Neural, Parallel, and Scientific Computations 22 (2014) 639-654

NEURAL NETWORK BASED INDOOR LOCALIZATION FOR WIRELESS SENSOR NETWORK

K. VADIVUKKARASI[1] AND R. KUMAR[2]

[1,2]Electronics and Communication Engineering Department
SRM University
KTR campus, Kancheepuram District-603203,
Tamilnadu, INDIA

Abstract. In Wireless Sensor Network (WSN), location estimation (Localization) is important for routing efficiency and localization-aware services. This paper examines the WSN application which allows indoor localization based on the neural network and grid sensor training phase for accurate localization of sensors. The communication between the modules is monitored during the experiment whereby the received radio signal strength indicator (RSSI) values are recorded by a mobile sensor node. The received data used for training the feed-forward type of neural network such as Levenberg–Marquardt (LM) and Back Propagation Algorithm (BPA). This paper provides a solution to discover sensor nodes in WSN's using the past and present values obtained from neighbouring nodes based on neural networks. LM and BPA algorithms are used to find shortest distance between node and coverage of the node. This solution can be also a way to discover the malfunctioning nodes that are not a subject of an attack. Being localized on the base station level, this algorithm is suitable even for large-scale sensor networks.
Keywords: Localization, Anchor, RSSI, Feed forward neural network.

1. INTRODUCTION

Applications regarding Wireless Sensor Networks (WSNs) have been explored in several areas, such as robotics, industrial monitoring, environmental monitoring, military surveillance, and many others. The location awareness is one of the most desired features when talking about WSNs. Frequently, the wireless sensors nodes are supposed to be monitoring some processes or systems variables (temperature, humidity, etc.) at some specific point of a geographic area. Therefore, making these readings without addressing the positioning information as well could become a meaningless action. The easiest way to keep the nodes up to date with their own positions would be through the use of one GPS (Global Positioning System) receiver for each node. However, it is not possible due to the small form factor of the devices, their low-power and low-cost profiles. In order to solve this issue, several localization algorithms have been proposed by the scientific community [1, 2].

With the rapid growth of Information Technology, network infrastructures are expanding widely to make the ubiquitous world reality, where users can access any network freely regardless of place. As a part of this ubiquitous world, the location of an object will become essential information. Node localization is the problem of determining

---

Received October 15, 2014

the geographical location of each node in the system. Localization is one of the most fundamental and difficult problems that must be solved for WSN. Localization is a function of many parameters and requirements potentially making it very complex. For example, issues to consider include: the cost of extra localization hardware, Number of existing beacons (nodes which know their locations) exist and its communication range, degree of location accuracy required, if the system is indoor/outdoor and the line of sight among the nodes. For some combination of requirements and issues the problem is easily solved. If cost and form factor are not major concerns and accuracy of a few meters is acceptable, then for outdoor systems, equipping each node with GPS is a simple answer. If the system is manually deployed one node at a time, then a simple GPS node carried along with the deployed system can localize each node, in turn, via a solution called Walking GPS. While simple, this solution is elegant and avoids any manual keying in the location for each node. Most other solutions for localization in WSN are either range-based or range- free [3].

Range-based schemes use various techniques to first determine distances between nodes (range) and then compute location using geometric principles. To determine distances, extra hardware is usually employed, e.g., hardware to detect the time difference of arrival of sound and radio waves. This difference can then be converted to a distance measurement. In range-free schemes distances are not determined directly, but hop counts are used. Distance between nodes is estimated using an average distance per hop, and then geometric principles are used to compute location. Range-free solutions are not as accurate as range-based solutions and often require more messages. However, they do not require extra hardware on every node.

Various techniques for location estimation exist. The TDOA (Time Difference of Arrival) protocol uses two types of signals of different speeds to obtain the distance information. The hardware needed for TDOA is comparatively expensive and it consumes a great deal of energy. Therefore this method is not suitable for low power sensor network devices [9]. TOA (Time of Arrival) is a general way of obtaining the distance information through the spread time of the signals. As there are limiting factors concerning the hardware embedded in the sensor network device and the battery capacity, this method requires a somewhat large capital investment. The RSS (Receive Signal Strength) protocol is a method of calculating the distance by using signal sensitivity, which estimates the distance by comparing the information with a database of the distance of the prior signal reception. This technique is relatively simple to deploy compared to the other techniques. Moreover, no extra hardware is needed for location estimation. However, due to the serious multi-path propagation in an indoor environment [9] accurate positioning is very difficult. Therefore, in order to overcome this problem, we will choose the concept of the virtual grid points used in ECOLOCATION. It stands for “Error COntrolling LOCAliza-TION”, which is a localization method that puts a priority on the strength of the RSS value [10, 11]. It can correct the error in case of estimating a higher RSS value, even though the distance from the target to the reference node is further. In ECOLOCATION, the virtual grid point is defined as the point where the grid lines intersect each other. This can be applied to correct errors through the comparison of the position (coordinate value) of a virtual grid point and the position (coordinate value) of the node.

