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Multiple Objective D-optimal Sensor Management for Group Target Tracking

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***Abstract*— A group target is moving in an area well covered by a network of passive sensor nods with known positions. Additionally, there are a number of mobile robots with active sensors. In order to obtain a robust estimate of the position of the target and decrease the amount of energy spent on active sensing and communications by the sensor network and the mobile robots a sensor management system optimises the spatial configuration of the mobile robots over time. A tracking algorithm predicts the position of the target over multiple steps. An estimate for the tracking accuracy for each possible sensor action is calculated based on a function of the expected resulting posterior inverse covariance (information) matrix given the position of the nodes of the sensor networks and the feasible position of the mobile robots in future time instants. We propose a novel approach for active sensor management that combines the Rao-Blackwellised particle filter/predictor and multi-objective D-optimal optimisation. The designed decentralised Rao-Blackwellised particle filter (RBPF) is composed of two parts: a decentralised Information or Kalman filter and a particle filter (PF). The sensor management framework that is based on the generalised D-optimal optimisation with slack variables is proposed.**

I. Introduction

Sensor management has been an active area of research over the last few years [1], [2]. Efforts are concentrated both on theoretical and practical issues of sensor networks. Typical advantages of using a senor network are the inherent robustness to sensor failures and coverage of a larger area. Common approaches to sensor management select the most informative observations after optimising information measures such as the Kullback-Leibler distance or Rényi divergence [3], [4], [5], [6]. However, most of the requirements for the system as a whole can be taken into account only by a multi-objective function which can reflect other requirements, e.g. communication issues, time restrictions, power and other constraints. In this paper we consider additionally other measures such as energy consumption and survivability of the sensors in addition to information gain. We consider the sensor tasking and the target tracking problems together within a decentralised information theoretic sensor management architecture. The chosen configuration of the mobile sensors in the vicinity of the target is based on the multi-objective D-optimal optimisation approach in order to satisfy various requirements. The presented approach can be used in many surveillance systems, robotics applications, and sensor networks.

The paper is organised as follows. Section II presents our previous formulation of the sensor management problem. The sensor management approach based on the RBPF and multi-objective D-optimal optimisation is proposed in Section III. Finally, conclusions are outlined in Section IV.

II. Problem Formulation

In this section we formulate the problem of active sensor management based on decentralised processing of sensor data and multi-objective optimisation.

Consider scenarios where the sensor data, e.g. range and bearing to the target are related to the states of the target through highly nonlinear relations, which together with nonlinear target dynamics makes it difficult or even impossible to use standard techniques such as the extended Kalman filter. A Rao-Blackwellised particle filter (RBPF) is therefore used which estimates the target position, speed and acceleration of the target. The filter also supplies a covariance matrix characterising the accuracy of the estimates.

The optimisation variables $\mathbf{a}(t+1)$ form the matrix of 2D Cartesian coordinates for S sensors at the next time step (t+1) [7]. In our previous work, the optimisation problem was formulated as follows [7]. Find the action matrix $\mathbf{a}(t+1)$ that is infinite-norm optimal with respect to the weighted objectives of (minimising) sensor power consumption of moving the sensors and (maximising) sensor separation. The selected action must satisfy the constraint set Ω which consists of constraints on the maximum sensor displacement, the minimum sensor separation and the trace of the resulting posterior state estimate covariance matrix.

$$\mathbf{a}^*(t+1) = \arg\min_{\mathbf{a}(t+1)} \left(Pow(\mathbf{a}(t+1)), Sep(\mathbf{a}(t+1)), W\right) \tag{1}$$

$$s.t. \quad \mathbf{a}(t+1) \in \Omega,$$

where W is the objective preference weight vector $W = [w_1, w2]$ for the two performance objectives. The performance objectives are defined as follows. The power consumption of a particular sensor placement $Pow(\mathbf{a}(t+1))$ is proportional to the Euclidean distance travelled by the sensor. The separation of sensors $Sep(\mathbf{a}(t+1))$ is defined using the resulting Euclidean distance between sensors for the particular action

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$\mathbf{a}(t+1)$ (see [7] for more details). The predicted positions of the target along a specified time horizon are calculated by the tracker which coupled with the range-dependant observation information contribution provides a mechanism for relating sensor actions to the resulting posterior estimate covariance matrix. The approach presented can be used for both non-myopic (over several time epochs) [8] and myopic (single epoch) [7] sensor management.

In our previous approach we considered only omnidirectional sensors and the single target case [7]. In this paper the main objective is to introduce a framework for sensor management that optimises the sensors field of view. For example, two mobile robots can emit signals that can be reflected by the group of targets and is received by sensor network (sensors in fixed locations). We also consider the case when the field of view covers only a part of the group of targets. In the next section we briefly outline the proposed multiple objective D-optimal sensor management framework for group target tracking.

