

# Tracking Manoeuvring Mobile Nodes in Wireless Sensor Networks with Range-Only Measurements

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**Abstract**—This paper addresses the problem of tracking mobile nodes in Wireless Sensor Networks (WSN). Our approach is based on a tracking with range-only measurements scheme, intended for implementation in WSN. The developed tracking system is designed for continuous estimation of the target's trajectory and two-axes velocity. A network of “anchor” wireless nodes is considered to be deployed at a specific region of interest. The anchor nodes collect data that correspond to the range between the anchors and the target. A multiple-modal Particle Filter (PF) algorithm is designed to process the ranging observations and produce an estimation of the target's kinematic variables in real-time. The reason for employing multiple models to represent the target's motion pattern, stems from the need to effectively track manoeuvring targets. Manoeuvring targets require more complex modeling which adequately represents the sudden changes of the position and velocity vectors. Simulations are provided to assess the performance of the proposed framework, considering real-world conditions. The proposed multiple model approach is evaluated on manoeuvring targets with constant as well as variable turning rate. Finally, this investigation reveals that the system's accuracy depends upon two important system parameters, the sampling period and the number of generated particles in the PF algorithm. The effect of these parameters is analyzed and amendments are proposed.

**Index Terms**—Wireless Sensor Networks, Target Tracking, Particle Filters

## I. INTRODUCTION

WIRELESS Sensor Networks (WSNs) have emerged as one of the most promising technologies in the area of pervasive and distributed computing. By encompassing a wireless communication module, various sensors and a low-power processor in a limited size platform, WSNs provide a mean that allows direct interaction with the physical world. The unique features that WSNs demonstrate, fostered an escalating interest along the direction of exploiting this technology in a number of interdisciplinary application domains. Some examples include, environmental and industrial monitoring, surveillance and security systems and pervasive healthcare [1].

One of the areas where WSNs are considered to be particularly suited for, is in applications where tracking of mobile targets is desired [2]. WSNs offer the ability of being deployed in large numbers and obtain a vast amount of information with high spatial and temporal resolution. These

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features render this technology suitable for locationing and tracking applications. The purpose of a WSN tracking system is to detect and track any moving object of interest (a.k.a. the target) that is moving within the network's coverage area. Tracking may refer to anything from coarse-grained localization of the target in an area, to specific positioning through estimation of its kinematic variables. In addition tracking can be performed non-continuously in a query based context or in a continuous manner where the target's position is updated continuously and in real-time. In general, the target's dynamics are inferred by processing specific information acquired by the network, mathematically associated with the target's kinematic characteristics. For example, various sensor readings can reveal the relative distance between the source and the sensor. The potential benefits of using WSNs in tracking can be applied to a number of application spanning from, locating personnel or assets in industrial infrastructures to wildlife monitoring and security systems.

Much research focuses on locationing and tracking in WSNs. A number of approaches, pertain to military surveillance scenarios where detection and classification of incoming targets is of greater importance than continuously estimating their dynamics [3]–[6].

This paper proposes a tracking system intended for deployment in WSNs. The system focuses on estimating the position and velocity of mobile nodes. A Particle Filter based, tracking algorithm is employed to achieve real-time tracking of mobile nodes based on a batch of range measurements provided from the wireless network. The proposed tracking system considers range observations between the target node and a number of anchor nodes to be the only type of information that becomes available to the system. Different to this, a number of related approaches, consider more than one type of data (ex. range and bearing) to be available to the system [7]–[9]. However to acquire bearing data in WSNs additional hardware (like micro-RADARS) must be attached to every anchor node. Such hardware is usually costly not to mention energy demanding. On the other hand, ample ranging between wireless nodes can be achieved using a variety of techniques which are relatively energy efficient and do not require any additional hardware. Examples include Time of Flight (ToF) and Received Signal Strength Indication (RSSI) [10], [11].

