MINIMIZATION OF SENSOR USAGE FOR TARGET TRACKING IN A NETWORK OF IRREGULARLY SPACED SENSORS

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ABSTRACT

We address the following scenario: a single target moves through a field of stationary sensors with known locations. At each time epoch, each sensor is either active or not; each active sensor outputs either target detected or not detected. The probability of target detection is a decreasing function of the distance from a sensor to the target. A particle filter is used to track the target through the sensor field using all active sensor outputs. A heuristic configuration strategy is used to determine which sensors should be activated; Monte Carlo simulations show that the configuration strategy leads to a significant reduction in required active sensors with little degradation in the tracker performance.

1. INTRODUCTION

In this paper, we address the following scenario: a single target that emits a signal moves through a field of stationary, arbitrarily located sensors; each sensor can be configured to be active or inactive at each time epoch, and the sensor locations are assumed to be known. At each time epoch, each active sensor outputs a binary observation indicating that a target has or has not been detected. The probability of a sensor detecting the target is a decreasing function of the distance from the sensor to the target. Thus, detection of the target by a given sensor provides information about the target position at a given time. The target trajectory is estimated from the time sequence of target detections by the various sensors.

We make two primary contributions in this paper:

1. A distributed detection, centralized tracking algorithm, which tracks the target through the sensor field using all active sensor outputs, is implemented by a particle filter.
2. Heuristic sensor configuration strategies are developed; these strategies activate and deactivate sensors to track the target, while at the same time attempting to minimize the number of active sensors (and hence power consumption) in the sensor network.

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Our sensor model and tracking methodology are similar to those used in [1–3], but our work is much more focused on the performance of sensor configuration algorithms.

This paper is structured as follows. We first describe the target and sensor models. We then describe the particle filter that implements the tracker. We then describe two sensor configuration strategies and evaluate their performance through simulation.

2. TARGET AND SENSOR MODELS

To estimate target position and velocity, we require probabilistic models of the target motion and the sensor performance. The target motion is modeled by a discrete-time linear system driven by white noise. The sensor performance model is obtained by analysis of the probability of detection given a particular target location.

2.1. Target Model

The target is constrained to motion in a plane. The target state is composed of the target's position and velocity at time t_k as measured in Cartesian coordinates. We use a discrete-time linear system driven by white Gaussian noise to model the target dynamics as shown in (1). We arrange the target's position two position values $x(t_k)$ and $y(t_k)$ and two velocity values $\dot{x}(t_k)$ and $\dot{y}(t_k)$ into a target state vector denoted $\mathbf{x}_k$:

$$\mathbf{x}_k = \begin{bmatrix} x(t_k) & y(t_k) & \dot{x}(t_k) & \dot{y}(t_k) \end{bmatrix}^T$$

The discrete-time system represents snapshots of the continuously evolving target position and velocity at evenly spaced times t_0, t_1, etc.; the difference between consecutive times

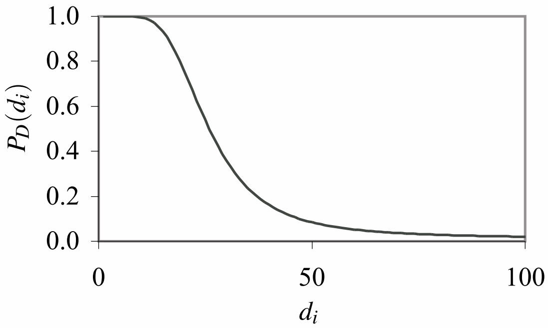

Fig. 1. Sensor detection probability as a function of target-sensor distance.

is Δt. The system dynamics are given by the following difference equation:

$$\begin{aligned}\mathbf{x}_{k+1} &= \begin{bmatrix} 1 & 0 & \Delta t & 0 \\ 0 & 1 & 0 & \Delta t \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \mathbf{x}_k + \mathbf{w}_k \\ &= \mathbf{A}\mathbf{x}_k + \mathbf{w}_k \end{aligned} \tag{1}$$

where $\{\mathbf{w}_k\}$ is a vector Gaussian white noise process with constant covariance matrix Q.

2.2. Sensor Model

Our sensor model is similar to that used in [4]. In our scenario, N sensors are at known locations in the target plane[1]. At each time k, each sensor may be configured to be active or inactive. At each time, each active sensor makes a decision about whether the target is present on the basis of M samples of a received signal. We assume that the time interval in which these samples are gathered is short relative to Δ, the time between estimates of the target state. The received signal at each sensor is the sum of noise and the signal emitted by the target (if present). The target signal is modeled as a discrete-time white Gaussian process whose variance is inversely proportional to the square of the distance between the target and the sensor. The noise is modeled as a discrete-time white Gaussian process that is independent of the target signal; the noise at each sensor is independent.

The sensor computes the energy in its received signal and compares this energy to a threshold to determine whether the signal received is from the target.

We denote the energy per sample of the signal received from the target as $\sigma_T^2(d)$. This energy is inversely proportional to the square of the distance d between the target and the sensor: $\sigma_T^2(d) = \sigma_{T_0}^2/d^2$, where $\sigma_{T_0}^2$ is the energy per sample of the target signal at a distance of 1 unit. The energy per sample of the noise at each sensor is σ_N^2.

