PART - C
MEDICAL AND ALLIED HEALTH SCIENCES

ROBUST LOCATION ESTIMATION USING MODIFIED CENTROID AND META HEURISTIC ALGORITHMS IN WIRELESS SENSOR NETWORKS

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ABSTRACT:

Advances in embedded and radio technologies have empowered the propagation of sensors. The aspect of the positions of the nodes in the area of deployment is considered to be a significant information for calculating the performance of the routing time and to transmit the appropriate data based pertaining to the place where the node is deployed. Because the data and information will be useful only if the nodes know their geographical coordinates, identification of the node location /position is very important and is termed as localization. The cost, power, and processing limits of these networks prevent traditional means of supplying this information. The algorithms based on the Meta heuristic techniques and the Received Signal Strength are pooled together for location identification of nodes. The error in the nodes position are reduced using the proposed algorithms and is evident in the simulation results. Results also claim high accuracy when compared with the similar algorithms.

***Index Terms*— RSSI, Localization, Sensor Network, Glow-worm Spam Optimization, Particle spam Optimization**

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1 INTRODUCTION

The sensors are tiny devices that are useful in measuring the data that is of interest and influences the applications that are developed for use in a variety of applications. There nodes are economical in terms of cost and are capable of sensing, aggregating and transferring the data that has been sensed by them. The advent of these sensors have increased their presence in all applications which involve engineering and science. As they are wireless, they fall under the category of wireless networks and have increased scope of research starting from the layers of the 5 layered architectures such as wireless layer, and Data link layer [1, 2], and also in the network and the transport layers [3, 4]. Some of the applications of the sensor networks are discussed in [5, 6, 7]. As the nodes are not placed uniformly, their positions are in a scattered manner. The node position is important due to causes listed (i) the data from undefined place is of no use. (i) Object tracing using sensors without location cannot be accomplished [8, 9, 10, 11] and (iii) Topographical applications and data routing need the location information precisely. The location of the event is important for majority of applications. For example identification of an onlooker in a college, movement of drones or the fighter planes, object detection etc. As and when the location of the node is identified, the routing path can be formulated to route the data in an efficient manner.

.In order to reduce overhead and power consumption, location information is also vital for WSN routing decisions. Furthermore, location data can help with event coverage optimization by finding uncovered areas and deploying sensors to such locations [12, 13]. When the sensors are hand-placed, the position of each sensor node can be manually introduced; however, when the number of sensors is enormous, this becomes a tiresome and error-prone technique of localization. The sensor nodes when connected or fixed with a Global Positioning System (GPS) is capable of receiving the position information with an increased cost. Furthermore, GPS systems do not work indoors, hence GPS cannot be used indoors. If proceeded with the only less sensors fixed with the GPS and if we are capable of measuring the positions of the other nodes using them with the help of localization algorithms it is economical. Some of the nodes are termed as Anchor nodes. These nodes have the GPS fitted with them and are capable of providing their x,y coordinates pertaining to location

.

In this research work, two methodologies that are in need of less number of anchor nodes are used. All that is required of the anchor nodes is that they broadcast beacon messages when required. Iterative localization requires only one communication with each unknown node's adjacent anchors. The first method, RMCL (Received Signal Strength based Modified Centroid Localization), is capable of avoiding the boundaries of GPS. RMCL is capable of identifying the nodes position using the two step positioning methodology. The methodology is carried in TWO phases. The two-step positioning method has reduced complexity levels when compared with the other methods. As the first phase, the received signal strength (RSS), one of the parameters used to monitor the signal strength, is evaluated. The node location of the target is approximated using the signal parameter. OAs and when the node's position is identified, it can be used to calculate the unknown nodes locations. This method repeats until as many nodes as feasible are estimated. The location of unknown sensor nodes is identified using the Glowworm spam optimization (GSO) algorithm, and particle swarm optimization algorithm (PSO)