The major challenge of this work is twofold. Since WSNs nodes are devices with limited energy supply and processing power, the range estimates acquired by the system will inherently contain an amount of noise. Thus, a great challenge for

such tracking systems is the robustness they demonstrate to noise. In addition, the system is intended to effectively track manoeuvring targets, which is the case in the majority of real-world tracking scenarios. For this, a multiple-modal approach is used to represent the dynamics of manoeuvring targets. Such an approach diversifies the proposed system with other approaches in the area that only consider a linear constant velocity (CV) model for describing the target's dynamics, thus providing limited support for manoeuvring targets [12]–[14]. By applying multiple models to represent the evolution of the target's dynamics in time, we demonstrate that the our design can effectively track manoeuvring targets. The system is tested against manoeuvring targets with constant as well as variable turning rate.

The rest of the paper is organised as follows. An overview of the system is provided in the next section. In Section III we formulate the tracking problem as a nonlinear estimation problem. In the following section the PF tracking algorithm, designed to solve the estimation problem is analyzed. Simulation results are presented in Section V. In the final section, concluding remarks and future directions are discussed.

## II. SYSTEM OVERVIEW

An illustration of the proposed system is given in Fig. 1 where four anchor nodes are deployed in known locations to provide the range estimates. A wireless mobile node is the object to be tracked. This target node can be strapped to the actual object of interest which can be an animal, a robot, a human or an object. The range data acquired by the anchor nodes are then fused to a higher level node, a cluster-head or a base station which is equipped with adequate processing power and is energy redundant, which executes the tracking algorithm and produces the estimates. The final estimates can then be utilized by a front-end user for monitoring and/or further processing.

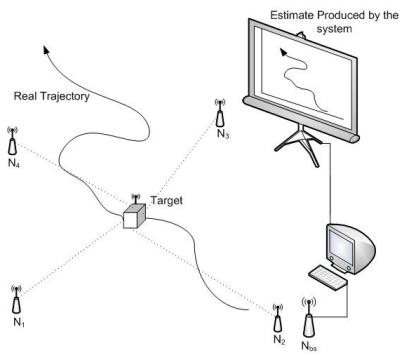


Fig. 1. Tracking System Overview

## III. PROBLEM FORMULATION

In order to best describe the target's kinematics the tracking problem is formed in a discrete-time nonlinear state-space approach. First of all, the system is considered to run for a total amount of time denoted as “ $T$ ”, divided into

several time steps according to the sampling period. In a state-space representation the state vector contains all the relevant information required to describe the system under investigation. Hence, at each time step “ $k$ ”, the state vector “ $\mathbf{x}$ ” to be estimated comprises of the planar coordinates and two axis velocity of the mobile target.

$$\mathbf{x} = [x \ y \ v_x \ v_y] \quad (1)$$

### A. State Dynamics

The state equation describes, in mathematical terms, the evolution of the state-vector in time. To capture the dynamics of manoeuvring target's a multiple model approach is used to form the state equation. Three motion models are used for this reason. At each time step  $k$  an integer regime variable indicates which model is in use during the sampling period from  $(k-1, k]$ .

$$\mathbf{x}_k = \mathbf{F}(\mathbf{r}_k)\mathbf{x}_{k-1} + \Gamma \mathbf{w}_{k-1} \quad (2)$$

- where,

$$\Gamma = \begin{bmatrix} T_s^2/2 & 0 \\ 0 & T_s^2/2 \\ T_s & 0 \\ 0 & T_s \end{bmatrix} \quad (3)$$

- $T_s$  is the sampling period,
- $\mathbf{w}_{k-1}$  is a  $2 \times 1$  noise vector sampled from a known distribution that represents the state noise (acceleration units are used)
- $\mathbf{x}_k$  is the state vector, defined in Eq. 1
- and  $\mathbf{r}_k$  is the regime variable which is modeled as a time homogeneous, three-state, first-order Markov chain with transitional probability matrix given by the following relationship:

$$\pi_{mn} \triangleq P\{\mathbf{r}_k = m \mid \mathbf{r}_{k-1} = n\} \quad (4)$$

The following figure illustrates the regime variable transitional probabilities.

