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An accurate range-only tracking system using wireless sensor networks

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Abstract

This paper discusses the design of a real-time tracking system targeted for deployment in wireless sensor networks. The proposed system, utilizes accumulated range data from a number of anchor sensor nodes to infer the position and other kinematic variables of a mobile target. To track manoeuvring targets three dynamic models are used. A particle filter inspired algorithm operates on the range measurements in real-time to produce an estimate of the target's position and two-axis velocity. The system is evaluated through simulations that reveal its ability to accurately (RMSE <10m) track manoeuvring targets.

Keywords: online target tracking, wireless sensor networks; particle filters;

1. Introduction

Wireless Sensor Networks (WSNs) are networks of interconnected autonomous devices usually equipped with various sensors. These devices are capable of sensing their environment and communicate their data in a wireless manner. In the past decade WSNs have received substantial research interest, particularly due to the flexibility they offer for a number of application domains. Possible application domains for WSNs span from environmental and industrial monitoring to security systems and pervasive healthcare environments.

This paper proposes a novel, range-only target tracking system for WSNs. The term "range-only" refers to the type of measurements that the systems utilizes to produce an estimation of the target's current position. Different to other approaches in this area, where two or even three types of measurements are available, the proposed system operates solely on range data. The reason for this choice is that range data can be obtained in a cost efficient way, in comparison to other modalities (bearings, velocity) that can be used for target tracking. The acquisition of these modalities in WSNs requires the use of additional hardware like micro-RADARS to be attached to the nodes. On the other hand, ranging between two wireless nodes can be obtained with techniques like time of flight (ToF) or received signal strength indication (RSSI).

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The system presented in this paper is an evolution of the work described by Mazomenos *et al.*[1] where we demonstrated the ability of range measurements to provide adequate support for tracking in WSNs. This paper focuses on expanding the ability of the system to include support for manoeuvring targets. To achieve this, we employ a motion model which is formed from three dynamic models in order to capture the abrupt changes in the position and velocity vectors of manoeuvring targets.

2. System Design and Overview

An overview of the proposed system is illustrated in Fig. 1a where four anchor nodes are deployed to form the wireless network and a mobile target (car) is the object to be tracked. To estimate the planar coordinates of a single manoeuvring target at least three anchor nodes must be deployed to provide range estimates. The system is aware of the positions of the anchor nodes. The range estimates are fused to a higher level node, which can be a cluster-head node or a central base-station node. A Particle Filter[2] (PF) tracking algorithm runs on that node and provides an estimate of the targets coordinates and two-axis velocity.

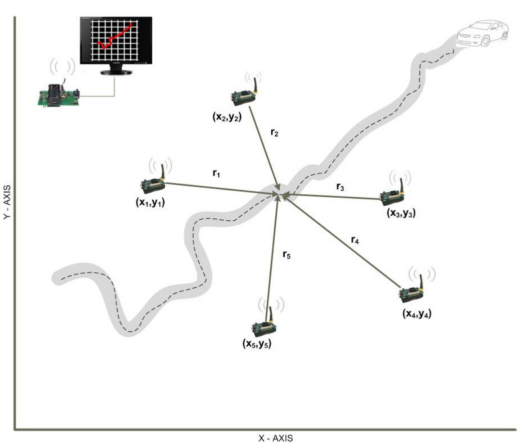
3. Problem Formulation

In order to best describe the target's movement the tracking system is modeled in a nonlinear state-space approach. In the state-space representation two vectors are defined. The state vector which comprises the target's kinematic variables (planar coordinates, two-axis velocity) and the measurements vector which comprises the range estimates acquired by the anchor nodes. Also two equations are used to complete the model. The state equation describes the evolution of the state vector in time and the measurements equation associates mathematically the observations (measurements) with the state vector. In details, the system runs for a total time denoted as *T*. At each time step "*k*" the state vector "$\mathbf{x}_k$" contains the planar coordinates and two-axis velocity of the target, thus;

$$\mathbf{x}_k = [x_k \ y_k \ v_{x,k} \ v_{y,k}] \tag{1}$$

3.1. Measurements Equation – Range Observations

At every sampling step "*k*" each of the "N_s" anchor nodes provide an observation which is an estimate of the distance between the anchor node and the target. The aggregated observations form the measurements vector "$\mathbf{z}_{k,Ns}$".



