Scenario Based Analysis of Localization of Sensor Nodes Using HMM

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Abstract. The Sensor Network Localization problem deals with estimating the geographical location of all nodes in Wireless Sensor Network. The focus is on those node sensors to be equipped with GPS, but it is often too expensive to include GPS receiver in all sensor nodes. In the proposed localization method, sensor networks with non-GPS nodes derive their location from limited number of GPS nodes. The nodes are capable of measuring received signal strength and the need for a framework that could benefit from the interactions of nodes with mixed types of sensors for WSN.In this paper, localization is achieved by incorporating Mobility Models with Hidden Markov Model (HMM). Scenario based mobility models like Random walk, Random Waypoint, Reference Point Group mobility (RPGM)and Semi-Markov Smooth mobility (SMS) model are used with Hidden Markov Model to estimate error, energy, control overhead, with respect to node density, time and transmission range.

Keywords: Localization, Hidden Markov Model, Mobility Model, Estimation error, Energy, Control overhead, Node density, Time and Transmission range.

1 Introduction

Sensor networks are composed of large numbers of sensors that are equipped with a processor, memory, wireless communication capabilities, sensing capabilities and a power source (battery) on-board. A fundamental problem in wireless sensor networks is localization – the determination of the geographical locations of sensors. While in most existing sensor networks sensors are static, some modern applications involve sensors that are mobile. A more reasonable [4] solution to the localization problem is to allow some nodes to have their location information at all times and allow other nodes to infer their locations by exchanging information with nodes. Range-based localization uses Received Signal Strength Indicator (RSSI), Time of Arrival (TOA), or Time Difference of Arrival (TDOA) to estimate the distance between the nodes that needs to discover its location and each reachable anchor that estimates the node's location based on these distances and the anchors' locations.

This paper presents a Localization algorithm to estimate the location of sensors. The main advantage of choosing this HMM is the use of hidden (or unobservable) states makes the model generic enough to handle a variety of complex real-world time

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series, while the relatively simple prior dependence structure (the "Markov" bit) still allows for the use of efficient computational procedures. However, there is an exception in cases when only RSSI sensors are used and the coverage is high. With the help of ns-2, the estimation error, energy, control overhead, with respect to node density, time and transmission range, the mobility model is used to learn the path of the hidden nodes that needs to be localized.

In this paper, section 2 investigates related researches. The Hidden Markov Model Algorithm is discussed in section 3.Section 4 presents the performance metrics.5 presents the simulation results. Finally section 6 concludes the paper.

2 Related Work

In [1] the approach is based on Markov localization and provides rational criteria for setting the robot's motion direction (exploration), and determining the pointing direction of the sensors so as to most efficiently localize the robot. In [2] numerical results show that the HMM method improves the accuracy of localization with respect to conventional ranging methods, especially in mixed LOS/NLOS indoor environments. In [3] the author has attempted to illustrate some applications of the theory of HMMs to simple problems in speech recognition, and pointed out how the techniques could be (and have been) applied to more advanced speech recognition problems.

3 Contributed Work

This section deals with Hidden Markov Model algorithm to localize the sensor nodes based on various Mobility Model.

3.1 Hidden Markov Model

A Hidden Markov Model (HMM) [5] consists of a set of N states, each of which is associated with a set of M possible observations. The parameters of the HMM include:

An initial matrix of state probabilities is known by assumption

$$\Pi = [P_1, P_{2,} \ldots\ldots\ldots P_N]^T \tag{1}$$

whose elements $P_{i,}$ $i \in [1, N]$, describe the position distribution probabilities of the node over the initial state set at the beginning $t = 1$.The Transition Probability is the matrix A that depends on the speed distribution of the node, on the geographical feature of the area and on the allowed transition. The Probability distribution from the observed signals is the matrix B.

The Fig.1. shows the value of the hidden variable x (t) at time t only depends on the value of hidden variable x (t-1). The value of the observed variable y (t) [11] only depends on the value of the hidden variable x (t).

Finally, the HMM parameter set is denoted by $\lambda = (A, B, \pi)$. As usual, the HMM have three problems [5]: First is the Evaluating problem, what is the probability of the observation O, given the model λ, i.e. $P\ (O/\lambda)$? => Solution: Forward or Backward algorithm. The effectiveness in forward and backward procedures is almost identical. The result $P\ (O/\lambda)$ is mainly used for criterion of training model.