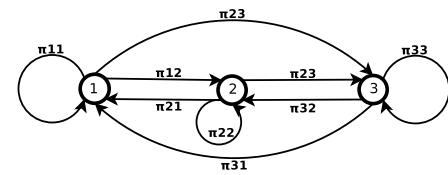


Fig. 2. Regime probability transition

The state transition matrix  $\mathbf{F}$ , at time  $k$  is defined according to the value of the regime variable  $\mathbf{r}_k$ ,  $(\mathbf{F}_{r_k})$  and is given as:

- The Constant Velocity Straight Line motion model

$$\mathbf{F}(1) = \begin{bmatrix} 1 & 0 & T_s & 0 \\ 0 & 1 & 0 & T_s \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (5)$$

- First Coordinated Turn model

$$\mathbf{F}(2) = \begin{bmatrix} 1 & 0 & \sin(\omega T_s)/\omega & (\cos(\omega T_s) - 1)/\omega \\ 0 & 1 & (1 - \cos(\omega T_s))/\omega & \sin(\omega T_s)/\omega \\ 0 & 0 & \cos(\omega T_s) & -\sin(\omega T_s) \\ 0 & 0 & \sin(\omega T_s) & \cos(\omega T_s) \end{bmatrix} \quad (6)$$

- Second Coordinated Turn model

$$\mathbf{F}(3) = \begin{bmatrix} 1 & 0 & \sin(\omega T_s)/\omega & (\cos(\omega T_s) - 1)/\omega \\ 0 & 1 & (1 - \cos(\omega T_s))/\omega & \sin(\omega T_s)/\omega \\ 0 & 0 & \cos(\omega T_s) & -\sin(\omega T_s) \\ 0 & 0 & -\sin(\omega T_s) & \cos(\omega T_s) \end{bmatrix} \quad (7)$$

- where  $T_s$  is the sampling period and,
- where  $w$  is the turn rate in rad/sec

Although the use of a multi-modal approach increases the complexity of the system due to the state equation becoming nonlinear. Manoeuvring targets require to be modeled in such a way in order for the system to cope with abrupt changes in the position and velocity vectors.

### B. Measurements Equation

The measurements vector contains the measurements that are made available to the system. The observations in this case correspond to the ranging data accumulated from the anchor nodes. Thus, at each time step  $k$ ,  $N_s$  anchor nodes provide range estimates of the target's Euclidean distance to them. The measurements equation provides the mathematical association between the observations vector  $\mathbf{z}_k$  and the state-vector  $\mathbf{x}_k$ . The dimension of the measurements vector is  $N_s \times 1$ . It is formed as:

$$\mathbf{z}_{k,N_s} = \sqrt{(y_k - y_{N_s})^2 + (x_k - x_{N_s})^2} + \mathbf{v}_k \quad (8)$$

- where time index  $k$ : is discrete:  $k = 1, 2, \dots, K$
- $x_k, y_k$  are the target's coordinates and  $x_{N_s}, y_{N_s}$  are the coordinates of the anchors
- $\mathbf{v}_k$ : is a  $N_s \times 1$  noise vector sampled from a known distribution that represents the additive measurements noise

## IV. TRACKING ALGORITHMS

### A. Particle Filters

This section provides insight in the design of the PF tracking algorithm that operates on the range measurements, acquired by the system, to infer the state vector of the target at each time step. PF are a class of recursive Bayesian Estimation methods inspired by the techniques of Importance Sampling and Monte Carlo Integration [15]. In the Bayesian Estimation framework the unknown state  $\mathbf{x}_k$  is estimated in a two-stage procedure given certain incoming measurements and a mathematical process model [16]. Specifically, the purpose of Bayesian Estimation is to produce an estimate of the state  $\mathbf{x}_k$  at time  $k$  based on the sequence of measurements  $\mathbf{Z}_k$  up to that time instance. To calculate a state estimate, the posterior pdf  $p(\mathbf{x}_k | \mathbf{Z}_k)$  of the state at time  $k$  should be estimated. After obtaining the posterior pdf  $p(\mathbf{x}_k | \mathbf{Z}_k)$ ,

an estimation of the state vector can then be produced with the use of a certain criterion like the Minimum Mean Square Error (MMSE). PF are probabilistic approaches that estimate an unknown probability density function (pdf) recursively in time using a set of weighted random samples called "particles". These particles are sampled from a proposal distribution and then weighted appropriately to approximate the state's pdf. Let's denote the evolution of the state vector up to time  $k$  as  $\mathbf{X}_k = \{\mathbf{x}_j : j = 1, 2, \dots, k\}$ . Similar to this, the measurements made available up to time  $k$ , are denoted as  $\mathbf{Z}_k = \{\mathbf{z}_j : j = 1, 2, \dots, k\}$ . The pdf  $p(\mathbf{x}_k | \mathbf{Z}_k)$  is approximated by a set of  $N$  particles denoted as  $\mathbf{X}_k^i$  and their corresponding weights,  $w_k^i$ . An approximation of the state pdf at time  $k$  is given from the following:

$$p(\mathbf{X}_k | \mathbf{Z}_k) = \sum_{i=1}^N w_k^i \delta(\mathbf{X}_k - \mathbf{X}_k^i) \quad (9)$$

where  $\delta$  is Dirac's delta function.

As mentioned previously, particles  $\mathbf{X}_k^i$  are sampled from a proposal distribution  $q(\mathbf{X}_k | \mathbf{Z}_k)$  and then assigned importance weights accordingly. The weight for each particle is computed from the following relationship:

$$w_k^i \propto \frac{p(\mathbf{X}_k^i | \mathbf{Z}_k)}{q(\mathbf{X}_k^i | \mathbf{Z}_k)} \quad (10)$$

One important issue of concern in PF is the degeneracy problem. In practical terms, after a number of iterations all but one particles have negligible weights. Thus, a substantial amount of computation is devoted in updating particles with minimal contribution to the approximation of the pdf. To avoid the effects caused by degeneracy in PF, a measure, called effective sample size  $N_{eff}$ , is introduced and defined as follows:

$$N_{eff} = \frac{1}{\sum_{i=1}^N (w_k^i)^2} \quad (11)$$

A resampling step is carried out whenever  $N_{eff}$  is found to be smaller than a pre-defined threshold  $N_{thr}$ . Resampling eliminates samples with low importance weights while multiplies samples with high importance weights.

### B. Range only Tracking Multiple Model Particle Filter Algorithm ROT-MMPF

To solve the nonlinear dynamic model presented in Section III-A, a multiple model PF algorithm is employed. Since multiple models are used, the state vector becomes an augmented vector which contains both the state  $\mathbf{x}_k$  and the regime variable  $\mathbf{r}_k$ . The augmented state vector is denoted as,  $\mathbf{y}_k = [\mathbf{x}_k \ \mathbf{r}_k]$ . Initial particles are drawn from two distributions  $p(\mathbf{r}_0)$  and  $p(\mathbf{x}_0)$  which represent the system's initial knowledge regarding the target's state. The transitional prior  $p(\mathbf{x}_k | \mathbf{x}_{k-1})$  is chosen as the importance density distribution to sample particles from, for the state  $\mathbf{x}_k$ , while particles for the regime variable are sampled according to the transitional probability matrix  $\Pi = [\pi_{mn}]$ . The rule that is followed

for that is; if  $r_{k-1}^i = m$ , then  $r_k^i$  should be set to  $n$  with probability  $\pi_{mn}$ .

Upon receiving a new measurement the weight for each generated particle is computed. Because the transitional prior is chosen as the importance density function, Eq.10, which calculates the weight for each particle, simplifies to  $w_k^i \propto p(z_k|y_k^i)$  which is the likelihood of the measurement vector (real observation)  $z_k$ , given the predicted observation  $z_k^i$ , calculated from Eq.8, using the sampled particle  $y_k^i$ . Assuming Gaussian statistics for the observations, each weight  $w_k^i$  for particle  $x_k^i$  ( $i = 1 \dots N$ ) is calculated from the following likelihood relationship:

$$\tilde{w}_k^i = L(z_k|y_k^i) = B \exp(-0.5 * (z_k - z_k^i) * (z_k - z_k^i)^T) \quad (12)$$

where  $B$  is a normalising constant which depends on the measurements noise distribution. The final step in the ROT-MMPF algorithm involves resampling, whenever  $N_{eff}$  is found to be smaller than  $N_{thr}$ .

An iteration of the ROT-MMPF algorithm is given in Algorithm 1 and the flowchart of the ROT-MMPF in Fig. 3.

