Prediction Based Object Recovery Using Sequential Monte Carlo Method

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Abstract - Object tracking in wireless sensor networks has been a hot research topic in a recent scenario, due to its wide-ranging applications. Most object tracking uses prediction scheme to minimize the energy consumption and to maintain low missing rate in a sensor network. However objects need to be localize, when object was found missing during tracking process. In this paper, we proposed sequential Monte Carlo method (SMCM) to accurately estimate the location of the missing object and the extensive simulations are also shown to demonstrate the effectiveness of the proposed sequential Monte Carlo method against the centroid and multilatertion methods to evaluate its performance in terms of network energy consumption and localization error.

Keywords: Wireless sensor network, Sequential Monte carol method, centroid method, Multilateration method, missing rate, energy consumption, Localization error.

1. INTRODUCTION

A Wireless sensor network (WSN) built with large number of autonomous and compact devices that are capable of both sensing and communication, whose increasing availabilities are driven by advances in micro electromechanical sensors, wireless networking and the embedded processing technology [1]. WSNs are created by deploying a large number of interconnected sensor nodes in a region for detecting purpose. These nodes used as a reporting device to attain specific types of data, as required by the application. In WSN, many sensor nodes need to keep on work together with neighbor nodes in order to track the moving object [2].

However in some of the sensor network, nodes are grouped in to different clusters and each cluster will have collection of sensor nodes with a header node [5]. The header node will communicate with rest of the nodes in the clusters and the clusters will communicate with other clusters via the header node to track the moving object.

Object tracking is one of the demanding sensor network application, which is used in wild life detecting, intrusion prevention, pervasive surveillance, robotics, manufacturing, military, air traffic control and building monitoring. The main task of an object tracking is to track a moving object and to report its latest location in the detection area to the application in a timely manner [13] [14]. Conversely object tracking place a burden on network resources such as energy consumption due to its wide applications. In this situation it is necessary to develop an energy efficient technique to minimize the energy consumption in object tracking [9]. But existing researches focused on optimizing the communication cost by inactivating radios or trading off computation for communication [10] [11]. Another side of energy conservation is achieved by optimizing the physical design of sensor nodes, by the researchers.

These sensor nodes sample the physical world for a sampling duration to obtain the properties of the object. During sampling, the MCU and the sensor components are activated for data collecting and processing. [12].The sensor nodes which detect the object in their detection area have to report to the base station with certain reporting frequency

Object tracking in WSN can be classified in to five schemes, such as Naïve, Scheduled Monitoring, Continuous Monitoring, and Dynamic Clustering [25] and Prediction-based scheme. Among them, the Continuous Monitoring, Dynamic Clustering and Prediction-based scheme are specially considered for solving the object tracking problem.

2. RELATED WORK

Most of the tracking schemes, such as Schedule monitoring and Continuous monitoring, based on sampling frequency, and uses a collection of sensors to monitor an object instead of using the entire sensor in the network. In [15], author uses a mobile agent to manage a group of sensors, foresee the task of monitoring the object. Continuous object detection and tracking algorithm, based on a dynamic clustering scheme for the monitoring of continuous objects in wireless sensor networks [23]. A dual prediction reporting mechanism reduces the energy consumption of radio components by minimizing the number of long distance between the base station and sensor [3]. To provide a better tradeoff between energy efficiency and tracking qualities, sleep scheduling protocols for object tracking have been proposed in recent times[10].

In [4], author proposed a distributed hop by hop localization method. It uses GPS principle, unlike in GPS, not all sensor nodes will have direct communication with nodes in a sensor network**.** In order to estimate the location of the object, author used [21] three smart sensor to measure the distance between the object and the sensors. In [22], author approached the location estimation problem using convex optimization based on semi definite programming. In [17], the author utilized a data mining method to derive object movement patterns and then used the derived patterns to predict the future location of the object. A study on the localization errors in WSN applications is done in [18].

The source of errors are identified and modeled at each step, all nodes that can triangulate their locations using distance measurements. A guarantee path has been established between the nodes and the base station for proper data delivery [24] and the jitter minimization algorithm is implemented in each node to minimize jitter and end-to-end delay. A distributed algorithm is implemented on a WSN and proposed for node localization [19] and the locations are determined by a global rotation and translation using noisy distance measurements. Author worked on sensors to measure the angle or distance to the object. In [20], author used sensor nodes, at each step to measure the distance between the sensor and the object and the object state is estimated using EKF.