The GRNN (Generalized Regression Neural Network) function approximation applies the concept of statistical regression analysis, which is used to improve the performance of localization. For instance, the GRNN, WCL (Weighted Centroid Localization) methods are applied in RSS-based localization [12, 13]. In the present work, we propose a GRNN and virtual grid based localization algorithm which refines the use of only the GRNN method to overcome the disadvantages of conventional RSS-based localization. The proposed algorithm is subdivided into two parts. In the first part, the first GRNN set is trained by using location coordinates (x, y) and the corresponding RSS values of the reference nodes as inputs and outputs, respectively. After that, the RSS values of the virtual grid-points are found by using the GRNN set. The most popular methods for estimating the distance between two nodes are Received Signal Strength Indicator (RSSI). RSSI measures the power of the signal at the receiver and based on the known transmit power, the effective propagation loss can be calculated. Next by using theoretical and empirical models we can translate this loss into a distance estimate. This method has been used mainly for RF signals. RSSI is a relatively cheap solution without any extra devices, as all sensor nodes are likely to have radios. The performance, however, is not as good as other ranging techniques due to the multipath propagation of radio signals.

Most of the related work found by the authors use analytical methods like trilateration and triangulation when estimating the nodes coordinates in the network. However, some of the well-known approaches use the connectivity information that is extracted from the messages exchanged among the nodes. The centroid algorithm [4] is a great example of this class of algorithms. This work proposes an Artificial Neural Network (ANN) approach to the localization problem. An optimization procedure is performed through the use of Levenberg–Marquardt (LM) and Back Propagation algorithm (BPA) to tune the feed forward ANN for the best operation point when localizing nodes in a certain WSN. This allows the solution to be more accurate while simultaneously avoid the trial and error procedure that can be seen in [5] - [7] when selecting the best suited ANN structure.

The remainder of this paper is organized as follows: In the next section, the basic theory regarding Artificial Neural Networks will be addressed; as well the basics about RSS based localization. Levenberg–Marquardt (LM) and Back Propagation algorithm (BPA) are explained in section 3 and section 4 respectively. In section 5, results will be discussed. This article is concluded in section 6.

2. NEURAL NETWORK

2.1. Artificial Neural Networks

Artificial Neural Networks are interconnection structures among artificial neurons (also called nodes). The artificial neurons are modeled in order to mimic biological neurons through the use of activation functions. Each neuron consists of multiple inputs, weights and a single output. Also, its transfer function is responsible for mapping its inputs to output.

Figure 1 shows the ANN architecture. Basically, an ANN is an adaptive system that receives a set of inputs, processes the data and provides an output. It may have a single or multiple layers in their structure having the following designations: input layer, hidden layer or output layer.

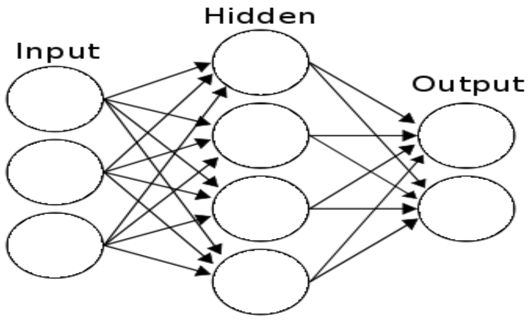

Fig.1 Artificial Neural network Architecture.

However, before using the ANN, there is still a need to train it. This process is performed by giving the correct answers for a set of inputs and adjusting the weights based on the response given by the network. When the outputs provided by the ANN are under a specific error limit, the training is done. This is called supervised training.

In Figure 2, the neural network based WSN Architecture is shown, which is used to calculate the weight of each neuron. Neural networks are typically organized in layers. Layers are made up of a number of interconnected 'nodes' which contain an 'activation function'. Patterns are presented to the network via the 'input layer', which communicates to one or more 'hidden layers' where the actual processing is done via a system of weighted 'connections'. The hidden layers then link to an 'output layer' where the answer is output. Most ANNs contain some form of 'learning rule' which modifies the weights of the connections according to the input patterns that it is presented with.

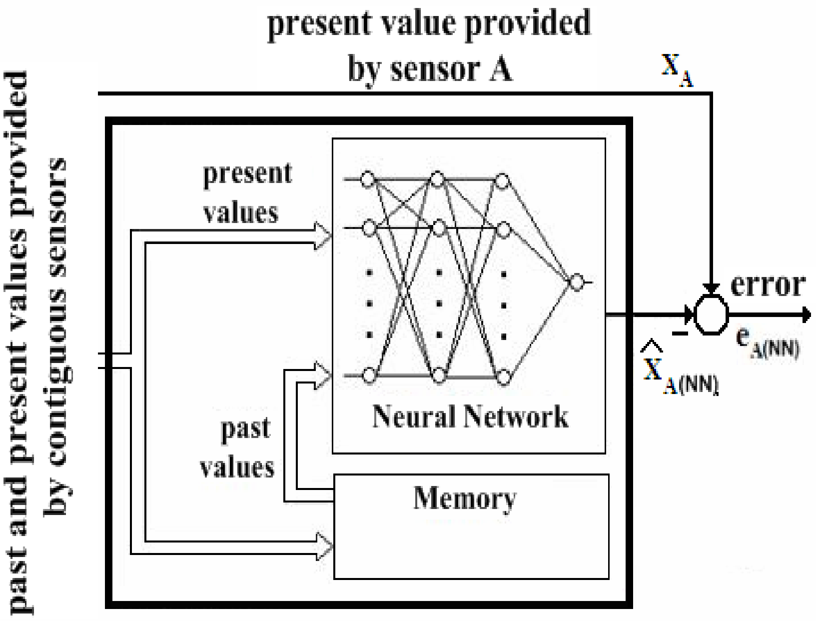

Fig. 2 WSN Construction Using Neural Networks

Figure 3 shows the Recurrent Neural Network (RNN). The fundamental feature of a RNN is that the network contains at least one feed-back connection, so that activation can flow round in a loop. That enables the networks to do temporal processing and learn sequences (e.g., perform sequence recognition/reproduction or temporal association/prediction). Learning can be achieved by similar gradient descent procedures to those used to derive the back-propagation algorithm for feed-forward networks.

