A Robust Frame of WSN Utilizing Localization Technique

J.Jasper Gnana Chandran
Department of EEE, Francis Xavier Engineering College
Tirunelveli - 627003, Tamil Nadu, India
Tel: +91-9443201279 E-mail: jasper_fx@yahoo.co.uk

S. P. Victor
Department of Computer Science, St. Xavier's College (Autonomous)
Tirunelveli - 627003, Tamil Nadu, India
Tel: +91-9486041594 E-mail: victorsp@rediffmail.com

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Abstract

Wireless sensor networks are becoming increasingly popular due to their low cost and wide applicability to support a large number of diverse application areas. Localization of sensor nodes is a fundamental requirement that makes the sensor data meaningful. A wireless sensor network (WSN) consist of spatially distributed autonomous devices using sensors to monitor cooperatively physical or environmental conditions such as temperature, sound, vibration, pressure, motion or pollutants at different locations. The development of wireless sensor networks was originally motivated by a military application like battlefield surveillance. Node localization is required to report the origin of events, assist group querying of sensors, routing and to answer questions on the network coverage. One of the fundamental challenges in wireless sensor network is node localization. This paper discusses different approaches of node localization discovery in wireless sensor networks. The overview of the schemes proposed by different scholars for the improvement of localization in wireless sensor networks is also presented.

Keywords: Localization, Particle Swarm Optimization, Received Signal Strength, Angle of Arrival.

1. Introduction+

A wireless sensor network consists of a large set of inexpensive sensor nodes with wireless communication interface. These sensor nodes have limited processing and computing resources. Thus algorithms designed for wireless sensor networks need to be both memory and energy efficient. In most of the algorithms for wireless sensor network, it is assumed that the sensor nodes are aware not only of their locations but also the locations of their nearby neighbors. Hence, localization is a major research area in wireless sensor networks. But, this problem has not been studied extensively in three dimensional WSNs due to various reasons. However, in some real world application scenario the deployed sensor network operates in a three dimensional volume rather than in a two dimensional area. Deployment of WSNs for surveillance of terrains, study of underwater ecosystem, space monitoring and exploration are some of the examples of such applications.

Localization in sensor networks can be defined as ``identification of sensor node's position''. For any wireless sensor network, the accuracy of its localization technique is highly desired. The existing algorithm

for localization can be broadly classified into two basic categories:
1. Range Based Technique
2. Range Free Technique

In range based mechanisms, the location of a sensor node can be determined with the help of the distance or angle metrics. These metrics are Time of Arrival (ToA), Time Difference of Arrival (TDoA), Angle of Arrival (AoA), Received Signal Strength Indicator (RSSI). Though range based techniques are highly accurate they should be equipped with highly expensive hardware moreover a lot of computation work is required. It increases the cost of the network and is inefficient in terms of computations. The various range based techniques are Radio Interferometric Measurement (RIM) (Gezici *et al.* 2008), Multidimensional Scaling (MDS) (Cheung *et al*. 2005), 3D - Landscape (Ji *et al*. 2004), DV-distance, DV-hop, Euclidean distance (Costa *et al*. 2006) etc.

In range free techniques, the position of sensor node is identified on the basis of information transmitted by nearby anchor node or neighboring nodes based on hop or on triangulation basis. The various range free techniques are APIT (Boukerche *et al.* 2007) chord selection approach three dimensional multilateration approach SerLOC centroid scheme etc . Many more techniques are discussed in (Sayed *et al*. 2005). The range free techniques have an error in accuracy up to 10% of the communication range of individual node (Patwari *et al.* 2003). But, these techniques are much cheaper compared to the range based techniques.

Energy efficiency is a critical issue in wireless sensor networks (WSNs) since the sensor nodes' batteries have limited capacit (Boukerche *et al.* 2007). Once a WSN is in place, its lifetime must last as long as possible based on the initially provided amount of energy. Consequently, techniques minimizing energy-consumption are required to improve the network lifetime. A widely employed mechanism is to schedule sensor nodes activity so that redundant nodes enter the sleep mode as often as possible. So far various studies have addressed the energy optimization issue without considering the impact of the number of reporting nodes on the WSN performance. In other words, how the network lifetime evolves with respect to the number of active reporting nodes.

