RSS based Localization of Sensor Nodes by Learning Movement Model

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Abstract: - Node Localization in Wireless Sensor Networks (WSNs) is widely used in many applications. Localization uses particle filter that provides higher network traffic due to continuous updates, which leads to high power consumption. The article presents a range-based localization for Mobile Nodes (MN) that builds up on Hidden Markov Model (HMM) algorithm. The proposed work is based on MN and the state is hidden in the Received Signal Strength (RSS) for outdoor applications. Hidden states uses explicit knowledge of the observation probability obtained from two-ray ground propagation model. HMM correlates these observations to predict the hidden states. The state transition and the observation of HMM help to estimate the most probable state sequence and the last state obtained is the predicted location. This work uses various mobility models for the movement of nodes. Varying the transmission range effectively controls the network connectivity. Results from simulation study have revealed the possible reduction of network traffic and power consumption with less estimation error. In addition, this work provides an efficient confidence interval for the estimation error.

Key-Words: - Estimation Error, Hidden Markov Model, Localization, Mobile Nodes, Received Signal Strength, State Estimation, Wireless Sensor Networks.

1 Introduction

Sensor networks are significantly different from traditional ad hoc networks. In general, sensor nodes are densely deployed, prone to failures and limited in power provision, computational complexity and memory when compared to ad hoc nodes. While most ad hoc networks communicate on a point-to-point basis, sensor nodes mainly use a broadcast communication paradigm [1]. In particular, location-based applications of WSNs are employed for locating people and tracking mobile objects in large buildings (e.g., warehouses, hospitals) using GPS. However, very few studies have indicated the use of WSN in outdoor environments to track people in wide outdoor areas, such as enemies in the battlefield.

The geographic location of nodes in a sensor network is determined for many features of system operation such as data stamping, tracking, signal processing, querying, topology control, clustering, and routing [2]. The selection of a suitable algorithm for a given application and its performance depends on several key factors such as the information available about known locations, difficulty in locating a cooperative node, the dynamics of change of location, the desired accuracy, and the constraints placed on hardware.

The estimated position of each MN (non-anchor node) can be computed by communicating with the static node (anchor node). The position of the node is obtained using only radio signals (RSS, an index of the received signal power). In reality, the nodes of the static network should be power-efficient when they are battery-operated, healthy to packet drop, easy to track in actual time, and finally, it should tolerate suitable localization accuracy even in the case of some static node failure.

The particle filter [3] solves the outdoor localization problem that incorporates multiple sensory data using both static and mobile multihop network. The node moves with random velocity attracts normal distribution and noise model are the particle filter assumptions to compare the results from RSS and Angle of Arrival (AOA, an estimate of the relative angles between nodes) sensor types. The simulation study and analysis reveal that an AOA sensor does not work when the network connectivity is low. The network containing 50 % of AOA and RSS sensors than the network dominated by individual-type sensors achieves better localization. Continuous updating at sufficient frequency to keep up with the node movement results in network traffic that consumes high power; this is a constraint in particle filter.

The current study proposes a network-based localization system, which is modeled as HMM, and the unobserved (hidden) state sequence in the RSS has been used to estimate MN location. The hidden markov state uses RSS and the MN location sequence to estimates the most likelihood probability and the last state attained is the estimated location. The original contributions provided in this paper are the capability to model and handle the range-based RSS through two-ray ground propagation [4], node movement follows the random pattern of mobility model such as Random Walk Model (RWM), Random Waypoint Model (RWP), and Reference Point Group Mobility model (RPGM) [5] perceives less estimation error. The proposed model emphasizes on outdoor localization using HMM and the MN location is estimated using the observation probability, which helps to minimize the traffic that consumes less power for the localization process.

The rest of the paper is organized as follows: section 2 summarizes the Existing localization methods and Motivation; the proposed model for localization is given in section 3, and the performance evaluation is discussed in section 4. Section 5 concludes the paper and discusses on the future work.

2 Existing Localization Methods and Motivation

Sequential Monte Carlo Localization (SMCL) is suitable for sensor networks, but it needs to address how the mobility model affects the localization accuracy [6]. In Improved MCL (IMCL), anchor constraint, neighbour constraint and moving direction constraint are proposed [7] to confine the region of the valid samples near the actual position of the normal nodes to improve the localization accuracy. Improving MCL uses Genetic Algorithm, which reduces the precision of the localization accuracy [8].

In the case of indoor localization, Bayesian Filtering [9] has used RSS to estimate the location on sample sets derived by Monte Carlo Sampling. The static path-planning problem of mobile beacon to localize sensors for uniformly deployed network approach is considered in [10]. The localization procedure needs to adjust the path for dynamic path planning. The approach for localization by using single mobile beacon is dealt [11], but inter-sensor localization methods can be used after the mobile beacon exits the deployment area. A Fade-skew-level Laplace signal strength statistical model applying particle filter is used to estimate the location [12] of moving and stationary people for wireless networks. RSS based sensor localization using unscented Transformation is dealt [13] for both cooperative and non-cooperative scenarios.

Incorporating multiple sensory data in both static and mobile multihop networks solves the localization problem using particle filter [3]. The limitations are that the continuous updating of the filter increases network traffic and high power consumption. The model could be improved by learning movement pattern (HMM) for mobile networks.

HMM is used in speech recognition [14], and directs the technique to be applied to more advanced speech recognition problems. For indoor environment, HMM method improves the accuracy of localization [15] with respect to conventional ranging methods, especially in mixed LOS/NLOS conditions for all radio links. HMM is used as a cascade model [16] for finding correlations among sensory inputs to learn a set of symbolic concepts for mobile robot. Multiuser decision feedback [17] uses HMM in which a linear filter based on the maximum target likelihood criterion is derived to remove the interferences. The Bayes Particle filter framework was compared with Hidden Markov Model [18] using Semi Markov smooth mobility model and it is seen that the localization accuracy was improved for HMM.