2 RELATED WORK

Node-to-node lengths, angles, or received signal strength [14, 15, 16, and 17] can be used to determine the location. The challenge in the range-based localization system is acquiring the range information between sensor nodes. The most difficult aspect of range-based localization systems is obtaining range information between sensor nodes. These methods utilize additional hardware and contains incorrect range data. Even if they offer better location accuracy, the number of components needed to calculate distances and angles grows. The range information is no longer a necessity [18, 19, 20, and 21]. This approach is preferred for its uncomplicated hardware and lower power consumption even though it has inferior localization. The sensor node's location is estimated with the aid of range information. They pose an additional hardware requirement. Time of Arrival (ToA) is the very basic methodology. This paper focusses on sensor positioning using TOA information. The algorithm albeit being straightforward requires a large number of anchors. The utilization of HEAP improves localization accuracy. However, the increase in number of anchors results in increased data dissemination and in the requirement of incremental beacon deployment. The point of intersection of medians from the triangles within which the sensor node lies is inferred as its location. Since there is an absence of anchors, the information regarding the distance between the nodes is relayed to the neighbor nodes. This is accomplished by sending out beacon messages. The Bat Algorithm, a new Meta heuristic technique based on bat echolocation behavior A popular Meta heuristic known as Particle swarm optimization, or PSO, employs the hybrid optimization technique. Hybridization involves combining two or more approaches and as a result the final algorithm inherits the best aspects of all the approaches involved. In glow-worm swarm optimization (GSO). In this approach, each sensor node is viewed as an individual glow-worm and each glow-worm is assumed to emit a luminant substance known as luciferin. Each sensor moves toward that neighbor with lower luciferin intensity. The spread of the sensing field is thus augmented as the sensor nodes gravitate toward areas with reduced sensor density. Avneet Kaur and Mandeep Kaur [22] employed a Particle swarm optimization (PSO) based approach. The researchers proposed that the disadvantage of a local minima can be circumvented by changing the threshold value.

3 PROPOSED WORK

3.1 RSSI based Modified Centroid Localized (RMCL) Algorithm

The nodes in the environment are scattered over a 2-dimensional monitored area. The environment where the sensor nodes are available consists of a total of ‘n’ nodes comprising of ‘u’ unknown nodes and ‘a’ anchor nodes, where (a<<u). The scattered nodes in the environment is shown in figure 1. Anchor nodes are fitted with a GPS which specifies the coordinates (xi, yi).

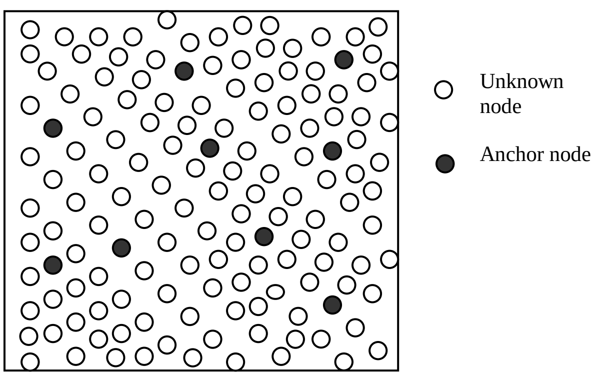


Fig 1: Node Distribution in Sensor Network

The environment where the sensor nodes are available consists of a total of ‘n’ nodes comprising of ‘u’ unknown nodes and ‘a’ anchor nodes, where (a<<u). The scattered nodes in the environment is shown in figure 1. Anchor nodes are equipped with more efficient hardware and a localization system with known coordinates (xi, yi).

3.1.1 Localization

Localization can be executed with minimal impact and at the same time no compromise on the size and shape of the node is required. The position estimation schemes which is taken into consideration is the *two-step positioning* process, which extracts signal parameters, and then estimates the position. The signal parameter Received Signal Strength (RSS) is estimated to start with and is proceeded with the estimation of location based on the functioning of the two-step positioning algorithm.

As and when the anchor nodes release the beacon messages, it is received by the other available nodes in the environment. High transmission power is utilized by the anchor nodes to send the beacon messages so as to reach all the nodes in the environment. The unknown nodes as and when they receive the beacon messages measure the strength of the beacon signal for location estimation. The beacon messages are transmitted by the nodes with GPS containing their IDs, their location and a hop count, initially set to zero, since this message is not intended for a specific sensor node, it is broadcast. The format of beacon message is shown in figure 2.

