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Localization in Wireless Sensor Network: An Optimistic Approach

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***Abstract*--- In wireless sensor networks, sensor node localization is important because sensor nodes are randomly scattered in the region of interest and they get connected into network on their own. Localization information is needed in routing of data, reducing energy consumption and in location dependent data acquisition. No prior knowledge of the noise distribution is the intelligence of a neural network. Noisy distance measurements can be used directly to train the network with the actual coordinate locations. The neural network is capable of characterizing the noise and compensating for it to obtain the accurate position. In this paper, we show that MLP can potentially achieve the highest localization accuracy and requires the least amount of computational and memory resources. Neural Network with its class MLP provides an optimistic solution of localization.**

***Keywords*--- Localization, Neural Network, Multi-Layer Perceptrons (MLP), and the Recurrent Neural Networks (RNN).**

I INTRODUCTION

Wireless sensor networks [1, 2, 3] have the potential to become the pervasive sensing (and actuating) technology of the future. For many applications, a large number of inexpensive sensors are preferable to a few expensive ones. The large number of sensors in a sensor network and most application scenarios preclude hand placement of the sensors. Determining the physical location of the sensors after they have been deployed is known as the problem of localization. [11].

Wireless sensor networks were an intense field of activity for military purpose. The localization methods could be divided into range-based methods, that would compute an estimation of the distances between two nodes, or range-free methods, that would not. Localization is used in location-aware applications to position a moving object on a coordinate system.

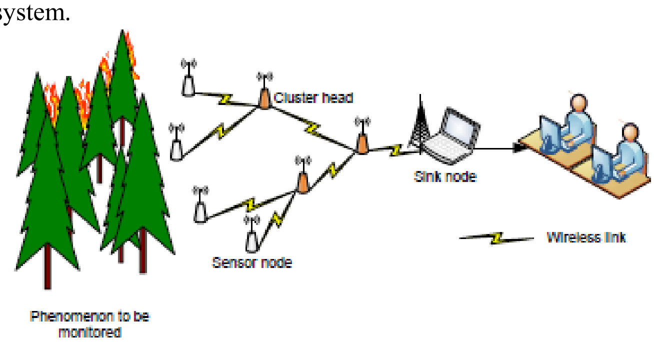

Fig.1: Wireless Sensor Networkk [8]

II PRELIMINARIES

Neural networks are modeled after biological nervous systems and are represented as a network of interconnections between nodes called "neurons" with activation functions. Different classes of neural networks can be obtained by varying the activation functions of the neurons and the structure of the weighted interconnections between them.

Examples of these classes of neural networks are the *Multi-Layer Perceptrons* (MLP), *Radial Basis Function* (RBF), and the *Recurrent Neural Networks* (RNN).

The **MLP** [10] network is "trained" to approximate a function by repeatedly passing the input through the network. The adapted perceptron are arranged in layers and so the model is termed as *Multilayer Perceptron.* The weights of the interconnections are modified based on the difference between the desired output and the output of the neural network. The final weights of the MLP network are entirely dependent upon the initial weights. Finding the set of weights that result in the best performance is a challenge and ultimately becomes a guess and check exercise.

RNN [10] networks are very similar to the MLP network structure except in one respect. MLP interconnections only flow from the inputs to the outputs in one direction. There are no connections between the output layers and the previous layers. RNN networks can posses such a feedback structure. The outputs of a node can be fed back as inputs to previous layers. This unique trait may lend itself well when localization using noisy measurements.

[12]Each sensor node finds its position with the help of RSS. The RSS is simply the signal strength from the anchor node. When the RSSs of the anchor nodes are represented by R, the position of the sensor node is estimated as

$$(X_{est}, Y_{est})=NN_k(R) \qquad \text{……... (1)}$$

III EXPERIMENTAL APPROACH

In the experiment we have considered that there are three anchor nodes or beacons and several sensor nodes, deployed on the intersection grid of 300*300 grid. Each intersection grid is of 30 * 30. The training data was collected by placing the mobile node at each intersection of the tiles and collecting distance measurements to each of the three beacons *S*1, *S*2, and *S*3. The distances from each of the beacons to the mobile node will be used as inputs and the neural networks will output positions that correspond to the location of the mobile node. In this way, input is of 121 samples with 3 elements and output is of 121 samples with 2 elements.