III. The Sensor Management Algorithm

A. Tracking Algorithm

The tracking scheme is based on a Rao-Blackwellsised particle filter [9], [10], [11], [12]. Rao-Blackwellisation is a technique for improving particle filtering by analytically mariginalising out some of the variables (linear, Gaussian) from the joint posterior distribution, and then the linear system model is estimated by a Kalman filter (KF), an optimal estimator, whilst the nonlinear part is estimated by a particle filter (PF). In this particular problem the positions of the target can be estimated by a PF, its speeds and accelerations (in x and y directions) with the KF (see Table 1). As a result of the marginalisation, the variance of the estimates is reduced compared to the standard PF and the computational complexity decreases as well. Additionally, this RBPF is *decentralised* because it uses the fused measurements from neighbouring sensors only. The PF can approximate the r-step ahead state predictive distribution $p(\boldsymbol{x}_i^{t+r}|\boldsymbol{z}_{1:t})$ of positions of the ith target. Here, $\boldsymbol{x}_i^{t+r}$ denotes the system state vector of the ith target at time instant $t+r$, and $\boldsymbol{z}_{1:t}$ is the vector containing measurements up to time instant t. These predictions are used for generating the next best sensor placement. A multi-objective decision making criterion is used composed by several terms, accounting for different requirements: tracking accuracy (through a variance calculated by the particle filter), minimum energy (for the control of the sensors) and spatial restrictions. Some of the requirements such as minimum power consumption and maximum target tracking performance are conflicting. Since we optimise the positions of the sensors with respect to the positions of the target, only the covariance from the PF is required by the optimisation framework, and we do not use the estimation error covariance from the KF. Other constraints such as maintaining minimum distance to obstacles can be easily accounted for by the optimisation framework.

For example, Fig.1 shows the actual, and estimated trajectory from the RBPF using measurements from neighbouring sensors.

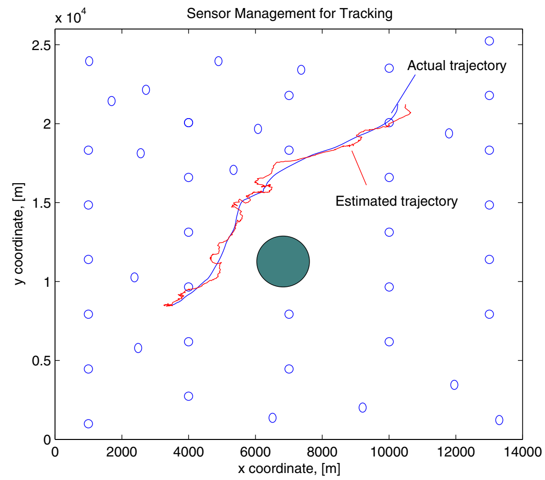

Fig. 1. Sensors' positions, the actual trajectory of the target, estimated trajectoriy by the RBPF

Table 1. A Rao-Blackwellised PF for sensor management

Initialisation
Generate initial samples for the states of the PF and the KF.
Set initial weights.

For k =1:simulation time

1) *Particle filter prediction step*
2) *Kalman filtering update step*. It uses the states predicted by the PF as measurements in the KF.
3) *Kalman filtering prediction step*
4) *Measurement update* based on the fused sensor data. Compute the weights and normalise them.
5) *Output*:
   - estimated target positions by the PF
   - estimated states (speed and accelerations) by the KF
   - covariance matrix from the KF (characterises the accuracy of the target speed and acceleration estimates)
   - variance matrix from the PF (characterises the accuracy of the target position estimates)
6) *Resampling step*

end

B. Actions Generation

In order to define the field of view it is necessary to introduce possible shapes of a covered region. In this paper we assume it is ellipsoidal. In order to define an ellipsoid we need to define its location and volume. The measure of volume of the ellipsoid is a determinan of information matrix $\det(\mathbf{M})$. The possible locations of the ellipsoid that defines a sensor field of view at future time $t+1$ depends on the previous location of the ellipsoid at time t and how fast we can change the field of view (the center of the ellipsoid). Therefore we arrive at the following optimisation problem for two moving sensors

$$[\mathbf{M}_1^*, \mathbf{M}_2^*, \mathbf{c}_1^{*t+1}, \mathbf{c}_2^{*t+1}] = \operatorname{argmin} \sum_{s=1}^{2} \log\det \mathbf{M}_s + R_s^2 + (\mathbf{c}_s^{t+1} - \mathbf{c}_s^t)'(\mathbf{c}_s^{t+1} - \mathbf{c}_s^t) \quad (2)$$