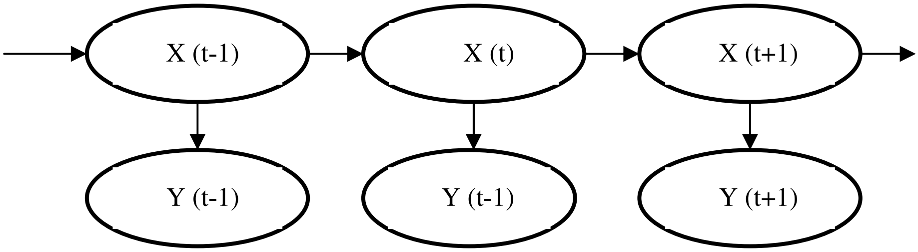

Fig. 1. Model of HMM

For the decoding problem, the solution for the most likely state sequence given the observation O is i.e. $\arg_s$ [max (P(S, O/λ)], the solution is Viterbi algorithm.

$$\delta_t(i) = \max_{q_1, q_2 \ldots q_{t-1}} P(q_{1,} q_{2\ldots} q_{t-1}, q_t = S_i, O_1, O_2 \ldots O_t / \lambda) \tag{2}$$

$\delta_t(i)$ is the highest probability along a single path at time *t*, which accounts for the first *t* observations and ends in state $S_{i.}$

By induction, we have $\delta_{t+1}(j) \left[\max_i \delta_t(i) a_{ij} \right] b_j(O_{t+1})$ (3)

The study shows that Viterbi algorithm creates a better trajectory than the traditional algorithm because Viterbi algorithm decides the real states depended on all states. The final one is the most likelihood states.

For Estimating problem, the estimate parameters given for the training observation sequences, λ * = arg $_\lambda$ [max *P O/* λ], the solution is Baum-Welch algorithm.

We define: $\xi_k(i, j) = \dfrac{\alpha_k(i) a_{ij} b_j(O_{k+1}) \beta_{k+1}(j)}{P(O/\lambda)}$ (4)

In which $\beta_{k+1}(i) = \sum \beta_{k+2}(j) a_{ij} b_j(O_{k+1}); \beta_k(i) = 1$ (5)

and we have: $\gamma_k(i) = \sum_{j-1}^{N} \xi_k(i, j) = \dfrac{\alpha_k(i) \beta_{k+1}(i)}{P(O/\lambda)}$ (6)

$$a'_{ij} = \sum_{k-1}^{K-1} \xi_k(i, j) \Big/ \sum_{k-1}^{K-1} \gamma_k(j) \tag{7}$$

The result: $b'_j(O_{k=i}) = \sum_{k-1}^{K-1} \gamma_k(j) \Big/ \sum_{k-1}^{K} \gamma_k(j)$ (8)

$$\pi'_i(k = 1) = \gamma_i(i) \tag{9}$$

Equation (7) (8) (9) produces a new set of training parameters of HMM system. The trained model $\lambda^{'} = (A^{'}, B^{'}, \pi^{'})$ has a property: $P\ (O/\lambda') \geq P\ (O/\lambda)$. This means that the trained model parameters are more suitable to observations than the former model. Furthermore, we can learn model parameters from K observation sequences in [5]. It is proven that the model λ' is becoming the real one when a range of K observation sequences is used.

3.2 Random Walk Mobility

In this mobility model [7], a Mobile Node moves from its current location to a new location by randomly choosing a direction and speed in which to travel. The new speed and direction are both chosen from pre-defined ranges, [*speedmin*, *speedmax*] and [0, 2π] respectively. Each movement in the Random Walk Mobility Model occurs in either a constant time interval *t* or a constant distance traveled *d*, at the end of which a new direction and speed are calculated. If a node which moves according to this model reaches a simulation boundary, it "bounces" off the simulation border with an angle determined by the incoming direction. The mobile node then continues along this new path.