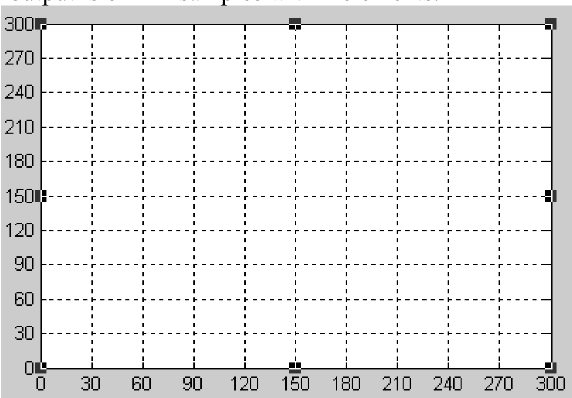

Fig.2: localization grid of sensor and anchor nodes.

This network was trained in MATLAB in Batch mode fashion for 200 epochs with a training goal of 0.001 errors.

In case of MLP, there are 2 no. of layers, the number of neurons in the hidden layer is 10, and the training function is *trainlm* and adaptation learning function is *learngd* with performance function *mse*. The transfer function for hidden layers is *tansig* and for the output layer is *purelin*.

In case of RNN, there are 3 no. of layers, the number of neurons in the hidden layer is 10 and 1 neuron is on second hidden layer, and the training function is *traingdx* and adaptation learning function is *learngdm* with performance function *mse*. The transfer function for hidden layers is *tansig* and for the output layer is *loglin*.

Both of them have 100 max_fail.that provide the maximum no. of iteration should be performed means the training continued until the validation error failed to decrease for six Iterations.

Regression plot is used to validate the network performance. This regression plots display the network outputs with respect to targets for training, validation, and test sets. For a perfect fit, the data should fall along a 45 degree line, where the network outputs are equal to the targets. For this problem, the fit is reasonably good for all data sets, with R values in each case of 0.93 or above.

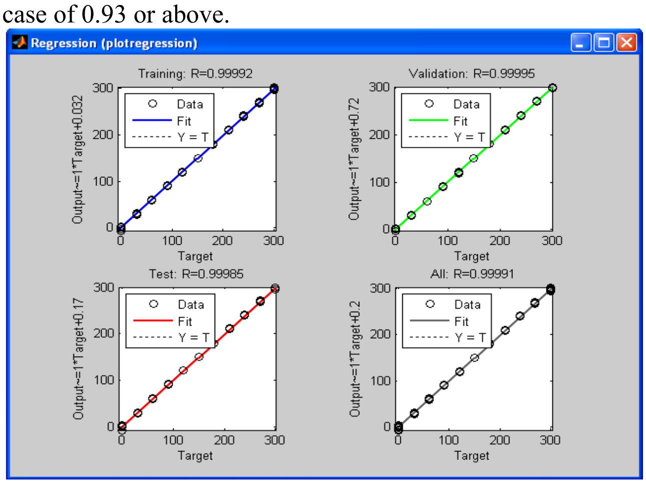

Fig.3: regression plot in MLP.

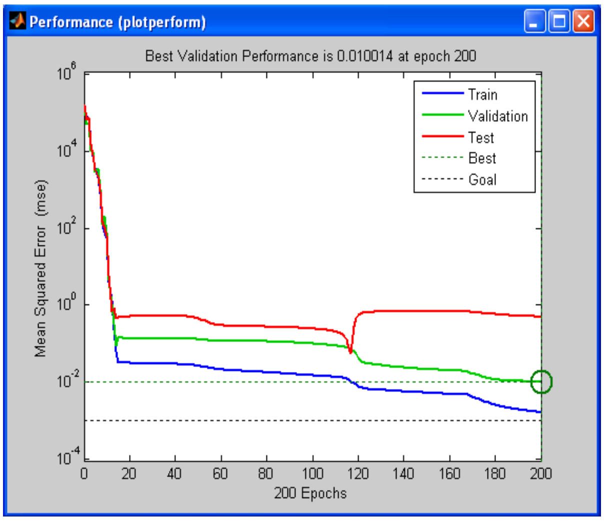

Fig.4: Performance plot in MLP.

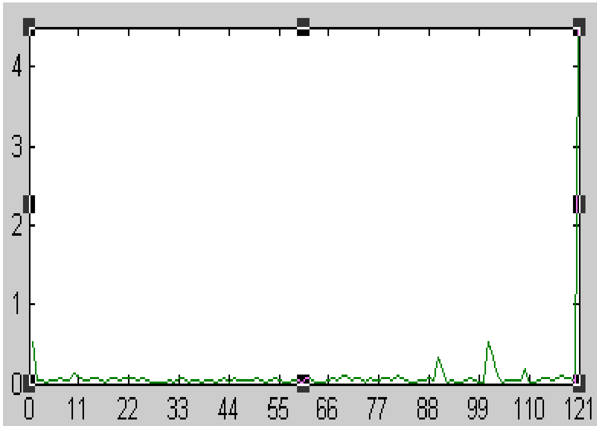

Fig.5: Localization error in MLP.

