Comparative Analysis of Bayesian Regularization and Levenberg-Marquardt Training Algorithm for Localization in Wireless Sensor Network

Ashish Payal*, C.S. Rai*, B.V.R. Reddy*

*University School of Information & Communication Technology, GGS Indraprastha University, New Delhi, India

ashish.ipu@gmail.com, csrai_ipu@yahoo.com, bvrreddy64@rediffmail.com

Abstract— **Wireless sensor networks (WSNs) has many applications in the field of disaster management, military, healthcare and environmental monitoring. Capability of WSNs is further enhanced by the efficient localization algorithms. Localization is the process by which a sensor node determines its own location after deployment. Neural approaches are gaining popularity in evolving new localization algorithms that are capable of optimizing various parameters of WSNs. In this paper, we analyse two backpropagation algorithms based on multi-layer Perceptron (MLP) neural network. The network is trained using static sensor nodes placed in a grid with their coordinates known. The input values are distances from each anchor nodes to a particular sensor node. The output is the actual coordinates of the sensor nodes. After training, the network will be able to predict the coordinates of unknown sensor nodes. This MLP model is analyzed for bayesian regularization and levenberg-marquardt training algorithm. Both algorithms are tested for the robustness and cross-validation. The simulation results demonstrate the effectiveness of the proposed model on localization error.**

Keywords— **Localization, Wireless Sensor Network, Backpropagation algorithm, Neural network, Bayesian regularization**

I. INTRODUCTION

Wireless sensor networks are composed of lightweight sensor nodes deployed in highly distributed manner to monitor the environment or system by the measurement of many physical parameters [1]. WSNs are capable of habitat monitoring, medical monitoring, and disaster monitoring [2]. MEMS (Micro-Electro-Mechanical Systems) technology has enabled the development of small, inexpensive, disposable, and smart sensors [3]. Application of WSNs is further enhanced by the efficient localization algorithms. It is necessary for a sensor node to know its location with reference to some base stations. In tracking and event detection applications some information must be available about where an event has happened. Sensors can be deployed in volcanic belt to report volcano eruptions. Sensor nodes can be designed to detect rise in temperature to trigger an alarm. Localization techniques actively work to minimize the hardware cost, power cost, and deployment cost in large scale WSNs. Global positioning system (GPS) is a well known location and tracking technique with iterative trilateration algorithms as base methodology [4]. Many different localization techniques have been evolved for wireless sensor networks. These approaches have significantly solved the problem by considering signal strength, network topology, and energy management. Broadly, these localization schemes are divided into two categories i.e. range-based and range-free localization techniques [5]. The range-based schemes use absolute point-to-point distance estimates (range) or angle estimates for calculating location. Received Signal Strength Indicator (RSSI) [7] and Link Quality Indicator (LQI) [8] are two schemes based on the power of signal to calculate the node's position. Time of Arrival (ToA) [9] rely on signal propagation time. Angle of Arrival (AoA) [10] estimate and map relative angles between neighbouring sensor nodes. In Time Difference of Arrival (TDoA) [11], time difference of received signals is calculated from two anchor nodes. In comparisons to range-based methods, range-free schemes use hop count and connectivity information of RF signals to identify the nodes and beacons in their radio range, and then estimate their position. DV-Hop [12] is based on classical distance vector routing. Centroid Method [13] is proximity based scheme that uses anchor beacons, containing location estimation to estimate the node positions. Approximate Point-In-Triangulation (APIT) is a novel-area based approach to perform localization by isolating the environment into triangular regions between anchor nodes [14]. A neural approach for localization in wireless sensor network has shown a huge impact on developing new research methodologies. Supervised or unsupervised are two ways of learning in neural network. Samples with inputs and outputs are required in the supervised learning but in the unsupervised only inputs are needed [15].

In this paper, we have implemented two back-propagation training algorithm based on Multi-Layer Perceptron (MLP) neural network. In this comparative analysis, the network is trained by using static sensor nodes placed in a grid with their coordinates known. The input values are distances from each Anchor Nodes (ANs) to a particular sensor node. The proposed artificial neural network will be trained to predict the actual coordinates of the unknown sensor nodes. The MLP is evaluated with Bayesian regularization (BR) and Levenberg-Marquardt (LM) training algorithm.