3. PREDICTION BASED OBJECT RECOVERY

In this paper we used prediction based scheme, that minimizes the sensor nodes participating in tracking process, and make the rest of sensor nodes in to sleeping mode [6] [14]. Prediction based scheme consist of prediction model, wakeup process and recovery process. Based on different prediction models, prediction can be classified as circle based, kinematics based and probability based. Circle based model is the simple and most commonly used prediction model, given the object Current location , prediction locations within a radius determined by the maximum velocity of the object. Kinematic based model is used when object movement is restricted. The probability model is used when object whose motion patterns follow some given distributions.

Finally Prediction models use the Wake-up Mechanism to wake up the neighboring sensor node before the object leaving its own detection area and entering the neighboring area. There still will be un-ignorable increase of missing rate when the object change its moving direction beyond the prediction, because only the sensor nodes which are on the predicted route of the object would wake up and monitor the object continuously and also all the sensor nodes on the object's traveling route are supposed to be active to monitor the object, then the energy consumption would be high [4] [6]. If the object missing rate occurs, then the recovery process has to be started to localize the missing object and return them to the network for object tracking [26].

However existing researchers concentrate on source, destination and neighbor recovery by activating all sleeping sensors to find out the missing object. If this case fails, which lead to flooding recovery (i.e.) wakes up all the nodes in the network and put the network in high energy consumption. Still Some of the factors that impact the energy consumption in object tracking they are number of moving objects, reporting frequency, data precision, sampling frequency, object moving speed, location models.[13]. In order to overcome this situation we propose a method known as SMCM to localize the missing object, when the object is not found by the sensor nodes during object tracking and at last we compare the simulated results of SMCM with the multilatertion and centroid methods, to visualize the result. We used here two metrics for performance evaluation such as network energy consumption, and localization error. Differ from other researches; our aim of this paper is to improve the energy efficiency and to minimize the localization error by using the proposed technique to extend the lifetime of the network.

In this paper we assume that the sensor nodes are motionless and that the network topology is well identified to base station and also the communication between sensor nodes and the base station is based on multi hop communication. We also assume low energy paging channel exist for a sensor node to wake up nearby sensor node while in sleep mode [7]. We also use the shortest path multi-hop routing algorithm for communications between the base station and sensor nodes [8] [11] and adopt energy consumption in WINS nodes [13] as the basis for our simulation, as shown in Table I.

Table I.
ENERGY CONSUMPTION IN WINS NODE.

Component	Mode	Energy consumption (mw)
MCU	Active	360
MCU	Sleep	0.9
Sensor	Active	23
Radio	Transmission	720
Radio	Reception	369

A. Object recovery using centroid method

In this method, a set of sensor nodes with known location (x_1, y_1), (x_2, y_2)… (x_n, y_n) and each object predictable location is computed as a centroid of the position of all connected sensor nodes to itself by

$$X_p, Y_p = \frac{x_1+\cdots+x_n}{N}, \frac{y_1+\cdots+y_n}{N} \qquad - (1)$$

Where (x_p, y_p) represents the predictable position of the object and N is the number of connected sensor nodes to the object.

B. Object recovery using multilateration method

Assume that we have a set of sensor nodes with known location (x_1, y_1), (x_2, y_2)… (x_n, y_n) and an object with unknown location (x_p, y_p) distributed in a plane, as shown in Fig.1. The distance between different sensor node and the object is respectively $d_1, d_2, \ldots\ d_n$. So that the location of the object can be calculated by solving non linear system of equation.

$$\begin{cases} (x_1 - x)^2 + (y_1 - y)^2 = d_1^2 \\ \vdots \\ (x_n - x)^2 + (y_n - y)^2 = d_n^2 \end{cases} \qquad - (2)$$

The system can be linearized [16] by subtracting the last equation from the first n-1 equations.

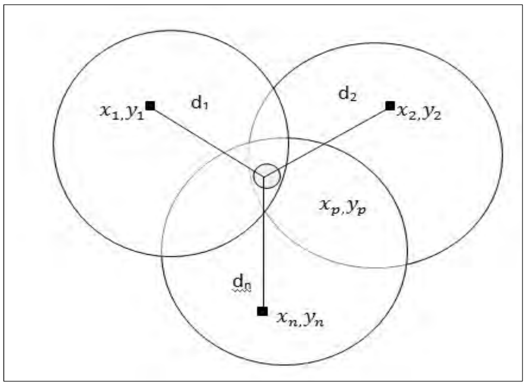

Fig 1. Multilatertion.

