Simulation-based Analysis of a Localization Algorithm for Wireless Ad-Hoc Sensor Networks

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ABSTRACT

Localization is a problem of estimating the spatial coordinates of wireless nodes in an ad-hoc network. Wireless Sensor Network is an example of such a network, where localization as a problem has been a challenging topic for many years. The position of sensor nodes can be either manually configured before deployment or a GPS receiver can be built into each of these nodes. The former approach is very tedious and error-prone while the latter is a costly proposition in terms of volume, money and power consumption. In this paper we discuss a localization algorithm with few beacons having known position estimates assisting unknown nodes in obtaining their positions based on simulation analysis and performance. We propose a Network model to depict a Wireless Sensor Network with 802.11 based wireless nodes available as part of the OPNET Radio Model. We present simulation scenarios and analyze them based on the number of beacon packets transmitted and the accuracy of position estimate obtained. A simple Node Model and Process Model implemented to carry out the localization algorithm is also discussed in detail. We also provide comparative analysis of the simulation results and the theoretically expected values for the scenarios considered.

INTRODUCTION

A wireless sensor network consists of a collection of wireless sensor nodes, each of which consists of sensing, processing and communicating components. The sensing component closely interacts with the physical world (e.g. measuring temperature or humidity); the processing component processes the measured data, while the communicating component delivers the processed data to a central agent or base station.

Consider a scenario involving a forest fire. Cluster of nodes thrown randomly and equipped with heat sensors detect the fire, and immediately report the event to a base station located at a safe distance. The base station will then have an accurate picture of the event and can trigger an immediate action. Another example could be where thousands of tiny wireless sensor nodes are sprinkled on a battlefield to monitor enemy movements without alerting the enemy to its presence. By self-organizing into a wireless sensor network, the sensor nodes would filter out raw data for relevance before relaying only the important findings to the central command.

For a sensor network to be useful, it is vital to know the position of the sensor nodes. In the scenario considered above, the sensor location information is important for the base station to deduce where exactly the event (forest fire) has occurred.

The problem of estimating the position or spatial coordinates of wireless sensor nodes is termed as localization. The position of sensor nodes can be either hand-placed, but this is a tedious and error-prone method especially when the number of sensors is increasingly huge. Alternatively, each sensor node could be equipped with a GPS (Global Positioning System) receiver, which is a costly proposition in terms of volume, money and power consumption.

In this paper, we consider a novel, robust and RF signal strength based distributed algorithm for localizing wireless sensor nodes. In our network very few nodes have a priori knowledge of their position called *beacons* while nodes, which estimate their position with the help of beacons, are called *unknowns*. The main focus of this paper is to give a brief overview of the position estimation algorithm and evaluate its performance using simulation-based analysis.

RELATED WORK

Numerous localization systems have been developed and deployed during the past few decades. While most of these systems rely upon a fixed infrastructure, fewer exists in the ad-hoc domain.

In 1993, the Global Position System (GPS) [1] was introduced which is based on the NAVSTAR satellite constellation. LORAN [2] operates in a similar fashion as GPS but uses ground-based beacons instead of satellites. In 1996, the US Federal Communications Commission (FCC) required that location information of all users in a cellular network be provided for Emergency 911 services.

Among the indoor localization systems, RADAR system [3] can track the location of users inside a building and is RF based, while the Cricket [4] location support system is ultrasound based.

In [5] an iterative multilateration is considered. The algorithm performs well when a large number of beacons are present, the graph connectivity is high and precise range measurements are available. In [6], the problem of cooperative multilateration is tackled. This method relies on precise range determination technique and then on solving a least square on a large order system. An interesting idea is explored in [7], where the problem of localization is considered in the absence of beacons. The nodes build local coordinate system and further aggregate them into a unique network coordinate system.

A method for estimating unknown node positions in a sensor network based exclusively on connectivity-induced constraints is described in [8]. Known peer-to-peer communication in the network is modeled as a set of geometric constraints on the node positions. The global solution of a feasibility problem for these constraints yields estimates for the unknown positions of the nodes in the network.