subject to

$$\begin{aligned}
&(\mathbf{x}_i^{t+1} - \mathbf{c}_1^{t+1})'\mathbf{M}_1^{-1}(\mathbf{x}_i^{t+1} - \mathbf{c}_1^{t+1}) \leq R_1^2,\\
&(\mathbf{x}_i^{t+1} - \mathbf{c}_2^{t+1})'\mathbf{M}_2^{-1}(\mathbf{x}_i^{t+1} - \mathbf{c}_2^{t+1}) \leq R_2^2,\\
&(\mathbf{c}_1^{t+1} - \mathbf{c}_1^{t})'(\mathbf{c}_1^{t+1} - \mathbf{c}_1^{t}) \leq \theta_1^2,\\
&(\mathbf{c}_2^{t+1} - \mathbf{c}_2^{t})'(\mathbf{c}_2^{t+1} - \mathbf{c}_2^{t}) \leq \theta_2^2,\\
&(\mathbf{c}_1^{t+1} - \mathbf{c}_2^{t+1})'(\mathbf{c}_1^{t+1} - \mathbf{c}_2^{t+1}) \geq d^2,\\
&i = 1...l,
\end{aligned}$$

where the solution of this optimisation problem are nonnegative definite matrices $\mathbf{M}_1^*$ and $\mathbf{M}_2^*$ and vectors $\mathbf{c}_1^{*t+1}$, $\mathbf{c}_2^{*t+1}$ that define the size and location of two ellipsoids (every ellipsoid corresponds to space that will be covered by a corresponding sensor at time $t+1$), in general, the number of ellipsoids corresponds to the number of the mobile robots; $\mathbf{c}_1^t$ and $\mathbf{c}_2^t$ are known position of the ellipsoid at time t; θ_1, θ_2 and d are predefined constants given by a user; $\mathbf{x}_i$ is a predicted position of the $i-$th individual target in the group where l is the number of individual targets in the group; R_1 and R_2 are values not equal to zero. In this formulation the size of the ellipsoid can be changed by varying the choice of the matrices $\mathbf{M}_1$ and $\mathbf{M}_2$ or vectors R_1 and R_2 but the large values of R_1 (R_2) should be penalised.

If we are interested in tracking the major part of the group then we can allow a few individual targets to be outside of the coverage space (ellipsoids) by introducing slack variables $\xi_{s,i}$ and a parameter $\nu \in [0, 1)$ (see [13], [14] for more details about slack variables and the parameter ν) which define the upper bound of the proportion of how many individual targets are permitted be outside of the coverage space.

$$[\mathbf{M}_1^*, \mathbf{M}_2^*, \mathbf{c}_1^{*t+1}, \mathbf{c}_2^{*t+1}] = \operatorname{argmin} \sum_{s=1}^{2} \log\det \mathbf{M}_s + R_s^2 + (\mathbf{c}_s^{t+1} - \mathbf{c}_s^t)'(\mathbf{c}_s^{t+1} - \mathbf{c}_s^t) + \frac{1}{l\nu}\sum_{i=1}^{l} \xi_{s,i} \quad (3)$$

subject to

$$\begin{aligned}
&(\mathbf{x}_i^{t+1} - \mathbf{c}_1^{t+1})'\mathbf{M}_1^{-1}(\mathbf{x}_i^{t+1} - \mathbf{c}_1^{t+1}) \leq R_1^2 + \xi_{1,i},\\
&(\mathbf{x}_i^{t+1} - \mathbf{c}_2^{t+1})'\mathbf{M}_2^{-1}(\mathbf{x}_i^{t+1} - \mathbf{c}_2^{t+1}) \leq R_2^2 + \xi_{2,i},\\
&(\mathbf{c}_1^{t+1} - \mathbf{c}_1^{t})'(\mathbf{c}_1^{t+1} - \mathbf{c}_1^{t}) \leq \theta_1^2,\\
&(\mathbf{c}_2^{t+1} - \mathbf{c}_2^{t})'(\mathbf{c}_2^{t+1} - \mathbf{c}_2^{t}) \leq \theta_2^2,\\
&(\mathbf{c}_1^{t+1} - \mathbf{c}_2^{t+1})'(\mathbf{c}_1^{t+1} - \mathbf{c}_2^{t+1}) \geq d^2,\\
&\xi_i \geq 0,\ i = 1...l,
\end{aligned}$$

The dual optimisation problem can be defined and solved using a similar approach described in [13]. In order to incorporate a prediction uncertainty of individual target locations $\mathbf{x}_i^{t+1}$ in the optimisation problems (2) and (3) the point $\mathbf{x}_i^{t+1}$ can be replaced by an ellipsoid that represents the accuracy of the prediction of the position of the target.

IV. Conclusions

This paper presents a D-optimal procedure for sensor management. The approach relies on multiple objective optimisation and Rao-Blackwellisation. The RBPF brings the advantages that the highly nonlinear part of the state vector is estimated by a PF, whilst the linear part is estimated by a KF. This reduces the computational complexity and improves the accuracy compared to the case when only a PF-based prediction is used. In order to find minimum *footprint* we propose the sensor management framework that is based on the generalised D-optimal optimisation with slack variables. This can reduce the amount of energy required for the active seeing and improve robustness of the sensor management system against outliers.

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