$$\begin{cases} x_1^2 - x_n^2 - 2(x_1 - x_n)x_p + y_1^2 - y_n^2 - 2(y_1 - y_n)y_p = d_1^2 - d_n^2 \\ \vdots \\ x_{n-1}^2 - x_n^2 - 2(x_{n-1} - x_n)x_p + y_{n-1}^2 - y_n^2 - 2(y_{n-1} - y_n)y_p = d_{n-1}^2 - d_n^2 \end{cases} \qquad - (3)$$

Reorder the terms gives a proper system of linear equations, such as

AX = B, where

$$A = 2 * \begin{bmatrix} x_1 - x_n & y_1 - y_n \\ \vdots & \vdots \\ x_{n-1} - x_n & y_{n-1} - y_n \end{bmatrix}$$

$$B = \begin{bmatrix} x_1^2 - x_n^2 + y_1^2 - y_n^2 + d_1^2 - d_n^2 \\ \vdots \\ x_{n-1}^2 - x_n^2 + y_{n-1}^2 - y_n^2 + d_{n-1}^2 - d_n^2 \end{bmatrix} \quad X = \begin{bmatrix} x_p \\ y_p \end{bmatrix}$$

Then the system is solved using a standard least square approach:

$$\hat{X} = (A^T A)^{-1} A^T B \qquad - (4)$$

C. Object recovery using Sequential Monte Carlo Method

Sequential Monte Carlo Method is used to work out Posterior distribution of the system. Here the sample set is represented by the system state. These samples are updated when new observations arrive. In order to estimate the location of the missing object, Bayesian filtering approach is used. Assume that the each object moving a distance (v) in a time step in any direction and the radio range of all sensors will have a mean and standard deviation.

There are three phases incorporated in Sequential Monte Carlo Method they are as follows.

Initialization phase: During this phase sensor nodes choose L samples from the initial distribution of the system and the sensor nodes use the neighboring nodes for weighting the samples. SMCM is proposed here to estimate the posterior distribution $p(x_{1:n}|y_{1:n})$ of the system, where the state variable is $(x_{1:n})$ and the measurement variable is $(y_{1:n})$. The entire system is formulated with Bayesian framework.

In order to calculate the object predictable position, assume$X_p, Y_p = p(x_{1:n}|y_{1:n})$. Using Bayes theorem, it is simple to obtain the following recursion.
State variable:

$$p(x_{1:n}) = \mu(x_1)\prod_{L=1}^{n} f\,(x_L|x_L - 1) \quad - (5)$$

Likelihood:

$$p(y_{1:n}|x_{1:n}) = \prod_{L=1}^{n} g\,(y_L|x_L) \quad - (6)$$

Where $f(x_L|x_L - 1)$ and $g(y_L|x_L)$ are the functions depending on the parameter x_L, y_L
Using Bayes rule, we get

$$p(x_{1:n}|y_{1:n}) = \frac{p(y_{1:n}|x_{1:n})p(x_{1:n})}{p(y_{1:n})} \quad - (7)$$

Where the measurement variable $p(y_{1:n})$ is given by

$$p(y_{1:n}) = \int p(\,(y_{1:n}|x_{1:n})p(x_{1:n})dx_{1:n} \quad - (8)$$

Prediction phase: In this phase, L samples are drawn from the distribution. Then the weight of each sample is computed using the observations. At time n, sensor node generates a new set of samples based on earlier set.

$$\begin{aligned} p(x_n|y_{1:n}) &= \int p(\,x_n - 1{:}n \mid y_{1:n-1)}dx_{1:n} \\ &= \int p(\,x_n|\,x_{n-1}, y_{1:n-1})p(x_{n-1}|y_{1:n-1})dx_{n-1} \\ &= \int f(\,x_n|\,x_{n-1})p(x_{n-1}|y_{1:n-1})dx_{n-1} \quad - (9) \end{aligned}$$

Filtering phase: During this phase, L samples are chosen with replacement from the current sample set according to their weights. It gradually removes the sample with lower weight and keeps the samples with higher weight. All possible locations are removed from the new set of samples. Bayesian filtering uses the position information obtained from neighboring sensor nodes. Each sensor node updates its samples in every time step using Sequential Monte Carlo Method with the following steps.

$$p(x_n|y_{1:n}) = \frac{g(y_n|x_n)p(x_n|y_{1:n-1)}}{p(y_n|y_{1:n-1)}} \quad - (10)$$

