Indoor 3-Dimensionally Localization of WSNs Using Neural Network

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Abstract - *In recent years, research on Wireless Sensor Networks (WSNs) has gained an increasing interest. WSN consist of several sensor nodes that measures data such as temperature, pressure, humidity etc and finally transmits those data to the base station. Data transmitted by sensor nodes are of importance only when the location of the particular sensor node in WSN is known. Idea originated from various researches and papers of localization methods in which all methods were flexible in localizing the sensor nodes when they were placed on the ground only. But as soon as we locate same sensor at some height then this leads to errors and predicts wrong location. This project's technique can be used to get location in both cases when sensor nodes are present on floor or space thus can be referred as improved 3-dimenssionally localization with more than 90-96% accuracy. Aim of our project is to make indoor localization system cost effective by limiting use of GPS nodes in WSNs and to increase its accuracy by use of machine learning neural network.*

***Key Words*: Wireless Sensors Communication (Zigbee S2C), 3d Localization Projects (MATLAB, XCTU), Received Signal Strength Indicator (RSSI), Neural Network, Cost Saving, etc.**

1. INTRODUCTION

Various researches on localization have been made like Time of Arrival (ToA), Time Difference of Arrival (TDoA) [5] which requires high synchronisation, thus they are avoided for point-to-multipoint communication.WSN is a network that is formed by sensor nodes. The sensor nodes are equipped with sensors that can measure essential environmental parameters such as temperature, pressure, humidity, soil property etc. And finally, the data is transmitted to the base station. So generally sensor nodes are equipped with a GPS [1] to get the exact global coordinates. GPS systems are accurate to a very high extent but they are expensive as well. So it's not at all wise to fit the GPS in every sensor node as WSNs consists of 100's of sensor nodes. An important area which can bring efficiency to WSNs is the localization process by which the sensor nodes in the network can identify their own location in the overall network. Localization process estimates the location of unknown sensor nodes by using the information and knowledge of few sensor nodes whose positions are fixed and known to the network. Sensor nodes with known location information are called anchor nodes and their locations can be obtained by using a global GPS. And the sensors whose location is unknown i.e. nodes whose location are to be estimated is known as Blind nodes as Fig 1.

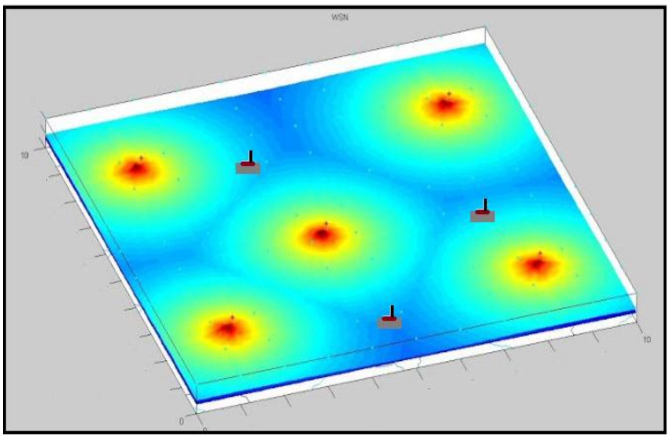

Fig -1: Illustration of Wireless Sensor Network

1.1 Wireless Sensor Nodes

The WSNs are mainly consists of sensor nodes. Usually readymade sensor nodes available in the market are of high cost. As we required around 7-9 sensor nodes to deploy a WSNs test-bed just to train and test our simulator, it was not at all feasible for us to buy those expensive sensor nodes. Hence, we opted for assembling and configuring of various low cost components required for building a sensor nodes. Those requirements can be completed as follows

a) Processing Unit: - ARDUINO Uno
b) Transceiver: - ZigbeeS2C, 2.4GHz, IEEE 802.15.4
c) Sensing Unit: - Digitalized Humidity-Temperature Sensor (DHT11)
d) Power Unit: - 9V battery or power banks or laptops (for indoor localization) via standard printer cables should be used. Moreover in case of zigbee Voltage is internally converted to 5V.

