# Target Tracking In Wireless Sensor Network Using Particle Filter

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**Abstract—**In recent years there has been immense growth in Wireless Sensor Technology and hence it has been the subject of intense research. One of the major application areas of Wireless Sensor Network is tracking of moving target which mainly consists of detecting and monitoring it within the region of interest. One of the widely used methods for prediction of trajectory for nonlinear conditions is by applying Particle Filter (PF) algorithm.The PFs can be applied to perform localization even when the initial target position is unknown and deal with systems that are affected by non-Gaussian noise. They are also relatively easy to implement. Hence it is a popular filtering algorithm in various localization problems. Human localization for indoor environment till date is an important issue since humans are unable to deliver the motion related information upon request. Apart from it GPS does not provide efficient and accurate results for indoor scenarios; this inefficiency is due to the weakness of signals emitted by GPS and their disability to penetrate through building materials. Thus to tackle such issues particle filter is used. Here the sensor nodes will sense the presence of target and determine its position using shortest distance based on received signal strength. This tracked position of the target is fed to proposed algorithm which will predict its next location.

***Keywords**-particle filter, indoor environment, human localization.*

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## I. INTRODUCTION

Wireless sensor network (WSN) can be described as a network containing large number ofcirculating, self-directing, low powered devices named sensor nodes .They are minute devices deployed within region of interest. They collect information related to velocity, position, pressure, temperature and other physical quantities and send such sensed data to base station for processing which is itself a challenging task.

Recently indoor localization based on wireless sensor networks (WSNs) has received immense attention in variety of fields including engineering and industrial [1]. Objects that are to be tracked in indoor environment are commonly classified into two groups. The first group includes mobile robots and vehicles that caneffectively interact and deliver useful information (e.g. like kinematics and dynamics) upon request. The second group includes humans and other equipment's that are unable to deliver such information. Thus till date accurate localization becomes an issue [1].

For the purpose of localization in outdoor environments, GPS plays a leading role and has also proven to be accurate for many real time applications now- days. Contradictory to it, for purpose of indoor environment as the strength of the emitted signal decreases their disability to penetrate through most building materials is reduced exponentially to large extent. Therefore it can be used for indoor environments where people are intended to spend most of their time. Although GPS devices are becoming more and more center of attraction and in near future would also provide sufficient precision for outdoor scenarios but still the technology demands indoor human/object tracking [2].

As a result of complexity that are tend to occur in indoor scenarios, their growth is highly affected with a set of challenges and issues like NLOS, multipath effect, and noise interference [2]. The impact of obstacles such as walls, equipment's, and human beings on the propagation of electromagnetic waves [3] leads to cause of such challenges. The mobility of people causes the variations in physical conditions of the environment, which directly or indirectly affect the behavior of wireless radio propagation. Though these drawbacks cannot be eliminated or ignored completely, in recent years researches are constantly working to improve the performance of indoor (human/object) tracking.

To avoid problems that arise in localization, use of optimal/ robust filters is done. The most renowned and classical approach is a Kalman filter (KF), which is highly optimal for linear Gaussian systems [4].They are serving as extremely useful for real time applications like robotics, communication systems, GPS, navigation systems, control systems, weather forecasting, multi-sensor data fusion, tracking of aircraft, satellites, any autonomous vehicles, humans and salmon, as well as some other applications that are trying to predict and manipulate the stock market [4]. They are easy to design, implement and they often provide good estimation accuracy for linear systems. The technicians are using various approximations to fit this approach for solving nonlinear problems.

The disadvantage using Kalman filter is that accuracy needs to be compromised for some practical cases, for variety reasons like:1) Rise of nonlinearities in the state space equations governing the physical system, 2) Very large covariance matrix, and 3) inaccurate or incomplete models of the underlying physical problem [5]. Such issues can be efficiently tackled by using the nonlinear class of filters which provide superior performance compared with the Kalman filter.