3.3 Random Waypoint Mobility

The Random Waypoint Mobility Model (RWP) includes pause times between changes in direction and/or speed. A Mobile node begins by staying in one location for a certain period of time (i.e., a pause time). Once this time expires, the mobile node chooses a random destination in the simulation area and a speed that is uniformly distributed between *[minspeed, maxspeed]*. The node then travels toward the newly chosen destination at the selected speed. Upon arrival, the node pauses for a specified time period before starting the process again. It is noted that the movement pattern of an MN using the Random Waypoint Mobility Model is similar to the Random Walk Mobility Model if pause time is zero and *[minspeed, maxspeed] = [speedmin, speedmax]*.

3.4 Reference Point Group Mobility

The movement of the group leader [7] determines the mobility behavior of the entire group. Each node has a speed and direction randomly deviating from that of the group leader. The movement in the group mobility can be characterized as follows

$$\left|\vec{v}_{member}(t)\right| = \left|\vec{v}_{leader}(t)\right| + random() \times SDR \times \max\_speed \tag{10}$$

$$\theta_{member}(t0 = \theta_{leader}(t) + random() \times ADR \times \max\_angle \tag{11}$$

SDR is the speed Deviation Ration and ADR is the Angle Deviation Ratio.SDR and ADR is used to control the deviation of the velocity of group members from that of member.

3.5 Semi-markov Smooth Mobility

Each SMS [9] movement, a node will randomly select a target direction φ_α and a target speed V_α. Each SMS movement contains three consecutive moving phases: Speed Up phase for even speed acceleration from 0 m/s to the target speed V_α; Middle Smooth phase for maintaining stable velocities which respectively fluctuate around V_α and φ_α in each time step; and Slow Down phase for even speed deceleration to 0 m/s. The node experiences a random pause time after each SMS movement.

4 Performance Metrics

In this section, the performance of HMM with various mobility models via simulation is evaluated. The key metric [6] for evaluating localization schemes is the location estimation error. Since the objective of localization schemes is to obtain higher localization accuracy using fewer controls overhead, the evaluation of control overhead is used as a secondary metric. Third Metric is the Energy. The definitions of these metrics are as:

Location Estimation error: The average distance between the estimated location $x_{n_{est}}$ and the actual location x_n of all sensor nodes. The location error is scaled as the percentage of transmission range r.

$$\text{Location Estimation error}=\left(\sum_{n=1}^{N} \| x_{n_{est}} - x_n \| / N\right)/ r \tag{12}$$

Control Overhead: The total number of control packets transmitted by the anchors to localize an unknown node in each localization process. Assume to localize a node n, B_n control packets should be transmitted by A_n packets. The control overhead for an unknown node is

$$\text{Control Overhead}= \sum_{n=1}^{N} \left(B_n / A_n\right) \tag{13}$$

Energy: Total Energy consumption of the sensor nodes during localization, which is measured in joules.

5 Performance Evaluation

In this section, we have conducted a simulation experiments to validate the effective of our solution using ns-2.The proposed work was implemented using ns-2, in order to evaluate and validate the performance of the HMM based localization. The network area has been set to 1000m X 1000m **.**The network area consists of 250 nodes and 5% of the total nodes are considered as a anchor nodes which know their position. All the nodes in the network have transmission range of 250m.Initally the energy level of each node is set to 5.1 joules. The transmission rate is 500Kb/sec of control packet size 512 bytes. The simulation was conducted for various mobility models such as Random walk Mobility, Random Waypoint Mobility, Reference point Group Mobility, Semi Markov Smooth Mobility with speed of 5m/sec.

The effect of node density on the estimation error is shown in Fig.2. The error estimate of RPGM proves to be a better. The reason is that, in RPGM each node move near each other as a group with almost similar speed and direction angle this mobility model has very high degree of spatial dependence because there is high similarity in motion of nodes in a group. But in comparison with other mobility models it has lowest relative speed because each of the nodes in a group chooses a random speed and direction according to the speed and direction of the group leader. For realizing group mobility in tactical scenarios, the RPGM model seems to be the better approach, as with an appropriate choice of parameters relative positions of nodes inside the groups can be modeled explicitly.

