SCHEDULING MULTIPLE SENSORS FOR TRACKING A HIGHLY MANEUVERING TARGET IN CLUTTER

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ABSTRACT

The problem of multiple sensor scheduling for tracking a highly maneuvering target in clutter is considered. The objective is to schedule the sensors one or multiple time steps ahead so that the overall tracking performance of the system can be improved while minimizing the cost of resources. In the proposed scheduling algorithm, under the constraint that only one sensor may be used at any time step, we predict the expected cost one or multiple time steps ahead as a function of the candidate sensor scheduling sequences, and pick the sequence that minimizes an expected performance metric. We use a random sampling approach coupled with switching multiple kinematic models for target motion, to generate future (pseudo-)states and (pseudo-)measurements which allows computation of the relevant performance metric. Tracking of highly maneuvering target is achieved by an effective suboptimal filtering algorithm based on interacting multiple model (IMM) filtering approach combined with probabilistic data association (PDA) technique and the proposed sensor scheduling scheme. The proposed algorithm is illustrated via a simulation example involving two geographically distributed radar sensors.

1. INTRODUCTION

Sensor scheduling (or sensor management, or multisensor resource allocation) is the allocation of sensing resources over time. How to task a sensor or a group of sensors when each sensor may have many modes and search patterns, while there may also be constraint on system resources. Sensor management (or multisensor resource allocation) problems have been considered in [3]-[7] and references therein. Such problems are an integral part of any agile beam tracking system [1],[2],[5]. Which sensor (or group of sensors) should "follow" which target from among a group of targets and how often should the followed target be visited, are some of the relevant problems. This is a stochastic control problem that involves optimization of an expected cost function over time. Although this optimization can be performed using dynamic programming [7], the computations involved can be prohibitive. Therefore, suboptimal solution have been sought [3],[4],[6]. An integral part of the relevant cost evaluation is target state estimation at the current time. Refs. [3], [4] and [6] do not allow multiple switching kinematic models for each maneuvering target, hence, are not suitable for tracking highly maneuvering targets.

Our basic approach will be similar to that in [3]-[4] except that we do not propose to use (random sampling based) particle filters for target state estimation; rather we will use IMM/PDA approaches for state estimation [1],[8]. Unlike [3],[4], we allow multiple kinematic models for the target to allow high degree of target maneuvers. The basic idea is to compute a relevant cost function for all possible sensor management scenarios and then pick the one that minimizes the cost. [3] uses an information theoretic cost whereas [4] picks the mean-square state estimation error for the next (future) time horizon (1 or more sampling intervals).

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2. TARGET TRACKING PROBLEM FORMULATION

Assume that the dynamics of the target can be modeled as one of the n hypothesized models. The model set is denoted as $\mathcal{M}_n := \{1, 2, \cdots, n\}$. The event that model i is in effect during the sampling period $(t_{k-1}, t_k]$ will be denoted by M_k^i.

For the j-th hypothesized model (mode), the state dynamics and measurements of the target are modeled as

$$x_k = F_{k-1}^j x_{k-1} + G_{k-1}^j v_{k-1}^j \tag{1}$$

and

$$z_k^l = h^{j,l}(x_k) + w_k^{j,l} \quad \text{for} \quad l = 1, ..., q, \tag{2}$$

where x_k is the system state of the target at t_k and of dimension n_x, z_k is the (true) measurement vector from sensor l at t_k and of dimension n_{zl}, F_{k-1}^j and G_{k-1}^j are the system matrices when model j is in effect over the sampling period $(t_{k-1}, t_k]$ for the target and $h^{j,l}$ is the nonlinear transformation of x_k to z_k^l $(l = 1, 2, ..., q)$ for model j. A first-order linearized version of (2) is given by

$$z_k^l = H_k^{j,l} x_k + w_k^{j,l} \tag{3}$$

where $H_k^{j,l}$ is the Jacobian matrix of $h^{j,l}$ evaluated at some value of the estimate of state x_k. The nature of the system state, the various matrices in (1) and (3), and the measurements is specified in more detail in Sec. 4. The process noise v_{k-1}^j and the measurement noise $w_k^{j,l}$ are mutually uncorrelated zero-mean white Gaussian processes with covariance matrices Q_{k-1}^j and $R_k^{j,l}$, respectively. At the initial time t_0, the initial conditions for the system state of the target under each model j is assumed to be Gaussian random vectors with known mean $\bar{x}_0^j$ and known covariance P_0^j. The probability of the target in model j at t_0, $\mu_0^j = P\{M_0^j\}$, is also assumed to be known. The switching from model M_{k-1}^i to model M_k^j is governed by a finite-state stationary Markov chain (same for all targets) with known transition probabilities $p_{ij} = P\{M_k^j | M_{k-1}^i\}$. Henceforth, t_k will be denoted by k. Note that, in general, at any time k, some measurements may be due to clutter and some due to the target, i.e. there can be more than a single measurement at time k.