AID	X coordinate	Y coordinate	HopCount

Fig 2: Format of the beacon message

Each unknown node listens for a fixed time period, receives the beacon message and collects the RSSI information of all the beacon messages, and identifies the three "closest" anchor nodes by looking for the largest RSSI value. The distances between the anchor nodes and the unknown nodes are determined using two methods (a) RSSI based distance measurement and (b) centroid determination. Both methods provide valid distance information between unknown sensor node and the anchor node.

3.1.2 Position Estimation

Multipath fading properties are barred as the RSS signals. Based on the above the average received power $\overline{P}(d)$ is calculated as specified in equation. (1). Average received power is measured in dB with a distance *d*.

$$\overline{P}(d) = P_o - 10n\log_{10}(d / d_o) \tag{1}$$

The received power is indicated as P_o. The received power is also measured in dB with the distance specified as d_o. The path loss exponent is indicated as ‘n’. In order to alleviate the effects due to the shadowing property the observation interval is kept short. The, the received power *P*(*d*) in dB can be expressed as

$$P_d \sim N(\overline{P}(d), \sigma_{sh}^2) \tag{2}$$

where $\overline{P}(d)$ is as given in equation (1). From the received power model in equation (2), the Cramer-Rao lower bound (CRLB) for unbiased distance estimators is expressed as:

$$\sqrt{Var\left\{\hat{d}\right\}} \geq \frac{\ln(10)\sigma_{sh} d}{10n} \tag{3}$$

where $\hat{d}$ represents an unbiased estimate for the distance *d*. Thus the distance is estimated using the above equations.

3.1.3 Modified Centroid Localization algorithm

In the modified centroid based distance estimation, each unknown node collects the RSSI information of all the beacon messages, all the signal strengths are assessed and the co ordinates of the anchor nodes with highest received signal strength are identified. Position estimation is performed using these messages through the following procedure.

- In the environment the nodes that are used for sensing is placed and a threshold value for the received signal strength is identified and is fixed in the sensor nodes.
- A beacon message is broadcast to unknown sensor nodes from the anchor nodes.
- Each sensor node measures RSSI value at the time it receives the packet. Selects the anchor nodes whose RSSI values are the highest.
- The weight estimation is carried over by the nodes, if there nodes have at least 3 or more beacon messages that has been transmitted by the anchor nodes
- Weights are assigned to the RSSI values based on the preset threshold value.
- The distance is estimated using the centroid formula.

The centroid formula is modified by adding weights to the coordinates. The weights will vary according to the change in their signal strengths. The weight *w is* a function depending on the RSSI measurement and the characteristics of the unknown sensor node's receiver. Every application scenario requires a different weight due to changed environment conditions.

Table 1 : Mapping of the received signal strength to the weights

S.No	al Strength P[dB	SI Level	Weights
	-113	0	1
	< *PR* < -108	1	2
	< *PR* < -103	2	3
	< *PR* < -98	3	4
	PR < -93	4	5
	PR < -88	5	6
	PR < -83	6	7
	PR < -78	7	8
	PR < -73	8	9
	PR < -68	9	10
	PR	10	11

$$P_{dbm} = -50xVoltage_{battery}x\frac{RSSI_{raw}}{1024-45.5}$$

(4)

Table 1 shows how RSSI levels are mapped from the received signal strength, based on the value of RSSI level the weights are assigned. Ten RSSI levels are used for simulation.

(X_1, Y_1) (X_2, Y_2),….,(X_n, Y_n) are the positions of the nodes with GPS. Nodes that o not know their location calculate the position using the beacon messages transmitted by the anchor nodes. In the centroid formulae the value of 'i' varies from 1,2,3,….N. The number of neighboring anchor nodes available are indicated as N available. :

$$X_{est}, Y_{est} = \left(\frac{w_1.x_1 + w_2.x_2 + w_3.x_3}{\sum w_i}, \frac{w_1.y_1 + w_2.y_2 + w_3.y_3}{\sum w_i}\right)$$

(5)

Figure 3 shows a simple example of modified centroid method using three anchor nodes.