Another original idea is presented in [9] where auto-calibration is used to improve the accuracy of a localization algorithm. The authors impose common sense constraints (e.g. the distance from A to B equals the distance from B to A, as well as the triangle inequality) on the position of the nodes, and thus auto-correct the range measurements.

LOCALIZATION ALGORITHM

In this section, we provide a brief overview of the proposed position estimation algorithm. Consider Fig. 1, which shows an example of a wireless ad-hoc network. A straight line between two wireless nodes shows that the two nodes are within each other's range. Every node in the network will belong to one of the two categories, *beacons* and *unknowns*. Beacons have a *priori* estimate of their own position, which can be either manually configured before deployment or equipped with a GPS receiver. Unknown nodes estimate their position with the help of assisting beacons.

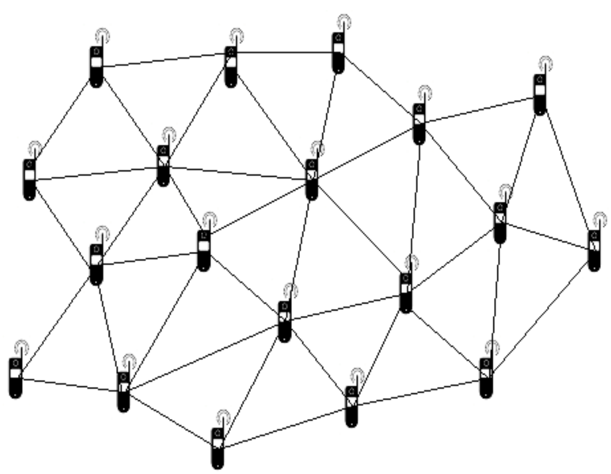


Fig. 1 A Wireless Ad-Hoc Network

Beacons send beacon packets, which are packets meant to assist unknown nodes in estimating their position. We assume that a range measurement method is available, i.e. an unknown node receiving a beacon packet will, with some confidence, estimate itself to be located within a ring given by circles of radii R_{i-1} and R_i.

Several range measurement techniques have been proposed. One such method uses ultrasonic impulses emitted by the beacons [10]. The distance is calculated from the propagation delay and the propagation speed, which is usually constant. Another method utilizes received signal strength (RSS) measurements, which is available in most of the current transceivers. Though this method is not as accurate as the acoustic one, it does not require additional hardware and hence a cheap solution. Also, this method is reliable only outdoors and its performance and accuracy falls considerably indoors due to fading, interference and multipath propagation. The position estimation algorithm presented in this section is RSS based and is specifically geared to capture the inaccuracy of radio signal strength measurements.

Every beacon node transmits beacon message, which includes its own position estimate, which is a point or a small area corresponding to GPS inaccuracy. An unknown node upon receiving a beacon message from a beacon node computes the constraint, which in this case is a transmission ring, and intersects the constraint with its current estimate to calculate the new position estimate. If the position estimate improves, it will broadcast its estimate to all its neighbors.

If the beacon message is from another unknown node, the constraint is slightly difficult to compute. The new constraint in this case is given by the Minkowski sum [11] of the position estimate and the transmission ring. Given two surfaces S_1 and S_2, their Minkowski sum is given by the union of all translations of S_2 in each and every point of S_1.

$$S_2 \circ S_1 = S_1 \circ S_2 = \bigcup_{p \in S_1} S_2 \text{ shifted to } p \qquad (1)$$

The new constraint is computed from the position estimate of the assisting node, which is obtained from the position estimate field as part of the beacon message, and the transmission ring which is obtained from a table as given in Fig. 2. The transmitted power is included in the beacon packet while the RSS is calculated during the reception of each packet. Every unknown node stores this table in some fashion and uses it to calculate the range/distance from assisting nodes. A table like this can be created from preliminary measurements and calibration [12], which is however beyond the scope of this paper.

Power Level	RSS			
	1	2	3	4
1	4m-20m	1m-10m	0-8m	0-5m
2	8m-30m	5m-15m	1m-12m	0-8m
3	15m-40m	10m-30m	5m-15m	0-10m
4	40m-70m	25m-50m	20m-30m	0-20m

Fig. 2 Range measurement table

SIMULATION MODEL

The localization algorithm described above was implemented and evaluated in OPNET Release 8.1A. We used the IEEE 802.11 Wireless LAN model with the ad hoc network configuration. We simplified many of the important issues with respect to the algorithm considered above, as will be shortly seen.