(a)

Algorithm 1 :ROT-MMPF Algorithm

Initialize
- Draw Initial Particles
for $i = 1$ to N **do**
  $\mathbf{r}_0^i \sim p(r_0)$ ($\sim$ denotes sampling from)
  $\mathbf{x}_0^i \sim p(x_0)$
end for
Sequential Importance Sampling Step
- Sample Particles and Calculate Weights
for $i = 1$ to N **do**
  $\mathbf{r}_k^i \sim \pi ij$
  $\mathbf{x}_k^i \sim p(x_k|x_{k-1})$
  $\tilde{w}_k^i = p(z_k|x_k^i, r_k^i)$ (using Eq.7)
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

(b)

Fig. 1. (a) Overview of the proposed system; (b) A single iteration of the ROT-MMPF algorithm

The measurements equation provides the mathematical relationship between the measurements vector and the state vector by using the Euclidean distance norm. Corrupting noise is also considered and denoted as "v_k".

$$\mathbf{z}_{k,N_s} = \left[\sqrt{(y_k - y_{k,Ns})^2 + (x_k - x_{k,Ns})^2} \right] + v_k \tag{2}$$

3.2. State Equation

The measurements equation is given in Eq. 3, where "w_k" represents the process noise. The process noise caters for any mismodeling effects or any unforeseen disturbances in the motion model.

$$\mathbf{x_{k+1}} = \mathbf{F}(r_k) \cdot \mathbf{x_k} + \mathbf{G} \cdot w_k \tag{3}$$

In the above formula r_k is the regime variable which indicates which of the three models is in use during the sampling period from $(t_{k-1,}t_k]$. The regime variable is modeled as a three-state first-order Markov Chain with probability matrix given in Eq. 4 and possible values 1,2,3. Matrices **F** and **G** are defined as follows in Eq. 5 and Eq. 6, with "T_s" being the sampling period and "ω" the turning rate. In Eq. 5, **F**(1) comprises the constant velocity model while **F**(2) and **F**(3) represent two coordinated turn models.

$$\pi_{m,n} = P\{r_k = m \mid r_{k-1} = n\} \tag{4}$$

$$\mathbf{F}(1) = \begin{bmatrix} 1\ 0\ T_s\ 0 \\ 0\ 1\ 0\ T_s \\ 0\ 0\ 1\ 0 \\ 0\ 0\ 0\ 1 \end{bmatrix},\ \mathbf{F}(2) = \begin{bmatrix} 1\ 0 & \frac{\sin(\omega T_s)}{\omega} & \frac{(\cos(\omega T_s)-1)}{\omega} \\ 0\ 1 & \frac{(1-\cos(\omega T_s))}{\omega} & \frac{\sin(\omega T_s)}{\omega} \\ 0\ 0 & \cos(\omega T_s) & -\sin(\omega T_s) \\ 0\ 0 & \sin(\omega T_s) & \cos(\omega T_s) \end{bmatrix},\ \mathbf{F}(2) = \begin{bmatrix} 1\ 0 & \frac{\sin(\omega T_s)}{\omega} & \frac{(\cos(\omega T_s)-1)}{\omega} \\ 0\ 1 & \frac{(1-\cos(\omega T_s))}{\omega} & \frac{\sin(\omega T_s)}{\omega} \\ 0\ 0 & \cos(\omega T_s) & \sin(\omega T_s) \\ 0\ 0 & -\sin(\omega T_s) & \cos(\omega T_s) \end{bmatrix} \tag{5}$$

$$\mathbf{G} = \begin{bmatrix} T_s^2/2 & 0 \\ 0 & T_s^2/2 \\ T_s & 0 \\ 0 & T_s \end{bmatrix} \tag{6}$$

4. Tracking Algorithm and Simulation Results

To solve the nonlinear system, a PF algorithm is employed. PF are a class of Bayesian Estimation techniques that have attracted substantial research interest particularly for estimation problems in dynamic nonlinear systems. Different to classic estimation methods like Kalman Filters, PF can be applied directly to nonlinear systems. The state-vector is estimated with a number (N) of particles (x_k^i) sampled from a proposal distribution $p(x_0)$, weighted (w_k^i) based on the likelihood (Eq. 7) of the current measurements vector and the use of a certain criterion (Eq. 8). Here the Minimum Mean Square Error (MMSE) is employed. The final step involves resampling of the particles whenever this is necessary. An iteration of the proposed Multiple Mode Particle Filter Algorithm for Range-Only Tracking (ROT-MMPF) is illustrated in Fig. 1b.