[1] The sensors may be placed in a regular pattern or placed randomly (as in our simulations).

The probability of false alarm and correct target detection can be computed as follows (see *e.g.* [5]):

$$P_{FA} = \frac{\Gamma\left(\frac{M}{2}, \frac{\beta}{2}\right)}{\Gamma\left(\frac{M}{2}\right)},$$

where β is a parameter chosen to give a desired probability of false alarm and $\Gamma(\cdot,\cdot)$ is the incomplete Gamma function. For a given β (and corresponding probability of false alarm), the probability of detection can be expressed as

$$P_D(d) = \frac{\Gamma\left(\frac{M}{2}, \frac{\beta}{2}\frac{1}{1+\frac{SNR_0}{d^2}}\right)}{\Gamma\left(\frac{M}{2}\right)}, \tag{2}$$

where $SNR_0 = \frac{\sigma_{T_0}^2}{\sigma_N^2}$ is the signal-to-noise ratio at a distance of one unit from the target. Figure 1 shows a typical plot of the probability of detection as a function of distance to the target.

2.3. Obtaining the Observation

The observation vector used by the target tracking algorithm has an element for each of active sensors at time k and is denoted $\mathbf{z}_k$. In this section, we describe the process by which the observation $\mathbf{z}_k$ is obtained and from this process determine an expression for the conditional probability distribution $P(\mathbf{z}_k|\mathbf{x}_k)$.

At a given time k, we number the active sensors from 1 to n; we denote the distance between the target and sensor i as d_i. From (2), the probability that sensor i detects the target is $P_D(d_i)$. If sensor i detects the target, then $z_k(i)$, the ith component of z_k, is set to one; otherwise, $z_k(i)$ is set to zero. The probability distribution of $z_k(i)$ is thus

$$p(z_k(i)|\mathbf{x}_k) = \left[P_D(d_i)\right]^{z_k(i)} \left[1 - P_D(d_i)\right]^{1-z_k(i)}.$$

We assume that each element of $\mathbf{z}_k$ is conditionally independent given the values d_1 through d_n. The probability distribution of the vector $\mathbf{z}_k$ is

$$p(z_k|\mathbf{x}_k) = \prod_{i=1}^{n} \left[P_D(d_i)\right]^{z_k(i)} \left[1 - P_D(d_i)\right]^{1-z_k(i)} \tag{3}$$

3. PARTICLE FILTER IMPLEMENTATION

We use a particle filter [6, 7] to track the target through the sensor network. We have implemented a particle filter in which the proposal distribution is the conditional state density $p(\mathbf{x}_k|\mathbf{x}_{k-1})$ obtained from the dynamics model (1); since the observations depend only on the target position and not velocity, we have Rao-Blackwellized this filter using the equations derived in [8]. The particle filter provides

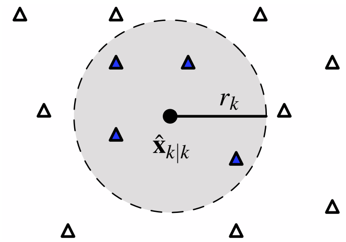

Fig. 2. Activation of sensors within a distance r_k of the target position estimate $\hat{\mathbf{x}}_{k|k}$.

a collection of particles $\left\{\mathbf{x}_k^{(j)}\right\}$ and associated weights $\left\{w_k^{(j)}\right\}$ from which the state estimate $\hat{\mathbf{x}}_{k|k}$ and its associated covariance matrix $P_{k|k}$ can be computed:

$$\hat{\mathbf{x}}_{k|k} = \sum w_k^{(j)} \mathbf{x}_k^{(j)} \tag{4}$$

$$P_{k|k} = \sum w_k^{(j)} \left(\mathbf{x}_k^{(j)} - \hat{\mathbf{x}}_{k|k}\right) \left(\mathbf{x}_k^{(j)} - \hat{\mathbf{x}}_{k|k}\right)^T \tag{5}$$

4. SENSOR CONFIGURATION

Our objective in sensor configuration is to accurately track the target through the sensor network, while at the same time attempting to minimize the number of active sensors; only active sensors provide observations. We have developed a heuristic sensor configuration algorithm in which sensors withing a given distance of the estimated target position are activated; the distance is chosen adaptively based on the accuracy of the target position estimate. Our simulation results show that this sensor configuration strategy provides accurate target tracks while significantly reducing the fraction of sensors within the networks that are active.

In the heuristic strategy, all sensors that are within a given distance of the estimated target position are activated as shown in Figure 2. We choose the distance r_k to be an increasing function of the expected squared error of the position estimate. Thus, when the error is low (and we have a high confidence in the accuracy of the estimate), few sensors will be activated; when the error is high, many sensors will be activated.