The network model for the wireless sensor network is shown in Fig. 3. The beacons and unknowns are very clearly indicated. A campus network of size (1000 x 1000) m^2 was chosen, but the size of the network is not a restriction. The position of sensor nodes can be arbitrarily chosen and are static. The number of nodes is also not fixed. Since the position estimation algorithm does not pose any limitation on the number of beacons required by each unknown node to estimate its position, number of beacons and unknowns for simulation were also arbitrarily chosen. However the number of beacons was kept significantly lower than the number of unknowns, which is the strength of the algorithm. The distributed nature of the algorithm helps unknown nodes estimate their position with few beacons in the network.

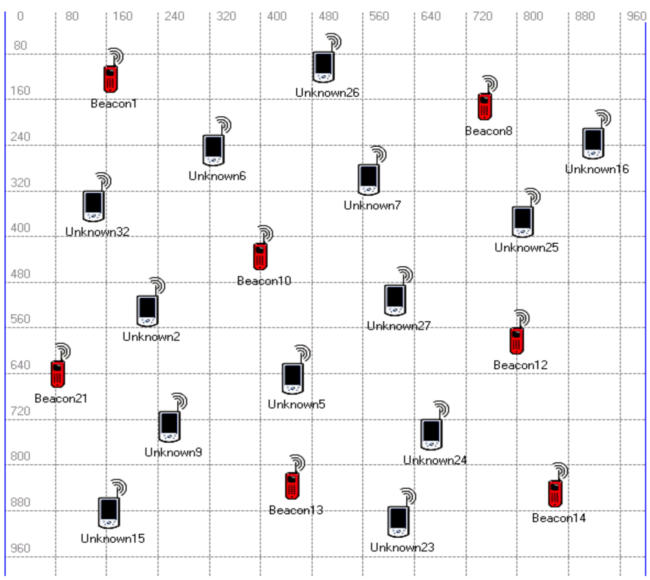


Fig. 3 Network model for wireless sensor network

The node model for the beacon and unknown node is shown in Fig. 4 and Fig. 5. The broadcast address is handled by a special value of (-1), which will send the beacon message to all the sensor nodes. In OPNET 8.1 version, we noted that there is no range limitation, i.e. a packet broadcast by a wireless station will reach all the nodes in the network. But in order to restrict the range, a receiving sensor node dropped packets if its distance from the transmitter is greater than a prescribed range R. Since the first step in the localization algorithm is to determine the distance or range, the method of restricting the range will seem contradictory. Since the main focus of this paper is to evaluate the performance of the algorithm, we assume that an RSS based range measurement technique is already available. That is, an unknown node receiving a beacon message will estimate the exact distance between itself and the node that generated the beacon message. The inaccuracy is produced by introducing a fixed or random error $\pm E$ meters. For e.g. if the unknown node calculates that it is located at a distance of 40m from the beacon, an error E of 8m suggests that the node is situated somewhere in the interval of 32m to 48m from the beacon. The inaccuracy on either side of the mean or actual estimate can also be different and random, say (E_1, E_2) meters. If the actual distance of the unknown node from its neighbor is S m, then the range interval is $(S - E_1)$ m to $(S + E_2)$ m.