Though various techniques have been proposed for localization, HMMs are the learning movement models that incorporate a notion of time directly into the model through an underlying markov chain. The HMM is proposed to locate the nodes by improving the location accuracy using various mobility models for the node movement.

2.1 Motivation

WSN localization targets to find the physical location of all nodes deployed in the region. The objective of the localization algorithm is to find the location of non-anchor nodes with the help of anchor nodes.

Particle filtering is a technique for executing recursive Bayesian filtering by Monte Carlo sampling. Particle filters allow Bayesian estimation to be carried out approximately in a structured and iterative manner. The estimated position on the nodes is represented by a probability distribution. Bayes Particle filtering framework can be used for both static and mobile nodes in sensor network localization [3]. The node movement drawn from random velocity follows normal distribution where RSSI uses free-space propagation model and the measured AOA is affected by the noise model. The particle filters are updated continuously at sufficient frequency leading to increase in network traffic and high power consumption.

This framework addresses the localization for mixed type of sensory capacities, rather than permitting individual RSSI or AOA sensor type. As recommended, this model could be improved by learning the movement patterns (models) for mobile networks. By using RSS sensor type in HMM, the location is estimated using the state sequence hidden in the signal strength based on the observation probability.

3 Proposed Model for Localization

WSN localization is a basic need for many applications. Node localization could involve tracking a single node moving across the plane or trying to identify the location of a fixed node. The proposed model assumes that the anchor nodes are static while the non-anchor nodes are moving dynamically over the network. The goal is to estimate the locations of the MN with the help of HMM and the following sections discusses about this method.

3.1 Gathering RSS values of non-anchor nodes

Limited number of anchor nodes use RSS capacity to achieve node localization. To predict the received signal power of each MN node, node localization uses two-ray-ground propagation model. With the support of anchor node, the RSS of the MN is collected with the nodeID. Because of the continuous movement of the node, the non-anchor node has many RSS values.

3.2 Location Estimation Using HMM

The proposed method locates the randomly scattered non-anchor nodes (MN) in the outdoor environment with the help of anchor nodes. The area of grid cell size n × n for node movement follows the pattern of mobility models to move from one grid to another. The server or base station estimates the location of non-anchor nodes. To estimate HMM parameters, each state represents a location in the discrete physical observation and an observation from a state represents an RSS reading from associated non-anchor node [19]. During the operational stage, RSS interpretation from each non-anchor node and the HMM parameters are the necessary input to estimate the most probable sequence of states that results in the estimated location.

3.2.1 Estimation of Probability Matrix in HMM

HMMs extend markov models by assuming that the states of the markov chain are not observed directly. Hence, this model shows how the states (positions) relate to the actual observations (localizations). HMM can be used for localization process because it can model sequential stochastic processes or states, where probability of a state depends on previous states.

An HMM can be represented as λ = (R,S,A,B,π) where:

R = {R1,R2,R3,…,RN} is the set of possible states,each state represents a grid location in the physical space.

S = {S1,S2,S3,…,SM} is the set of observations from the model,each observation is an ordered pair of (non-anchor nodeID,RSS).

A = {aij} is the state transition probability matrix,where aij = P[qt+1 = Sj|qt=Si],1≤ i, j ≤ N and qt is the state at time t.

B = {bj(k)}is the observation symbol probability distribution in state j, where bj(k) = P[Sk at t|qt =Rj], 1≤ j≤ N, 1≤ k ≤ M and Sk are the output symbols at time t.

π = { π i} is the initial distribution, where π i = P[q1 = Ri].

Therefore, the problem in brief: With a given sequence of observations O = (O1,…,OT), where T is a system parameter and each Oi ∈ S, 1 ≤ i ≤ T, the most probable sequence of location (states) Q = (q1,…,qt), where each qi ∈ R, 1 ≤ i ≤ T must be found.

The purpose is to build the HMM and estimate its parameters for the localization. The state transition matrix is obtained by the random node movement either in forward, backward, upward or downward direction and each state represents a location in the grid. The node existence is identified by its transition probability of signal strength. The transition sequence length parameter is assumed to be 'N'. The transition probability matrix is denoted by An for the nth node and it is of the form

$$A_n = \begin{pmatrix} a_{11}^{(n)} & a_{12}^{(n)} & .. & a_{1N}^{(n)} \\ a_{21}^{(n)} & a_{22}^{(n)} & .. & a_{2N}^{(n)} \\ . & . & . & . \\ a_{N1}^{(n)} & a_{N2}^{(n)} & .. & a_{NN}^{(n)} \end{pmatrix} \quad (1)$$

Further, the observation matrix (B) is attained by the location of anchor node to estimate the observation probability inside the cell. The anchor nodes direct the beacon messages and based on the response of RSS of the MN, B can be obtained. The observation sequence length parameter is assumed to be 'M'. The observation probability matrix is denoted by Bn for the nth node and it is shown in (2)

$$B_n = \begin{pmatrix} b_{11}^{(n)} & b_{12}^{(n)} & .. & b_{1M}^{(n)} \\ b_{21}^{(n)} & b_{22}^{(n)} & .. & b_{2M}^{(n)} \\ . & . & . & . \\ b_{N1}^{(n)} & b_{N2}^{(n)} & .. & b_{NM}^{(n)} \end{pmatrix} \quad (2)$$

Algorithm 1 is developed for iteratively computing B_n.

