Detection and Tracking Using Wireless Sensor Networks

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1. Introduction

Research in Wireless Sensor Networks (WSN) is widespread and pervasive in many disciplines because of the potential to embed tiny, inexpensive, low-power sensors in diverse environments to provide a wide range of surveillance and monitoring applications. Tracking with WSN, on the other hand, is extremely challenging since it requires real time decision making, high frequency sampling, multi-modal sensing, and complex signal processing and data fusion. In this work, we investigate the use of inexpensive off-the-shelf WSN devices for ground surveillance. We explore the design tradeoffs for using WSN for implementing a system that is capable of detecting and tracking objects of interest. Our system estimates and tracks the target based on the spatial differences of the target objects signal strength detected by the sensors at different locations.

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

2. PF Based on TBD Bayesian Algorithm

There are several advantages of using the PF based estimator, namely:

- The possibility of a target to be present is modeled by the probability function and is explicitly available from the filter.
- The method can track targets moving randomly in the field of the deployment. It is not limited to tracking targets that only move in a straight line.
- Non-Gaussian noise in sensor readings can be incorporated into the filter by estimating the distribution function of this 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 plane, which corresponds to a square region of dimension \(N \times M\). Next, we randomly generate \(N\) number of particles in the format of:

\[
p_k = \{[x_i, y_i, v_i^x, v_i^y, I_k, E_k] \}
\]

(1)

Where \(k\) is a discrete time-step, \(x_k = (x_i, y_i)\) and \(v_k = (v_i^x, v_i^y)\) 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. Hence, we can model the transitional probability of the target birth ($P_b$), and death ($P_d$) as follows:

$$P_b = P(E_k = 1 | E_{k-1} = 0)$$
$$P_d = P(E_k = 0 | E_{k-1} = 1)$$

(2)

In previous work, it is assumed that these probabilities are known a priori. However, if they are not known they are usually assigned a very low value (e.g., 0.1). Each sensor provides a measurement (acoustic in our case) at a discrete instance of time $k$, and each of these measurements is modeled as follows:

$$Z_{k}^{(i,j)} = \begin{cases} h_{k}^{(i,j)} + w_{k}^{(i,j)} & \text{if } E_k = 1 \\ w_{k}^{(i,j)} & \text{otherwise} \end{cases}$$

(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.

The contribution of the target intensity to the measurement can be estimated as follow:

$$h_{k}^{(i,j)} = \frac{I_k}{(\sqrt{(x_i - x_j)^2 + (y_i - y_j)^2})^\epsilon}$$

(4)

Here, $(x_i, y_i)$ is the position of the sensor, $(x_j, y_j)$ is the position of the target and $\epsilon$ is the path loss exponent of the signal strength. Note that the initial values of $I_k$ and $(x_j, y_j)$ are unknown. They are recursively estimated over time using equation (4) and the matrix $Z_k$ of complete measurements recorded at a time $k$:

$$Z_k = \{Z_{k}^{(i,j)} : i = 1...N, j = 1...M\}$$

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 previous measurements:

$$p(x_i, E_i = 1 | Z_{i-1}) =$$
$$\int p(x_i, E_i = 1 | x_{i-1}, E_{i-1} = 1, Z_{i-1})p(x_{i-1}, E_{i-1} = 1 | Z_{i-1})dx_{i-1}$$
$$+ \int p(x_i, E_i = 1 | x_{i-1}, E_{i-1} = 0, Z_{i-1})p(x_{i-1}, E_{i-1} = 0 | Z_{i-1})dx_{i-1}$$

3. Prototype Implementation

25 of the Xbow MicaZ motes were programmed to perform high frequency sampling to measure the acoustic (@ 5kHz) and magnetic signals (@ 50Hz) generated by the target (a remote controlled toy car). These MicaZ motes were deployed in a grid. Summary statistics (sum and square of sum instead of raw measurements) are transferred over the wireless link to the base station for executing the PF algorithm. The base station computes the intensity and variance of the collected summary statistics (offline) and the system tracks the movement of the target by analyzing the collected sensory data.

4. References

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**Goal**

Our goal is to design and implement a Wireless Sensor Network (WSN) system, capable of detecting and tracking targets and consisting of inexpensive off-the-shelf hardware.

**Approach**

The WSN devices are capable of sensing acoustic and magnetic signals generated by different target objects. The system is able to estimate and track the target based on the spatial differences of the target object's signal strength detected by sensors at different locations. Particle Filters (PF) based data fusion is employed to handle both environment and sensing noises associated with these inexpensive sensors.

This is extremely challenging, as it requires high frequency sampling, multi-modality sensing, complex signal processing and data fusion, and distributed coordination.

**Prototype System Implementation**

25 of Xbow MicaZ motes deployed in a grid perform high frequency sampling to measure the acoustic and magnetic signals generated by the target (a remote controlled toy car). Summary statistics (sum and square of sum instead of raw measurements) are transferred over the wireless link to the base station for executing a Track-Before-Detect PF- based data fusion algorithm. The system tracks the movement of the target by analyzing the sensory data collected by the deployed sensor nodes.

**Previous work:**

Sensor readings are assumed to be not influenced by noise, which is quite unrealistic for real world deployments.

Threshold-based algorithms do not perform well for low SNR data because the signal data below the threshold are interpreted as noise.

Costly specialized hardware is also energy expensive.

**Advantages of using PF based estimator**

Can track targets moving randomly in the field of the deployment.

Non-Gaussian noise in sensor readings can be incorporated into the filter by estimating the distribution function of this noise through calibration.

Non-Threshold based - Can detect targets with variable levels of intensity.