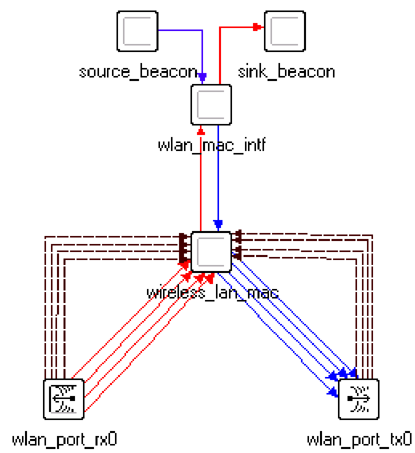


Fig. 4 Node model for a beacon

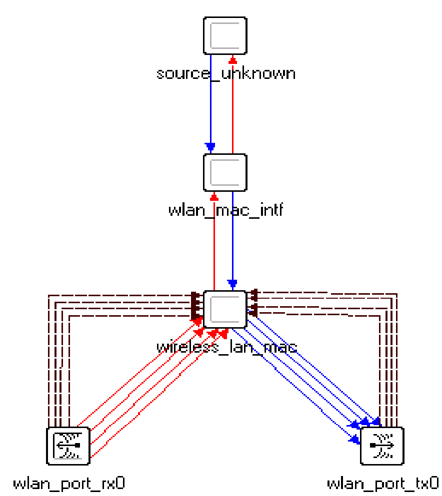


Fig. 5 Node model for an unknown node

The process model for *source_beacon* is shown in Fig. 6. The beacon will generate a beacon packet at a rate that is set by the user. In our simulation, the packets were generated at a rate uniformly distributed between (1-2) sec. The packet format of the beacon message is shown in Fig. 7. The node type indicates whether it is a beacon or an unknown. Every node has a unique node number called Node ID to identify itself. The (x, y) position of the node is also enclosed within the beacon message. This is used by the receiving nodes to calculate the range or distance. The position estimate is a point in the case of a beacon, while it is an estimate in the case of an unknown.

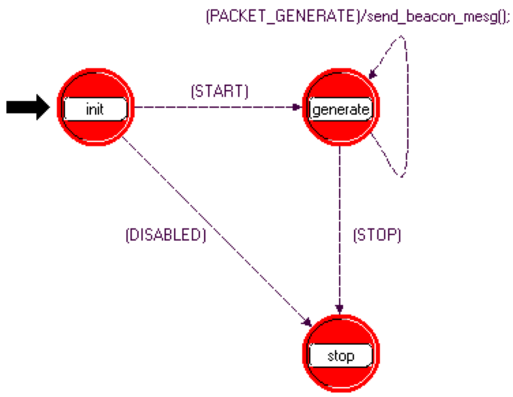


Fig. 6 Process model for *source_beacon*

Node Type	Node ID	X Position	Y Position	Position Estimate

Fig. 7 Packet format of a beacon message

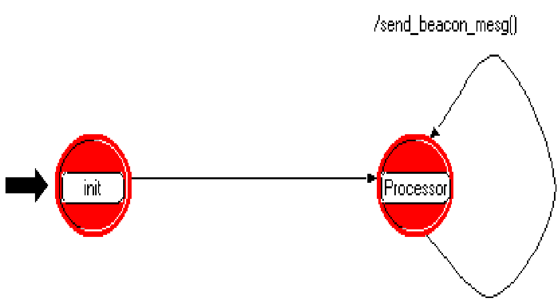


Fig. 8 Process model for *source_unknown*

The process model for *source_unknown* is shown in Fig. 8. The *Processor* state will loop around, waiting for a beacon message. Once a beacon message is received, it will compute the new estimate and if the position estimate improves, it will broadcast a beacon packet by executing the function *send_beacon_mesg*.

PERFORMANCE ANALYSIS OF THE LOCALIZATION ALGORITHM

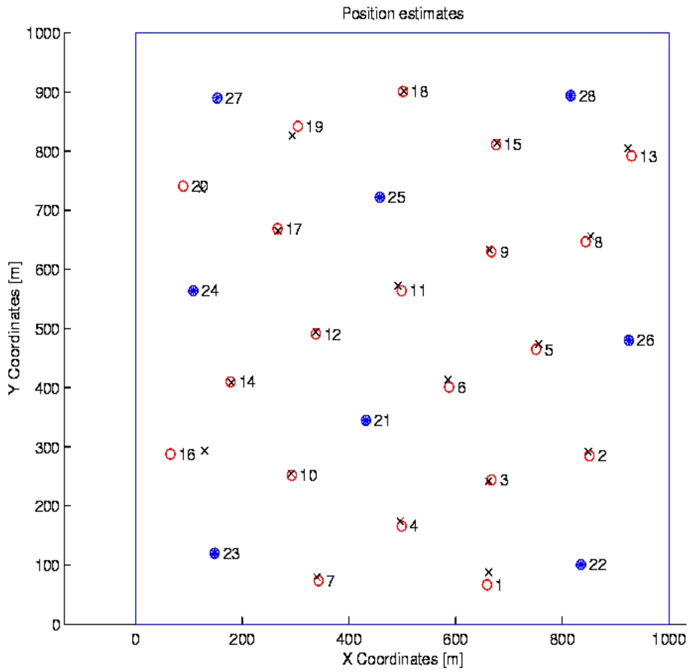
In this section we consider various simulation scenarios and discuss its performance. Every node in the network has a communication range of 300m with a constant and same transmission power. The simulation area is divided into a rectangular square grid of (100 x 100) squares. Each square having an area of 100 square meters is represented by a bit. Thus the position estimate can be easily fit into a kilobyte packet. Moreover, the position estimate field in the packet format is variable. Since the position estimate may only keep getting smaller after every intersection, the size required to store the estimate is lesser at subsequent iterations.