2.1. IMM/PDA filter

The IMM/PDA filter is given in detail in [1],[8]. It is a suboptimal filter that yields the following state estimates, the corresponding covariance matrices at time k given all the relevant measurements up to time k (denoted by $\mathcal{Z}^k$), and several other entities:

$$\widehat{x}_{k|k} := E\{x_k|\mathcal{Z}^k\} \tag{4}$$

and the associated error covariance matrix

$$P_{k|k} = E\{[x_k - \widehat{x}_{k|k}][x_k - \widehat{x}_{k|k}]'|\mathcal{Z}^k\} \tag{5}$$

where x_k' denotes the transpose of x_k. Also obtained are "mode-" (or model-) conditioned state estimates, corresponding covariances, and aposteriori probabilities ($\forall j \in \mathcal{M}_n$):

$$\widehat{x}^j_{k|k} := E\{x_k|M_k^j, \mathcal{Z}^k\}, \tag{6}$$

the associated error covariance matrix

$$P^j_{k|k} := E\{[x_k - \widehat{x}_{k|k}][x_k - \widehat{x}_{k|k}]'|M_k^j, \mathcal{Z}^k\}, \tag{7}$$

and the conditional mode probability

$$\mu_k^j := P[M_k^j|\mathcal{Z}^k]. \tag{8}$$

Furthermore, it is assumed throughout that the conditional density of x_k given the mode M_k^j and observations $\mathcal{Z}^k$, is Gaussian:

$$p\left(x_k|M_k^j, \mathcal{Z}^k\right) \sim \mathcal{N}\left(x_k; \widehat{x}^j_{k|k}, P^j_{k|k}\right) \tag{9}$$

where

$$\mathcal{N}(x; y, P) := |2\pi P|^{-1/2}\exp[-\frac{1}{2}(x-y)'P^{-1}(x-y)]. \tag{10}$$

For details, the reader is refered to [8] (also [1]).

3. SENSOR SCHEDULING

Our basic approach will be as in [3]-[4] except that we do not propose to use (random sampling based) particle filters for target state estimation; rather we will use the IMM/PDA approach for state estimation. Unlike [3],[4], we allow multiple kinematic models for the target to allow high degree of target maneuvers. The basic idea is to compute a relevant cost function for all possible sensor management scenarios and then pick the one that minimizes the cost. [3] uses an information theoretic cost whereas [4] picks the mean-square state estimation error for the next (future) time horizon (1 or more sampling intervals). We will follow [4] in this respect.

To make matters more concrete, we will consider a very simplified case. With a time horizon of 1 sample, let $\hat{x}^{(s)}_{k+1|k+1}$ denote the state estimate at time $k+1$ given measurements up to time $k+1$ using a particular sensor management scenario s. Then we may pick s to minimize the cost

$$\mathcal{C} := E\{\|x_{k+1} - \hat{x}^{(s)}_{k+1|k+1}\|^2\}. \tag{11}$$

In the case of two sensors, s takes two values: $s = 1$ implies use sensor 1 and $s = 2$ implies use sensor 2 where we are restricted to use only one sensor at a given time. Since neither x_{k+1} nor the measurement at time $k+1$ (hence $\hat{x}^{(s)}_{k+1|k+1}$) is available, one can not compute (11). Therefore, as in [3],[4], we resort to Monte Carlo methods (random sampling) to generate future (pseudo) states and measurements in order to try out all possible sensor management scenarios.