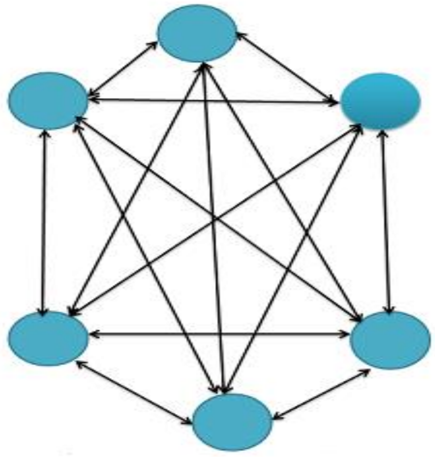

Fig.3 General Recurrent Neural network Architecture

This work is to define a path cost function based on the summation of decreasing multiplicative factor which takes into consideration the concentric converge nature of WSN communication. Moreover, the design cost function is the computation and maintenance of a minimum cost values and so the weighted neural network can be done without any extra communication overheads or significant computation overheads.

2.2. Localization based on Received Signal Strength

Localization algorithms require a distance to estimate the position of unknown devices. One possibility to acquire a distance is measuring the received signal strength of the incoming radio signal. RSSI is a unit less metric used to measure the power of the received radio signal [14] [15]. It is represented by one-byte integer and can assume any value in the range 0 to 255. TelosB motes are used for measuring RSSI values. Each TelosB mote has an inbuilt IEEE 802.15.4 radio (CC2420) with an integrated 2.4 GHz – 2.4835 GHz antenna [17]. CC2420 chip has an inbuilt RSSI register and its value is RSSI_VAL [16].

CC2420 has a built-in RSSI (Received Signal Strength Indicator) providing digital values that can be read from the 8 bit, signed 2’s complement RSSI_VAL register. The RSSI value is always averaged over 8 symbol periods (128 μs). The RSSI_VALID status bit (indicates when the RSSI value is valid, meaning that the receiver has been enabled for at least 8 symbol periods. The RSSI register value RSSI_VAL can be referred to the power P at the RF pins by using the following equations:

$$P = RSSI\_VAL + RSSI\_OFFSET \text{ [dBm]}$$

where RSSI_OFFSET, is a calibration offset value, found empirically during CC2420 system development from the front end gain. This value was found to be approximately -45. For example, if the TelosB mote reading a value of –20 from the RSSI register, the RF input power is approximately –65 dBm. The RSSI register value RSSI_VAL is calculated and continuously updated for each symbol after RSSI has become valid.

The RSSI can be used to find the power P of the RF signal in dBm, using the following equation,

RSS = RSSI_VAL + RSSI_OFFSET [dBm]

Hence the Received Signal Strength (RSS) can be expressed as

RSS = RSSI_VAL – 45 [dBm]

The entire experiment has been carried out in an indoor environment for various power levels. The RSS measurements are prone to noise and interference, which leads to error in localization. All the deployed nodes are kept at the same altitude from surface of the floor, with their antennas pointing upwards and directly facing each other.

In TelosB mote, the default or highest power level 31 is 0dBm. At specific distance, for different combination of sensors and power levels, 40 RSSI values are measured to get the average RSSI.

Fig.4 shows the structure of the RSS based indoor localization system. The Access Point (AP) measure and gather the RSS from all of the reference nodes. The information regarding the location coordinates (x, y) of all the reference nodes are then matched with the RSS values of the corresponding reference nodes. The AP also gather the RSS values of the unknown target node and send these data to the central server for further processing.

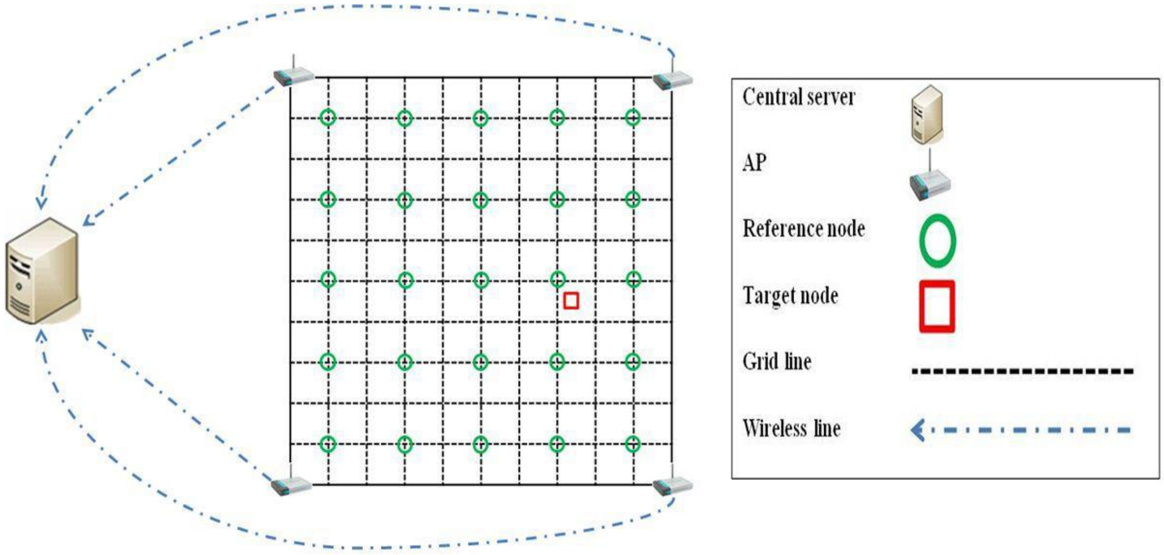

Fig.4 The structure of the RSS based indoor localization system.