#### Algorithm 1 :ROT-MMPF Algorithm

```

Initialize
- Draw Initial Particles
for i = 1 to N do
     $r_0^i \sim p(r_0)$  ( $\sim$  denotes sampling from)
     $x_0^i \sim p(x_0)$ 
end for

Sequential Importance Sampling Step
- Sample Particles and Calculate Weights
for i = 1 to N do
     $r_k^i \sim \pi_{ij}$ 
     $x_k^i \sim p(x_k|x_{k-1})$ 
     $\tilde{w}_k^i = p(z_k|x_k^i, r_k^i)$  (using Eq.12)
end for

- Calculate total weight
 $t = \sum_{i=1}^N \tilde{w}_k^i$ 
- Normalize weights
for i = 1 to N do
     $w_k^i = t^{-1} \tilde{w}_k^i$ 
end for

Resampling Step
if  $N_{eff} < N_{thr}$  then
    - Resample with replacement to obtain N new particles distributed according
     $p(y_k|Z_{0:k})$ 
end if

```

## V. SIMULATION - RESULTS

This section provides results from simulating the proposed tracking system under various two-dimensional scenarios. The robustness of the tracking system with respect to the additive noise that corrupts the state model and measurements is examined. In the simulation environment considered a single mobile node is the target that the system focuses on tracking. To acquire the ranging information the mobile node is always considered to be within the communication range of the anchors. In particular, we investigate the effects of Sampling Period (sampling interval) and number of Particles on the achieved accuracy of the tracking system.

A wireless sensor network consisting of four anchor nodes is considered to be deployed. The coordinates of the anchor nodes are,  $s_1 = [10m \ 0m]$ ,  $s_2 = [50m \ 0m]$ ,  $s_3 =$

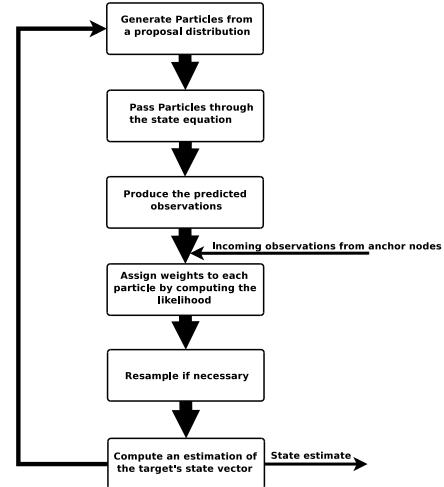


Fig. 3. The flowchart of the ROT-MMPF algorithm

$[10m \ 25m]$ ,  $s_4 = [50m \ 25m]$ . The state vector of the target evolves in time as defined in Eq. 2, while the observations that become available to the system from the anchor nodes, are associated to the target's state according to Eq. 8. The sampling period is set to  $T_s = 1sec$  and the system evolves for  $T = 75sec$ . In the implementation of the ROT-MMPF tracking algorithm  $N = 500$  particles were used. The turning rate is considered to be constant and set at  $\omega = \pi/4 \text{ rad/sec}$ . The measurements and state noise sources are considered to follow zero mean Gaussian distributions. Specifically:

$$\mathbf{w}_k \sim \mathcal{N}(0, 2\mathbf{I}_2)$$

$$\mathbf{v}_k \sim \mathcal{N}(0, 2.5\mathbf{I}_4)$$

The regime variable is defined as a first order homogeneous Markov chain with transition probability  $m = 0.8$  thus the transition probability matrix is,

$$\mathbf{P}(r_t | r_{t-1}) = \begin{bmatrix} 0.8 & 0.1 & 0.1 \\ 0.1 & 0.8 & 0.1 \\ 0.1 & 0.1 & 0.8 \end{bmatrix} \quad (13)$$

The target's initial state vector is  $\mathbf{x}_0 = [1m \ 1m \ 2m/s \ 2m/s]$ . Initial particles for the regime variable  $\mathbf{r}_t$  are sampled with equal probability  $\mathbf{P}_0 = (0.333 \ 0.333 \ 0.333)$ , while initial particles for the state  $\mathbf{x}_k$  are drawn from a Gaussian distribution of mean equal to the objects initial location thus  $\mu_0 = \mathbf{x}_0$  and covariance matrix  $S = \mathbf{I}$ . To quantify the accuracy achieved in estimating the target's position the Root Mean Square Error (RMSE) is used.