This triggers the usage of nonlinear class of filters for estimation like the extended Kalman filter (EKF) and the unscented Kalman filter (UKF) [6]. It is verified by using a set of stimulations that UKF are more accurate than the EKF for highly nonlinear systems for Non-Gaussian systems. But both of them have well defined drawbacks since they need prior information about initial position, stateestimation and noise, which is often unavailable [8],[9] at that moment .They arealso not capable in handling errors, such as sampling errors and errors in noise statistics.

Hence a nonlinear method which has been derived and opted on basis of the Monte Carlo Stimulations is known as particle filter (PF) or Monte Carlo localization (MCL) [10] is opted. It has gained high attention since it provide more accuracy for localization as it does not require knowledge about initial position and noise. The stimulations indicate that they more reliable as well as accurate than the EKF and UKF for highly nonlinear systems inspite of presence of intensive Gaussian or even non-Gaussian noise conditions.

## II. Target Tracking In Wireless Sensor Network

### A. *Target Tracking*

Target tracking is a one of the typical WSN application. Target tracking can be defined as the prediction of the future location of any dynamic system based on various estimates and measurements. Generalized idea about target tracking is shown in Fig 1. The target can be an enemy vehicle, human, wild animal etc. First of all, the presence target is sensed by the sensor nodes .Then data collected is process then tracking is done according to trajectory generation .Target localization can be prediction-based, tree based, cluster based and so on.


Figure 1. Generalized block diagram for Target Tracking.

Target Tracking Approaches: They are classified as above each having pros and cons.

Tree-Based:Nodes present in the network are organized in a hierarchical treestructure or represented in form of a graph format. Actually the root of this tree is the sensor which is nearest to the target and other sensors get added or removed as the target moves rapidly. As the distance between the root node and the target increases or decreases, the rate at which the reconfiguration of the tree also need to be adjusted accordingly. Hence this structure is not sufficient for tracking of high speed targets.

Cluster-Based: This approach consists of different stages like:

- Formation of clusters
- Cluster head selection
- Data aggregation
- Data transmission to sink node

The nodes present in the cluster identify the target and submit the data collected to cluster heads. Cluster heads process all collected data from the surrounding nodes and determine target location and report to sink node. It can be static or dynamic. Instead of reporting to a centralized sink node, cluster members are to report to their cluster head only, which saves energy by prolonging lifetime of network.

Prediction-Based:It Predicts the target trajectory and its next location, only activate special nodes of network for tracking and rest of nodes remain in sleep mode for energy saving.It can efficiently deal with unexpected direction changes but does not deal with varying speeds of a moving target.

Prediction algorithm predicts the target path, after that certain sensor and communication takes place for a finite time and after completion of predefined time period sensors put themselves into deep sleep state. The nodes which are not involved in the tracking procedure are kept in sleep state to preserve energy resources.

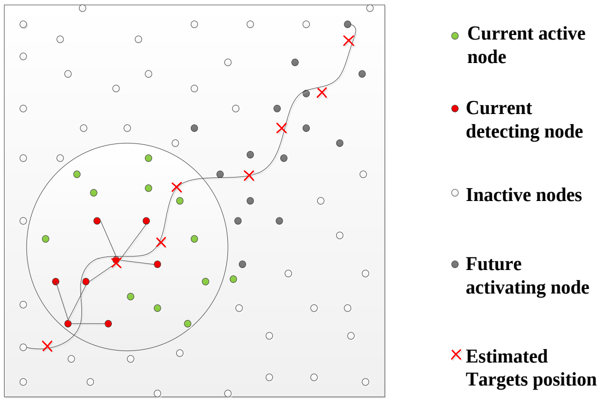


Figure 2. Example of a Prediction-Based Scheme [7]

Target tracking scheme comprises of three interrelated subsystems which are shown in Fig. 3. The sensing subsystem is used to sense the target i.e. it comprises of the node that first detects the target and other nodes which gradually take part in detecting the target. The Second subsystem is based on prediction algorithm which can be used to locate the path of the desired target. The last one is communication subsystem which is used to send the information from one node to another.