Suppose that (via IMM/PDA of Sec. 2) we have the conditional state estimate $\hat{x}^j_{k|k}$ at time k given measurements up to time k and conditioned on mode j at time k ($\equiv M_k^j$), and the corresponding state estimation error covariance matrix $P^j_{k|k}$ $\forall j \in \mathcal{M}_n$. We first randomly sample the mode in the duration $(t_{k-1}, t_k]$ according to the distribution μ_k^j; let the selected mode be $\tilde{j}^{(m)}$ (m denotes the m-th random sample). With selected mode $\tilde{j}^{(m)}$ in effect in the duration $(t_{k-1}, t_k]$, randomly select the mode $\tilde{i}^{(m)}$ for the duration $(t_k, t_{k+1}]$ according to the transition probabilities $p_{\tilde{j}^{(m)}i}$. The state x_k is sampled from the distribution $\mathcal{N}(x_k; \widehat{x}^{\tilde{j}}_{k|k}, P^{\tilde{j}}_{k|k})$ as $\tilde{x}_k^{(m)}$. Similarly generate the process noise $v_k^{\tilde{i}^{(m)}}$ to get a sample of x_{k+1} denoted by $\tilde{x}^{(m)}_{k+1}$ from the equation

$$\tilde{x}^{(m)}_{k+1} = F_k^{\tilde{i}^{(m)}}\tilde{x}_k^{(m)} + G_{k+1}^{\tilde{i}^{(m)}}v_k^{\tilde{i}^{(m)}}. \tag{12}$$

Then use the sensor measurement equation with randomly generated noise vector with the specified statistics, to generate a pseudo-measurement at sensor l at time $k+1$, denoted by $\tilde{z}^{l(m)}_{k+1}$ (see also (1) and (2)). Here m ($m = 1, 2, \cdots, N$) indexes the m-th random sample and l indexes the sensor. Then we replace (11) with

$$\hat{\mathcal{C}} := (1/N)\sum_{m=1}^{N}\|x^{(m)}_{k+1} - \hat{x}^{(s),(m)}_{k+1|k+1}\|^2 \tag{13}$$

where $\hat{x}^{(s),(m)}_{k+1|k+1}$ is obtained by operating on $\tilde{z}^{l(m)}_{k+1}$ ($l = 1, 2, \cdots, q$) under sensor management scenario s using IMM/PDA and related approaches. The cost (13) is then used to select suitable (optimal) sensor scheduling and to get the actual measurements at time $k+1$ on which the actual state estimate is based using IMM/PDA; then the process is repeated.

Although above we presented (one time-step: time horizon of one sample) myopic scheduling, extension to multi-time steps (time horizon greater than one sample) scheduling is straightforward. In this case, the cost will be evaluated for all possible sensor sequences. If total number of sensors are q and if the sensors are to be scheduled p-stage ahead, then total number of possible sequences are q^p. The sequence with the minimum cost is selected for sensor allocation at every time step.

4. SIMULATION EXAMPLE

We now consider tracking a highly maneuvering target in the presence of clutter with two sensors where only one sensor can be deployed at any given time. Both sensors are radars located at two different positions. We carry out state estimation for the target kinematic components using the IMM/PDA filter in which the states are updated with the measurements obtained from the scheduled sensor, allocated by the proposed sensor scheduling algorithm. With the proposed scheduling algorithm, we carry out one-stage and two stage scheduling and compare the results with the no-scheduling case. The details of the simulation example are as follows:

The True Trajectory: The (2-D) target starts at location [19689 10840] in Cartesian coordinates in meters. The initial velocity is [-8.3 -299.9] in m/s. The target moves with a constant speed of 300.01 m/s. Its trajectory is a straight line with constant velocity between 0 and 20 sec., a coordinated turn of -0.15 rad/s with a constant acceleration of 45 m/s^2 between 20 and 35 s, a straight line with a constant velocity between 35 and 55 s, a coordinated turn of 0.1 rad/s with a constant acceleration of 30 m/s^2 between 55 and 70 s, and a straight line with a constant velocity between 70 and 90 s.

The Target Motion Models: In each mode the target dynamics are modeled in Cartesian coordinates as $x_k = Fx_{k-1} + Gv_{k-1}$ where state of the target is position, velocity and acceleration in each of the two Cartesian coordinates (x and y). Thus x_k is of dimension 6 (n_x=6). Three models are considered in the following discussion. The system matrices F and G are defined as

$$F = \begin{bmatrix} F_b & 0 & 0 \\ 0 & F_b & 0 \\ 0 & 0 & F_b \end{bmatrix}$$

$$G = \begin{bmatrix} G_b & 0 & 0 \\ 0 & G_b & 0 \\ 0 & 0 & G_b \end{bmatrix}.$$

- Model 1: nearly constant velocity model with zero mean perturbation in acceleration:

$$F_b^1 = \begin{bmatrix} 1 & T & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

$$G_b^1 = \begin{bmatrix} \frac{T^2}{2} \\ T \\ 0 \end{bmatrix}$$

  where T is the sampling period. The standard deviation of the process noise of model M^1 is 5m/s^2.