2. Related Works

Localization approaches can be classified into range-based approaches, and range free approaches. The main difference between them is the way to get the distance information. The former relies on distance or angle measurement with radio signals such as TDoA (Doherty *et al.* 2001) and AoA, and needs expensive measurement hardware. The latter uses special protocols to eliminate the need for radio signal measurement. The proposed DRL is a range-free mobile localization approach for outdoor environments.

(Gezici *et al*. 2008) is a range-based approach for mobile WSNs which use only local information. It uses range measurements between nodes to build a network co-ordinate system. It has shown that despite possible range measurement errors and motion of the nodes, the algorithm provides enough stability and location accuracy. However, the amount of information exchange as well as graph calculation is quite huge, and it needs hardware capable of supporting the TOA to obtain the range between two mobile nodes.

DV-Hop (Patwari *et al.* 2003) is used in static wireless networks which make use of multi-hop information. It is a range-free approach. An anchor floods its location to the whole network with a packet containing the anchor's position. With hop-count from that anchor and average hop-distance, this node can derive its own position by triangulation. In the triangulation, the distance between a node and an anchor is estimated as the multiplication of hop-count and hop-distance.

MCL (Sayed *et al.* 2005), is a range-free approach for mobile WSNs. MCL periodically updates its samples, which are node's probabilistic distribution of locations by repeating the prediction and filtering process. It predicts samples' next time step distribution with node velocity and filters out impossible samples with new observations. Observations include the conditions that the node hears a seed directly (i.e. they are one-hop away), or some of the node's neighbors are one-hop away from certain seeds (i.e. such seeds are two-hop away from the node). However, if a node has no seed within two-hop away from it, it cannot locate itself. Also, the prediction and filtering process may consume lots of iterations if it keeps failure of guessing a possible position. Moreover, this repeating failure condition may be an infinite loop if none of the samples can be filtered successfully. MCL has no solution to this.

Recently (Gezici *et al.* 2008), a new approach to source localization was proposed. It utilizes Received Signal Strength (RSS) measurements. In particular, the spatially distributed sensors measure the power of the signal due to the source that arrives at their location. In the sequel, using an energy-decay model, each sensor is able to extract some information about its distance to the source of interest. Finally, the required location of the source is derived by proper fusion of the information extracted at a number of active sensor nodes. Note that a sensor node is characterized as active if its measurement is greater than a predetermined threshold. In order to avoid the ambiguities that arise due to the unknown transmit power of the source it was proposed to compute ratios of measurements taken at pairs of active sensors.

In (Biswas *et al.* 2006), maximum likelihood multiple-source localization based on RSS measurements was considered. In the problem of source localization was formulated as a coverage problem and estimates of the necessary sensor density which can guarantee a localization error bound were derived. In (Albowicz et al. 2001), a distributed "incremental sub gradient" algorithm was proposed to yield iteratively the source location estimate.

More recently, a distributed localization algorithm enjoying good convergence properties was proposed. In (Sayed *et al*. 2005), a non-linear cost function for localization was proposed and it was proved that its gradient descent minimization is globally converging. However, all the aforementioned approaches require knowledge of the energy decay model and/or the transmit power of the source of interest.

In (Doherty *et al.* 2001), the case of unavailable information about the energy decay model and the transmit power of the source (i.e. model-independent case) was considered. The location of the source was derived by properly averaging the locations of active sensor nodes.

3. Approaches to measure distance between two nodes

There are different ranging approaches to measure distance between two nodes.
TOA: time of arrive
AOA: anger of arrive
TDOA: time difference of arrive
RSSI: Received signal strength indication
Noise issue:
Interferometric:

For example, ranging method used in GPS is TOA. By multiplying the time shift to the speed of radio propagation, we can calculate the distance. The popular approaches used for ranging in WSN are TDOA. A mote working in TDOA is often equipped with a sound signal or ultra-sound signal transceiver in addition to the radio transceiver. When a mote does ranging, it sends simultaneously RF signal and sound signal, known as piggy-back signals. Time stamps are often inserted in the radio messages. When a mote receives a radio message indicating that a sound signal is accompanying with it, the mote start a counter to count the time shift between radio arriving and sound arriving. Compared to the propagation speed of radio, the sound speed is quite slow. We can consider that the time shift of these two signals arriving at the receiver is the time needed by the sound signal flying from the transmitter to the receiver. By multiplying the time shift to the speed of wave, we can calculate the distance between these two nodes.