Figure 3. Target Tracking Scheme [7]

### B. *Particle Filter Algorithm*

A *particle filter* can be defined as recursive, Bayesian state estimator that uses discrete particles to approximate the posterior distribution of the estimated state [6].They are general Bayesian based approach to solve filtering problems arising in signal processing.
They can be applied to optimally solve for highly nonlinear and non-Gaussian problems.The key concept lies in representation of the particles, with corresponding Weights are used to form an approximation of a probability density function (PDF). They

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452 – 458

have been widely used for tracking applications since then provide results for nonlinear systems.

The PF algorithm is composed of the following basic steps as shown in Fig.4:
Step 1: Initialization
To generate random N particles each of them having same weight and initialize states.

$$\text{Particles} = \left(x^i(t), \widetilde{w}_t^i\right)(1)$$

$$\text{Initial weight: } w^i(t-1) \sim p(w(t-1))(2)$$

Where i=1,…,N

Step 2: Sample particles.
The algorithm performssampling of the initial states particle locations in two ways:

1) Initial position and covariance — If initial state functions are known then on need to provide the initial pose and covariance. This initialization helps to cluster particles closer to the known estimation so tracking done is more effective from the start.

2) State limits — If initial state functions are unknown then specify the possible limits of each state variable. The particles that are highly distributed particles are not as effective at tracking, because fewer particles are near the actual state. This approach uses more particles, computation time, and iterations to converge to the actual state estimate.

Step 3: Predicting the new locations of particles.
This step makes the use of previous state functions to predict the current state value based on a given system model.

$$\text{Prediction: } p(x_k \mid z_{1:k-1}) = \int p(x_k \mid x_{k-1}) p(x_{k-1} \mid z_{1:k-1}) dx_{k-1} (3)$$

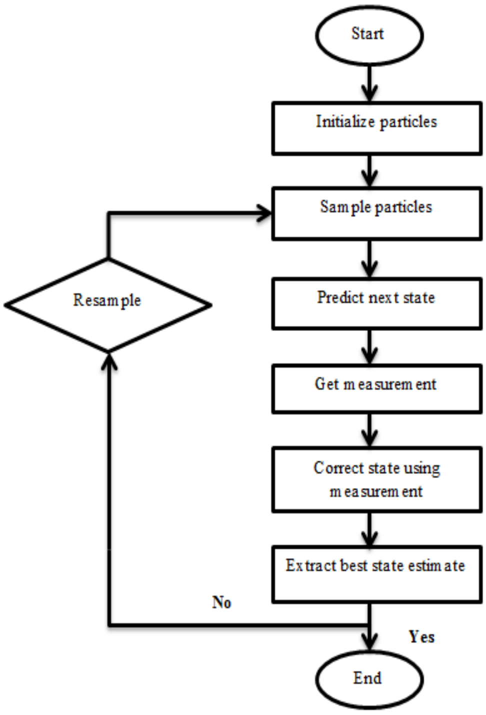


Figure 4. Flow chart of PF Algorithm

Step 4: Get measurement values
The data collected from sensors are used in the next step to correct the current predicted state.

Step 5: Computation and updation of weights
It makes the use of the current sensor data values for correction of the state estimate. Then adjustment of the predicted state is done as per needs.

$$\text{Update states: } p(x_k \mid z_{1:k}) = \frac{p(z_k|x_k)\, p(x_k|z_{1:k-1})}{p(z_k|z_{1:k-1})}(4)$$

Where $x_k$ = denotes present state

$z_{1:k}$ = denotes previous state

Step 6: Resample and normalize weights.
It periodically redistributes, or resamples, the particles to match the posterior distribution of the estimated state. It is required to update the estimation as the state changes in subsequent iterations.

$$\text{Normalization: } \widetilde{w_t^i} = \frac{w_t^i}{\sum_{j=1}^{N} w_t^j}(5)$$

Step 7: Continue till maximum iterations are achieved or exact best match is achieved.

