Efficient multi-sensor path scheduling for cooperative target tracking

Lingtong Meng1, Wei Yi1, Tao Zhou1
1University of Electronic Science and Technology of China, Chengdu, People’s Republic of China
E-mail: kussoyi@gmail.com

Abstract: This study deals with path scheduling problem of cooperative target tracking by multiple sensors with bearings only measurements. First, the authors derive a closed-form expression of the determinant (D-optimality criterion) of the Fisher information matrix (FIM) as the cost function, which contains the knowledge of the target and the locations of sensors. Second, a penalty function is introduced to modify the cost function for threats avoidance and physics constraints are applied to limit directions of sensors. Then, an efficient strategy based on steepest descent is proposed to solve the optimisation problem. Finally, the effectiveness of the proposed algorithm is demonstrated both in localisation of a stationary target and tracking a moving target. Simulation results show the trajectories of sensors for cooperative target tracking are almost identical to a grid-based search method; however, the computational complexity is reduced by several orders of magnitude.

1 Introduction

The availability of real-time high-accuracy tracking is essential for current and future wireless applications. Reliable tracking and navigation with mobile sensors is a critical component for a diverse set of applications including logistics, security tracking, medical services, search and rescue operations, control of home appliances, automotive safety and military systems [1, 2]. In recent years, the demand for moving sensors has increased and the research community has been called upon to solve the many issues that arise from using sensor network.

Considerable effort has been dedicated to moving sensors path scheduling with numerous approaches [3]. Generally, path scheduling of cooperative tracking by multiple sensors is implemented based on the information theory [4, 5]. The decision processes are determined by minimising or maximising cost function [6, 7] associated with measurements. In [8], an approach of maximise the Fisher information matrix (FIM) is proposed to track known target, which is the inverse of Cramer–Rao lower bound (CRLB). In [9], the posterior CRLB (PCRLB) is employed as the cost function obtained from the measurements of multiply sensors with bearings only measurements to find the optimal trajectories. This literature also introduces a search technique to compute the inverse of PCRLB over a grid, and the simulation results show that performances of multi-step scheduling is better than scheduling of single step. More recently, the value of information gain is present in [10] as the objective function while tracking target. In [11], a receding horizon approach is presented to predict the FIM for the potential course of action set. An information theoretic approach in [12] is proposed to control the sensor to search a single stationary target by minimising the entropy of the target distribution. Three reward functions under two information criteria are discussed in [13]. This paper also proposes a grid-based search method to solve the optimisation problem. The literature [14] introduces a cost function related to global position error covariance of cooperatively sensors, which also derives the analytical lower and upper bounds of the target and sensors localisation errors. In [15], a greedy algorithm is developed for emitter localisation using FIM. The steering algorithm is used to determine the next positions of sensors by maximising the determinant of an approximated FIM, which shows that it can get accurate localisation performance.

In this paper, we address the problem of optimal motion scheduling of multiple moving sensors for cooperative tracking with bearings only measurements. Our contributions in this work offers much valuable flexibility not found in existing approaches. First, a closed-form expression of the determinant of the FIM is derived and it is used as the cost function. Second, we introduce a penalty function to modify the cost function for threats avoidance and employ turning angle constraints to limit directions of sensors. Third, an efficient strategy based on steepest descent is proposed to solve the optimisation problem. Finally, we verify the effectiveness of the proposed strategy by comparing it with a grid-based search method.

The remainder of this paper is organised as follows. In Section 2, we describe the target-tracking model in bearings only measurements. In Section 3, we first derive the cost function based on FIM and then introduce the constraints to limit sensors. Section 4 describes the efficient optimisation algorithm based on steepest descent strategy. Section 5 presents the results of the simulation, and finally, Section 6 contains our conclusions.

2 Target tracking model

As shown in Fig. 1, we consider the problem of a two-dimensional target tracking by a cooperatively moving sensors with bearing only measurements. The moving platform positions at discrete time instants \( k, k = 1, 2, \ldots \) are denoted by \( \xi_k = [p_1, p_2, \ldots, p_k]^T \), \( p_i = [x_i, y_i] \). The dynamical equation of the target is given by

\[ \mathbf{x}_{k+1} = F \mathbf{x}_k + \mathbf{v}_k \tag{1} \]

where \( \mathbf{x}(k) = [x_k, x_{k+1}, y_k, y_{k+1}]^T \) is the state vector of the target at time step \( k \), which include location and speed of the target in Cartesian coordinates. \( F \) is the state transition matrix of the target that explains how current states of the system influences the next step states, which is presented by

\[ F = \begin{bmatrix} 1 & T_s & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & T_s \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{2} \]

The process noise \( \mathbf{v}(k) \) is contaminated with a Gaussian noise of zero-mean with covariance matrix \( \mathbf{Q} \), i.e. \( \mathbf{v}_k \sim \mathcal{N}(0, \mathbf{Q}) \). \( T_s \) is the time interval between successive measurements. The
measurements sequence $Z_k$ of cooperative sensors at discrete time $k$ is

$$Z_k = h(x_k) + w_k$$  \hspace{1cm} (3)$$

where the measurement function $h(x_k)$ is described by

$$h(x_k) = \begin{bmatrix} \tan^{-1}\left(\frac{x_k - x_1}{y_k - y_1}\right) \\ \vdots \\ \tan^{-1}\left(\frac{x_k - x_n}{y_k - y_n}\right) \end{bmatrix}$$  \hspace{1cm} (4)$$