Algorithm 1 Observation matrix

- *Input: Set the location of the transmitter co-ordinate T_x, T_y for each anchor node in the grid cell.*
- *Output: Generate the observation probability matrix for each non-anchor node from the known anchor node location coordinates in the grid cell.*

1. *Declare the variables for the states as i, j, k=1.*
2. *Set the constants G_t, G_r, h_t, h_r, P_t, π, λ*
3. *Initialize an array of grid cell size NxM for the observation matrix B[i][j]*
4. *begin*
5. *Divide the grid into smaller cells to observe the movement of nodes*
6. *for i varying from 1 to N sequence length do*
7. *for j varying from 1 to M sequence length do*
8. *for (R_Y = (i-1)*100; R_Y < i * 100; R_Y = R_Y +0.1) i.e., receiver Y co-ordinate do*
9. *for (R_X = (j-1)*100; R_X < j * 100; R_X = R_X + 0.1) i.e., receiver X co-ordinate do*
10. *Compute the distance d = sqrt ((R_X - T_X) * (R_X - T_X) + (R_Y - T_Y) * (R_Y - T_Y));*
11. *Compute crossover_dist = (4 * π * h_t * h_r) / λ;*
12. *if (d <= crossover_dist),then*
13. *J = λ / (4 * π * d);*
14. *P_r = (P_t * G_t * G_r * (J * J)) / L;*
15. *else*
16. *P_r = P_t * G_t * G_r * (h_r * h_r * h_t * h_t) / (d * d * d * d * L);*
17. *endif*
18. *rssi = 10*log 10(P_r);*
19. *rs = (int) rssi ;*
20. *B[k] [rs] + = 1;*
21. *end for*
22. *end for*
23. *Increment k by 1;*
24. *end for*
25. *end for*
26. *Find sum of each row in observation matrix*
27. *Divide each element in observation matrix with its respective sum*
28. *Generate the observation probability matrix B[i][j]*

Once these factors are clearly understood, the system is ready to find the location estimate of the non-anchor node.

3.2.2 Evaluating the Sequence using Forward-Backward Algorithm

The main approach is to estimate the location of the MN using RSS values. The observation sequence $O = (O_1, O_2, \dots, O_t)$ is considered to find the location where the non-anchor node exists at the end of the state sequence. The sequence evaluation is obtained by the probability of the observation O, given the model λ, i.e. to find $P = (O/\lambda)$.The forward or backward algorithm is used to evaluate the sequence for location estimate [14].

The forward probability calculation is based on the grid cell, considering there are only N states (node location at each time in the grid), all possible state sequences will merge into those node locations, no matter how long the observation sequence. The initial forward variable is defined as $\alpha_t(i) = P(O_1, O_2, \dots, O_t, q_t = i|\lambda)$ where $\alpha_t(i)$ is the probability of observing the partial sequence $(O_1, O_2, \dots, O_t)$ such that the state q_t is i. At times, there is a need to calculate values of forward variable, where each calculation involves only N previous values. The effect in forward and backward procedures is almost identical. The result P (O/λ) is mainly used for training the model.

3.2.3 Estimating the sequence using Viterbi Algorithm

Given the observation O, the most likely state sequence is obtained using the decoding problem by Viterbi algorithm [14]. This algorithm involves initialization, recursion and termination. The Viterbi algorithm creates a better trajectory than the traditional algorithm because it decides the real state that depends on all states and the final one is the most likelihood state. The observation sequence will keep on varying based on the known anchor node location. The focus is to compute the most probable state sequence $Q = (q_1, q_2, \dots, q_t)$, hence the Viterbi decoding algorithm is used to find the state sequence with the help of observation probability. The state sequence for each node is found and the last state estimated, i.e. qt is returned as the estimated user location. By increasing the observation sequence length that adds more states, the location estimation attains high accuracy. As the localization process proceeds, each non-anchor node location is estimated and converges faster to a more concentrated location estimate.

The HMM Model uses the location information from the anchors, which is implicitly contained in the observed state sequence estimation for each unknown non-anchor node. The advantage of our model is that it uses the sequence of states to find the estimate location that does not require continuous sampling and updates as required by the particle filter framework.

4 Performance Evaluation

The performance of Bayes Particle Filter and proposed HMM model with RWM, RWP and RPGM model have been evaluated using NS2 simulation. Location estimation error, Control overhead and Average energy dissipation are considered [20] as the key metric for evaluating localization schemes.

(i) Location Estimation Error: It is the average distance between estimated location and actual location of all sensor nodes. The location error is scaled as the percentage of transmission range.

(ii) Control Overhead: It is the total number of control packets transmitted by the anchors to localize an unknown node in each localization process.

(iii) Average Energy Dissipation: It is the average amount of energy spent by a sensor node during communication in the network.

Table 1: Simulation Parameters

Simulation area	1000m X 1000m
Antenna Type	Omni Directional
Propagation Model	Two-ray ground
Traffic Type	CBR
Speed	2 – 10 m/sec
Initial Energy	5.1 J
Packet size	512 bytes
Pause Time	5 sec
Mobility Model	RWM, RWP, RPGM

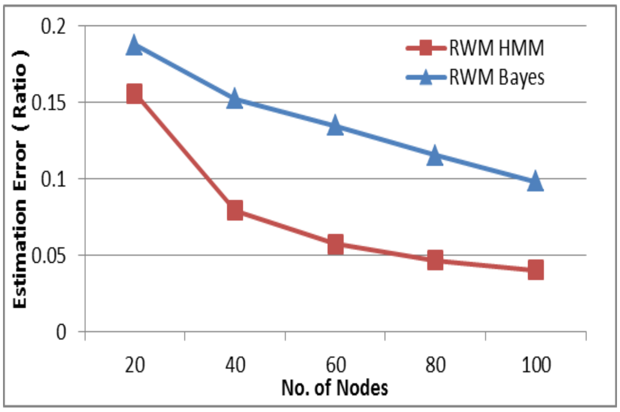
Table 1 shows the simulation parameters. The performance metrics are analysed for validating the algorithm by varying the node density, transmission range and speed. 10% of the total nodes are assumed as anchor nodes [3] and the network area is deployed with 100 nodes. The particle filter has total number of 200 particles at each node. The transmission range is set to 150m that leads to a coverage of 100%. The transition sequence length parameter N is fixed at 100 and the observation sequence length parameter M is fixed at 119.

