Detection and Tracking Using Wireless Sensor Networks

Nadeem Ahmed, Yifei Dong,
Tatiana Bokareva, Salil Kanhere, Sanjay Jha
Computer Science and Engineering,
University of New South Wales,
Sydney, Australia.
{nahmed, ydong, tbokareva,
salilk, sanjay}@cse.unsw.edu.au

Travis Bessell, Mark Rutten,
Branko Ristic, Neil Gordon
Defence Science and Technology,
Organisation (DSTO), ISR Division,
Edinburgh, Australia.
{travis.bessell, mark.rutten, branko.ristic,
neil.gordon}@dsto.defence.gov.au

Abstract

Target detection and tracking is a well-established area of research. However, a majority of proposed solutions in existing literature rely on expensive and specialized sensors, which often have limited coverage. Using low cost sensor nodes is an attractive and complementary approach to scalable target detection and tracking applications. However, tracking with low cost Wireless Sensor Network (WSN), presents its own challenges, namely real time decision making, high frequency sampling, multi-modal sensing, complex signal processing, and data fusion. In this work, we investigate the use of inexpensive off-the-shelf WSN devices for ground surveillance. Our system estimates and tracks a target based on the spatial differences of the target object's signal strength detected by the monitoring sensors at different locations.

Categories and Subject Descriptors

J.m [**Computer Applications**]: Miscellaneous

General Terms

Performance, Experimentation

Keywords

Target tracking, sensor networks

1 Introduction

Previous experimental work on tracking using WSN either used simple threshold-based algorithms or required extra hardware on each tiny sensor device to perform complex signal processing tasks. Threshold-based algorithms have the potential of disregarding useful sensor data and thus may not be suitable for low SNR WSN systems. Additional special purpose hardware adds to the cost and energy consumption of these self powered and low cost devices. In this work, we explore the use of a centralised data fusion algorithm referred to as Particle Filter for Track-Before-Detect (TBD-PF) in [1].

Initial experimental results are promising and show that the Particle Filter (PF) based estimator is suitable for detection and tracking using inexpensive WSN devices such as the Xbow MicaZ motes.

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2 Particle Filter for Track-Before-Detect

There are several advantages of using a PF based estimator over a threshold-based estimator, namely:

- Target presence and absence are explicitly modeled by the probability function.
- The method can track targets moving randomly in the field of deployment.
- Non-Gaussian noise in sensor readings can be incorporated into the filter by estimating the distribution function of this noise. This incorporates the noise due to calibration errors in sensors in addition to the environmental noise.
- It permits us to detect targets with variable levels of intensity.

In order to use the PF, we begin by assuming that the sensors are deployed in a grid of $n \times m$ sensors at known positions. Next, we randomly generate $\overline{N}$ number of particles in the format of:

$$p_k = \{x_k, y_k, v_k^x, v_k^y, I_k, E_k\} \tag{1}$$

where k is a discrete time-step, (x_k, y_k) and (v_k^x, v_k^y) denote the position and velocity of a target, I_k corresponds to the intensity of the target (intensity of the physical phenomenon, acoustic in our case) and E_k is an indicator whether the target is present or not. The variable E_k can take on two values, namely $E_k = 0$ indicating the absence of the target and $E_k = 1$ denoting its presence. The target can appear at any place and at any time-step. Following its appearance, the target proceeds on a trajectory until it disappears, i.e., the intensity of the target signal strength falls below the sensor's sensitivity level. We can model the transitional probabilities of the target birth (P_b), and its death (P_d) as follows:

$$P_b = P\{E_k = 1 | E_{k-1} = 0\}$$

$$P_d = P\{E_k = 0 | E_{k-1} = 1\} \tag{2}$$

It is assumed that these probabilities are known a priori. However, if they are not known a very low value is assumed (e.g., 0.01). Each sensor provides a measurement (acoustic in our case) at discrete instants of time k, and each of these measurement is modeled as follows:

Figure 1. Target and Experimental Setup

$$z_k^{(i,j)} = \begin{cases} h_k^{(i,j)} + w_k^{(i,j)} & \text{if } E_k = 1 \\ w_k^{(i,j)} & \text{otherwise} \end{cases} \tag{3}$$

where $w_k^{(i,j)}$ is the amount of noise in a measurement and $h_k^{(i,j)}$ is the contribution of the target intensity to the measurement. In general, the background noise function is assumed to follow the Gaussian model, which is not necessarily true in real world deployments. In this work, we derive the characteristics of the background noise function by calibration.