Mathematically, the expected squared position estimate error, which we denote as e_k, is the sum of the two upper left diagonal elements of $P_{k|k}$:

$$e_k = P_{k|k}^{1,1} + P_{k|k}^{2,2}$$

The distance r_k is an increasing function of e_k. For our configuration heuristic, we chose the following relationship:

$$r_k = Ce_k,$$

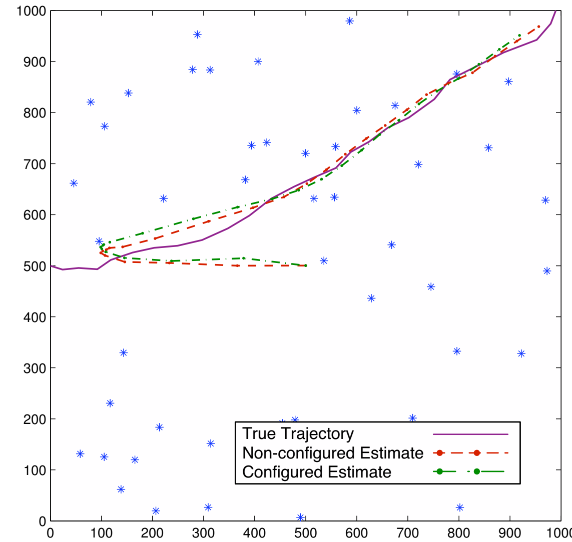

Fig. 3. Sensor laydown with true track and estimates for the configured and non-configured networks.

where $C = \frac{1}{36}$ is a constant gain that we have chosen empirically based on the the result of several Monte-Carlo trials of the tracking filter. We believe that in actual operation, good performance could be obtained by creating a table of best fit gains associated with particular classes of sensor distributions.

In order to configure the sensors at time k, the target estimate from the previous time step $\hat{\mathbf{x}}_{k-1|k-1}$ and associated covariance matrix $P_{k-1|k-1}$ are computed by the particle filter. Then the distance r_k is computed, and sensors withing this distance of the estimated target position are activated. The active sensors obtain observations which are then used by the particle filter to update the state estimate.

5. SIMULATION RESULTS

The performance of the simulation was evaluated using two sets of 500 runs: one set with all sensors active and the other set using the configuration heuristic described above.

The target was tracked by 50 sensors randomly distributed in a 1km square area. For the simulation, a true target trajectory was generated for 25 time steps. In each set of 500 simulation runs, the target track was estimated from simulated sensor detections with all sensors enabled and with the heuristic.

Figure 3 shows simulation results for 500 iterations of the simulation for each of the two sensor configuration strategies. The sensor locations, the true target track, and the mean estimated tracks obtained with configured (heuristically activated sensors) and non-configured (all sensors active) simulation Monte Carlo runs are shown in Figure 3.

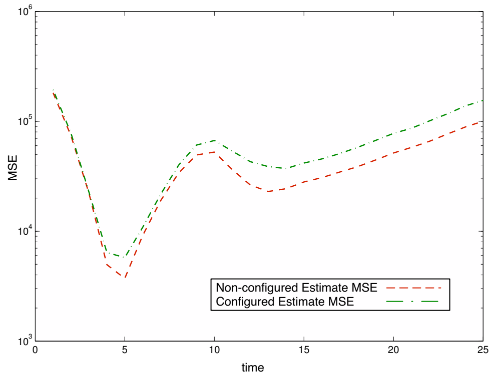

Fig. 4. Mean squared estimate error (averaged over 500 simulation runs) for the configured and non-configured networks.

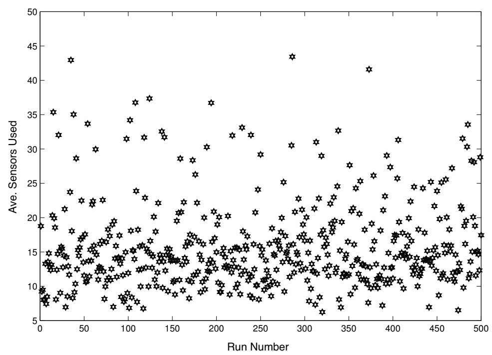

Fig. 5. Average number of sensors used for each simulation run. The average over 500 simulations is 15.7 sensors.

The mean squared error for both configured and non-configured simulation runs are shown in Figure 4.

A histogram of mean sensors used for each of the 500 runs is shown in Figure 5. As can be seen in Figure 5, the heuristic sensor configuration strategy offers a significant reduction in the number of sensors used; tracking with sensors configured using our empirical heuristic requires less than 30% of the sensors while Figure 4 shows only slightly larger estimate errors (less than 10% increase on average).

6. CONCLUSIONS AND FUTURE RESEARCH

We have developed a target tracker for an ad-hoc sensor network, and have investigated a heuristic approach to sensor configuration. We have found that the number of active sensors can be dramatically reduced without significant increases in tracking error.

In our future work, we plan to continue to investigate the effect of sensor configuration on tracking performance and on required sensor resources. Whether the number of needed sensors can be further reduced without significant increase in the estimate error is an open question. We also plan to extend the target tracking and sensor configuration algorithms to multiple targets and investigate the issues associated with distributed tracking and sensor configuration.

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