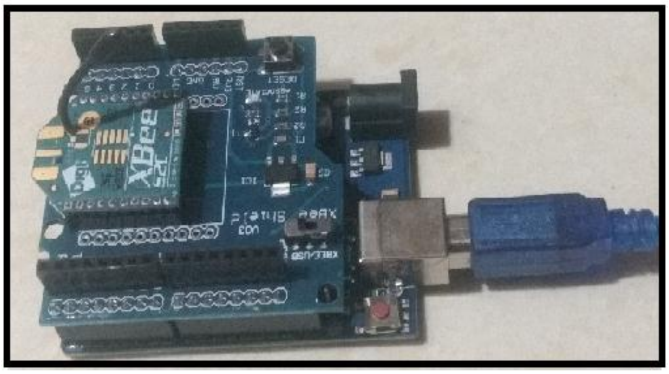

Fig -2: ZigbeeS2C Sensor Node

To get RSSI we need to configure our sensor nodes (Zigbee or Crossbow Iris) and RSSI will be directly available. Or for only prototype one can use this formula [2] to get RSSI which is needed for training of neural network.

$$RSSI=pt-pl-(10 \times n \times \log (d/d0))$$

Pt: - Transmitted power at 0db,
Pl: - Path loss,
n: - efficiency of indoor environment= 4,
d: - distance between anchor node blind node,
d0: - RSSI obtained for distance 1m.

1.2 Need of Artificial Neural Network

The localization process consists of algorithms which include calculations. The calculations involve formula's which theoretically proves to be valid but real environment conditions are hard to be defined by a formula. As in physical deployment of WSNs, there are various parameters that provide interference and noise which affect the signal quality. And it's tough to define noise and interference by formula precisely. Computers are incapable of learning on their own and take the decision based on situations; each and every situation has to be predefined by the programmer in the program. And in the real environment, there are various conditions and situations which can affect the WSNs. Thus ANN is preferred. It is trained for the set of examples and can even produce outputs for examples which are somewhat related to the examples it has been trained for. For better results, it is required to train the network for a larger set of examples. In proposed approach Supervised training is used to train MLP[3] (Multi-Layer Perceptron) net with Back-propagation technique and Levenberg –Marqaduart[3] algorithm for location estimation of WSNs 3-Dimensionally.

2. PROPOSED EXPERIMENTAL APPROACH & SETUP

The Fig 3 represents the proposed approach for the completion of the project. After assembling and configuring nodes we need to perform following tasks.

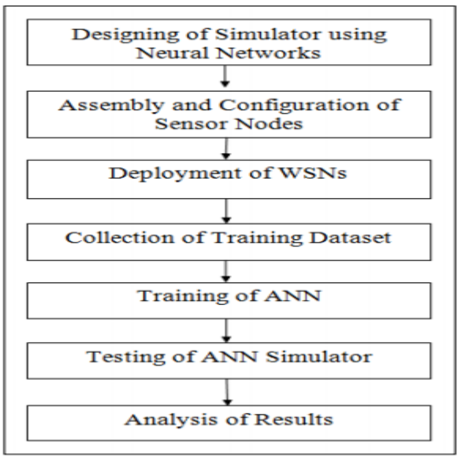

Fig -3: Proposed Approach

2.1 Deployment of Wireless Sensor Networks

To collect the training dataset for neural network training and to check the validation of the designed simulator it is required to physically deploy the Wireless Sensor Network in a real environment. From Fig 4 it can be seen that we deployed Wireless sensor network in an indoor environment of a 10 X 10 X 10 meters. The area is divided into 1 square meter equal parts and formed the grid. Then as shown in the Fig 4 where the anchor nodes A, B, C, D, E (denoted by *) are plotted such that a minimum number of nodes will cover the overall area efficiently. The anchor nodes are the nodes whose position is fixed and it is predefined. In the given example, the position of the anchor nodes are A (1.5, 8, 0), B (8.5, 8, 0), C (1.5, 2, 0), D (8.5, 2, 0), E (4.5, 4.5, 7) made hanging deliberately for having symmetry as shown in Fig 4 To get more data we used drone to get RSSI of each locations.