The RMSE for position is,

$$\text{RMSE} = \sqrt{\frac{1}{T} \sum_{t=1}^T (x - x_{est})^2 + (y - y_{est})^2} \quad (14)$$

The results from a single run of the above scenario are illustrated in Fig. 4 for the target's trajectory and in Fig. 5 for the target's two-axis velocity.

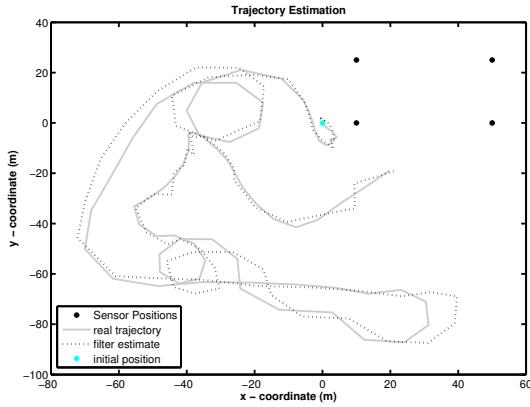


Fig. 4. True and Filtered target trajectory

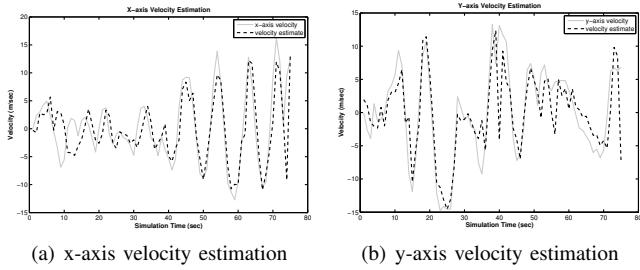


Fig. 5. Two-axis velocity estimation

The RMSE for this run was calculated,  $\text{RMSE} = 4.9318m$ . To evaluate the robustness of the tracking system, the previous scenario is simulated multiple times. The RMSE is calculated in every execution. Results are presented in Fig. 6. In 85% of the executions the RMSE remains below 40m and in 77% below 20m. These results justify the robustness of the system under a noisy environment ( $\mathbf{w}_k \propto N(0, 2)$ ,  $\mathbf{v}_k \propto N(0, 2.5)$ ).

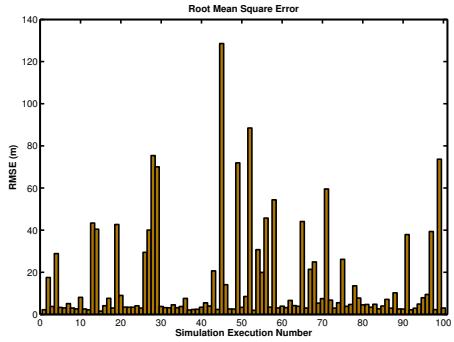


Fig. 6. RMSE for 100 executions

To analyze the factors that affect the accuracy of the proposed system in a real-world scenario, simulations were

conducted for different values of the Sampling Period  $T_s$ . The deployment parameters and noise sources were kept similar as before. The number of particles used in the ROT-MMPF algorithm implementation also kept the same  $N = 500$ . The total simulation time remained  $T = 75\text{sec}$  and the system was simulated for increasingly Sampling Period  $T_s = 2, \dots, 7\text{sec}$ . For each Sampling Period the system was simulated a total of 100 times. At each execution the RMSE for position was calculated and finally the average RMSE was calculated for the total of 100 runs.

From Fig. 7(a) it is clear that the achieved tracking accuracy, is heavily dependent upon the Sampling Period as denoted by the increase of the average RMSE when the Sampling Period increases. Low Sampling Period indicates, increased temporal resolution of the collected data, leading to improved accuracy of the tracking system. The Sampling Period is heavily dependent on the amount of time required by the anchor nodes to collect and fuse the ranging estimates. Moreover the Sampling Period is also affected by the time the system requires to run the tracking algorithm and produce an estimate of the target's state. The Sampling Period, also plays an important role on the maximum speed of the mobile node that can be effectively tracked. Fast moving targets, require high temporal resolution among the collected ranging data.