4.1 Simulation Results and Analysis

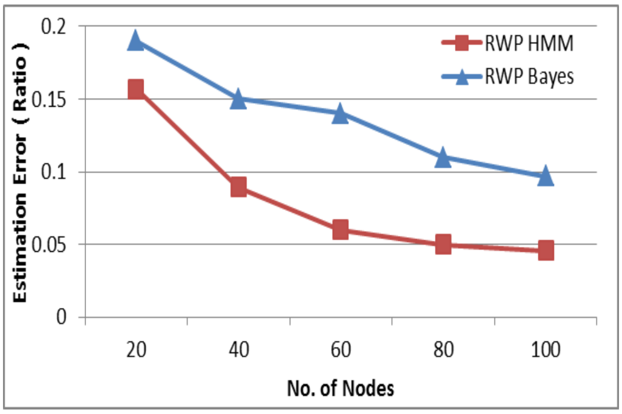
The simulation results for the proposed HMM are analyzed to study the effect of node variation, varying transmission ranges for connectivity and various speeds.

4.1.1 Effect of varying the number of nodes

The evaluations on estimation error or localization accuracy over number of nodes are analyzed for the proposed method. Increase in the number of nodes improves the localization accuracy for different mobility models as shown in Fig 1 (a)–(c).

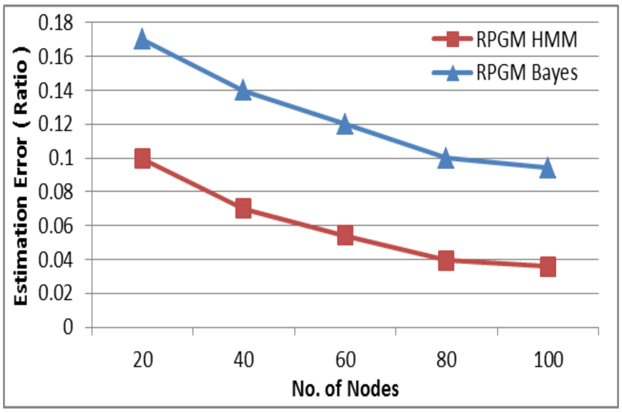


(a)



(b)

As expected, higher node density lowers the estimation error. The error estimate of HMM RPGM proves to be better because each node moves near the other as a group with almost similar speed and direction.

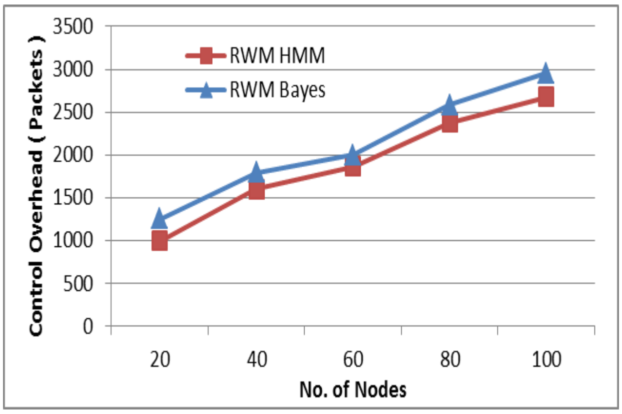


(c)

Fig 1: Impact of Node density on Estimation Error (a) RWM (b) RWP (c) RPGM

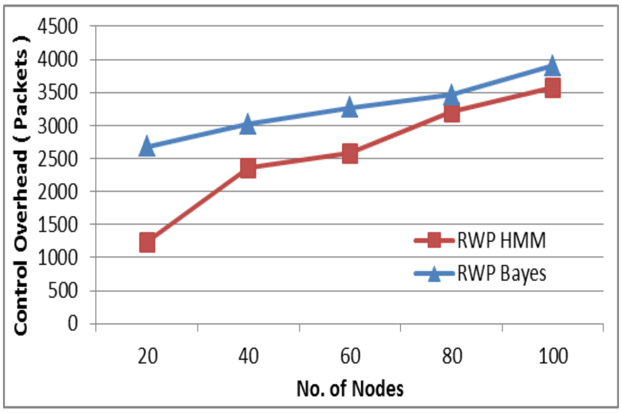
However, in comparison with other mobility models, it has lowest relative speed because each node in a group chooses a random speed and direction according to the group leader. This specifies that for the proposed work, nodes with RSS tend to adapt mobility and converge faster when compared with particle filter.

The performance of control overhead over node density is shown in Fig 2 (a)–(c). The anchor node transmits a packet within its range to gather information from the neighbouring node that increases control overhead. Non-anchor nodes overhearing this packet reply their known information to anchor node.



(a)

The simulation endorses that HMM takes 10% less compared to existing method because of the state sequence rather than continuous updating of filters.



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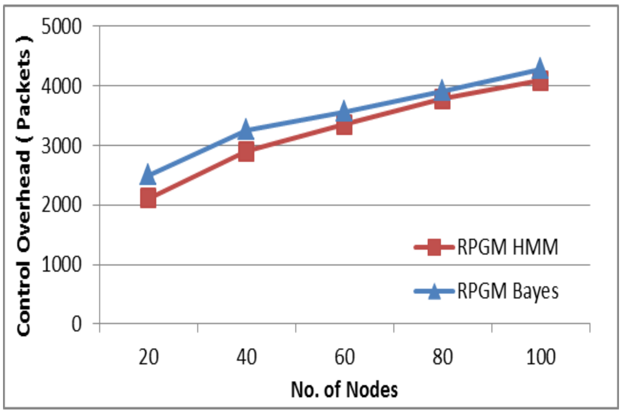


(c)

Fig 2: Impact of Node density on Control Overhead (a) RWM (b) RWP (c) RPGM

Overall, the mobility model behaves as per the functionality of the model, taking more overhead increases nodes density.

The effectiveness of average energy dissipated with respect to total number of nodes is shown in Fig 3 (a)–(c). The average energy spent when in movement is more, but actual energy spent in localization process is less. This shows that energy consumption varies due to increase in the node density. It is observed that for different mobility model, average energy dissipation gradually decreases for larger density of nodes. The existing method in the RPGM model consumes more energy due to the particle size that requires continuous updating of the filter.

