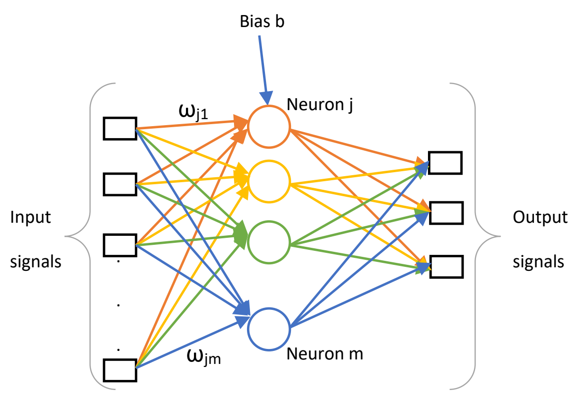

Fig. 1. MLP (synaptic weights, input layer, hidden layers and output layer).

Because MLP uses a supervised learning method, an error signal is produced in the training part which is:

$$e_j = d_j(n) - y_j(n)\, j \qquad (1)$$

where e is error signal, d is desired output, y is output and j is the neuron number.

A popular method for training of MLP is the back-propagation algorithm. In this case the algorithm has three distinct phases:

1) In the forward phase, the synaptic weights of the network are fixed, and the input signal is propagated through the network, layer by layer, until it reaches the output. The induced local field at the output of the synaptic weight is:

$$v_j(n) = \sum_{i=0}^{m} w_{ji}(n) y_i(n) \qquad (2)$$

where w_{ji} is synaptic weigths between i[th] and j[th] neurons and m is the total number of inputs.

2) In the backward phase, an error signal is produced by comparing the output of the network with a desired response. The resulting error signal is propagated through the network, again layer by layer, but this time the propagation is performed in the backward direction.

In this second phase, successive adjustments are made to the synaptic weights of the network. Calculation of the adjustments for the output layer is straightforward, but it is much more challenging for the hidden layers. The total correction on synaptic weight is:

$$\Delta w_{ji}(n) = -\eta e_j(n) \varphi_j'(v_j(n)) y_i(n) \qquad (3)$$

where η is learning rate parameter φ and is activation function.

III. Preparing the Data Set and Implementing to the Algorithm

In the given data set [15] there are seven Wi-Fi routers and their received signal strengths are measured. The setup is at an office in Pittsburgh, USA. Signal strength from these routers are used to categorize the location of the user in four different rooms. The Sample Data is shown in Table I.

TABLE I. Sample Data Set

WS1	*WS2*	*WS3*	*WS4*	*WS5*	*WS6*	*WS7*	*Room*
-64	-56	-61	-66	-71	-82	-81	1
-68	-57	-61	-65	-71	-85	-85	1
-42	-53	-62	-38	-66	-65	-69	2
-44	-55	-61	-41	-66	-72	-68	2
-48	-54	-50	-49	-61	-81	-84	3
-54	-53	-54	-50	-63	-79	-77	3
-58	-56	-47	-62	-36	-85	-84	4
-61	-52	-49	-56	-46	-84	-83	4

WS represents Wi-Fi signal strength for each router. The average of all router's signal strength is -63.1195, median is -61, mode is -59, standard deviation is 14.4591

Before beginning to simulate the algorithm, all Wi-Fi signal strength is normalized between the values -1 and 1 while the original data set values are between -98 and -10. Also, the bias in all neurons is chosen -1.

The output values, room numbers in this case, are converted to 4-digit binary values. At each room only one value is 1 then the other values are 0. Each value 1 represents each room. The key idea is to normalize all values between -1 and 1 then the calculations and MATLAB functions work correctly.

IV. Experimental Results and Discussion

A. *K-fold Cross Validation Method*

In supervised machine learning methods, the data set is separated into train and test set. To obtain a reliable result at the end of experiment or simulation, randomizing the data is crucial. While separating the data as test and train the k-fold cross validation method is used to obtain more accurate and comparable results. In k-fold cross validation, the data set is divided into k equal parts. The training data is selected from k-1 of these parts, and the remain is used as the test data. The average error value is obtained as a result of k experiments indicates the validity of the method.

B. *Simulation*

In this study, MLP back-propagation algorithm is performed on MATLAB. The normalized data is used and the number of k-fold and hidden neuron numbers are changed.

There are several performance metrics to show a system's or an algorithm's performance. The most common used metrics are mean squared error (MSE), mean absolute error, root mean squared error and R^2. To compare the results of the simulation, MSE is used as performance metric.

The number of input neurons is 7, the number of hidden neurons is chosen between 4 and 19, and the number of output neurons is 4. Learning-rate parameter value is 0.75. The output is separated for each 4 rooms. To obtain a comparable results k fold cross validation is chosen with k=5 and k=10.

The successful criterion in the simulation is every output must be bigger than 0.5 while the remaining outputs must be smaller than 0.5 to determine each room.

The simulation results for 15 hidden neuron and k-fold cross validation number with 5 and 10 are in Table II.

TABLE II. The Classification Rates of the simulation

K-Fold Number	Train Data	Test Data	Correctness
5	400	1600	93.25
10	200	1800	95.25

With using different k-fold cross validations, the number of test data to train the neural network is changed. 10 k-fold cross validation has better results than 5 k-fold cross validation. It is an expected result.