We consider the number of beacon messages received and the localization accuracy as the two important performance evaluation parameters. The total number of beacon messages received by any unknown node in the system is bounded by the product of the number of beacons in the system and the total number of neighbors of that sensor node [12]. The scalability of the algorithm is substantiated by the linear complexity of the algorithm in the number of neighbors and constant complexity in the total number of nodes. If the number of neighbors of the unknown node is $(b+u)$, where b is the number of beacon neighbors and u is the number of unknown neighbors, and the total number of beacons in the network is N, the bound B_n on the number of beacon messages received by any unknown node is given as follows.

$$B_n = (b+u) \times N \qquad (2)$$

With the position estimate represented by squares, the unknown node may be present in a square with a probability of either zero or one. This is a black and white solution where a black (or gray) square is part of a node's position estimate while a white square does not include a node's estimate. Once the final position estimate is computed, the best position estimate $(\hat{x}, \hat{y})$ is calculated by using the weighted average. Representing (x, y) as the center of the squares, $p(x, y)$ as the probability at each square, and $x_{\min}, x_{\max}, y_{\min}$ and $y_{\max}$ as the bounding coordinates of the deployment area, the best estimate is given as follows.

$$(\hat{x}, \hat{y}) = \left(\frac{\sum_{x_{\min}}^{x_{\max}} \sum_{y_{\min}}^{y_{\max}} x \times p(x, y)}{\sum_{x_{\min}}^{x_{\max}} \sum_{y_{\min}}^{y_{\max}} p(x, y)}, \frac{\sum_{x_{\min}}^{x_{\max}} \sum_{y_{\min}}^{y_{\max}} y \times p(x, y)}{\sum_{x_{\min}}^{x_{\max}} \sum_{y_{\min}}^{y_{\max}} p(x, y)} \right) \qquad (3)$$



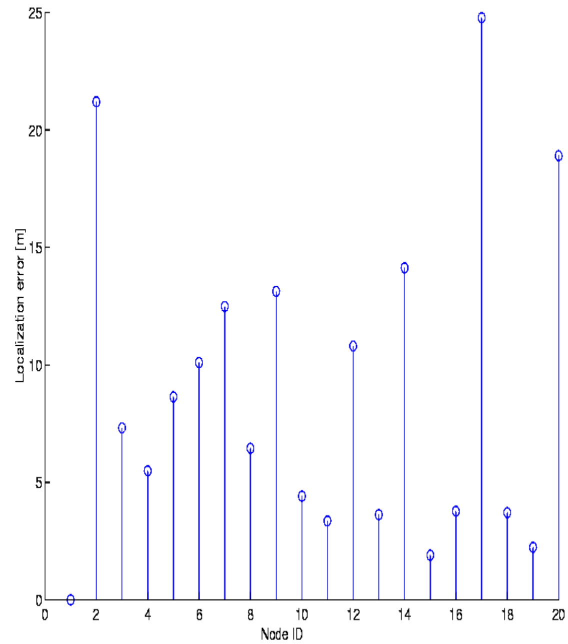
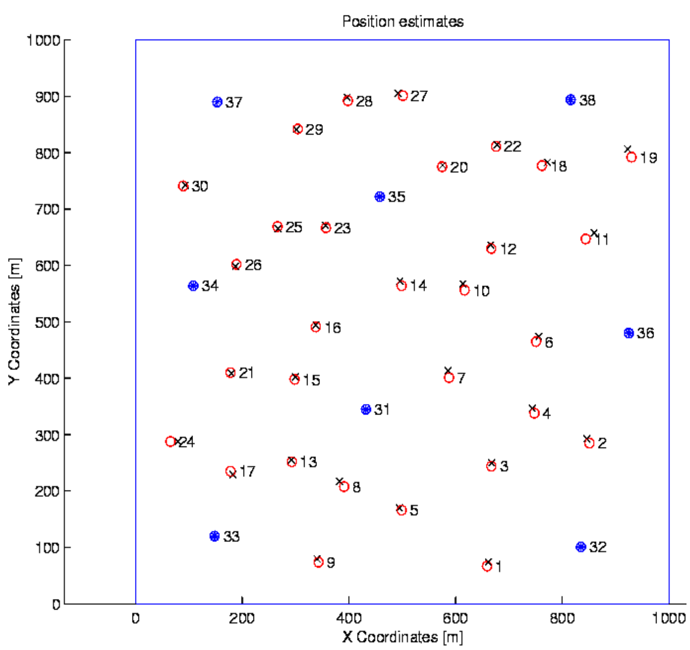