One way to amend the lack of accuracy due to increased Sampling Period is to employ more particles in the implementation of the ROT-MMPF algorithm. A system with the same deployment parameters as before is simulated for increasingly number of particles. The system operates with a sampling period of  $T_s = 2\text{sec}$  and the ROT-MMPF utilizes  $N = 700, 1000, 1500, 2000, 2500$  particles. Similar to the investigation carried out previously the system was simulated for a total of 100 times for each particle size. For  $N = 500$  particles the average RMSE was found to be  $\text{RMSE} = 51.03m$ . Fig. 7(b) depicts the average RMSE against the different particle sizes. By employing 5 times more particles the system achieves more than 50% improvement in position accuracy.

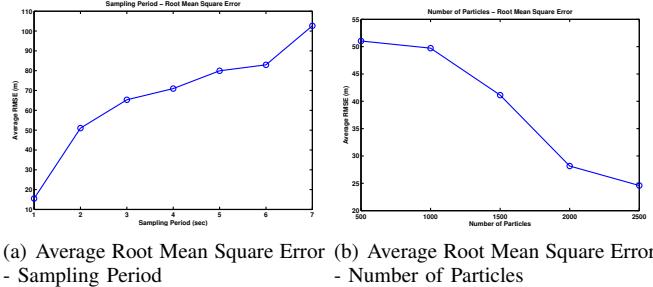


Fig. 7.

To extend the investigation on more complex trajectories, a scenario where the target performs manoeuvres with variable turning rates ( $\omega$ ) is simulated. The turning rate is defined as the magnitude of the acceleration divided by the current speed of the target [17]. Whenever a turn is performed ( $\mathbf{F}(2)$

and  $\mathbf{F}(3)$  are used to describe the target's dynamics) the acceleration is set to be drawn from  $N(0, 8)$ . The target's initial state vector is  $\mathbf{x}_0 = [1m \ 1m \ 1m/s \ 1m/s]$ . The rest of the parameters are kept as previously. Results from simulating this scenario are given in Fig. 8 for trajectory and Fig. 9 for velocity. The RMSE for this exemplar run was calculated and found to be  $RMSE = 6.7380$ .

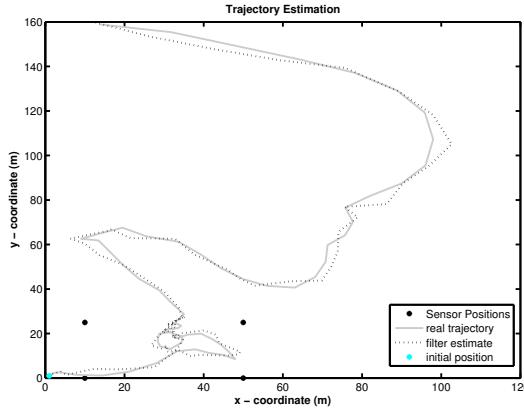
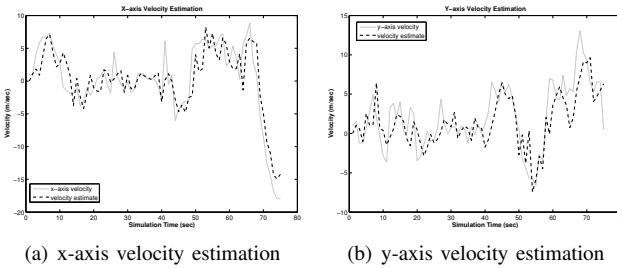


Fig. 8. True and Filtered target trajectory - variable turning rate



(a) x-axis velocity estimation (b) y-axis velocity estimation

Fig. 9. Two-axis velocity estimation - variable turning rate

## VI. CONCLUSIONS - FUTURE WORK

In this paper, a collaborative approach for tracking mobile nodes in ad-hoc WSNs is presented. The proposed system achieves tracking based on the accumulated information from a number of stationary anchor nodes which collect range estimates and fuse them to a central node which executes the tracking algorithm. Through simulations we demonstrated the ability of the proposed tracking system to perform robustly under noisy conditions and to achieve substantial accuracy  $RMSE < 10m$ . The design of the ROT-MMPF algorithm focuses on manoeuvring targets and simulations revealed the ability of the algorithm to effectively track manoeuvring targets with constant and variable turning rate. The sampling interval between successive data readings as well as the number of particles used in the algorithm's execution, affect the performance of the system significantly. High sampling period means less sampling steps which translates to less amount of data to be accumulated on the same amount of time. Ultimately, performance diminishes. Increasing the number of particles results in improved performance.