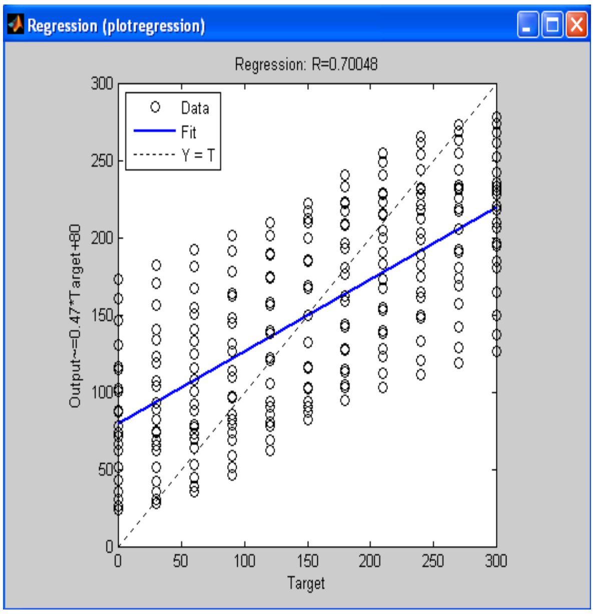

Fig.6: Regression plot in RNN.

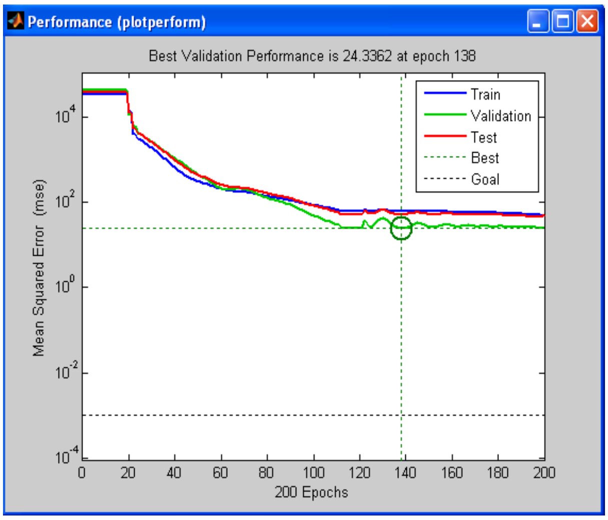

Fig.7: Performance plot in RNN.

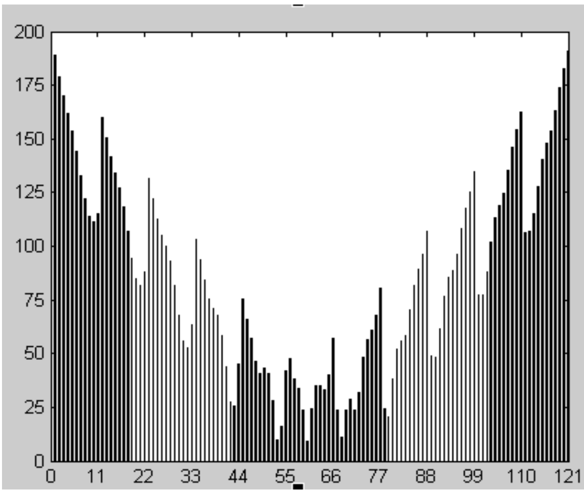

Fig.8: Localization error in RNN.

Our results expose that the neural networks with the RNN have a higher percentage of errors. Comparing the RNN with the MLP neural network, the MLP network has a lower percentage of errors and if we see regression plot that also provides better fit in case of MLP. All the above plots shows the better performance of MLP in localization of wireless Sensor Network over the RNN (Elman back propagation). MLP also requires less computation and memory usage requirements.

So Neural Network with its class MLP provides an accurate result over the RNN for the problem of *Localization.*

IV CONCLUSION

This paper shows that MLP can potentially achieve the highest localization accuracy, performance and it requires the least amount of computational and memory resources. So Neural Network with its class MLP provides an optimistic solution of localization.

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