We know that measurement variable from eq – (8)

$$p(y_{1:n}) = \int p(\,y_{1:n}|\,x_{1:n})p(x_{1:n})dx_{n-1}$$

Decomposition of the measurement variable is given by

$$p(y_{1:n}) = p(y_1)\prod_{L=2}^{n} p\,(y_L|\,y_{1:L-1})$$

Where

$$p(y_L|\,y_{1:L-1}) = \int p(\,y_L, x_k|y_{1:L-1})dx_L$$

$$p(y_L|\,y_{1:L-1}) = \int p(\,y_L|x_L)p(x_L|y_{1:L-1})dx_L$$

$p(y_L|\ y_{1:L-1}) = \int g(\ y_L|x_L) f(x_L|x_{L-1}) p(x_{L-1}|y_{L-1}) dx_{L-1}$

If L samples are chosen for node M, then the weight of the i-th sample is normalized as - (11)

$$\frac{Wt_i(M)}{\sum_{j=1}^{m} Wt_j(M)} \qquad - (12)$$

Using the Monte Carlo loacalization algorithm, each node maintains a set of weighted samples denoting its possible locations. The location of a node is estimated as the weighted mean of its samples. Each node updates its samples in every time step. This algorithm uses information about the neighboring sensors at filtering phase only, for removing the impossible samples, thereby minimizing the number of iterations. This method repeat until desired number of sample is reached. The SMCM parameters are given in Table II and the pseudo code for the SMCM given in Algorithm 1.

Algorithm 1. SMCM

1. Initialize state variable $(x_{1:n})$
2. Initialize measurement variable $(y_{1:n})$
3. If L=a then
4. Calculate $p(x_{1:n}|y_{1:n})$
5. else
6. Calculate $p(x_n|y_{1:n})$
7. update $Wt_i(M)$
8. If L=0 then
9. Stop

Our aim is to get the optimal object location estimate and reduce the localization error using SMCM. After Initialize the state variable $(x_{1:n})$ and measurement variable$(y_{1:n})$, check the condition if samples are found in the observation, then calculate $(x_{1:n}|y_{1:n})$, otherwise calculate$p(x_n|y_{1:n})$ and update the sample weight$W_i(M)$. Check the samples are found in the observation, if not stop the method.

Table II.
SMCM PARAMETERS

Radio range	10
Mean	0.1
Standard deviation	0.2
Distance	0 ~ 5

Table III.
SIMULATION SETTINGS

Number of sensors	100 sensors
Detection region	100 x 100 m^2
Sensor range	10m
Object speed	5m/s

4. PERFORMANCE EVALUATION

To evaluate the proposed localization methods in a comprehensive manner, different scenarios and settings have been implemented using a standalone simulator. The simulation carried out in a 100x100 m^2 detection area. It is assumed that each sensor node will have a coverage range of 10m. Refer Table III. For a summary of simulation settings. As for energy consumption, we have adopted the WINS energy consumption for sensor nodes. Fig.2. Shows sensor node and object deployment. Different graphs depicting performance under variations of preceding parameters. To evaluate the proposed scheme, we use following performance metrics.

A. Localization error

The distance between the predictable position and actual position of the object. Let (x_p, y_p) be the predictable coordinate and (x_a, y_a) be the actual coordinate of the object.

$$\text{Localization error} = \sqrt{(x_p - x_a)^2 + (y_p - y_a)^2} \qquad - (13)$$

B. Average Localization error

The average distance between the predictable position and the actual position of all objects.

$$\text{Average Localization error} = \frac{\sqrt{(x_p - x_a)^2 + (y_p - y_a)^2}}{No\ Of\ Objects} \quad - (14)$$

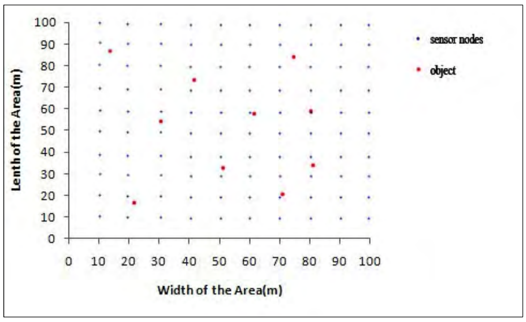

Fig 2. Sensor node and object deployment.

C. *Network energy consumption analysis*

We tested and compare SMCM with Centroid and multilatertion methods in the context of network workload, which is represented by the number of moving objects in the network. If the network has a large number of moving objects, then the most ideal scheme would be SMCM. In the case of centroid and multilateration, more sensors has to be activate and results in higher energy consumption, as shown in Fig.3. We noticed dramatic reduction in the energy consumption gap between SMCM and both Centroid and multilateration methods.