Fig. 9 a) Position estimate of 20 unknown nodes b) Localization error for the 20 unknown nodes



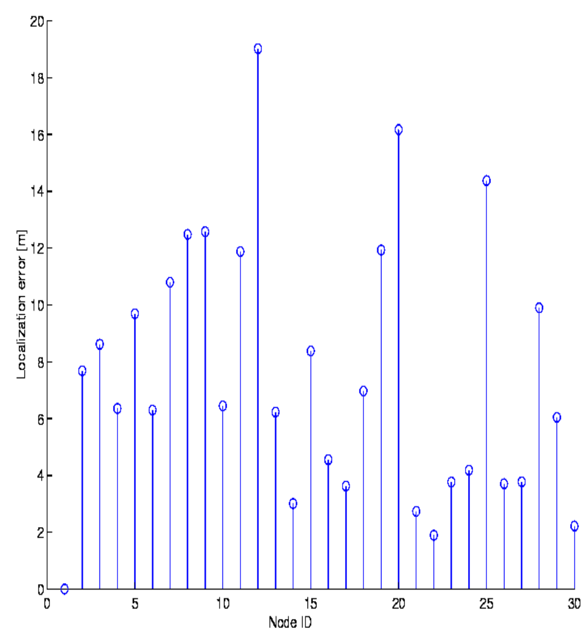


Fig. 10 a) Position estimate of 30 unknown nodes b) Localization error for the 30 unknown nodes

The localization accuracy is determined by the closeness of the best estimate to the actual position of the unknown node. The closer the position estimate is to the actual estimate, the better the localization accuracy of the algorithm. Simulation scenarios discussed below help us evaluate the scalability of the algorithm and accuracy of the position estimates. Consider Fig. 9 (a), which shows the position estimates for 20 unknown nodes assisted by 8 beacons. The unknown nodes were able to estimate the range from its neighbors within ±25m. The beacons are shown as blue circles, the actual position of unknown nodes are represented by red circles, while the best position estimate obtained after simulation are shown as ‘x’.

On the average every unknown node had 1.8 beacon neighbors and 7 unknown neighbors. Fig. 9 (b) shows the localization error for the unknown nodes. Considering a ranging error of 25m, the nodes are localized to a very good accuracy. The average error is also found to be 8.8m. Keeping the same number of nodes as in Fig. 9 (a), without changing their actual positions, we added 10 additional unknown nodes at random locations to view the effect in the final position estimates obtained. As we can see in Fig. 10 (a), the position estimates obtained are exceedingly good. Every additional unknown node will behave like a beacon assisting other unknown nodes. The average error in the position estimate of unknown nodes (Fig. 10 (b)) also reduced to 7.51m. The average error is found to be even lesser with decreasing ranging error. The mean distance estimated is not always accurate considering RSS based range measurement. In this case, the position estimate of the unknown node is hurt (as the node will capture the wrong interval) and may deviate well from the mean [13]. However, the final position estimate does not depend on one beacon message and every good beacon message will improve the position estimate of the unknown node.