## III. System Model

### A. System Model

For the purpose of tracking in indoor environment it is supposed that the target move uniformly and linearly in a two-dimensional plane. For tracking purpose, reliable detection should be provided and the position information of the target should be reported according to the specified sensing period.

ISSN: 2454-4248
452 – 458

Thepositionofthehuman is observed in a 2-D plane at (x,y). The human 2-D velocity is considered as $(\dot{x}, \dot{y})$ and assumed that it is constant within the sampling time interval T. The human is moving at discrete-time index k according to a known dynamic model [1]:

$$x_k = x_{k-1} + T\dot{x}_k (6)$$

$$y_k = y_{k-1} + T\dot{y}_k (7)$$

$$\dot{x}_k = \dot{x}_{k-1} (8)$$

$$\dot{y}_k = \dot{y}_{k-1} (9)$$

Here the target is equipped with a mobile tag that transmits a signal that is received by each of the receivers.The receivers' exact coordinates $(x_i, y_i)$ ,i =1,2,3,4, are known. The time at which the target presence is sensed is sensed based on the received signal strength known as $(x_k, y_k)$ where $d_i$ distance between target and recievers.

$$d_i = \sqrt{((x_k - x_i)^2) + ((y_k - y_i)^2)} (10)$$

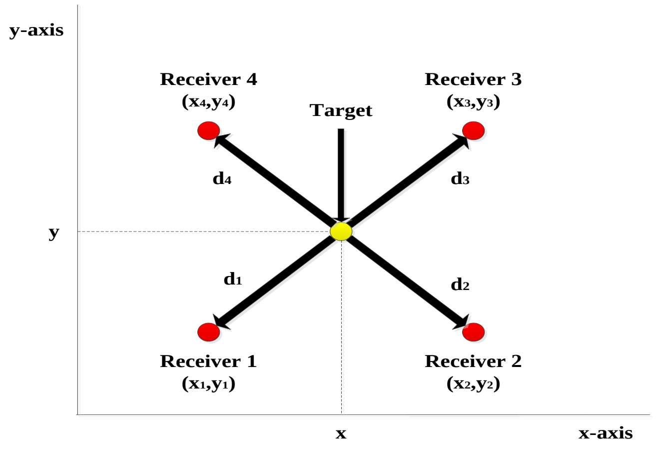


Figure 5. Two-dimension schematic indoor floor space geometry of human and four recievers.

The human motion can be modelled in state space as follows where state vector is denoted as:

$$x_{k,}y_k = [x_k, \dot{x}_k, y_k, \dot{y}_k, I_t]^T (11)$$

$$x_k = f_{k-1}(x_{k-1}, w_{k-1}) (12)$$

$$= \begin{bmatrix} 1 & 0T & 0 \\ 0 & 10 & T \\ 0 & 01 & 0 \\ 0 & 00 & 1 \end{bmatrix} x_{k-1} + \begin{bmatrix} T/2^2 & 0 \\ 0 & T/2^2 \\ T & 0 \\ 0 & T \end{bmatrix} w_{k-1}$$

where wk−1 $\in \Re^2$ is the process noise vector with the covariance Qk−1 and vk $\in \Re^4$ isa zero-mean measurement noisevector withthe covariance Rk [1].

## IV. Stimulation Analysis and Results

### A. Stimulation Analysis

Here the target is assumed to move within a monitoring field of size 100*100m covered by N=100 sensors. The sensing range of each sensor is 3m. Therefore, at each time step, the target is sensed by nearest 4 active sensor nodes. Based on received signal strength using Euclidean distance the target position is estimated which is send to particle filter algorithm for further prediction. In our stimulation following assumptions are considered.

**Assumptions:**

1. Target is moving in diverse direction with different velocities.
2. The sensors are deployed randomly
3. Targets motion is based on random walk model.
4. Velocity of target is constant within given sampling instant.