$$w_k^i = L(z_k \mid x_k^i) = \sum_{i=1}^{N} exp((-0.5 \cdot (z_k - z_k^i) \cdot (z_k - z_k^i)^T) / B \tag{7}$$

where B: is a normalizing constant which depends on the measurements noise distribution

$$\widehat{\mathbf{x}}_k = \sum_{i=1}^{N} x_k^i \cdot w_k^i \tag{8}$$

4.1. Simulation Results

The proposed system was evaluated through simulations. In the simulation environment considered, a single target is the object to be tracked. Four anchor nodes are deployed in the following coordinates, s1= [10m, 0m], s2= [50m, 0m], s3= [10m, 25m], s4= [50m, 25m] to provide range estimates. The total simulation time "T" is 50sec and the sampling period "T_s" is set to 1sec. The target's initial state "x_0" is [20m/s 20m/s 1m/s 1m/s]. The number of particles "*N*" utilized by the algorithm is set to 500. The process "w_k" and measurements noise "v_k" follow Gaussian distributions $N(0,0.5)$ and $N(0,2)$ respectively, while the distribution "$p(x_0)$"; to sample initial particles from, is also considered to be Gaussian $N(x_0,1)$. Finally the regime variable transition probability "m" is set to 0.85. The metric used to quantify the achieved accuracy is the Root Mean Square Error.

$$RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(x_t - x_{est})^2 + (y_t - y_{est})^2} \tag{9}$$

In Fig. 2 we illustrate results from simulating the system. Fig. 2a illustrates an exemplar run of the system where the RMSE was calculated to be 5m. Fig. 2b and Fig. 2c depict the estimation of the target's two-axis velocity, while in Fig. 2d we prove the robustness of the proposed tracking system by simulating the same scenario for 100 runs and calculating the RMSE in each run. In 96% of the executions the RMSE remains lower than 10m.

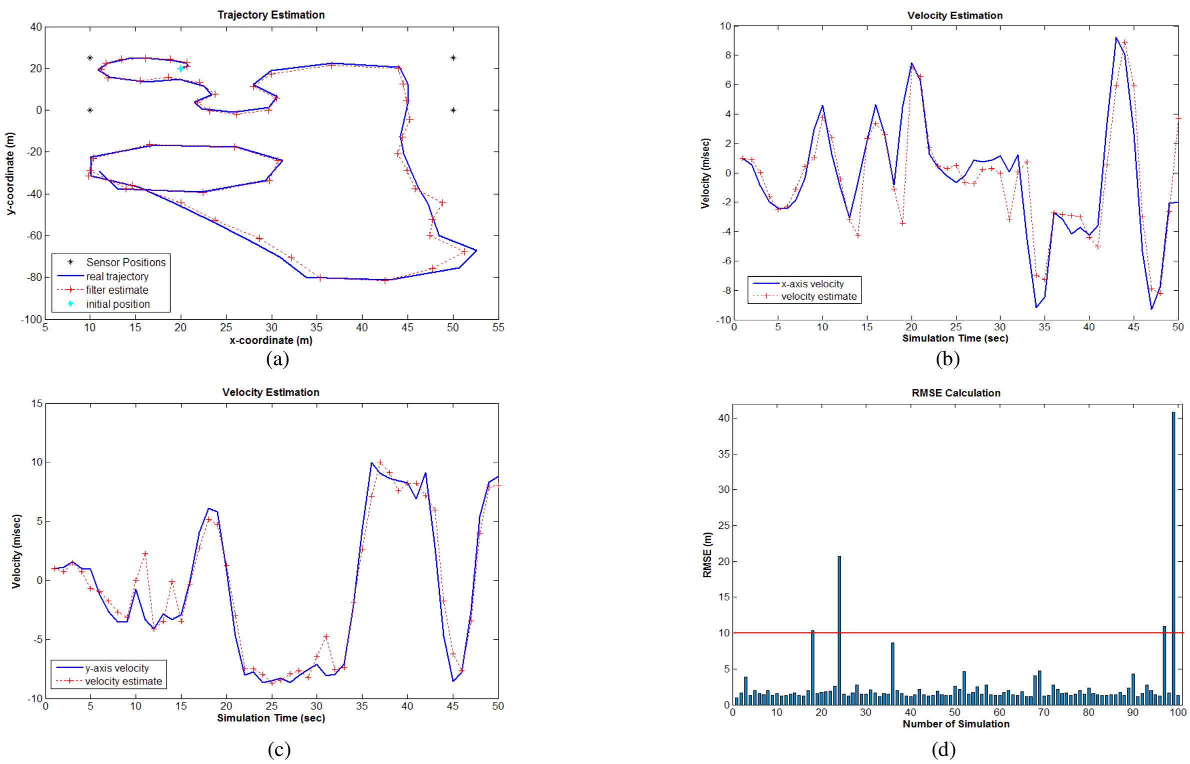


Fig. 2. Simulation Results: (a) trajectory estimation; (b) x-axis velocity estimation; (c)y-axis velocity estimation; (d) RMSE for 100 executions

5. Conclusions and future work

This paper discusses the development of a range-only tracking system for wireless sensor networks. Simulation results demonstrate that good accuracy can be achieved (RMSE <10m) even under noisy environments (~2m). The evolution of the work presented in this paper will be the implementation on hardware of the proposed system and the investigation of its performance in real-world experiments.

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