However, it should be noted that increasing the number of particles, results in an increase in the execution time of the algorithm. In conclusion, the application requirements in accuracy as well as the specifications of the hardware to be used will dictate the optimum trade-off between performance accuracy and time constraints.

The evolution of the work presented in this paper is the implementation of the proposed system in hardware. Low-power Zigbee compliant nodes are going to be used as anchors, while more powerful hardware will fuse the ranging data and execute the tracking algorithm. Specifically our own laboratory results have demonstrated that ranging with up to 1m accuracy between node is feasible with a ToF technique. This ranging technique is expected to be included in the implementation.

## REFERENCES

- [1] D. Culler, D. Estrin, and M. Srivastava, "Guest editors' introduction: Overview of sensor networks," *IEEE Computer*, vol. 37, pp. 41–49, 2004.
- [2] J. Hightower and G. Borriello, "Location systems for ubiquitous computing," *Computer*, vol. 34, no. 8, pp. 57–66, August 2001.
- [3] A. Arora et al, "A line in the sand: a wireless sensor network for target detection, classification, and tracking," *Comput. Netw.*, vol. 46, no. 5, 2004.
- [4] T. He, S. Krishnamurthy, J. A. Stankovic, T. Abdelzaher, L. Luo, R. Stoleru, T. Yan, L. Gu, J. Hui, and B. Krogh, "Energy-efficient surveillance system using wireless sensor networks," in *MobiSys '04*, 2004.
- [5] T. He, P. Vicaire, T. Yan, L. Luo, L. Gu, G. Zhou, R. Stoleru, Q. Cao, J. Stankovic, and T. Abdelzaher, "Achieving real-time target tracking using wireless sensor networks," in *Proc of IEEE RTAS 2006*, 04-07 April 2006.
- [6] T. Bokareva, W. Hu, S. Kanhere, B. Ristic, N. Gordon, T. Bessell, M. Rutten, and S. Jha, "Wireless sensor networks for battlefield surveillance," in *LWC 2006*.
- [7] M. Borkar, V. Cevher, and J. McClellan, "Estimating target state distributions in a distributed sensor network using a monte-carlo approach," in *MLSP 2005*.
- [8] M. Coates, "Distributed particle filters for sensor networks," in *IPSN 2004*.
- [9] M. Coates and G. Ing, "Sensor network particle filters: motes as particles," in *SSP 2005*.
- [10] K. Whitehouse, C. Karlof, and D. Culler, "A practical evaluation of radio signal strength for ranging-based localization," *SIGMOBILE Mob. Comput. Commun. Rev.*, vol. 11, no. 1, pp. 41–52, 2007.
- [11] S. Lanzisera, D. T. Lin, and K. S. Pister, "Rf time of flight ranging for wireless sensor networks localization," in *WISES '06*.
- [12] X. Sheng and Y. H. Hu, "Sequential acoustic energy based source localization using particle filter in a distributed sensor network," in *ICASSP '04*.
- [13] X. Sheng, Y.-H. Hu, and P. Ramanathan, "Distributed particle filter with gmm approximation for multiple targets localization and tracking in wireless sensor network," in *IPSN 2005*, April 2005, pp. 181–188.
- [14] H. Ma and B.-H. Ng, "Distributive target tracking in wireless sensor networks under measurement origin uncertainty," in *ISSNIP 2007*.
- [15] R. Srinivasan, *Importance Sampling: Applications in Communications and Detection*. Springer-Verlag, 2002.
- [16] B. Ristic, S. Arulampalam, and N. Gordon, *Beyond the Kalman Filter - Particle Filters For Tracking Applications*. Artech House Publishers, 2004.
- [17] M. Efe and D. Atherton, "Maneuvering target tracking using adaptive turn rate models in the interacting multiple model algorithm," in *Proc IEEE CDC*, vol. 3, Dec 1996, pp. 3151–3156.