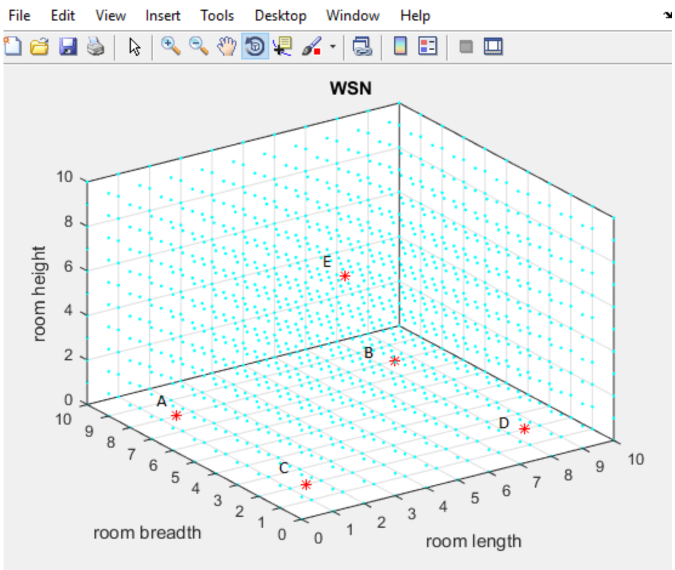

Fig -4: Deployment of WSNs

2.2 Collection of Training Data Sets

For the training of Neural Networks, training dataset is essential because ANN keeps on manipulating its weight until it has not achieved the target output. We wanted the ANN to understand that the signal strength received at a closer distance from transmitter is strong. Moreover, it goes on decreasing as the distance from the transmitter increase. In addition, the decrease in signal strength is not linear decay rather it's an exponential decay in real life environment. To achieve this we made the 5 anchor nodes A, B, C, D and E to send the signal to a moving node called as Node X. Node X was placed at every grid point and received signal strength was measured. As the room of 10m × 10m × 10m is divided into grid of 1m, there are in total 1000 grid points. So, at every grid point RSSI values from 5 anchor nodes were noted thus having 5000 raw RSSI dataset.

Here we are teaching neural network like for RSSI values from A, B, C, D, E the respective location is x, y, z as shown in table 1 below.

Table -1: RSSI from 5 Anchor Nodes for Training

RSSI from 5 Anchor Nodes for Training								
NO.	COORDINATES			RSSI VALUES FROM ANCHOR NODES (dBm)				
	X	Y	Z	A	B	C	D	E
1	0	0	0	-93	-98	-73	-94	-95
2	0	1	0	-93	-98	-74	-93	-96
3	0	2	0	-93	-98	-79	-93	-98
4	0	3	0	-93	-99	-79	-95	-98
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1000	10	10	10	-99	-96	-98	-95	-104

Now to better represent and understand the signal strength of Anchor Nodes, a signal strength map is plotted by the help of RSSI data collected as shown in the Fig 5 in which the red areas represents the strong signal strength near the anchor node.

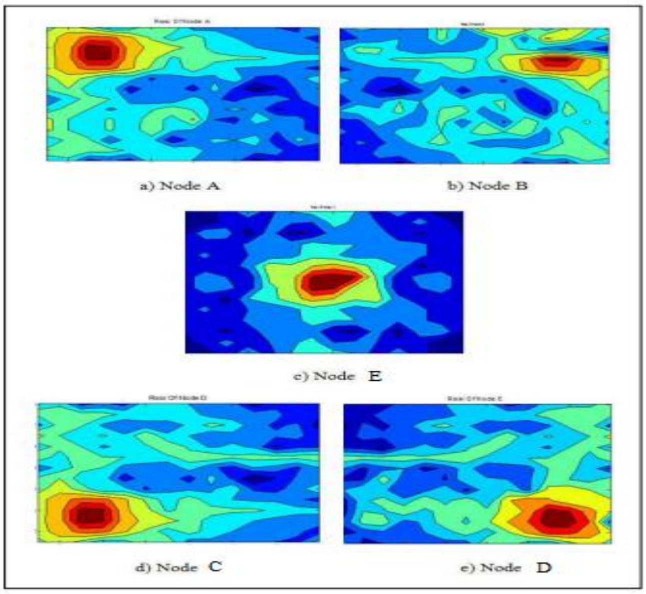

Fig -5: Received Signal Strength Map for Anchor Node A, B, C, D and E

2.3 choosing Training algorithms of ANN

There are various training algorithms that can be applied to neural network for its training but it's a challenging task to determine which algorithm will be appropriate and fast for a given problem. It depends on many parameters, such as whether the network is supervised or unsupervised, the type or the nature of problem, the input and the target data points, and whether the network is being trained for competitive or reinforcement learning or pattern recognition or function approximation.