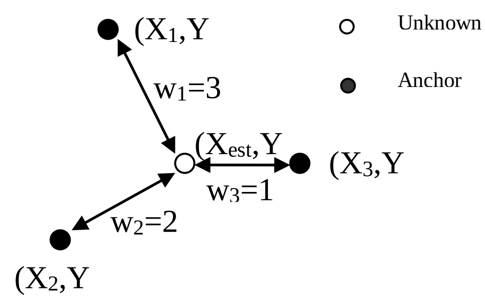


Fig 3: Simple example of modified weighted centroid method

3.1.4 Computation of localization error:

The accuracy of estimation is characterized by localization error E_L. Let (X_{est}, Y_{est}) be the estimated coordinates of the node from equation (5), and (X_i, Y_i) be its real coordinates. The

Localization error, E_L is calculated using the equations (6) and (7)

$$E_L = \left|(X_{est}, Y_{est}) - (X_i, Y_i)\right| \quad (6)$$

$$E_L = \sqrt{(X_{est} - X_i)^2 + (Y_{est} - Y_i)^2} \quad (7)$$

3.2. METAHEURISTIC ALGORITHM

3.2.1 Glowworm Spam Optimization Algorithm

GSO algorithm is commonly used for function optimization problems.

The function optimization using GSO algorithm is described in figure 4 requires the following seven steps:

1: All the required values are assumed for t
us parameters.
2: Place a population of *n* glowworms
omly
3: The variable $l_i(t)$ indicates the levels of
erin linked with the glowworm 'i' with
ds to time 't'.
bjective function identified by $J(x_i(t))$ is
ined with the luciferin level and is represen

$$l_i(t) = (1-\rho)l_i(t-1) + \gamma J(x_i(t))$$

lecay value of luciferin indicated by ρ varie
een 0 and 1. The enhancement level of
erin is indicated as γ.
4: The neighbour of the glowworm is
ted based on the value of luciferin. Whenev
alue of luciferin is higher than its own valu
f it lies within the variable neighbourhood
r the neighbour is selected.

5: Calculate the probability that each
worm *i* move toward a neighbour *j*. $N_i(t)$ is
r in which d is the Euclidean distance
een glowworm i and j at time t.

$$p_{ij}(t) = \frac{i_j(t) - l_i(t)}{\sum_{k \in N_i(t)} l_k(t) - l_i(t)}$$

6: Glowworm *i* using the roulette method
ts a neighbour *j* and moves toward it. Updat
cation of the glowworm *i*. S represents step
nd || || is the Euclidean norm operator

$$x_i(t+1) = x_i(t) + s * \left\{\frac{x_j(t) - x_i(t)}{\|x_j(t) - x_i(t)\|}\right\}$$

7: Update the value of the variable in
bourhood range.

$$r_d^i(t+1) = min\left\{r_s\ max\{0, r_d^i(t) + \beta(n_t - |N_i(t)|)\}\right\}$$

umber of the nodes within the vicinity is
ated as n_t and a constant value s indicated w

Fig 4. Glowworm Spam Optimization Algorithm

3.2.2 Particle Spam Optimization Algorithm

One of the most important techniques is PSO . based on the available velocity a new velocity is identified every time based on the distance from the global best position as shown in figure 5. The value of the next pixel for the movement of the particle is identified using the velocity. The same methodology is carried out continuously until the value of the error is below the admissible value