4. Proposed Method

The ad hoc localization problem (AHLP) has the task of finding the physical location of all nodes. Only the subset of nodes named as location-aware (LA) nodes, know their exact location.

Given a network graph G = (V, E) where {Vgps} is a subset of the nodes in {V} i.e.{Vgps} $\subset$ {V} are LA nodes. The locations of non-LA nodes can be found by {V} – {Vgps}. .

The AHLP is non-trivial for a number of reasons:
To find the location,
1. A node should know
• The locations of at least three LA nodes
• Distance between the node and any of these LA nodes.
2. Or it should measure
• The distance and an (absolute) angle between any one LA node and node
Though the measurements are correct, it is not possible for the LA nodes to surround each regular node. This is because
• MANETs may be randomly arranged
• Only a small percentage of nodes are LA nodes.

Hence estimating node locations based on other nodes' location (multi-hop information) is a better solution for this. Some sensory devices are needed to provide such reading the algorithms require distance or angle measurements. All nodes do not have the same sensory capacity. These algorithms need to work in a heterogeneous environment with different location sensory capacities.

Let us first consider the scenario in which the sensor reading consists of no measurement noise interference. In order to locate a node, at least three RSSI readings from different LA nodes and only two AoA readings are needed. Only one RSSI reading and one AoA reading from the same LA nodes are essential to locate the node when both measurement types are available. In such a case, better coverage must be provided by AoA readings for locating more nodes than RSSI readings.

In PSO the individuals are termed as particles. These particles spread in the multi- dimensional search space representing a possible solution to the multidimensional problem. Each particle has fitness values for optimization and it can be evaluated by the fitness function. These particles have velocities to direct their movements. Initially PSO contains a group of random solutions and by means of updating generations it searches for optimal solution.

In iteration, updating of each particle is done by following two "best" factors.
Pbest: It is the best fitness the particle has achieved so far and stored in memory.
Gbest: It is the "global best" value obtained so far by any particle in the population
Lbest: It is the "best" value obtained so far by any particle in the population in its topological neighbors.

After every iteration, if more optimal solution is found by the particle and population then the pbest and gbest (or lbest) are updated respectively. The fitness function, f, is based on the signal strength (RSSI) and an angle of arrival (AoA) of the LA node. For a node n, the fitness function can be calculated by

$$f = A o A(n) / RSSI(n)$$

The position of the particle is based on its previous position, n p and its velocity over a unit of time:

$$P_{n+1} = P_n + V_{n+1}$$

The velocity of a particle is computed as follows:
The pseudo code is as follows:
1. Get AoA and RSSI values for LA node.
2. Initialize population with random positions and velocities
3. Non LA nodes associate with another node based on the maximum signal strength received from each LA node, thus forming mini swarms
4. Evaluate fitness of each particle in swarm as per (2).
5. For each particle in each mini swarm
5.1. Find particle best (pbest) – compute fitness of particle.
5.2. If current pbest pbest < , then
    5.2.1. pbest = current Pbest
    5.2.2. location current location = Pbest
5.3. End if
5.4. Find local best (lbest) for the mini swarm
5.5. Lbest location = location of min (all pbest in this mini swarm)
5.6. Update velocity of particle as per (3)
5.7. Update position of particle as per (2)
6. End For
7. Repeat steps 5.1 through 5.7 until termination condition is reached.

5. Evaluation Methods

Measurement error is in proportion to the distance between the sensor and the target. A mean of the absolute value is 10% of distance, for example, if distance between a sensor and a target is 10m, measurement error is given as a random value between -2m and 2m. Measurement error is independent of distance and the mean of the absolute value is 1m. This is based on the assumption that sensors near the target do not always measure the precise effects of such obstacles. This follows the upper boundaries of both the above two models. If a system can manage such a large error model, it's no exaggeration to say that it is free of measurement error.

6. Challenges exist when implementing localization in WSN

As we discussed earlier, WSN is a resourced constraint network. Because of the battery power supply and in order to avoid interference, the effective communication range is limited to some extent. The sensed data may arrive at the destination via multi-hop. The reliability of a routing path is not guaranteed, so the routing path between the data source and data sink may vary with time. When we try to use multi-hop routing path to estimate the distance between a node and the beacons, the errors caused in these approximation have adverse impact on the accuracy of localization in WSN.