2.3. The Grid Points

The grid points are the virtual points where the perpendicular grid lines meet each other. In this work, the grid points are used as the positions for the virtual sensor nodes. By using the grid points, the accuracy becomes more precise as the number of sensor nodes increases. The location coordinate and corresponding RSS value of each grid point works as a virtual sensor node. The GRNN training set, which is composed of the data from the reference nodes, is used to obtain the RSS value for each grid point. The training process is performed in the central server. All of the grid points contain location coordinates and the corresponding RSS values as for the actual reference nodes. Therefore, each grid point acts as a virtual sensor node.

3. LEVENBREG- MARQUARDT ALGORITHM

The Levenberg–Marquardt algorithm, which was independently developed by Kenneth Levenberg and Donald Marquardt, provides a numerical solution to the problem of minimizing a nonlinear function. It is fast and has stable convergence. In the artificial neural-networks field, this algorithm is suitable for training small and medium-sized problems. LM algorithm combines the advantages of gradient-descent and Gauss-Newton methods.

Algorithm for shortest Path:

1. Create random set of nodes and segments.
2. Generate edges between some of the nodes.
3. Randomly generate the starting and ending node id.
4. Find out the shortest distance and path between randomly generated nodes using the following steps.
5. Create a table using sparse matrix which is used to compress the zero elements.
6. Starting and ending node id are same then the shortest distance between the node is zero.
7. If the number of input arguments is less than 4, compute shortest path for all the nodes.
8. If the number of input arguments is greater than 4 then terminate the algorithm.
9. Executing string of nodes.
10. Update the table.
11. Find out the neighbourhood nodes in the segmentation list.
12. Calculate the distance to the neighbouring nodes and keep track of paths.
13. Find out the minimum non-zero value in the table and save it.
14. Input arguments is less than 4 then find the distance and path arrays for all the nodes.
15. Input arguments are greater than 4 return the distance and path for the ending node.
16. Plot the output graph and draw the shortest path between the nodes.

4. BACK PROPAGATION ALGORITHM

The Back propagation algorithm is used to learn the weights of a multilayer neural network with a fixed architecture. It performs gradient descent to try to minimize the sum squared error between the network’s output values and the given target values.

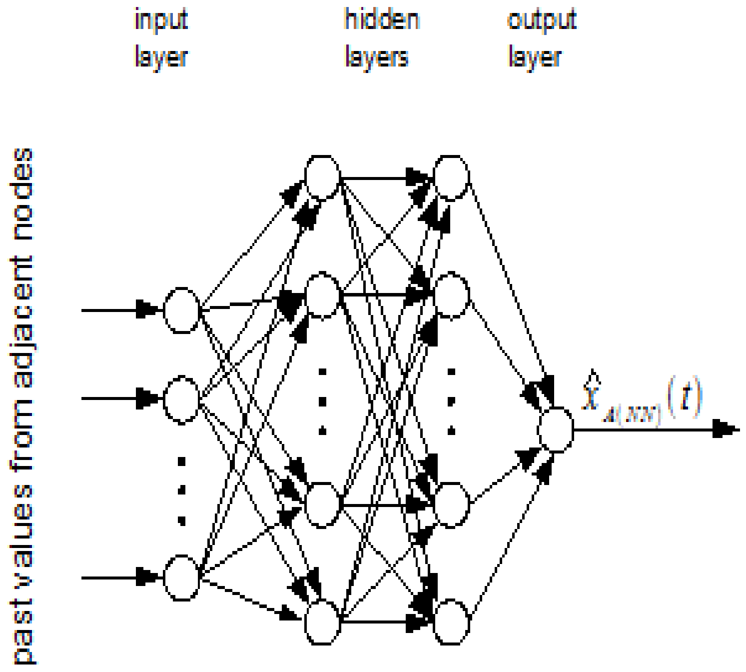

Fig.5 Back propagation Neural Network

BPA is shown in figure 5.It is a supervised learning technique used for training Artificial Neural Networks (ANN). It is most useful for feed-forward networks (networks that have no feedback). It requires that the transfer function (Sigmoid) used by the artificial neurons (or ‘‘nodes’’) be differentiable. This algorithm is also known as ‘‘the generalized delta rule’’. The errors propagate backwards from the output nodes to the input nodes. Back propagation calculates the gradient of the error of the network in regards to the network's modifiable weights [9]. This gradient is almost always used in a simple stochastic gradient descent algorithm to find weights that minimize the error. Often the term "back propagation" is used in a more general sense, to refer to the entire procedure encompassing both the calculation of the gradient and its use in stochastic gradient descent. It allows quick convergence on satisfactory local minima for error in the kind of networks to which it is suited.

The back propagation algorithm for calculating a gradient has been rediscovered a number of times, and is a special case of a more general technique called automatic differentiation in the reverse accumulation mode. It is also closely related to the Gauss–Newton algorithm, and is also part of continuing research in neural back propagation.