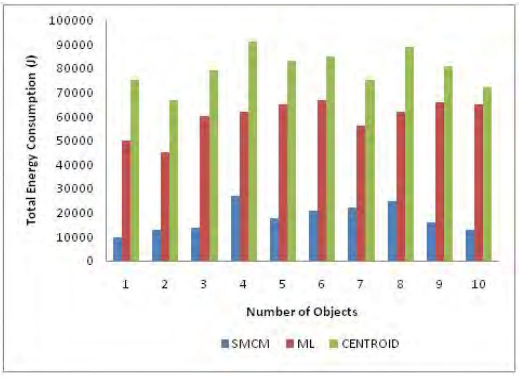

Fig 3. Network energy consumption analysis

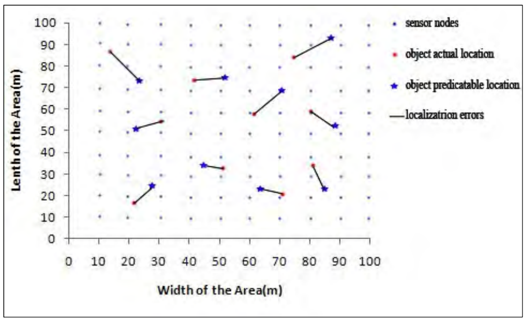

Fig 4. Object recovery using centroid

D. *Localization error analysis*

We simulated the location estimation methods for comparison such as centroid method, multilatertion method and SMCM. Fig. 4-6 shows the results of location estimation and Fig.7 shows the localization error results for each objects. The simulated results are summarized in Table IV. It can be observe that the average localization error is 0.84 (m) for SMCM and the average localization error for the multilatertion and centroid is 2.29(m) and 3.48(m). Thus the results proven SMCM maintain acceptable localization error, when compare with multilatertion and centroid.

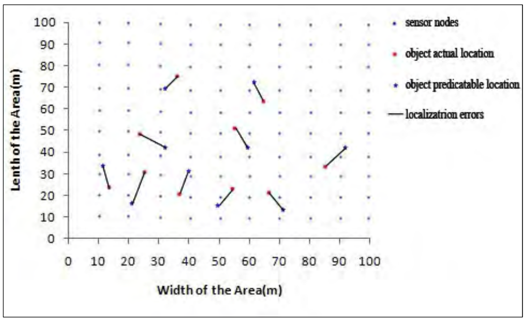

Fig 5. Object recovery using multilateration

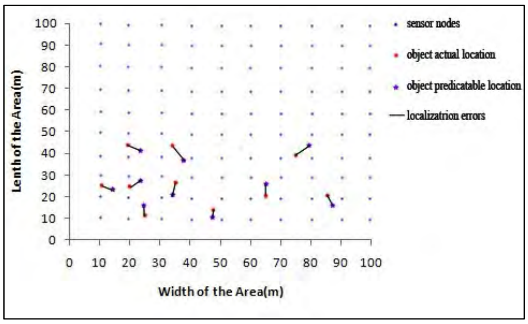

Fig 6. Object recovery using SMCM

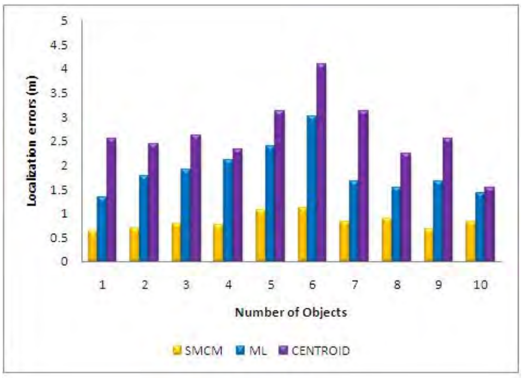

Fig 7. Localization error comparison

Table IV.
SIMULATION RESULTS

Methods	Min. Localization Error (m)	Max. Localization Error (m)	Avg. Localization Error(m)
Centroid	2.54	4.10	3.48
Multilatertion	1.33	3.01	2.29
MCL	0.61	1.45	0.84

5. CONCLUSION

In this paper, we have presented and described the object recovery problem. This problem amounts to find the predicted location of a missed object, given a set of sensor node coordinates. We proposed sequential Monte Carlo method to estimate the location of the missing object, by means of frequent updating of weighted samples with the help of the fine tuned algorithm. Furthermore we have simulated the proposed method, along with multilatertion and centroid methods. It has been proven that SMCM outperform other methods by keeping low network energy consumption and having minimized localization error.

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