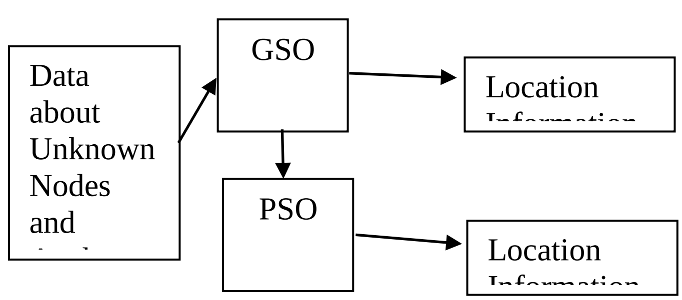


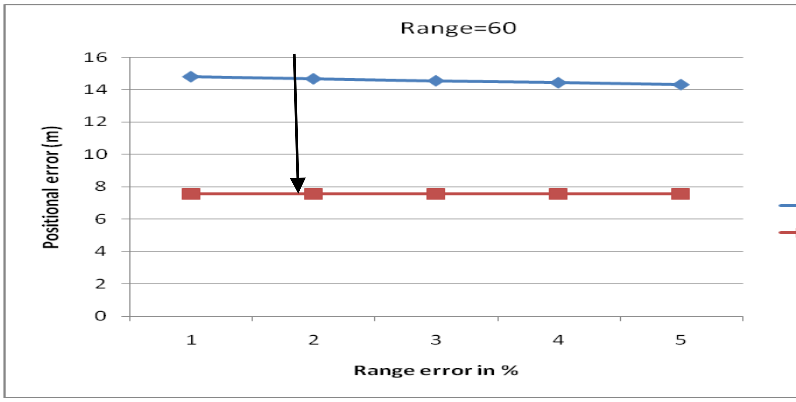
Fig 5. Methodology

4 PERFORMANCE ANALYSIS

A custom simulator has been developed using the Matlab software in order to verify the proposed approach. Based on the results of the simulations of the two algorithms for a scattered deployment of 300 nodes, in an environmental area of about 200m x200m, the accuracy of the estimation of the nodes position is increasing. The selection of anchor nodes are done in a rotational manner in a uniform fashion. The selected anchor nodes generate the x and y coordinates to indicate their position. The error in the location of the nodes is calculated as the difference in distance between the calculated positional value and the original positional value. Using the value of the location error, the accuracy of the algorithm is identified. The location error is inversely proportional to the estimation accuracy. In the sensor networks the range of the nodes should be larger because they will be distributed in large area. For large areas RSSI based Modified Centroid Localization (RMCL) algorithm gives a better result than the existing RDV hop method

4.1 Range Error

4.1.1 Range Of Nodes Is 60m and 50m, Varying the Range Error



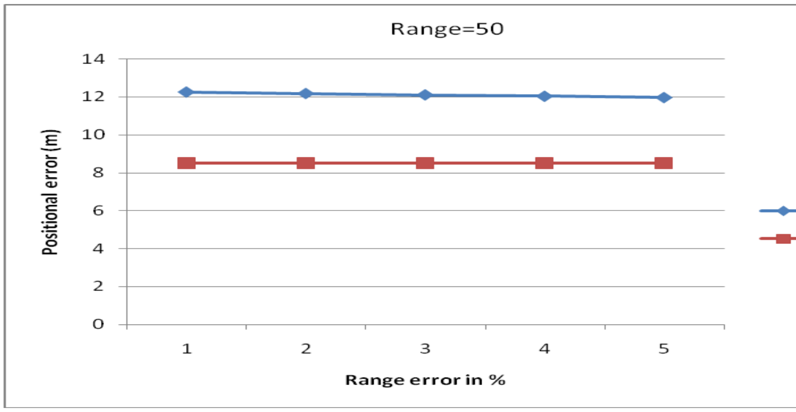


Fig 6 : Positional error for radio range of 60 and 50 m

Here, the error in the RMCL method is constant because the range is large and due to this, most of the unknown nodes come in coverage of the anchor nodes in the first iteration itself. This reduces the error propagation in the forth coming iterations. But in the case of RDV hop method as the range is large the approximation causes more error. In the practical conditions the range of the nodes are comparable with the total area of the network. So this makes the range of 60m to be acceptable. With this range RMCL is more appropriate for approximating the locations of the unknown nodes. This is similar to that of the range 60m. The RDV hop method doesn't have any improvement in the error. But in the case of the RMCL method there is decrease in the performance,this is because there are more number of nodes to be estimated in the consecutive iterations where the approximation error propagates.