4.1. Back propagation Neural network training

BPNN will establish the number of hidden neurons and the neural network weights by performing successive training sessions using Levenberg-Marquardt method. For the hidden layers hyperbolic tangent activation function is used and for the output layer linear activation function is used. This training step is done off-line, prior to the neural network implementation on the base station.

4.2. Back propagation Neural Network testing

The basic idea of BPNN works as follows. Each node chooses a set of forwarding candidates with different priorities. In each time step, each source attempts to broadcast a packet subject to 802.11 MAC. The nodes within a source's forwarding candidate set that actually receives the packet, runs a protocol to agree that the highest priority node keeps the packet and all the other nodes drop the packet to prevent unnecessary multiple forwarding of the same packet. If the packet is not received by any node in the source's candidate set, the source broadcasts the packet again until it is received by at least one node in the candidate set or the maximum. If the number of trials is reached then each node other than the sink node waits for a period of time to create opportunity for receiving multiple packets from different sources, which are then compressed, packetized, and forwarded.

At the next time step, each source has a new packet to deliver. Intermediate nodes which have received packets to forward are also considered as new sources. The original and new sources repeat the same process. Note that at any time, several nodes may have packets to transmit, which could result in packet collision. We just apply 802.11 MAC to resolve this issue. After an appropriate period of time, the forwarding candidate set of each node is updated by using the information collected in the past.

Power Allocation Technique (water filling algorithm) is performed to monitor the energy consumed and data transmitted through the minimum power and maximum capacity node. Selecting a minimum number [of any size set] of these sets ensures that the sets you have picked contain all the elements that are contained in any of the sets in the input. Additionally, the cost of the sets should also be minimized. This approach is called Set Covering Problem. The parameter q gives weight based on the number of clusters, or closed sets of connected vertices, including isolated points. If $q = 1$, it is one cluster model, if $q > 1$ prefers more clusters and if $q < 1$ fewer clusters are preferred. This technique is called Clustered Random Model. The major aim is to perform Energy Efficient Data Gathering from all Nodes to the Sink with less time delay and maximum distance coverage. Based on these the algorithm is developed.

Back Propagation Algorithm steps:

1. Initialize the number of nodes in a network
2. Build the random location of a mobile node of n.
3. Initialize the linear neuron by neural networks (Neuron=number of nodes(n))
4. Initialize weights(connection links between nodes) (Initial weight of a neuron(node)=0)

5. Compare the Euclidean distances by using formula between the nodes.
6. Distance ((x, y),(a, b))=$\sqrt{((x-a)^2+ (y-b)^2)}$
7. Tracking the node location based on neural network from x to (N-1)
8. Associated by supervised training method (Determine the weights on connection)
9. Each linear neuron for all x is optimized with respect to activation function of each and every neuron
10. Output response is optimized by a function of Euclidean distance f(x)=x; for all x for every neuron in operation of feed forward methodology
11. If x=0, then go to step 8.
12. If x#0, Feed forward for f(x) of every neuron in a network
13. End

5. RESULTS AND ANALYSIS

LM and BPA algorithms are trained using the real time RSSI values. This value is taken using TelosB motes in an indoor environment. MATLAB is the software tool used to test the performance of both the algorithm. Following graphs describes the results of the algorithm.

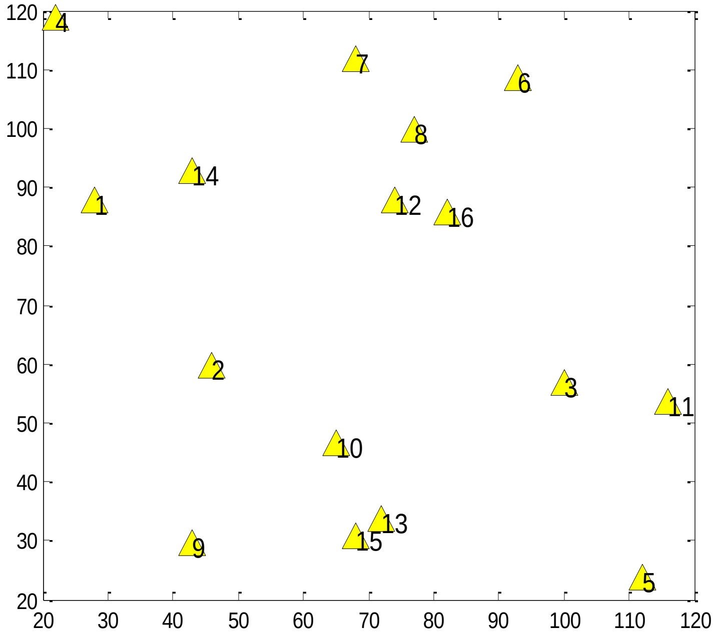

Fig.6. Sensor Nodes in WSN

Figure 6 describes that Wireless Sensor Network is being constructed in such that 15 nodes are distributed randomly in 25*25m area. Also implies that the 15 nodes are interconnected to each other with respect to initial node. Figure 7 describes the coverage area of 15 nodes.