### B. Parameters

Table 1 indicates the initial stimulation parameters considered. Here the targets initial states are known and particles are generated with zero mean and covariance 0.2.Here the rate at which particles are sampled is considered as 0.05s. The threshold at which resampling of particles is done to generate new particles is defined as 0.08 m .

TABLE I. PARAMETERS

| Parameter | Value |
|---|---|
| Environment | Indoor |
| Area | 100*100 m |
| No of Nodes | 100 |
| No of nodes active at sensing interval | 4 |
| Sensing Range | 3m |
| No of particles | 5 |
| Sampling Time | 0.05 |
| Mean | 0 |
| Covariance | 0.2 |

### C. Result Analysis

Fig.6. indicates random deployment of 100 sensors within 100*100m region.

ISSN: 2454-4248
452 – 458

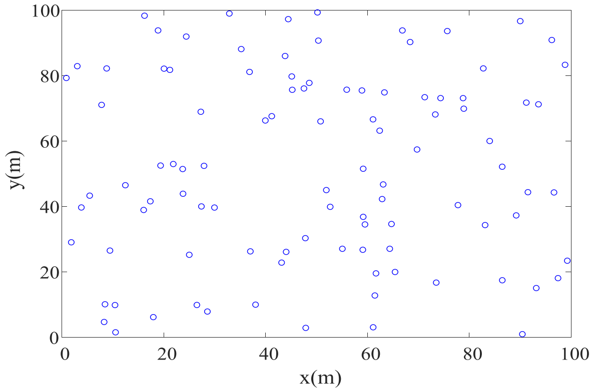


Figure 6. Sensor Node Deployment.

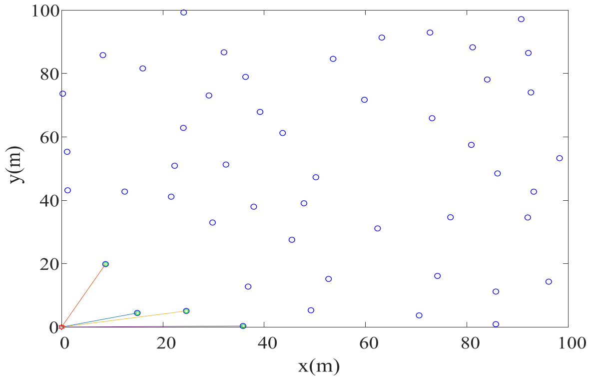


Figure 7. Target tracking in WSN using Particle Filter.

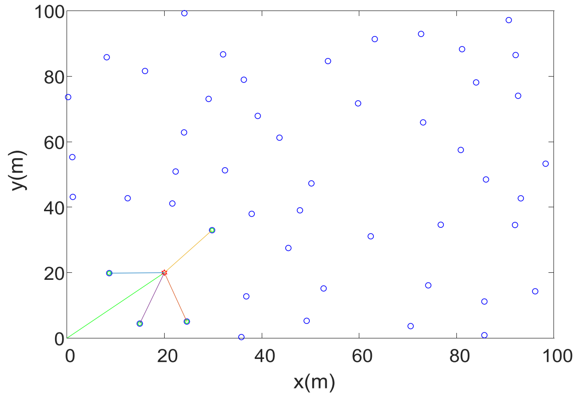


Figure 8. Target tracking in WSN using Particle Filter.

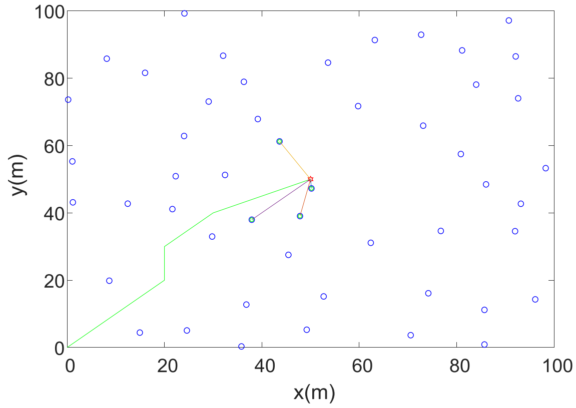


Figure 9. Target tracking in WSN using Particle Filter.