Another factor influencing localization accuracy is the ranging errors. Whatever kind of ranging approaches is adopted, there will always exist some noise in the ranging measurements. Moreover, because the characteristics between each transmitter-receiver pair may not be the same, this kind of ununiformity between different motes also exerts negative impact on the accuracy of localization. Before we begin to implement localization in WSN, we will have to do the simulation first to see what accuracy is expected concerning localization in multi-hop WSN.

7. How to simulate localization processes using NS2?

If we have a network topology we know the coordinates of each node in the topology and also the distance matrix between each node. However, as simulation input, we use only part of the distance matrix and choose three typical nodes as beacons. The localization goal is to figure out the unknown coordinates of other nodes except the beacons. After that, we can evaluate the error distributions by comparing the estimated coordinates of each node and their original coordinates.

By specifying the number of nodes, distance of grid unit and the random noise relative to the spacing of each grid, we can programme to generate a random pattern of the network which means that we can get an array of nodes with the known co-ordinates and also we know the full distance matrix between any nodes. In order to simulate the process of localization, instead of using the full distance matrix, we will have to reduce the direct connectivity in the full distance matrix.

8. Experimental Results

We show that each distinct region formed in this manner can be uniquely identified by a location sequence that represents the distance ranks of reference nodes to that region. We present an algorithm to construct the location sequence table that maps all these feasible location sequences to the corresponding regions by using the locations of the reference nodes. This table is used to localize an unknown node (that is, the node whose location has to be determined) as follows. The unknown node first determines its own location sequence based on the measured strength of signals between itself and the reference nodes. It then searches through the location sequence table to determine the "nearest" feasible sequence to its own measured sequence. The centroid of the corresponding region is taken to be its location.

In order to evaluate the described approaches to sensor network localization, many numerical tests were performed. We performed a variety of simulation experiments to cover a wide range of network (number of nodes), the radio range, and the distance measurement error and computation time. The key metric for evaluating all the listed methods was the accuracy of the location estimates which versus the deployment, communication and computation cost. The table 1 shows the transmission ranges of different networks

Due to measurement uncertainty, it is difficult to find a good metric to compare the results obtained using different localization methods. The localization error is denoted as LE. It is expressed as a percentage error. It is normalized with respect to the radio range to allow a comparison of results obtained for different size and range networks. Figure 6 shows that the localization error decreases as the number of nodes increases. Increasing the density of anchors makes localization easier, but it increases the network size and deployment cost. The value of the transmission range r determines the number of neighbours of each node in the network. The radio range considered from the interval [0.21 – 0.02].

9. Conclusion

In the sensor networks the nodes move randomly within the coverage area. The problem considered in this paper is the exploration of an unknown environment with the goal of finding the nodes at an unknown location(s) using location aware (LA) nodes. This work has demonstrated the use of a distributed PSO algorithm with a novel adaptive RSS weighting factor and angle of arrival AoA factor to guide LA nodes for locating target(s) in high risk environments. Essentially, to reduce the energy consumption only a small number of sensors are activated to track and localize the target; while others are turned into sleep mode. The proposed method is evaluated on various mobility models and localization is performed by learning movement patterns and their parameters. The results show that our approach is better than the previously proposed approaches for range free localization techniques for three dimensional wireless sensor network in terms of beacon overhead, localization time, localization error, computation and space required for any per-cent of mobile sensor nodes.