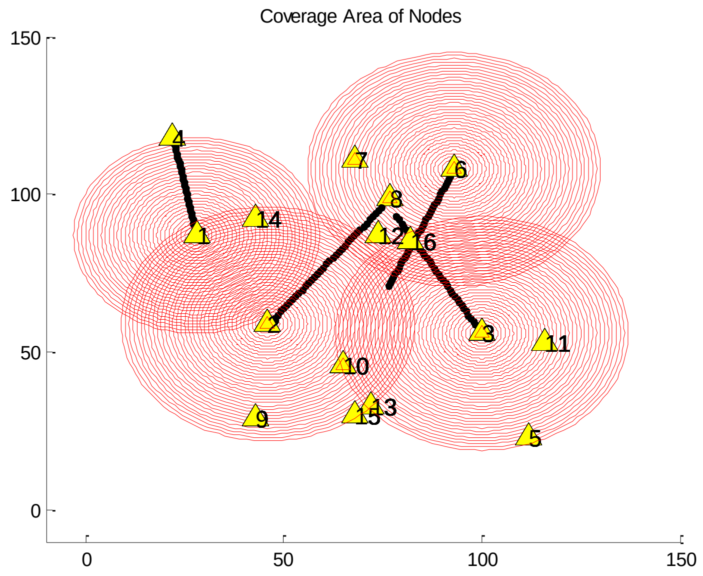

Fig. 7 Coverage Area of Nodes

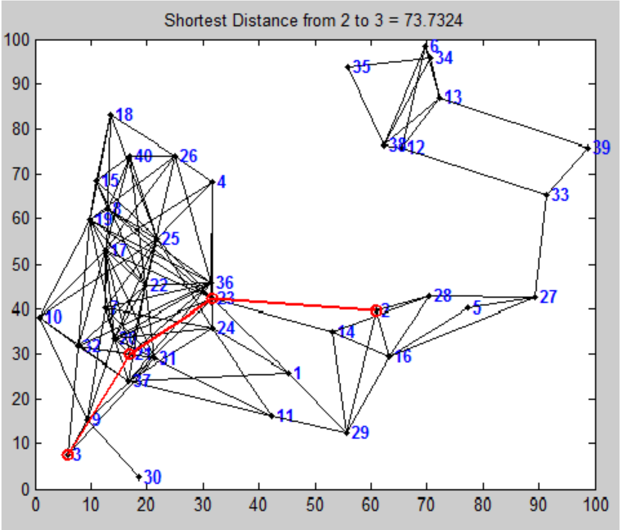

Fig. 8 Shortest Distance between node 2 to 3 using LM algorithm

Figure 8 and 9 describes the shortest distance between nodes found using LM algorithm. The shortest distance between nodes 2 to 3 is 73.73 m from figure 8 and nodes 27 to 18 is 24.93m from figure 9.

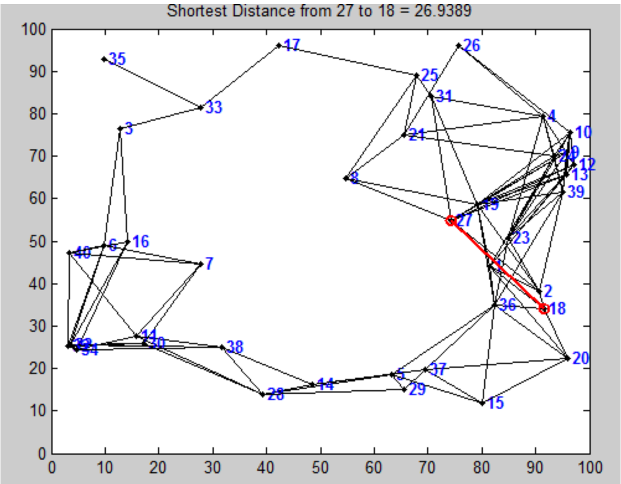

Fig. 9 Shortest Distance between nodes 27 to 18 using LM algorithm

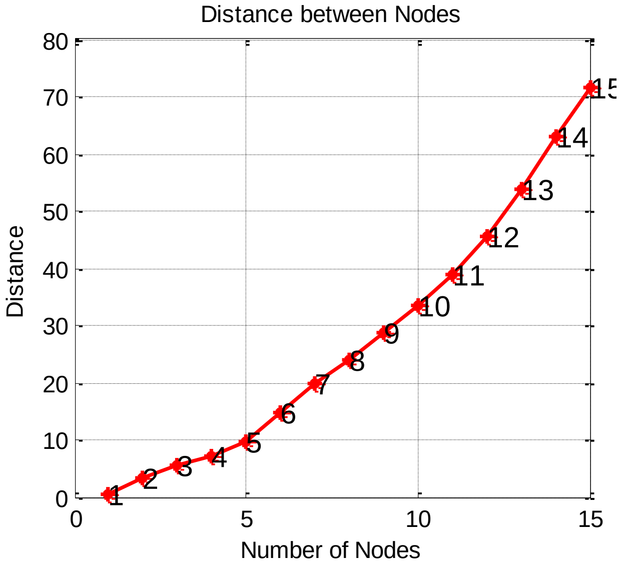

Fig.10. Distance between Nodes using BPA

Figure 10 shows the shortest distance between nodes using BPA. Shortest distance between nodes 8 to 10 is 9.4821 m and nodes 1 to 5 is 9.2178 m

Figure 11 and 12 shows shortest path detection using LM algorithm and BPA respectively. For both cases 15 nodes are distributed randomly in 25*25m area. Shortest distance between the nodes 1 to 6 using LM algorithm is 12m and BPA is 6m. BPA is efficient than LM algorithm to find shortest path between nodes.