Thus in our proposed approach we used Supervised learning in which we made Feed-Forward net of Multi layered Perceptron (MLP) with its main algorithm for pattern recognition as Back-Propagation algorithm [3].

Once the outputs get generated after 1st epoch in forward path, back-propagation algorithm generates local gradients using outputs generated & starts computing errors, weights backwards to initial neuron stages of hidden layer.

The training and learning of neural networks is equivalent to a curve fitting problem, where we aim to construct a curve, which is best fitting to a series of data (target) points. Thus in our proposed approach we used Levenberg-Marquardt algorithm which is a curve fitting algorithm which is simple, at the same time robust, method for approximating a function and activation functions used in hidden layer and output layer perception is non-linear (TANSIG) and linear (PURELIN) respectively [3].

2.4 Analysis of Results

Now after completion of training we thrown 4 blind nodes (dark blue dots) anywhere in the Lab-room and collect RSSI from all 3 nodes from each 5 anchors and fed to neural network thereby getting their locations (dark pink squares) via Neural network as shown in Fig 6 shown below.

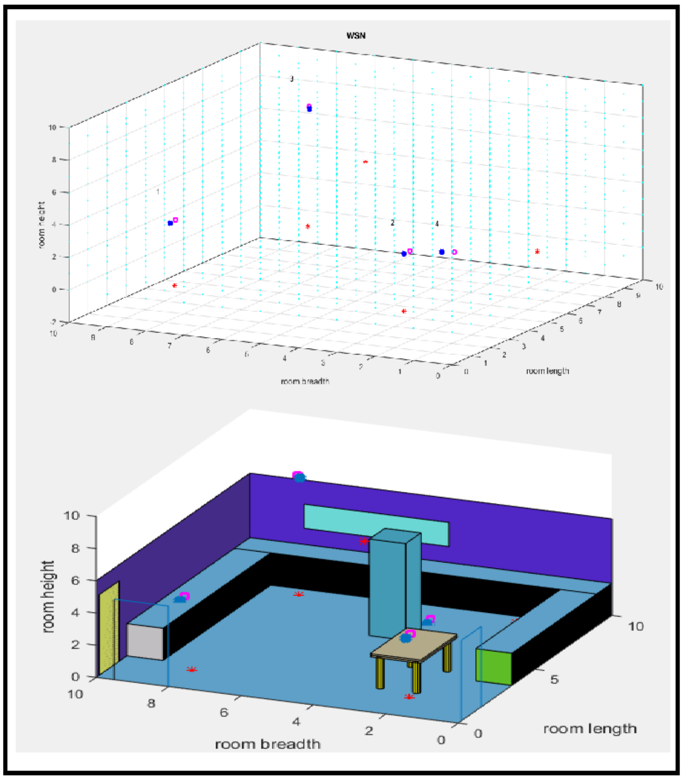

Fig -6: Positions estimated by Neural Networks

The best epoch represents the iteration at which the validation performance reached a minimum. The training, validation and test curves are very much similar which indicates there is no problem with the training. When over fitting occurs during the training then test curve increases drastically before the validation curve increases. This is not the case here as shown in Chart 1 where blue, red and green curves are of train, test and Mean Square Error validate curves.

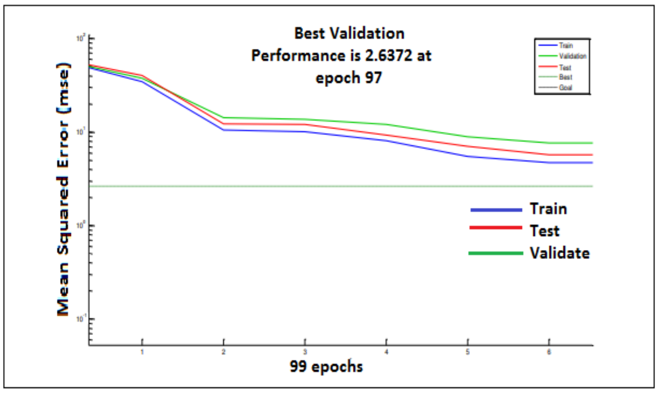

Chart -1: Best epoch plot

Regression plot: - It is the relation such that Estimated output equal to the actual target means training is perfect which is rare in neural networks. The value of R can range from 0 to 1, where R = 1 represents that the estimated output is exactly equal to the tactual target i.e. there is linear relationship between them. R=0 represents there is no relation between them. In our case, training data shows R=0.967[4].