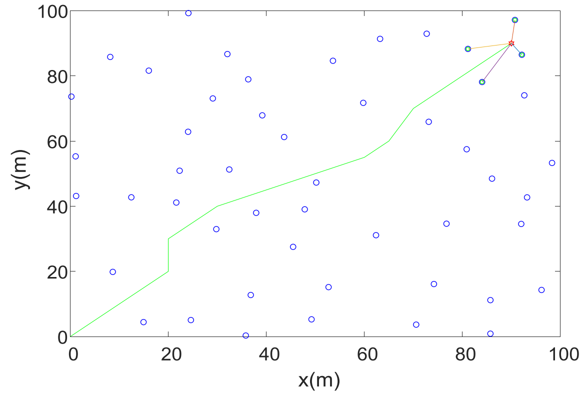


Figure 10. Target tracking in WSN using Particle Filter.

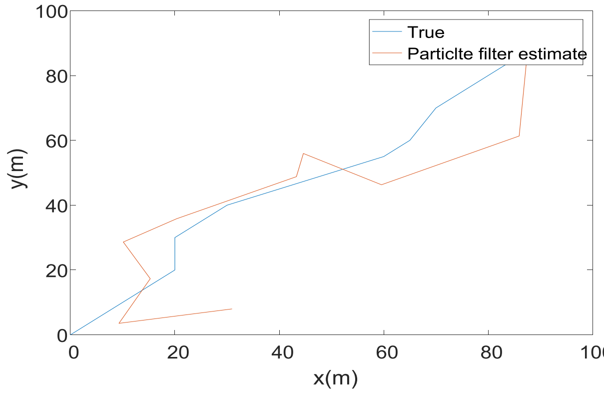


Figure 11. No of Particles (N)=100.

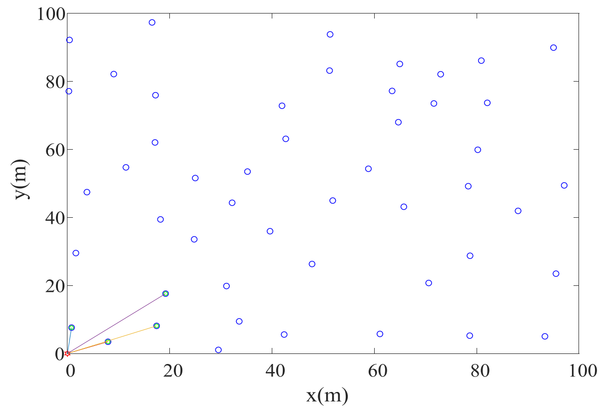


Figure 12. Target tracking in WSN using Particle Filter.

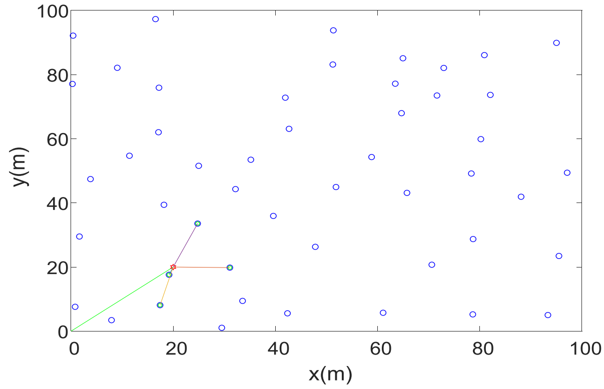


Figure 13. Target tracking in WSN using Particle Filter.