- Model 2: Wiener process acceleration (nearly constant acceleration motion):

$$F_b^2 = \begin{bmatrix} 1 & T & \frac{T^2}{2} \\ 0 & 1 & T \\ 0 & 0 & 1 \end{bmatrix}$$

$$G_b^2 = \begin{bmatrix} \frac{T^2}{2} \\ T \\ 1 \end{bmatrix}.$$

  The standard deviation of the process noise of model M^2 is 7.5m/s^2.

- Model 3: Wiener process acceleration (model with large acceleration increments, for the onset and termination of maneuvers): Here $F_b^3 = F_b^2$ and $G_b^3 = G_b^2$. The standard deviation of the process noise of model M^3 is 40m/s^2.

The initial model probabilities for three targets are identical: $\mu_0^1 = 0.8$, $\mu_0^2 = 0.1$ and $\mu_0^3 = 0.1$. The mode switching probability matrix for three targets is also identical and is given by

$$\begin{bmatrix} p_{11} & p_{12} & p_{13} \\ p_{21} & p_{22} & p_{23} \\ p_{31} & p_{32} & p_{33} \end{bmatrix} = \begin{bmatrix} 0.8 & 0.1 & 0.1 \\ 0.1 & 0.8 & 0.1 \\ 0.3 & 0.3 & 0.4 \end{bmatrix}.$$

The Sensors: Two radar sensors, one located at (0,0)m and the other at (0, 12000)m in Cartesian coordinate system, are used to obtain the measurements. The measurements are range and azimuth. The range and azimuth transformations, respectively, are given by

$$r = (x^2 + y^2)^{1/2}, \quad a = \tan^{-1}(y/x).$$

The measurement noise $w_k^{j,l}$ for sensor l ($l = 1, 2$) is assumed to be zero-mean white Gaussian with known covariance matrices $R^1 = \text{diag}[400\text{m}^2,\ 49\text{mrad}^2]$ and $R^2 = \text{diag}[400\text{m}^2,\ 49\text{mrad}^2]$. The sampling interval is $T = 1$s. and it was assumed that the probability of detection $P_D = 0.98$ for each sensor. But for evaluation of cost function with the scheduling algorithm, the probability of detection was assumed to be $P_D = 1.0$ for each sensor.

The Clutter: For generating false measurements in simulations, the clutter was assumed to be Poisson distributed with expected number of $\lambda = 100 \times 10^{-6}$/m mrad for each sensor. These statistics were used for generating the clutter in all simulations. However, a nonparametric clutter model was used for implementing all the algorithms for target tracking.

Other Parameters: The gates for setting up the validation regions for the sensor were based on the threshold $\gamma = 16$ [1],[8]. With the measurement vector of dimension 2, this leads to a gate probability $P_G = 0.9997$ (see [1, p. 56]).

Simulation Results: The results were obtained from 100 Monte Carlo runs for state estimation based on actual measurements. Furthermore, $N = 100$ in (13), i.e. for random sampling we used 100 samples at each time-step. Fig. 1 shows the true trajectory of the target. Fig. 2 shows the RMSE (root mean-square error) for the filtered position estimate for the target with one-time-step scheduling and no-scheduling (either sensor 1 for all times or sensor 2 for all times). It is seen from Fig. 2 that the overall tracking performance has been improved after scheduling. Fig. 3 shows the RMSE for the filtered position estimate for the target with two-time-step scheduling and no-scheduling. It is seen from Figs. 2 and 3 that increasing the time-steps from one to two does not yield any improved performance at the onset of maneuvers; rather, the performance is degraded around the onset of maneuvers. This is so because the target trajectory does not necessarily follow our three target motion models with the specified transition probabilities. Therefore, pseudo-state/measurement generation via random sampling does not necessarily reflect the true target motion. This discrepancy between the true state and the pseudo-state worsens with increasing time-steps.