For a point target of intensity I_k at position (x_k, y_k), the target contribution to intensity at sensor (i, j) can be estimated as follow:

$$h_k^{(i,j)} = \frac{I_k}{\left(\sqrt{(x_k - x)^2 + (y_k - y)^2}\right)^{\varepsilon}} \tag{4}$$

Here (x, y) is the position of the sensor (i, j), (x_k, y_k) is the position of the target and ε is the path loss exponent of the signal strength. Note that the initial values of I_k and (x_k, y_k) are unknown. They are recursively estimated over time using Equation No 4. The complete measurement recorded at time k is an $n \times m$ matrix denoted as

$$Z_k = \left\{ z_k^{(i,j)} : i = 1 \ldots n, j = 1 \ldots m \right\} \tag{5}$$

The goal of the PF is to compute recursively the posterior density of target presence/absence E_k and the target state (position, velocity, intensity) using all the previous measurements:

$$\begin{aligned} &\mathrm{p}(\mathrm{x}_k, E_k = 1 | Z_{k-1}) = \\ &\quad \int \mathrm{p}(\mathrm{x}_k, E_k = 1 | x_{k-1}, E_{k-1} = 1, Z_{k-1}) \\ &\quad \mathrm{p}(\mathrm{x}_{k-1}, E_{k-1} = 1 | Z_{k-1}) dx_{k-1} \\ &\quad + \int \mathrm{p}(\mathrm{x}_k, E_k = 1 | x_{k-1}, E_{k-1} = 0, Z_{k-1}) \\ &\quad \mathrm{p}(\mathrm{x}_{k-1}, E_{k-1} = 0 | Z_{k-1}) dx_{k-1} \end{aligned} \tag{6}$$

3 Prototype Implementation

Twenty-Five of the Xbow MicaZ motes were programmed to perform high frequency sampling to measure the acoustic signals ($@5kHz$) generated by the target (a remote controlled toy car). These MicaZ motes were deployed in a grid (Figure 1). Summary statistics (sum and square of sum instead of the raw values) were transferred over the wireless link to the base station for executing the PF algorithm. The system tracks the movement of the target by analyzing (off-line) the collected sensory data.

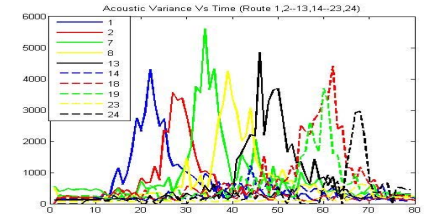

Figure 2. Acoustic Variance vs Time

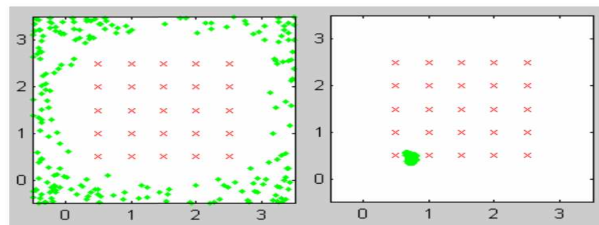

Figure 3. Particle Filter Convergence

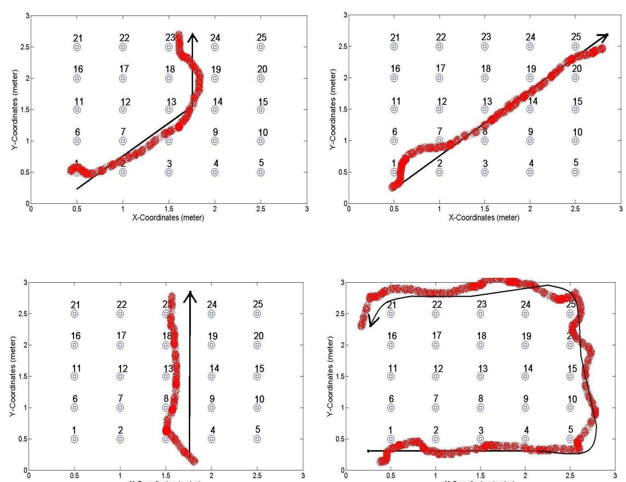

Figure 4. Tracking Results

Figure 2 shows the acoustic variance with time for some of the deployed sensors while Figure 3 illustrates the convergence of the PF to estimate the trajectory of the target. Here, initial set of particles are shown on the left, and the set of alive particles after a number of measurements is shown on the right. Some of the tracking results are shown in Figure 4 where actual and estimated paths are shown in black and red lines respectively. These results demonstrate that the PF based estimator performs very well in tracking different trajectories of the target using real data collected by off-the shelf WSN devices.

4 References

[1] B. Ristic, S. Arulampalam, and N. Gordon. *Beyond the Kalman Filter: Particle Filters for Tracking Applications*. Artec House, 2004.