II. RELATED WORK

Cricket location support system [16] used a combination of RF and ultrasound signals to compute a maximum likelihood estimate of location. Position-Velocity (PV) and Position-Velocity-Acceleration models of the Kalman filters [17][18] were compared for accuracy, robustness for solving localization problems. The RADAR [19] system provided good accuracy as it used received signal strength to calculate user locations from three fixed base stations thus eliminating multipath and shadowing effects. Neural approaches have been proposed for localization considering the noisy distance measurement in wireless sensor network [20]. SeNeLEx analysis explored the self-localization performance for arbitrary sensor network based on Cramer-Rao bound [21]. Trained neural network can combine many other parameters of WSNs such as anchor node density, anchor nodes radio power to evolve better model of sensor network [22]

III. MULTI-LAYER PERCEPTRON

Multi-Layer Perceptron (MLP) is a type of feed forward neural network that is an extension of the Perceptron model with atleast one hidden layer of neurons as shown in Figure 1. MLP can solve difficult and diverse problems in supervised manner with error back-propagation algorithm. In back propagation algorithm error is to be back propagated to adjust the weights to reduce the error between the actual output and the estimated output. Backpropagation is the generalization of the Widrow-Hoff learning rule to multiple-layer networks and nonlinear differentiable transfer functions. Standard back-propagation is a gradient descent algorithm, in which the network weights are moved along the negative of the gradient of the performance function. After network weights and biases are initialized it is ready for training. The weights and biases of the network are iteratively adjusted to minimize the network performance function. The default performance function for feed-forward networks is mean square error (MSE). It is average squared error between the network outputs and the target outputs.

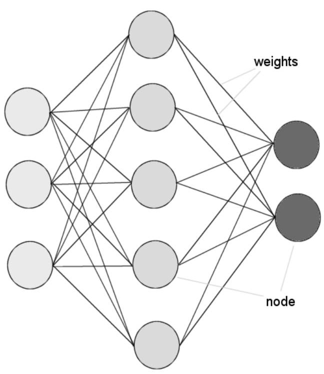

Figure 1. MLP Architecture

IV. MLP LOCALIZATION SCENARIO

To train the network, a WSN containing 3 Anchor Nodes (ANs) and 121grid sensors deployed on the intersection grid of 300cm*300cm grid as depicted in Figure 2. The training data is generated by measuring Euclidean distance between 3 ANs (AN_1, AN_2, and AN_3) and 121 grid sensors. This distance will be used as inputs and the MLP will output estimated X and Y coordinate location of 121 grid sensors.

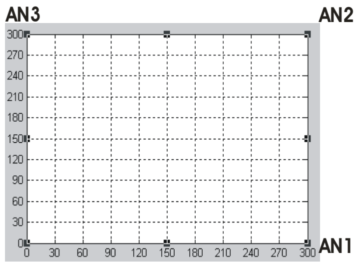

Figure 2. Localization grid of sensor and anchor nodes

The coordinates for three anchor nodes (ANs) is given in Table 1.

TABLE 1. Coordinates for Anchor nodes

Anchor Node	Coordinates(X,Y)
AN1	(300,0)
AN2	(300,300)
AN3	(0,300)

V. SIMULATION RESULTS

Our feed-forward neural network is implemented using MATLAB 7.9.0. We have used an ANN with 3-dimensional inputs and one hidden layer with 15 neurons and two outputs. Both log-sigmoid and tan-sigmoid is employed as transfer function for hidden layer and linear transfer function for output layer. For training the network 121 data sample have been created. Table 2 shows the example data sample.

Table 2. Training data sample

Training sample	AN1	AN2	AN3	X_a	Y_a
1	300	424.264	300	0	0
2	270	403.608	301.496	30	0
…..	240	384.1874	305.941	60	0
121	300	0	300	300	300

The learning rate (lr) in NN toolbox was set to 0.6. It determines the changes in weights and biases. Training goal is set to 0.0001 indicating the performance function measure.

Localization error (LE) is the distance between the estimated coordinates (X_{est}, Y_{est}) and the actual coordinates of sensor node (X_a, Y_a).

$$LE = \sqrt{(X_{est} - X_a)^2 - (Y_{est} - Y_a)^2} \tag{1}$$

Table 3 summarizes the statistical results for different transfer function and training algorithm.

TABLE 3. Performance of BR and LM Training Algorithm

S.No	Transfer Function		Training Algorithm	Localization Error (LE in meter)		
	Hidden layer	Output layer		Max	Min	Std. Dev.
1.	Tansig	Linear	Levenberg-Marquardt (LM)	9.82	0.27	1.28
2.	Logsig	Linear	Levenberg-Marquardt (LM)	6.81	0.17	1.36
3.	Tansig	Linear	Bayesian regularization (BR)	0.49	0.004	0.08
4.	Logsig	Linear	Bayesian regularization (BR)	1.43	0.005	0.14

It can be seen from figure 3 the maximum localization error is 9.82 meters after the network is trained by Levenberg-marquardt and *tansig* as transfer function.