Nevertheless, short-term scheduling (1-step) does provide significant performance gains relative to fixed sensor assignment. Note the increase in error at the onset of maneuvers.

5. CONCLUSIONS

We proposed a new sensor scheduling algorithm for a highly maneuvering target tracking application. In the proposed scheduling algorithm, under the constraint that only one sensor may be used at any time step, we first predict the expected cost one or multiple time steps ahead as a function of the candidate sensor scheduling sequences, and then pick the sequence that minimizes an expected performance metric. We used a random sampling approach coupled with switching multiple kinematic models for target motion, to generate future (pseudo-)states and (pseudo-)measurements which allows computation of the relevant performance metric. Tracking of highly maneuvering target is achieved by an effective suboptimal filtering algorithm based on interacting multiple model (IMM) filtering approach combined with probabilistic data association (PDA) technique and the proposed sensor scheduling scheme. The proposed algorithm was illustrated via a simulation example involving two geographically distributed radar sensors.

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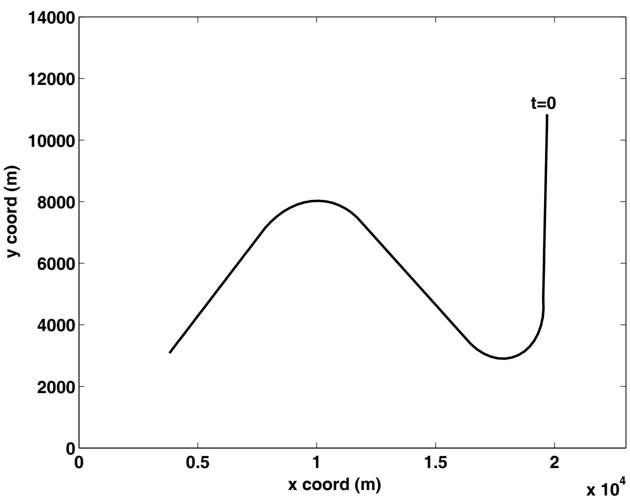


Figure 1. Target trajectory.

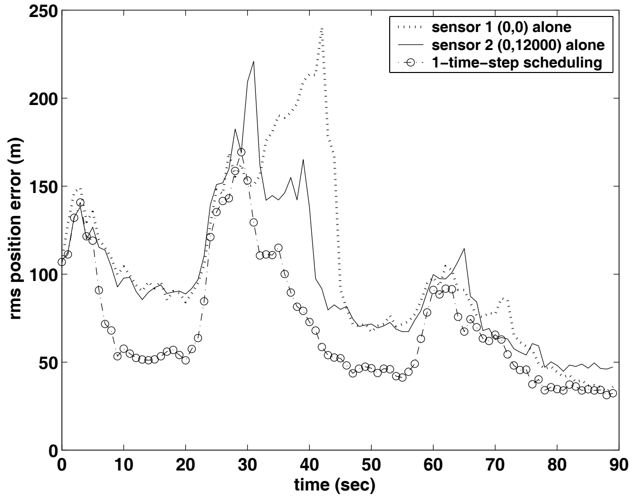
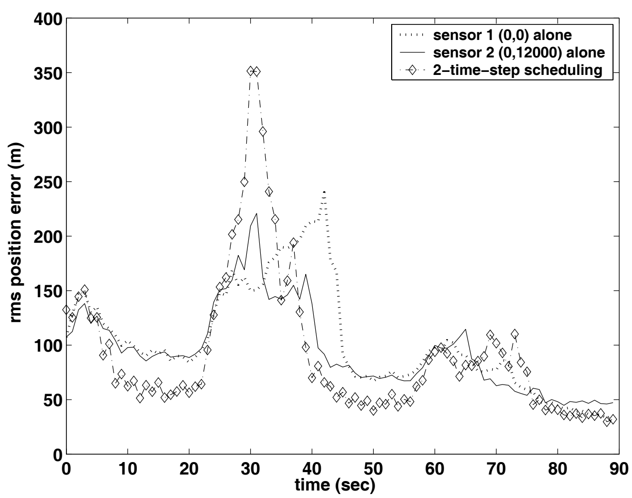


Figure 2. Root mean-square error (RMSE) in position for IMM/PDAF with 1-time-step scheduling and without scheduling.



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