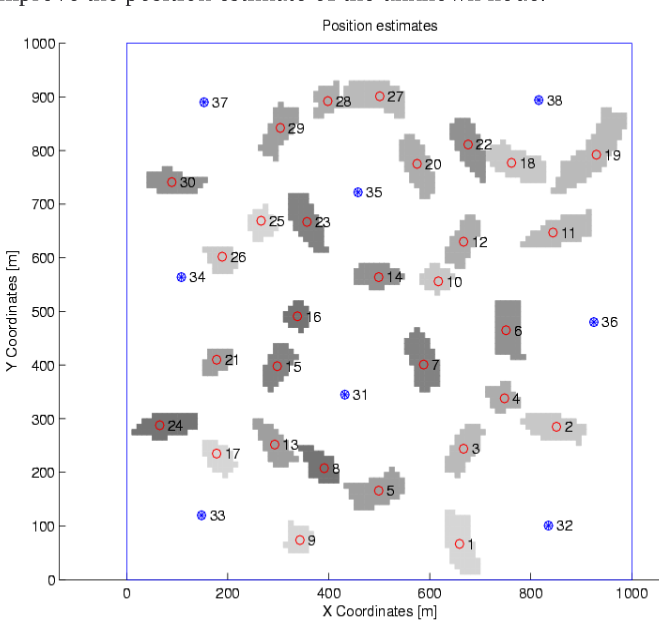


Fig. 11 Position estimate of unknown nodes

Fig. 11 shows a better view of the position estimate of unknown nodes. The nodes in the center, which receive more number of beacon messages, have a better estimate than the nodes at the periphery, which receive fewer beacon messages.

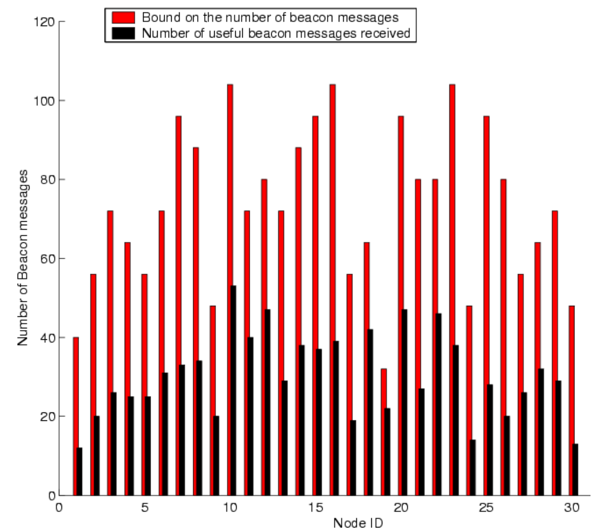


Fig. 12 Comparison of bound on the number of beacon message with the actual number of messages received.

Fig. 12 shows the comparison of bound on the number of beacon messages with the actual number of beacon messages received by sensor nodes. We observe that the actual number of messages received is well bounded by the theoretical number of messages received. This is because of the aggregating nature of the algorithm, where every unknown node may aggregate multiple beacon messages and then broadcast its estimate to all its neighbors. The simulation was stopped once every unknown node in the network received beacon messages arising from every beacon, as beacons are the true source of information. We also understand that there are other ways of stopping the simulation. For e.g. once the area of position estimate of an unknown node reaches a particular threshold, the node stops localizing itself. The best position estimate that an unknown node can attain is πE^2 square meters, where E is the ranging inaccuracy.

CONCLUSION

In this paper we discussed a position estimation algorithm for localizing unknown nodes in a wireless sensor network. The performance of the algorithm was evaluated based on the number of beacon messages received by unknown nodes in the network and the accuracy of position estimate obtained with respect to the actual estimate. The algorithm is very scalable in that it has linear complexity in the number of neighbors and constant complexity in the total number of nodes. Simulation results show that the actual number of useful beacon messages received by every unknown node is far lesser than the theoretical bound. The position estimates obtained from simulation were also found to be very accurate, even with a considerable ranging inaccuracy.

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