The number of epoch vs MSE for k-fold cross validation 5 and the number of epoch vs MSE for k-fold cross validation 10 is shown in Fig 2 and Fig 3 respectively. For both cases the number of hidden neuron is 15.

It is seen from the figures that after 1000 – 1500 number of epochs the MSE is flat and trained synaptic weights can be used. This values can be used in future studies.

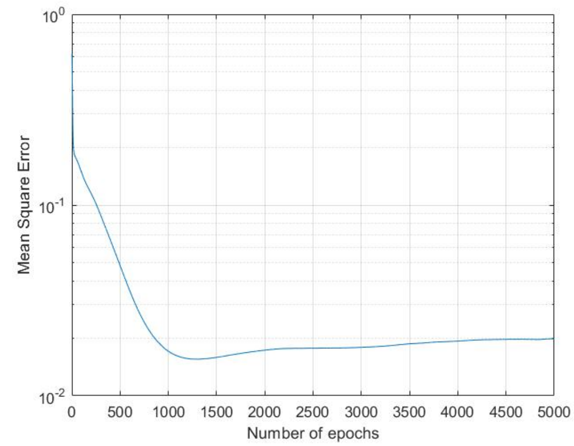

Fig. 2. MSE vs number of epochs

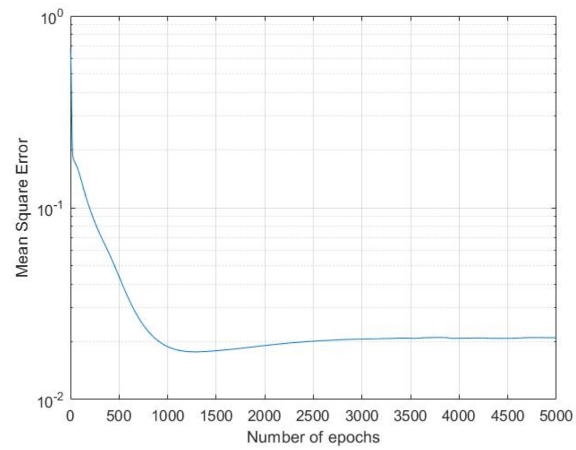

Fig. 3. MSE vs number of epochs

After the first results, k-fold cross validation is chosen 10. In the second half of the simulation the number of hidden neurons are changed. The results are in Table III.

TABLE III. The Classification Rates of the simulation

Hidden Neuron Number	K-Fold Cross Validation	Correctness
4	10	88.15
6	10	95.70
8	10	96.30
9	10	95.75
10	10	95.50
11	10	96.10
12	10	96.05
13	10	95.75
15	10	95.25
17	10	94.80
19	10	95.75

The number of hidden neurons is chosen between 4 and 19. The effect of the results is as in Table III. Correctness of the output is better with increasing the number of hidden neurons. When the hidden neuron number is 8 the results are above 96% correct. In [13] the results are 95.16% correct. Also, our results show that better results are obtained when the number of hidden neurons between 6 and 15. To make a fair compare these values are included in Table III.

The number of epoch vs MSE for k fold cross validation 10 and the number of hidden neurons is 12 is shown in Fig 4.

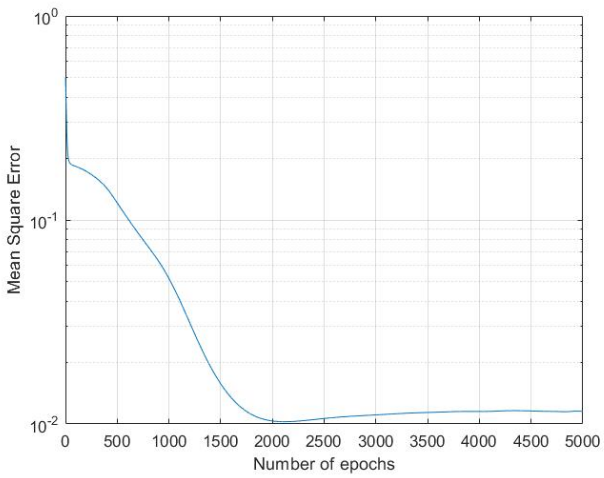

Fig. 4. MSE vs number of epochs

The simulation result shows that after 2000 number of epochs, the MSE is flat. The MSE is less than $0.9x10^{-2}$. This value can be used for future studies with 12 number of hidden neurons to train the synaptic weights.

In both cases k-fold cross validation is chosen 5 and 10, the results do not change dramatically. The most effective result is obtained when the number of hidden neurons is 8.

In this study, it is shown that similar results as in [13] is obtained with implementing MLP back-propagation algorithm. Also, the complexity of the system is reduced because these results are obtained without using fuzzy-hybrid algorithm before training the neural network and it is shown that the number of hidden neurons can be reduced.

V. Conclusion

The indoor localization with Wi-Fi solution is a simple way to solve the problem. Without any additional hardware implementation to the facilities and without spending more resources it can be determined which room the user is in. In this study neural network algorithm, MLP back-propagation method is used. The number of hidden neurons, and k-fold cross validation values are changed and compared. In the case of k-fold cross validation is 10, the classification rates are better than the k-fold cross validation 5. The simulation results are above 96% correct in average of all 4 rooms. Also, when the hidden neuron is 6 and 15 the classification rates are above 95%. the simulation results are more accurate when 8 hidden neurons are used.

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