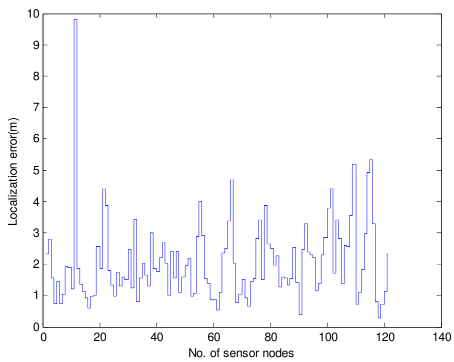

Figure 3. Simulation result of localization error (LM with tansig)

It can be seen from figure 4 the maximum localization error is 6.81 meters after the network is trained by Levenberg-marquardt and *logsig* as transfer function.

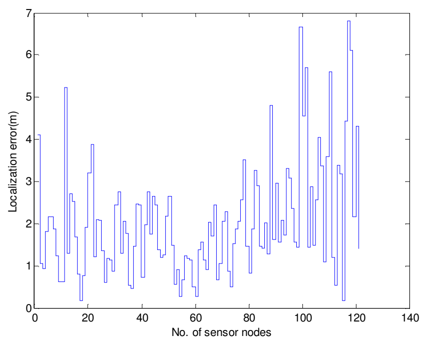

Figure 4. Simulation result of localization error (LM with logsig)

It can be seen from figure 5 the maximum localization error is 0.49 meters after the network is trained by Bayesian regularization and *tansig* as transfer function.

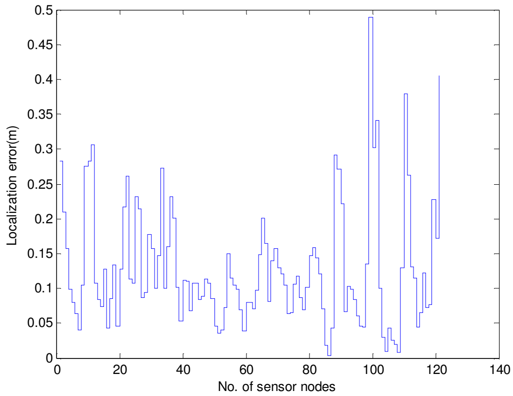

Figure 5. Simulation result of localization error (BR with tansig)

It can be seen from figure 6 the maximum localization error is 1.43 meters after the network is trained by Bayesian regularization and *logsig* as transfer function.

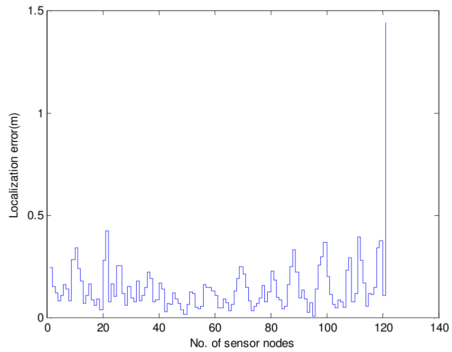

Figure 6. Simulation result of localization error (BR with logsig)

In figure 7 the statistical result of localization error is depicted. It clearly shows that Bayesian regularization training algorithm is best as compared to Levenberg-marquardt.

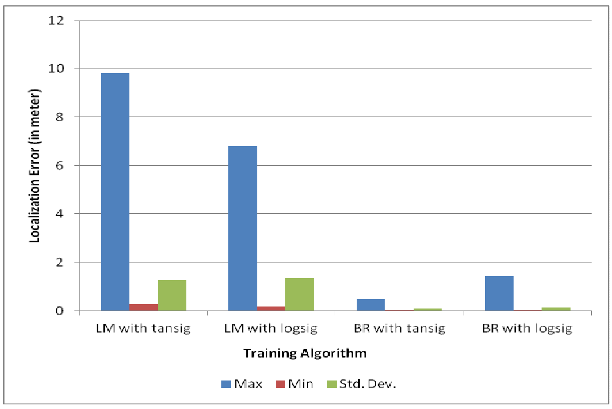

Figure 7. Statistical result of localization error

VI. CONCLUSIONS

In this paper, analysis of two training algorithms Bayesian regularization and Levenberg-marquardt based on MLP neural network is presented. In our analysis we have simulated the MLP network and computed the localization error. The positions of unknown sensor nodes are calculated with an accuracy of 0.49 meters in 300x300 m^2 area. The Bayesian regularization algorithm is more accurate as compared to Levenberg-marquardt algorithm. Bayesian regularization algorithm reduces the need for lengthy cross-validation. It provides an efficient criterion for stopping training process and prevents overtraining of the network. This ability of Bayesian regularization training algorithm makes it a more adaptive and robust backpropagation network for evolving localization algorithms for wireless sensor network.