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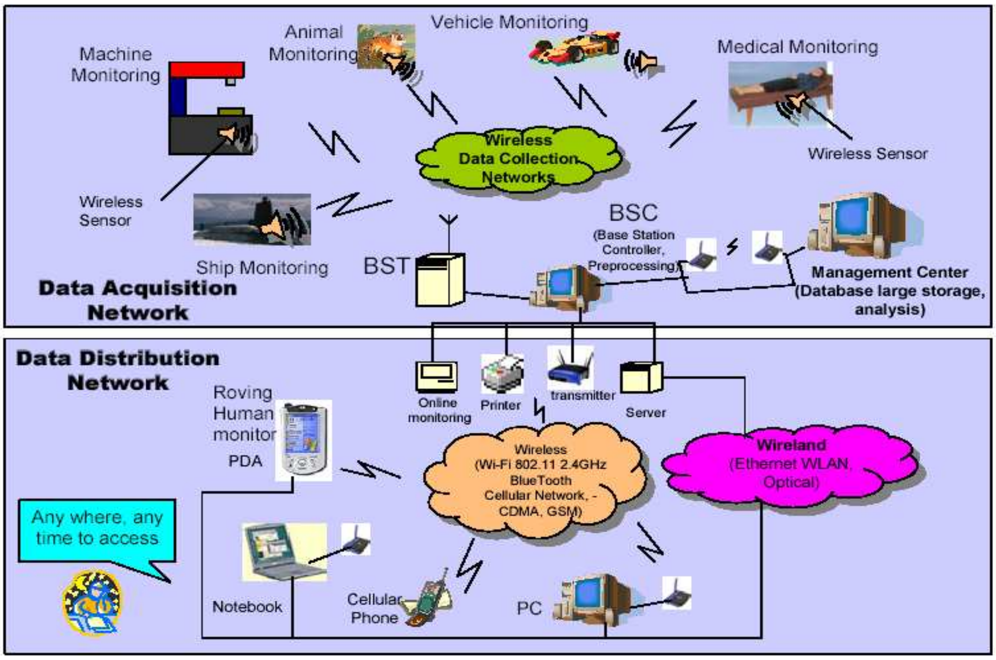

Figure 1. Complexity of Wireless Sensor Networks

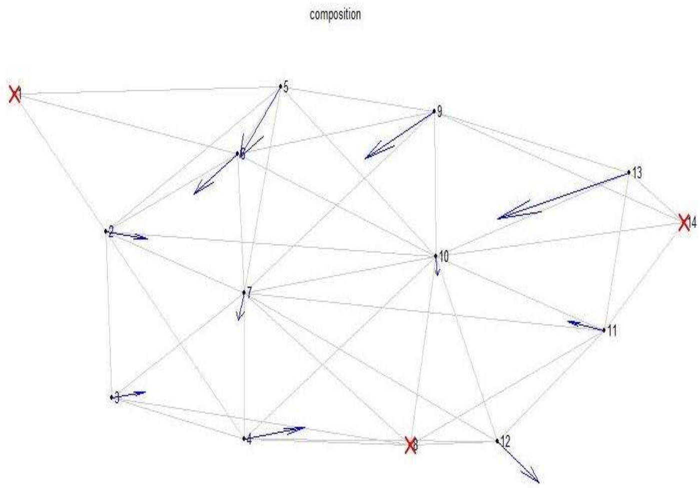

Figure 2. Node Distribution

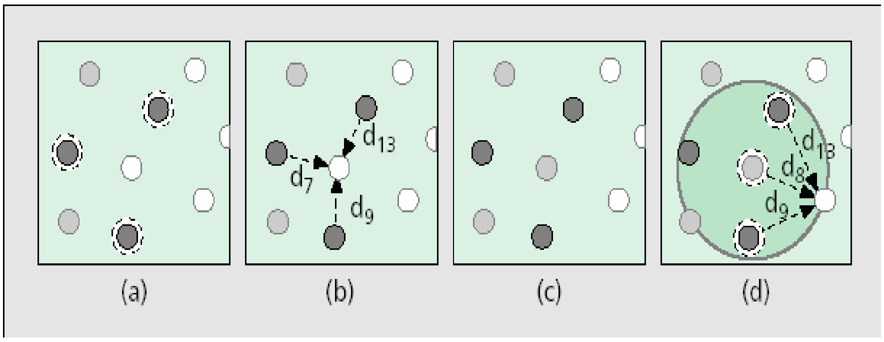

Figure 3. Node Connectivity

a) An unknown node determines its reference nodes;
b) The unknown node estimates its distance to these references;
c) The unknown node computes its position using multilateration;
d) Now the unknown node becomes a settled node and assists other nodes in position estimation.