Training State Plot: - Gradient is value of back-propagation gradient on each iteration in logarithmic scale. 4.8e-8 means that reaching the bottom of minimum local gradient of your goal function. Validation fails are iterations when validation MSE increased its value. A lot of fails means overtraining, but in generalized case it's OK. MATLAB automatically stops training after 6 fails in a row as shown in Chart 2.

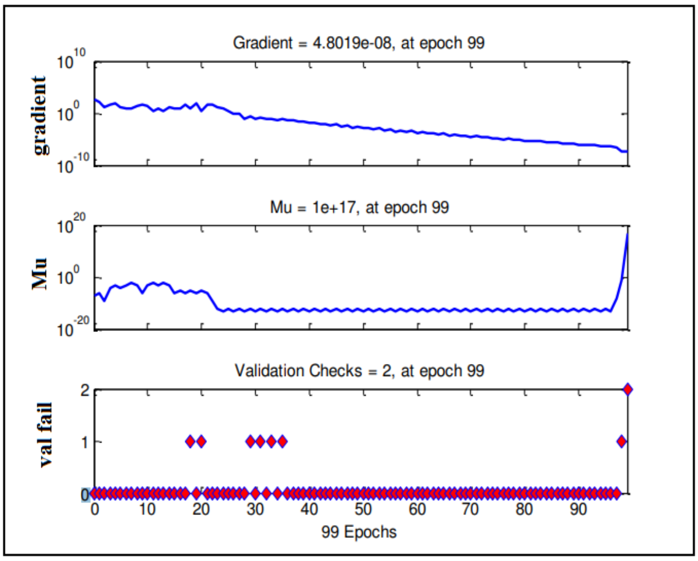

Chart -2: Training State Plot

There should be at least 3 anchor nodes used for good training and localization because for anchors less than three have always a possibility where we find same set of RSSI at two different locations due to symmetry, therefore increasing huge errors.

3. CONCLUSION

In this project, we propose and investigate a localization technique for WSNs using NN. We consider the NN for building a flexible mapping between RSSI and position of sensor nodes. In this technique, the NN is trained using the RSSI values and grid sensors. The positive feature of system is that it is cost effective by the use of RSSI, as well as system is efficient by the use of Neural Network. Simulation experiments show that the location accuracy can be increased by increasing the grid sensors density and anchor nodes.

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REFERENCES

[1] Bo Cheng, Rong Du, Bo Yang, "An Accurate GPS-based Localization In Wireless Sensor Networks: A GM-WLS Method," International Conference on Parallel Processing Workshops, 2011.

[2] Mingji Yang , Chenyi Zhan and Haoqun Shi," Localization Algorithm of Transmitting Station Based on RSSI and GPS," International Journal of Smart Home, Vol. 10, No. 5 (2016), pp. 195-206.

[3] Laslo Gogolak," Indoor Fingerprint Localization in WSN Environment Based on Neural Network," SISY 2011 IEEE 9th International Symposium, September 8-10, 2011.

[4] Uzair Ahmad, "In-building Localization using Neural Networks", IEEESeptember 2006.

[5] Ravindra S and Jagadeesha S N, "TIME OF ARRIVAL BASED LOCALIZATION IN WIRELESS SENSOR NETWORKS: A LINEAR APPROACH," An International Journal (SIPIJ) Vol.4, No.4, August 2013.

[6] YoungMin Kwon," Resilient Localization for Sensor Networks in Outdoor Environments," University of Illinois.

[7] Vu N.P. Dao," Performance Comparison of Different Back Propagation Neural Networks Methods," Lawrence Livermore National Laboratory.

Sharul Agrawal, Mr. Ravi Prakash," Implementation of WSN which can simultaneously monitor Temperature conditions," Nirma University, India.