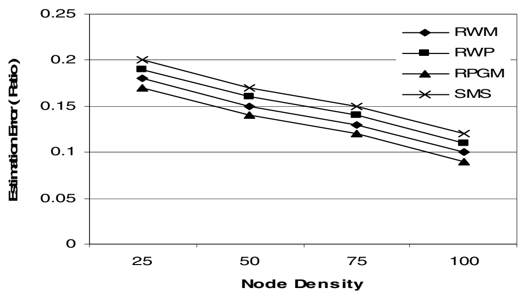

Fig. 2. Impact of network size over Estimation Error

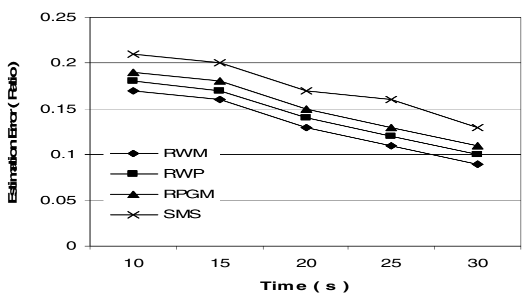

Fig. 3. Impact of Time over Estimation Error

The impact of time on estimation error is shown in Fig.3.As the time increases the estimation error decreases because more anchors get localized that results in faster convergence. As the increase in the time leads to decrease in Estimation error, the reason is that due to the increase of reference nodes.The random walk model shows better estimate because there is no pause time.However Random waypoint uses pause time, part of the time is spent for pause state.In all cases, the estimation error is low due to recursive back tracking of most likelihood of location estimates using Baum Welch algorithm.

The effect of transmission range on the estimation error is shown in Fig.4. The result shows that the error is low in random waypoint model. The reason is that as the simulation starts, each node randomly selects one location in the simulation field as the destination. It then travels towards this destination with constant velocity chosen uniformly and randomly from $[0, V_{Max}]$.Upon reaching the destination, the node stops for a defined by the 'pause time' parameter. If $T_{Pause} = 0$, this leads to continuous mobility. After this duration, it again chooses another random destination. During pause time, the node localization is better. The effect of coverage becomes high when the network is sparse, i.e., increase in transmission range. The estimation error increases due to increase in the transmission range.

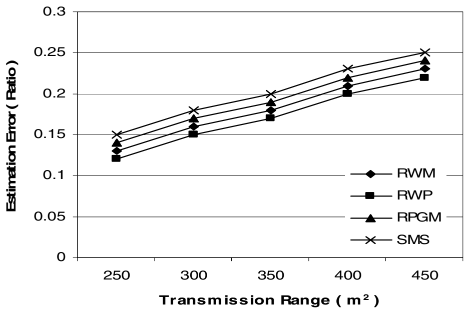

Fig. 4. Impact of Transmission Range over Estimation Error

The Fig.5. shows the performance of Node density over Control Overhead .With the node density growing, the control overhead decreases gradually. More denser the nodes, the anchor node becomes closer to the unknown nodes. Localization is achieved with minimum control overhead. In the case of RWP and RPGM there are slight variations. Comparing all four mobility models, the overhead is low in the case of RPGM. This effect is due to exchange of control packets only depends on the group leader.

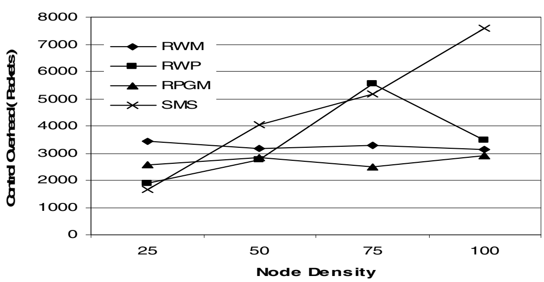

Fig. 5. Impact of network size over Control Overhead

Control overhead gradually increases as shown in Fig.6 and gets consistent with increase in time due to the earlier Localization. As the simulation time increases the reference nodes also increases, the algorithm uses only the control packets from first hop neighborhood. Hence the control overhead rises to certain level and goes to consistent. The overhead is more in the case of SMS Mobility model.

The control overhead packets get increased as shown in Fig.7 due to sparse node availability with increase in Transmission Range. As the transmission range increases the overhead increases in RWM. In the case of RWP, RPGM the overhead is consistent. RPGM mobility minimizes the overall control overhead during localization due to its implicit characteristics. In SMS mobility, there is more variation in the control overhead.