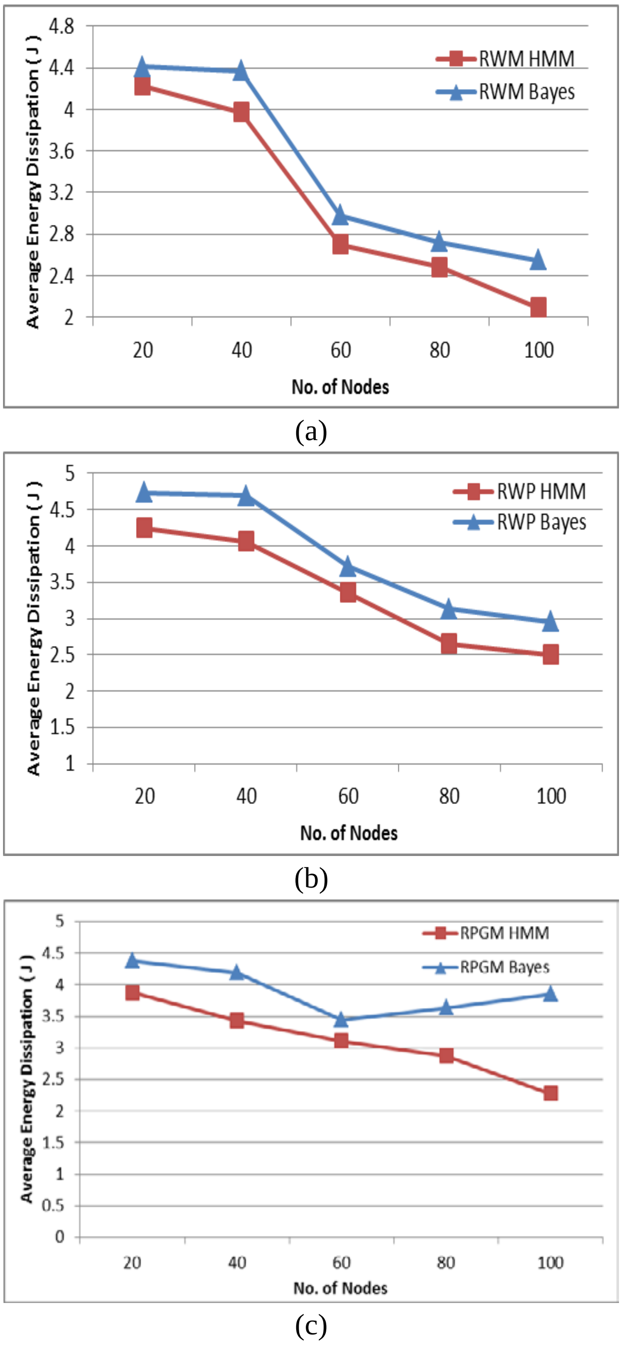


Fig 3: Impact of Node density on Average Energy Dissipation
(a) RWM (b) RWP (c) RPGM

4.1.2 Effect of the coverage

The impact of estimation error against coverage to a transmission range of 150m for 100 nodes with the speed of 10m/s is shown in Fig 4 (a)–(c). The effect of coverage becomes low when the network is dense, i.e., increase in transmission range. The estimation error increases due to increase in the transmission range for higher node density. The network connectivity is efficiently controlled by varying the transmission range. The anchors eventually propagate throughout the network of varying transmission ranges and allow non-anchor nodes to localize themselves using the state sequence estimation provided by HMM. The estimation error for HMM RPGM appears to be better when compared with other mobility models.