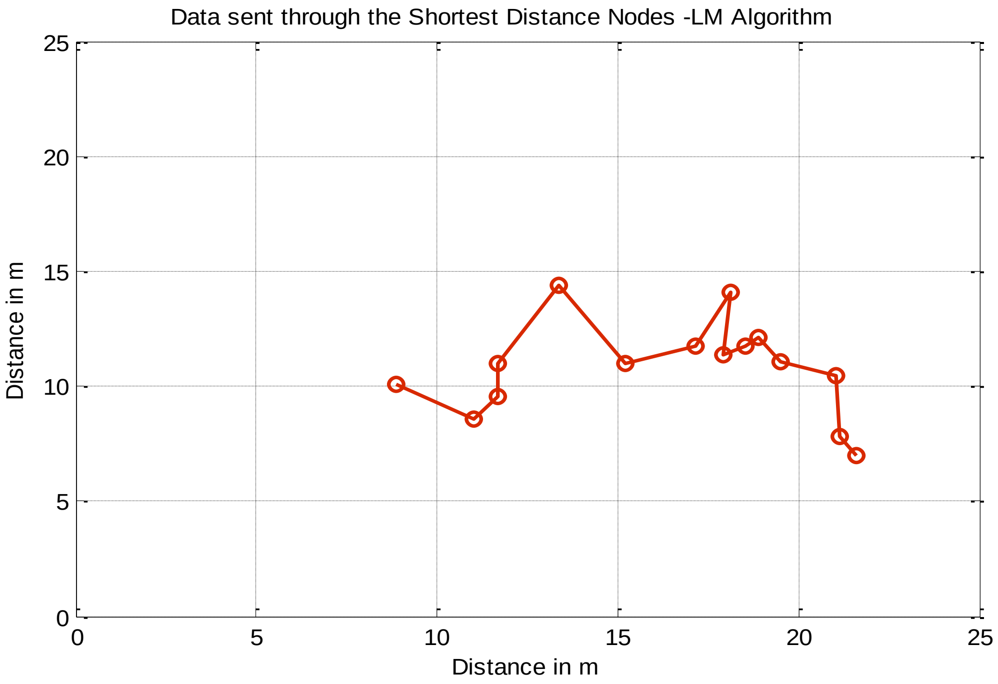

Fig.11 Shortest Distance using LM algorithm

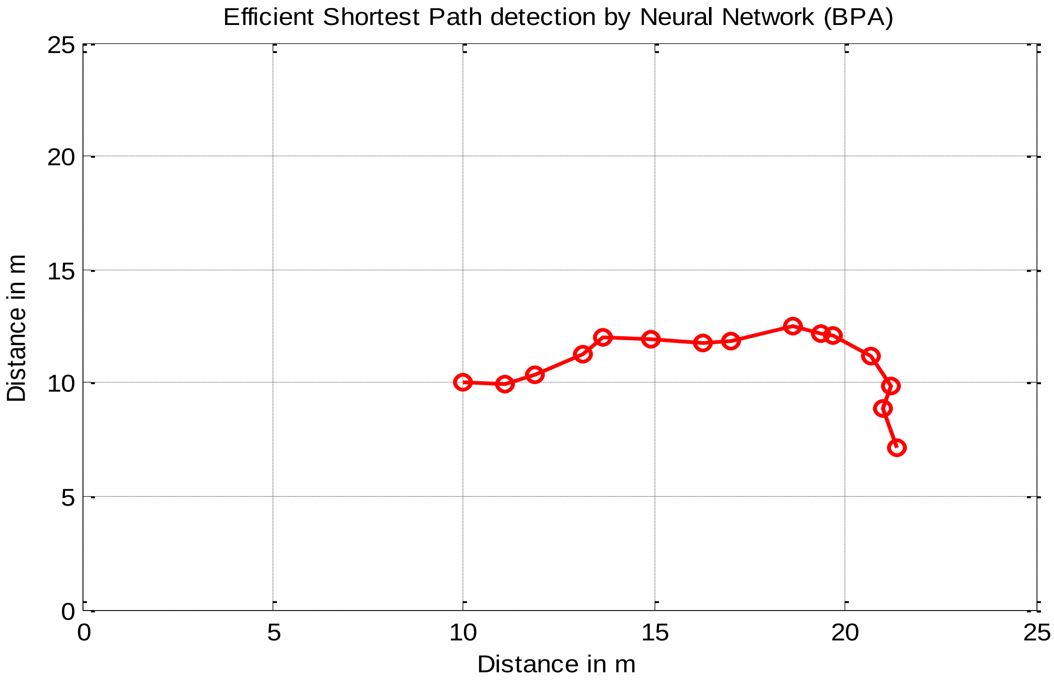

Fig.12 Shortest Distance using BPA

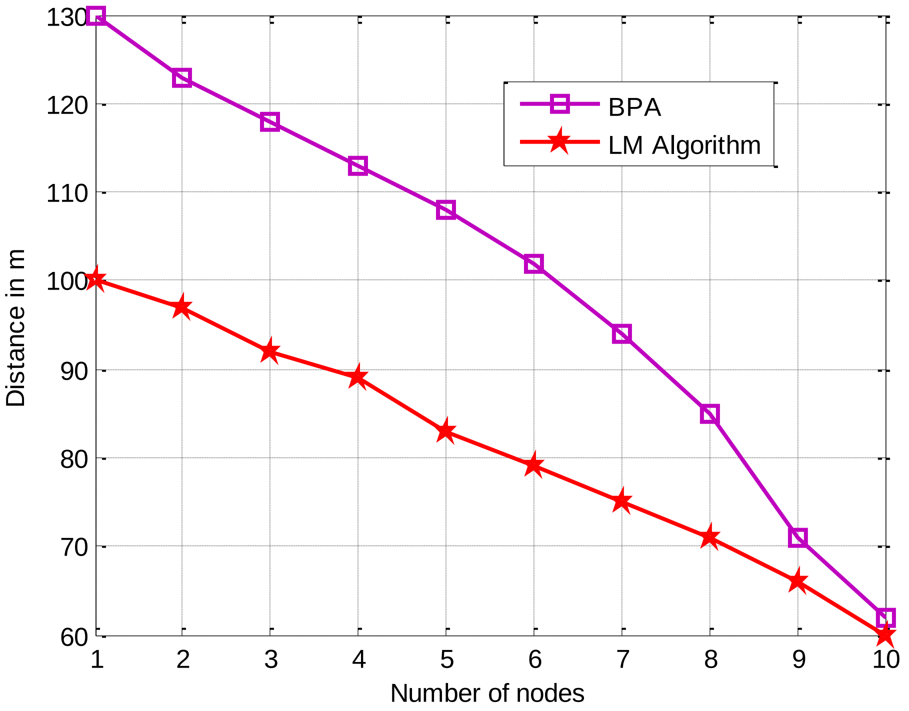

Fig.13. Total coverage area using LM algorithm and BPA

Figure 13 shows that for 10 nodes in a network total coverage area by LM algorithm and BPA. Total coverage area using LM algorithm is 40 m and BPA is 70m. Hence the total coverage of nodes with respect to transmitted power in a network can be enhanced using BPA.

6. CONCLUSION

The distance between the nodes which is distributed in a network is calculated by both Levenberg-Marquardt and Back propagation algorithm. Shortest distance found using back propagation algorithm is efficient than Levenberg-Marquardt. Computational complexity is reduced in determining the shortest path using BPA algorithm compare to LM algorithm. The total coverage area of 10 nodes in a network is simulated by both Levenberg- Marquardt and Back propagation algorithm. In which by Back propagation algorithm the total coverage area and localization (determining the position of node) is enhanced.

REFERENCES

[1] I.F.Akyildiz,W.Su, Y.Sankarasubramaniam and E.Cayirci. (2002). Wireless Sensor Network: A survey, Computer networks, Vol 38, No 4 , pp-393-422.

[2] T. He, C. Huang, B. Blum, J. Stankovic, T. Abdelzaher. (2003). Range-free localization schemes for large scale sensor networks, in Proceeding of the ninth annual international conference on Mobile computing and networking (MobiCom 2003), San Diego, California, , pp. 81–95.

[3] Guoqiang Mao, Baris Fidan, Brian D.O.Anderson. (2007). Wireless Sensor Network localization techniques, computer networks, vol.51, No.10, pp-2529-2553.

[4] M. K. Oh, M. J. Kim, and J. Y. Kim(2006). Low data-rate location UWB technology for ubiquitous home, *ETRI Electronics and Telecommunications Trends* ,vol. 21, pp. 30-39.