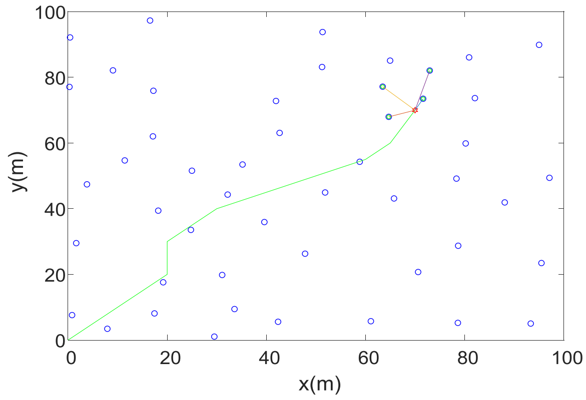


Figure 14. Target tracking in WSN using Particle Filter.

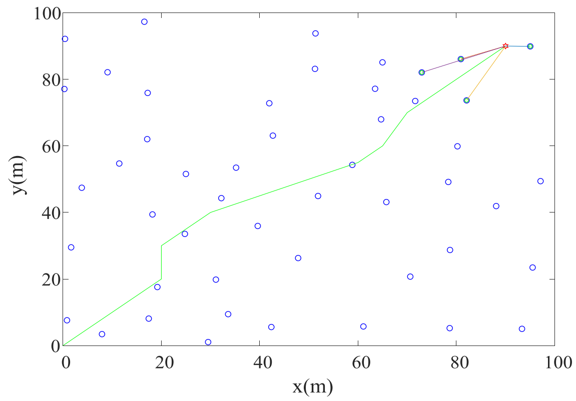


Figure 15. Target tracking in WSN using Particle Filter.

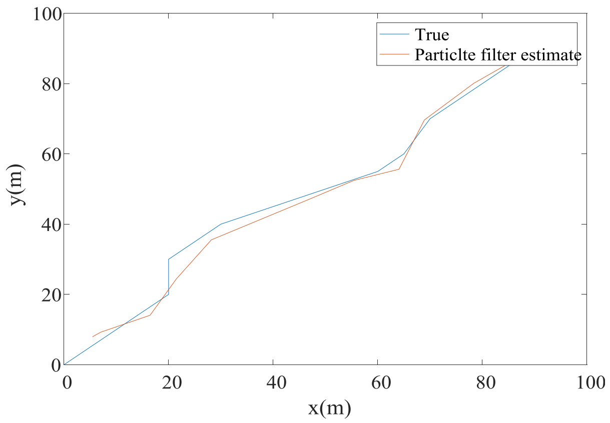


Figure 16. No of Particles (N)=1000.

For Fig.7 to Fig.11 illustrates results for no of particles N=100 Fig.7. illustrates target tracking using nearest 4 nodes. Fig .8. Fig.9. and Fig.10. indicates that based on position of target which is applied to PF to determined next instant where target may be present based on known previous states. Fig.11 indicates true and estimated PFs targets path.

Fig.12 to Fig.16 illustrates readings for no of particles N=1000. Fig.16 indicates that better accuracy is seen as no of particles increases and also rmse reduces.

TABLE II. ROOT MEAN SQUARE ERROR

| NO OF PARTICLES | RMSE |
|---|---|
| 100 | 0.1814 |
| 300 | 0.104 |
| 500 | 0.0811 |
| 700 | 0.06 |
| 1000 | 0.0054 |

Table 2 indicates that as no of particles increase root mean square error reduces which increases tracking accuracy. But it increases complexity and also time to resample particles increases.

## V. CONCLUSION

Particle Filter are proved to be more accurate and provides efficient tracking among all other nonlinear filters. When sensor nodes sense presence of target and its location is determined andit is applied to Particle Filter block which provides further tracking.
Here different cases are considered with varying no of particles (i.e. N=100 to 1000) and result is obtained. Then difference between initial is calculated and RMSE is obtained. It is observed that if no of particles are more it provides better tracking accuracy.If we decrease no of particles pf may suffer from sample impoverishment. To avoid this resampling should be properly done.

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452 – 458

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