REFERENCES

[1] I. F. Akyildiz, W. Su, Y. Sankarasubramaniam, and E. Cayirci, "A Survey on Sensor Networks," *IEEE Communications Magazine*, pp. 102-114, 2002.

[2] C. Y. Chong and S. P. Kumar, "Sensor Networks : Evolution, Opportunities, and Challenges," in *Proc. of IEEE*, 2003, vol. 91, no. 8, pp. 1247-1256.

[3] C.S. R. Murthy and B.S. Manoj, *Ad Hoc Wireless Networks*, 2nd ed., Pearson Education, 2004

[4] P. Enge and P. Misra, "Special Issue on GPS: The Global positioning system," *in Proc. of the IEEE*, vol. 87, pp. 3-15, 1999

[5] T. He, C. Huang, B.M. Blum, J.A. Stankovic, and T. Abdelzaher, "Range-free localization schemes for large scale sensor networks," in *Proc. MobiCom '03*, 2003, p. 81.

[7] L. Girod and D. Estrin," Robust Range Estimation Using Acoustic and Multimodal Sensing", in *Proc. IROS*, 2001, vol. 3, pp.1312-1320.

[8] K. Benkič, M. Malajner, P. Planinšič, and Ž. Čučej, "Using RSSI value for distance estimation in Wireless sensor networks based on ZigBee," *in Proc. IWSSIP*,2008,pp. 303-306.

[9] N. Patwari, A. O. H. Iii, M. Perkins, N. S. Correal, and R. J. O. Dea, "Relative Location Estimation in Wireless Sensor Networks," *IEEE Transactions On Signal Processing*, vol. 51, pp. 2137-2148, 2003

[10] Niculescu, D., "Ad hoc positioning system (APS) using AOA", in *Proc. INFOCOM* ,2003, pp.1734-1743.

[11] P. Bahl and V.N. Padmanabhan, "RADAR: An In-building RF-Based User Location and Tracking System", in *Proc. INFOCOM*, 2000, vol. 2, pp. 775–784.

[12] D. Niculescu and B. Nath, "Ad hoc positioning system (APS)," in *Proc. GLOBECOM, 2001,* pp. 2926-2931.

[13] N. Bulusu, J. Heidemann, and D. Estrin, "GPS-less low-cost outdoor localization for very small devices," *IEEE Personal Communications*, vol. 7, pp. 28-34, 2000.

[14] T. He, C. Huang, B.M. Blum, J.A. Stankovic, and T. Abdelzaher, "Range-free localization and its impact on large scale sensor networks", *ACM Transactions on Embedded Computing Systems*, vol. 4, pp. 877-906.

[15] A. Awad, T. Frunzke, and F. Dressler, "Adaptive Distance Estimation and Localization in WSN using RSSI Measures," i*n Proc. DSD,* 2007, pp. 471-478.

[16] N. B. Priyantha, A. Chakraborty, and H. Balakrishnan, "The Cricket Location-Support System," in *Proc. MobiCom,* 2000*,* pp. 32-43.

[17] Y. Zhu and A. Shareef, "Comparisons of Three Kalman Filter Tracking Algorithms in Sensor Network", *International Workshop on Networking, Architecture, and Storages*, 2006, pp. 61-62.

[18] A. Shareef, Y. Zhu, and M. Musavi, "Localization Using Neural Networks in Wireless Sensor Networks," in *Proc. MOBILWARE*, 2008.

[19] P. Bahl and V.N. Padmanabhan, "RADAR: An In- building RF-Based User Location and Tracking System", i*n Proc. INFOCOM,* 2000, vol. 2, pp. 775-784.

[20] S. Yun, J. Lee, W. Chung, E. Kim, and S. Kim, "A soft computing approach to localization in wireless sensor networks," *Journal of Expert Systems with Applications*, vol. 36(4), pp. 7552-7561, 2009.

[21] S. Chaurasia and A. Payal, "Analysis of Range-Based Localization Schemes in Wireless Sensor Networks : A Statistical Approach," *in Proc. ICACT,* 2011, pp. 190-195.

[22] J. Tian and H. Shi, "Study of localization scheme base on neural network for wireless sensor networks," in *IET Conference on Wireless, Mobile and Sensor Networks,* 2007, pp. 64-67.