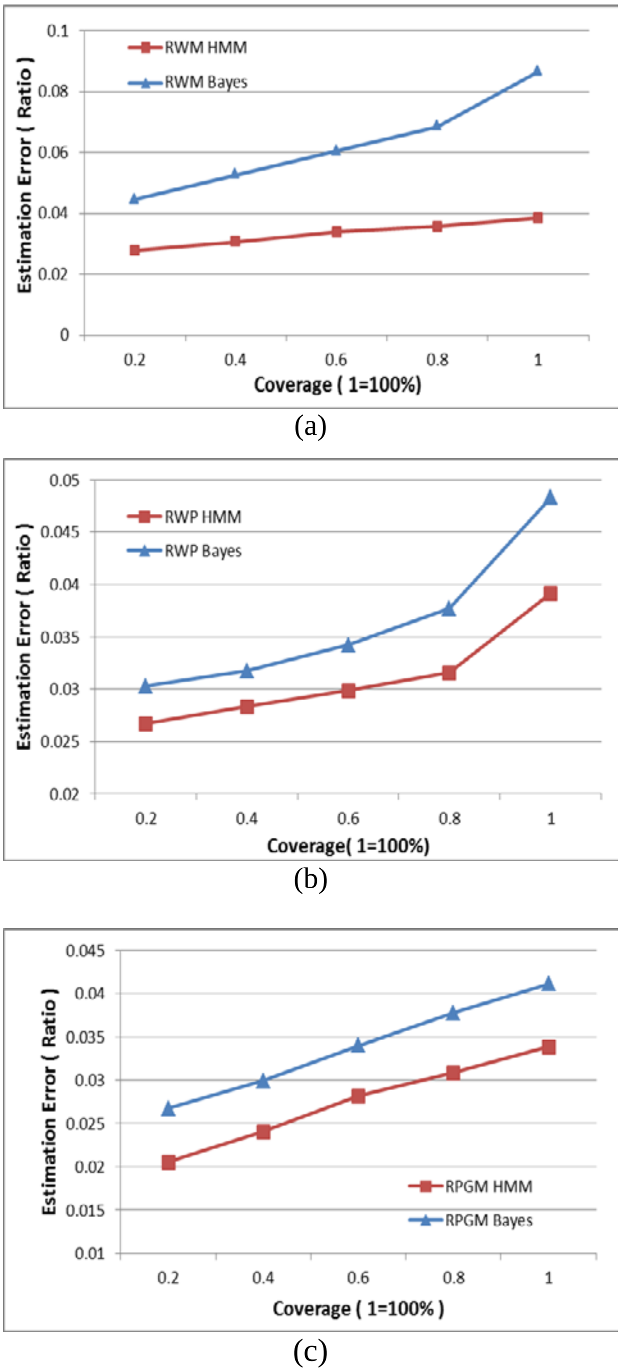
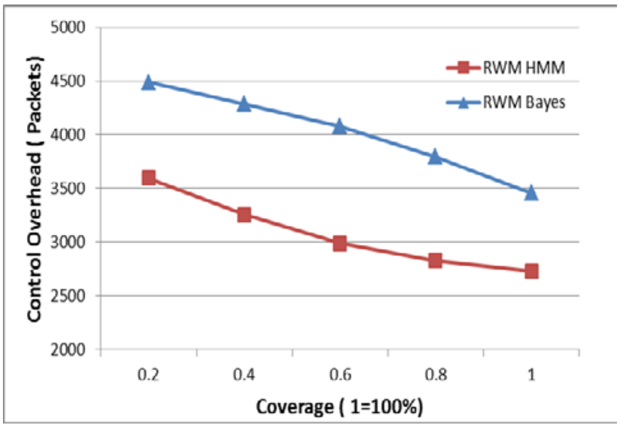
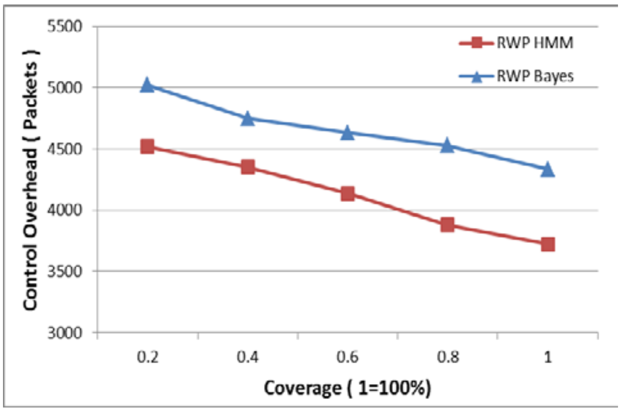


Fig 4: Impact of Coverage on Estimation Error
(a) RWM (b) RWP (c) RPGM

The control overhead packets differ as shown in Fig 5 (a)–(c) with increase in transmission range for varying mobility models. The control overhead packet gradually decreases for increasing transmission range for higher nodes. As anticipated, the estimated locations become more accurate as more information is exchanged among neighbors. The overhead packets are decreased to increase the node density for 80 to 100% of coverage. RPGM consumes more overhead packets when compared to the other mobility model because the member nodes follow the leader node.



(a)



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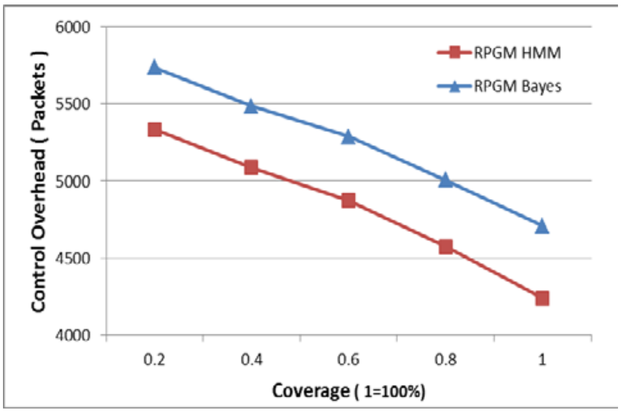
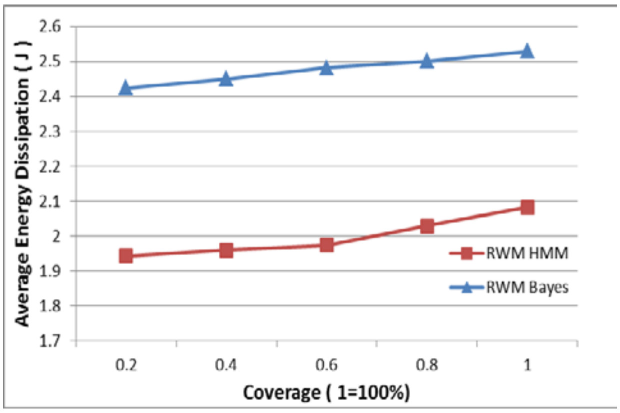


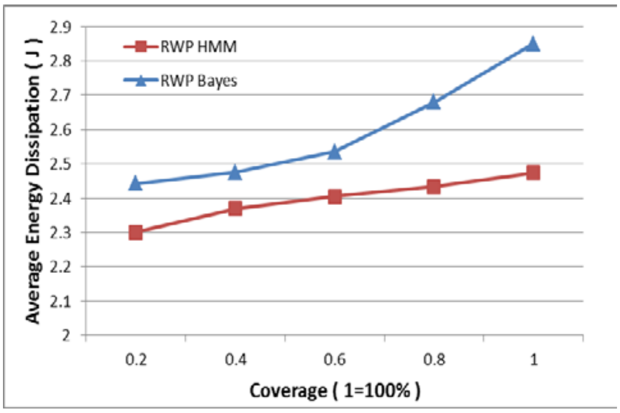
(c)

Fig 5: Impact of Coverage on Control Overhead
(a) RWM (b) RWP (c) RPGM

The impact of coverage over the average energy dissipation shows minor difference as shown in Fig 6 (a)–(c).