4.1.2 Range Of Nodes Is 40m Varying the Range Error

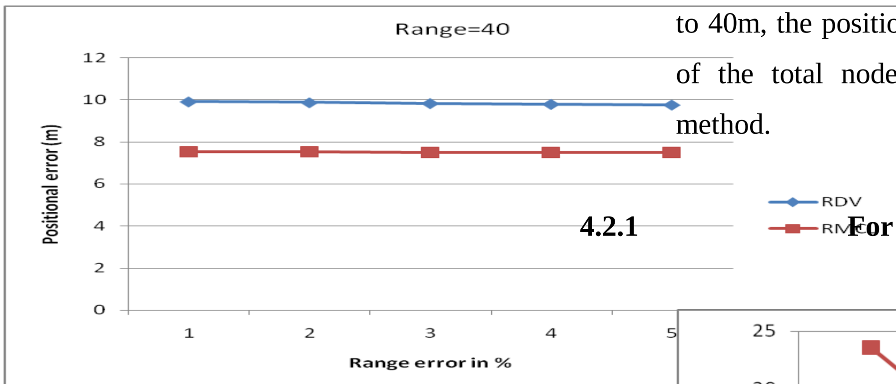


Fig 7 : Positional error for radio range of 40m

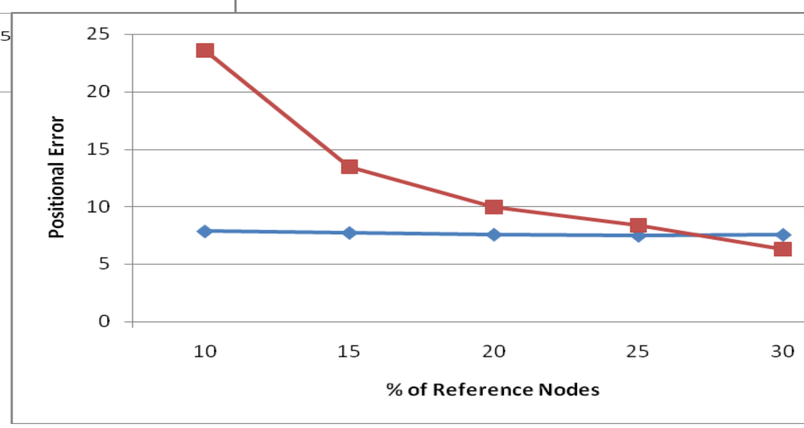
With the range as 40m there is improvement in the both methods. As the range is reduced the error in the RDV method is reduced. In the case of RMCL the error propagation is reduced due to the pattern in which the nodes are distributed.

4.2 ANALYSIS OF RMCL BY VARYING THE PROPORTION OF ANCHOR NODES

The initial conditions assumed for the above simulation is with a total node density of 300 nodes deployed in a area 200m x 200m. The range error is fixed to be 5% and the simulations are executed to find the positional error.

Even when the amount of anchor nodes is increased there is no improvement in the RDV hop method. But in the case of RMCL method when the amount of anchor nodes is varied there is improvement in the positional error. The error is maximum for the 10% of anchor nodes for a range of 30m; this is because more number of iterations is required to approximate the co- ordinates of the nodes in the entire network. In this case as the range is increased to 40m, the positional error gets reduced after 15% of the total nodes are anchor nodes in RMCL method.