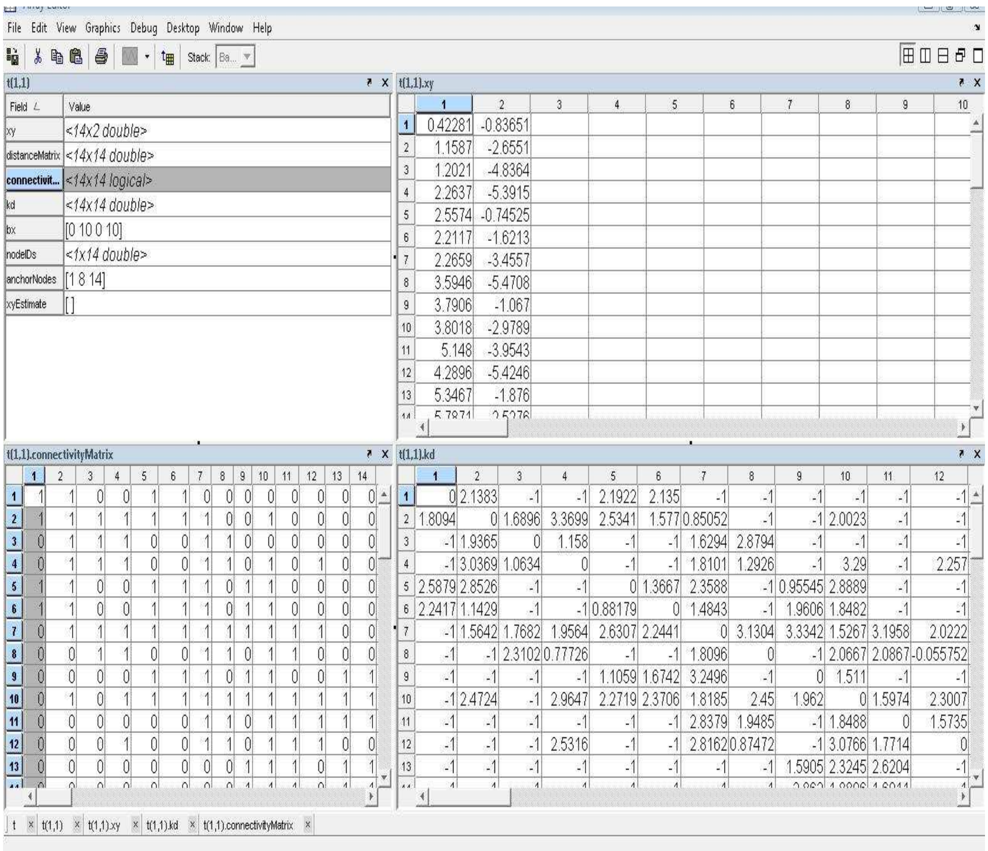

Figure 4. Centroid Measurement

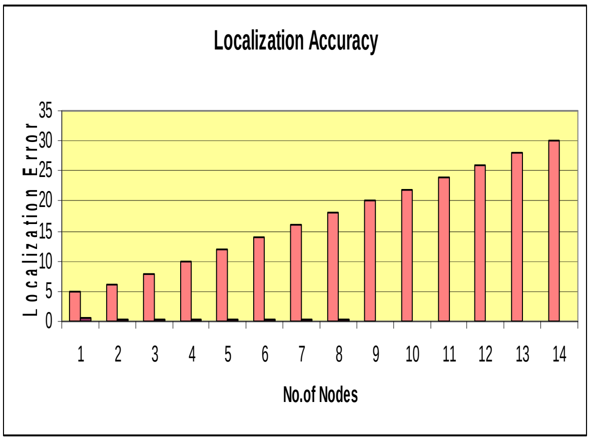

Figure 5. Impact of Nodes with Localization Accuracy

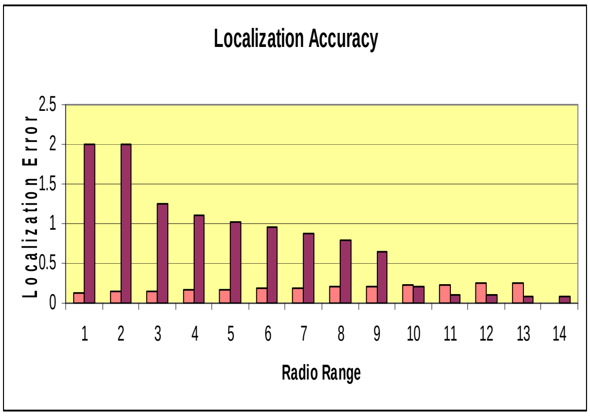

Figure 6. Radio Range Vs Localization Accuracy

Table 1. Number of Nodes Vs Radio Range

Number of Nodes	Radio Range
100	0.21
200	0.17
500	0.15
1000	0.11
1500	0.08
2000	0.06
2500	0.04
3000	0.02