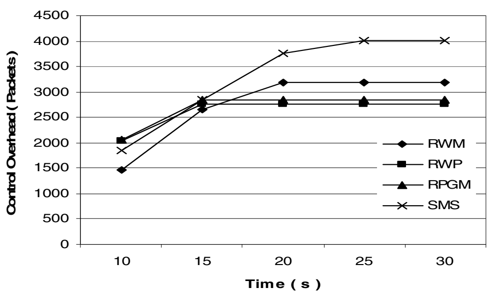

Fig. 6. Impact of Time over control overhead

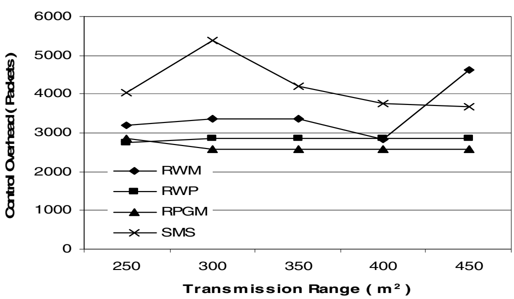

Fig. 7. Impact of Transmission Range over control overhead

Energy over the node density is shown in Fig.8. This shows energy consumption gets varied due to increase in the node density. The average energy dissipated during localization gets increased as the node density increases in RWP and RWM, SMS and slight variation in RPGM model then its goes to consistent state. However, the energy spent during in movement is more, but the energy spent in localization process is low. Hence the average energy spent by each node shows moderate variation.

The energy consumption in Fig.9 decreases and becomes consistent as there is increase in time because the node gets localized very fast in the initial stage. The energy

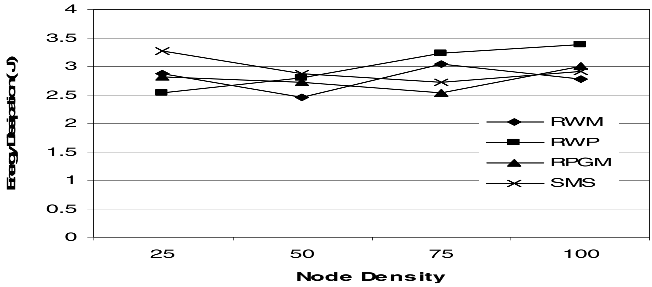

Fig. 8. Impact of network size over Energy

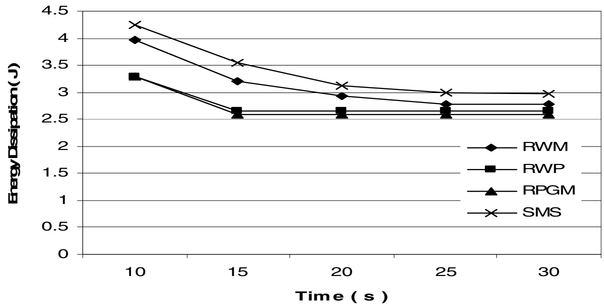

Fig. 9. Impact of Time over Energy

dissipation slightly decreases as the time increases and then it goes to consistent. This effect is due to the increase in the more no. of localized nodes called anchors.

In Fig.10 the energy consumption in HMM shows as the transmission range becomes more the energy gradually decreases due to sparse connectivity of the sensor nodes. Although the network becomes sparse as the sensor range increases, the energy spent in localization is low due to fast prediction of HMM method by exchange of location estimates with its single hop neighbor.

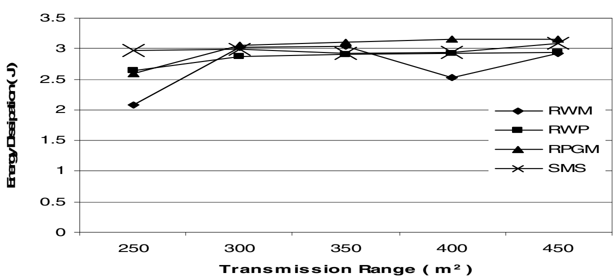

Fig. 10. Impact of Transmission Range over Energy

6 Conclusions

Our analysis and simulation studies validate the effectiveness of combining sensor capacities of RSSI with learning movement model using HMM.The movement of nodes can be predicted fast with exchange of location estimates in multihop way using HMM .Furthermore, our analysis shows that employing RSSI sensors can achieve better localization using HMM in wireless sensor networks. This model could be further improved for AoA sensor capacity. More importantly, this framework allows the networks consisting of nodes with different sensor types to collaborate in the Localization process.

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