(a)



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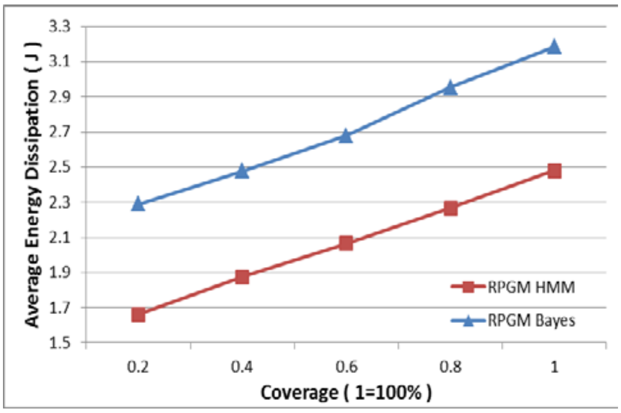


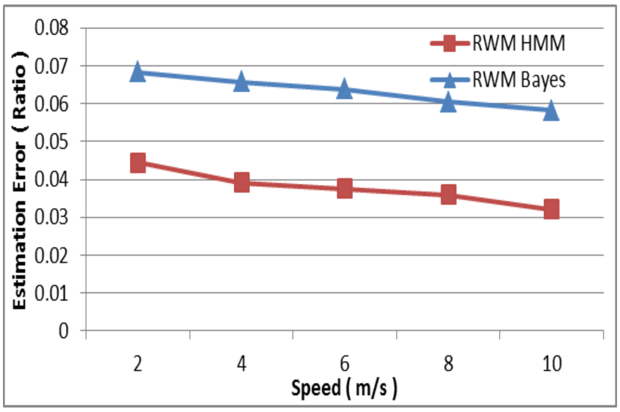
(c)

Fig 6: Impact of Coverage on Average Energy Dissipation
(a) RWM (b) RWP (c) RPGM

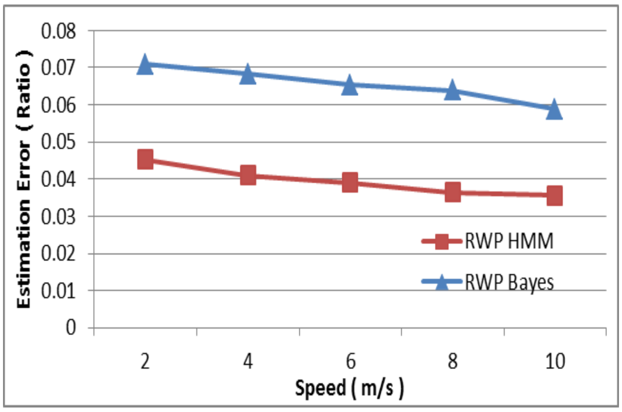
As the beacon node percentage varies over the deployment area, the average energy dissipated indicates that more nodes are localized for varying transmission range. The energy spent in proposed localization is less due to state sequence compared to continuous updating in the existing work. It can be seen that the RPGM model consumes less energy when compared to other models because the members follow the leader nodes to be localized.

4.1.3 Effect of varying the Speed

The effect of varying speed over the estimation error is shown in Fig 7 (a)–(c).



(a)



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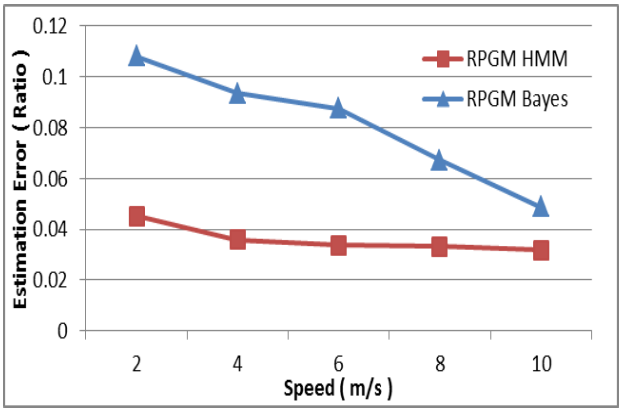
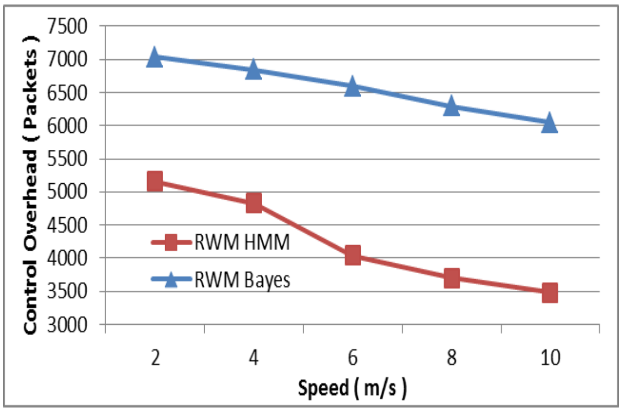


(c)

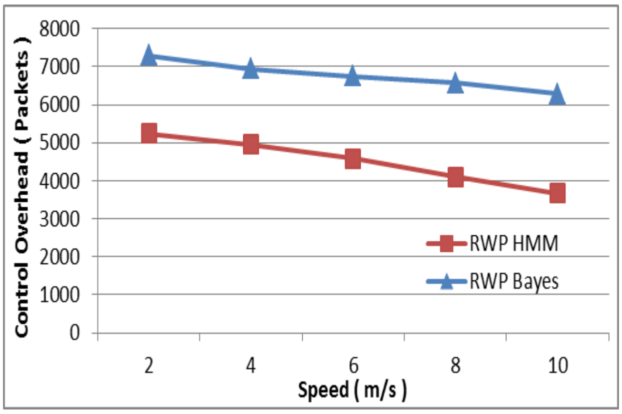
Fig 7: Impact of Speed on Estimation Error
(a) RWM (b) RWP (c) RPGM

All the nodes in the network have communication range of 150m. As the speed increases, the localization error progressively decreases.The estimation error obtained for HMM RWM is lesser than the particle filter with various moving speeds. RWP pauses for few seconds and chooses the speed to move to the next destination. RPGM behaves differently from the other two models by choosing the appropriate angle and speed deviation, which controls the velocity of group members from that of the leader.