[5] Z. Yan, Y. Chang, Z. Shen, and Y. Zhang.(2009).A grid-scan localization algorithm for wireless sensor network, *CMC '09, International Conference on Communications and Mobile Computing*.

[6] S. A. Mitilineos, D. M. Kyriazanos, O. E. Segou, J. N. Goufas, and S. C. A. Thomopoulos. (2010). Indoor localization with Wireless Sensor Networks, *Electromagnetics Research*, vol. 109, pp. 441-474.

[7] U. A. Khan, S. Kar, and J. M. F. Moura. (2009). Distributed sensor localization in random environments using minimal number of anchor nodes, *IEEE Transactions on Signal Processing*, vol. 57, issue 5.

[8] B. Xiao, L. Chen, Q. Xiao, and M. Li. (2010). Reliable anchor-based sensor localization in irregular areas, *IEEE Transactions on Mobile Computing*.

[9] M. Ghavami, L. B. Michael, and R. Kohno. (2004). *Ultra Wideband Signals and Systems in Communication Engineering*: John Wiley &Sons Ltd., UK.

[10] D. S. Hwang.(2007). A study on localization using Wireless Sensor Networks and position pattern, *Master's thesis,* Inha University, Incheon, Korea.

[11] K. Yedavali, B. Krishnamachari, S. Ravula, and B.Srinivasan. (2005). Ecolocation: A sequence based technique for RF localization in Wireless Sensor Networks, *IPSN '05 of the 4th international symposium on Information processing in sensor networks, IEEE Press* ,USA.

[12] M.S.Rahman.(2009). Algorithms of high accuracy position estimation in VLC, RFID and WSN, Ph.D. thesis, Kookmin University, Seoul, Korea.

[13] M. S. Rahman, Y. Park, and K.-D. Kim. (2012). RSS based indoor localization algorithm for wireless sensor network using generalized regression neural network, *Arabian Journal of Science and Engineering*.

[14] Jungang ZHENG Chengdong WU Hao CHU peng JI. (2010). Localization algorithm based on RSSI and distance geometry constrain for Wireless Sensor Network, IEEE, pp-2836-2839.

[15] Hyochang Ahn and Sang-Burm Rhee.(2010). Simulation of a RSSI-Based indoor localization system using Wireless Sensor Network, IEEE.

[16] http://www.xbow.com

[17] htttp://www.tinyos.net