4.2.1 For range = 30m and 40m



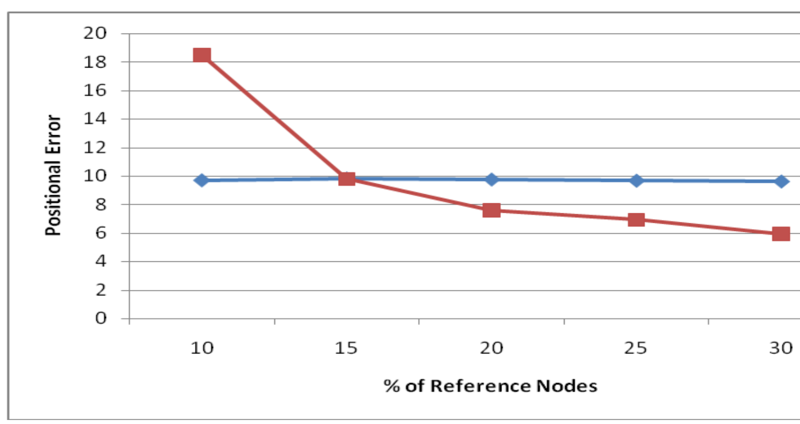


Fig 8 : Location error vs anchor nodes for ranges 30m and 40m

4.2.2 For range=50m and 60m

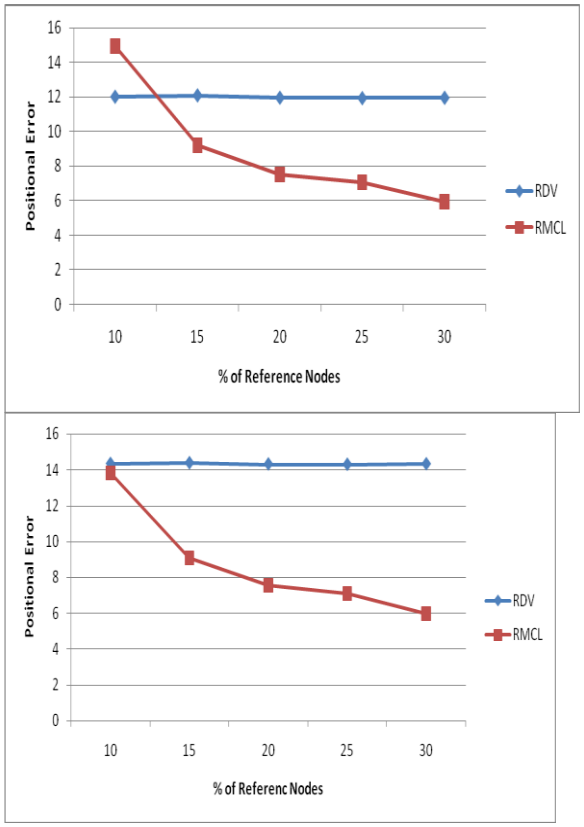


Fig 9 : Location error vs anchor nodes for ranges 50m and 60m

As the range is more the error in the RDV hop method is more. But in the case of RMCL method it is reversed. As range increases the error gets reduced in the RMCL method. By further increasing the percentage of the anchor nodes the positional error gets reduced rapidly. For range of 60m the positional error is always less in the RMCL method. By further increasing the proportion of the anchor nodes the positional error gets reduced rapidly.

4.3 ANALYSIS OF RMCL BY VARYING THE RANGE BY KEEPING THE PROPORTION OF ANCHOR NODES CONSTANT:

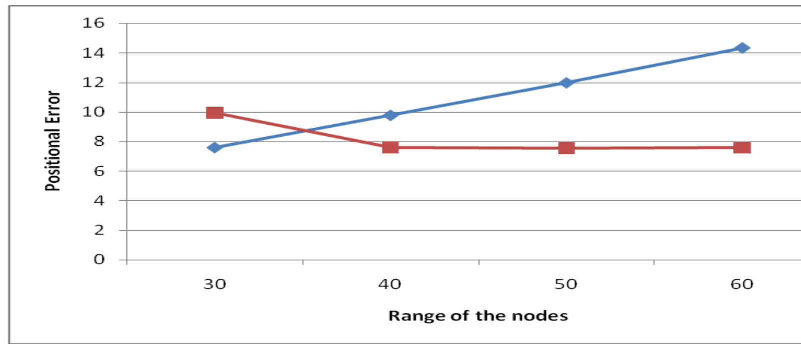


Fig 10 : Range of nodes Vs Positional error

For 20% of the nodes are anchor nodes then by varying the range of the nodes the positional error becomes constant. This is because the approximation error in the modified centroid formula cannot be reduced beyond certain limit. So the graph of the RMCL is constant above range 40m. But in the case of RDV hop method as the range increases the error is also increased. This show that the RMCL method is more effective for practical ranges and for more proportion of the total nodes is anchor nodes.

5. CONCLUSION:

Thus the results and analysis clearly shows that the RMCL algorithm outperforms RDV Hop algorithm in estimation accuracy of the co-ordinates. The RMCL method is also more efficient than most of the currently available localization algorithms. Position error is greatly reduced when more anchor nodes are deployed initially. The position error can also be reduced when the anchor nodes have a larger range. On contrary the error in RDV Hop algorithm is very less when the range of the node is less. But in practical scenario during initial deployment of nodes the range of all the nodes are always high. Thus practically RMCL algorithm scores over RDV hop algorithm. In RMCL algorithm, the position error when compared to RDV hop algorithm gets reduced by 31% for 16% anchor node density in the total nodes deployed for a specified coverage distance.

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