Variation of speed over the control overhead is shown in Fig 8 (a)–(c). The increase in the speed gradually decreases the control overhead. RWM and RWP have lower overhead when compared to RPGM. RPGM follows the speed and angle deviation so that the overhead was slightly high at initial speed of 2m/s.

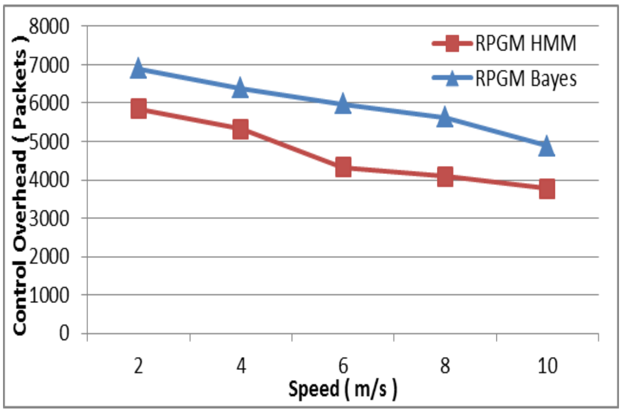


(a)



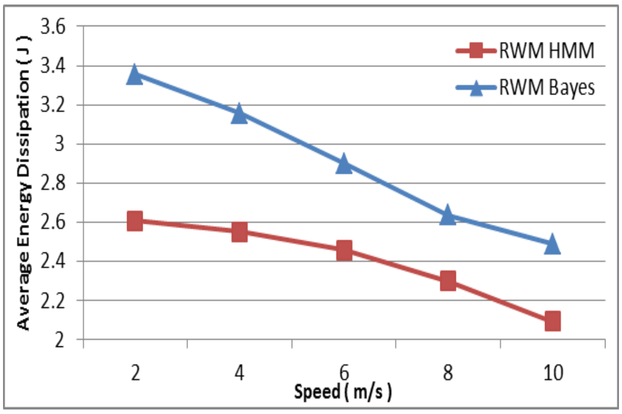
(b)

The performance of average energy dissipation for varying speed is shown in Fig 9 (a)–(c). The energy is gradually reduced due to the increase in speed for RWM. In all the three mobility models, the energy drops down at higher speed. For RWP and RPGM, since it pauses for a few seconds to take decision for the next movement to reach the destination, it spends more energy than RWM.

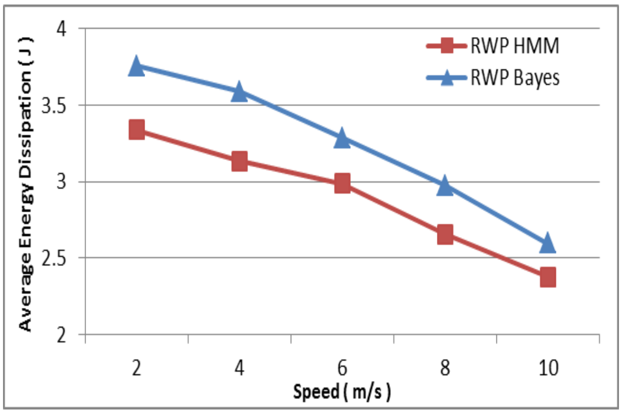


(c)

Fig 8: Impact of Speed on Control Overhead
(a) RWM (b) RWP (c) RPGM

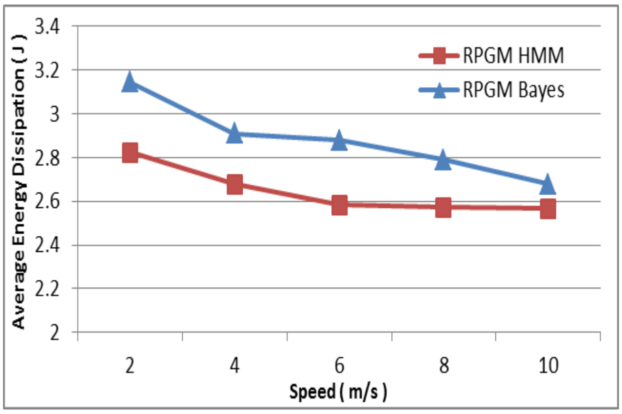


(a)



(b)

The estimation error is calculated as the difference between the most probable estimated value and the actual location. The χ^2 - test is used to test the statistical significance of difference between estimated and actual location; the data collected for multiple runs claims a 98 % level of confidence for RWM and RWP, while 99 % for RPGM communicating about the fact that networks with higher anchor ratio, higher speed produce better estimations.



(c)

Fig 9: Impact of Speed on Average Energy Dissipation
(a) RWM (b) RWP (c) RPGM

Summarizing the above observations of the proposed work, the estimation error reduces and converges faster for varying node density, various transmission ranges and varying speed for different mobility model. These observations show that the state sequence estimates for location of non-anchor nodes are more accurate and converge faster by minimizing the traffic rate and reducing the power dissipation using various mobility models.

5 Conclusion and Future Work

The knowledge of physical location of mobile nodes is more useful to geographical routing in the wireless sensor network. Extensive literature is available for indoor sensor network whereas only minimal studies focused on outdoor. The current work helps to obtain better location accuracy in the outdoor environment through RSS measurement by two-ray propagation model using HMM. The proposed approach exploits the RSS measurements to estimate the position of a mobile node. The network connectivity is controlled by varying the transmission range; hence the traffic is avoided by the state sequence estimation; longer the sequence, better the location accuracy. In addition, through a comparative simulation study of various mobility models it has been observed that RPGM improves the location accuracy. The advantage of the proposed work is rapid convergence of the state sequence, which directly helps to reduce the traffic and subsequently consumes low power consumption. This work can be extended for uniform and non-uniform deployment of the nodes using multiple sensory data with other propagation model.

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