The measurements noise $w_k$ is corrupted with a zero-mean white Gaussian process with covariance matrix $R_k$, i.e. $w_k \sim \mathcal{N}(0, R_k)$, and $R_k$ is expressed as

$$R_k = \begin{bmatrix} \sigma^2_j & 0 \\ \vdots & \ddots \\ 0 & \sigma^2_n \end{bmatrix}$$  \hspace{1cm} (5)$$

where $\sigma_j$ is the standard deviation of measurements for $j$th sensor at time $k$. Furthermore, we assume that the measurement noise processes of the different sensors are independent, which is also not related to processing noise.

In this paper, the extended Kalman filter (EKF) algorithm is used to estimate the relative position and velocity of the target. Each sensor uses local measurements to estimate the state of target. Then, these estimates are exchanged and fused to produce global estimates of target. The measurements are combined using the following simple but general fusion relations [16].

$$P^{\text{fused}}_k = \sum_{i=1}^{N} (P_i^{-1})^{-1}$$  \hspace{1cm} (6)$$

$$\hat{x}^{\text{fused}}_k = P^{\text{fused}}_k \sum_{i=1}^{N} (P_i^{-1})^{-1} \hat{x}^i_k$$  \hspace{1cm} (7)$$

where $\hat{x}^i_k$ and $P^i_k$, $i = 1, 2, \ldots, n$, are the local state estimates and estimate error covariance matrix. $P^{\text{fused}}_k$ is the fused estimate error covariance matrix, and $\hat{x}^{\text{fused}}_k$ is the fused estimate of the target position. Obviously, the tracking accuracy depends on where the moving sensors cooperate in their sensing and their trajectories. Therefore, the objective of path scheduling is to find the optimal locations of moving sensors to obtain the best estimates of the target.

3 Cost function based on Fisher information matrix

In this section, we derive the cost function based on FIM, which contains the contributions of all moving sensors measurements and their positions. We also modify the cost function for threats avoidance and apply physics constraints to limit directions of sensors.

3.1 Signal model

As the measurement model is independent of target velocity, we only consider target position in the derivation of FIM. We use the target state vector $x_k = [x_k, y_k]$ to denote the target position component only when the closed-form expression is derived of FIM as follows [13]. Under certain conditions, any estimator has a lower bound of variance, the variance of the estimate can only be greater than or equal to this lower bound, this lower bound is called the Cramer–Rao lower bound. If $\hat{x}_k$ is the unbiased estimate of $x_k$ based on the measurement at time $\tilde{k}$, then

$$\text{Var}(\hat{x}_k) \geq \text{CRLB}(\hat{x}_k)$$  \hspace{1cm} (8)$$

The CRLB for the error covariance is defined as the inverse of the FIM $G_k$ [17], which is

$$\text{CRLB}(\hat{x}_k) = E[(\hat{x}_k - x_k)(\hat{x}_k - x_k)^T] \geq G_k^{-1}$$  \hspace{1cm} (9)$$

The inequality in (9) means that $\text{CRLB}(\hat{x}_k) - G_k^{-1}$ is a semi-definite matrix. Generally, FIM is calculated by (10) in which $a$ is the observation, $x$ is the position of target which has to be estimated, and $p(a|x)$ is the probability density function of the observations.

$$G_k(x) = E[(V_k \ln p(a|x))(V_k \ln p(a|x))^T]_{a = x_k}$$  \hspace{1cm} (10)$$

If $p(a|x)$ is subject to a Gaussian distribution, it is easy to get FIM [15] by (11)

$$G_k(x) = J^T R_k^{-1} J$$  \hspace{1cm} (11)$$

where $R_k$ is the covariance matrix of the measurement noises and $J$ is the Jacobian matrix. The measuring error $e_k$ is calculated by (12).

$$e_k = z_k - Z_k(x)$$  \hspace{1cm} (12)$$

where $\hat{z}_k$ is the vector of bearings only measurements and $Z_k(x)$ is the vector of exact angle values. On the basis of (12), the Jacobian matrix can be written as

$$J = \frac{\partial c_k}{\partial x} = \begin{bmatrix} \frac{\partial c_1(x)}{\partial x} & \frac{\partial c_2(x)}{\partial x} & \cdots & \frac{\partial c_n(x)}{\partial x} \end{bmatrix}^T$$  \hspace{1cm} (13)$$

If the derivation of (13) is calculated by $x_k$ and $y_k$, thus each component of it can be expressed as

$$\frac{\partial c_k(x)}{\partial x} \bigg|_{x=x_k} = \begin{bmatrix} \frac{y_k - y_1}{d_1^k} & \frac{x_k - x_1}{d_1^k} & \cdots & \frac{y_k - y_n}{d_n^k} & \frac{x_k - x_n}{d_n^k} \end{bmatrix}^T$$  \hspace{1cm} (14)$$

where $d_i^k$ is the distance between target and $i$th sensor, i.e. $d_i^k = (x_k - x_i)^2 + (y_k - y_i)^2$. Using (11), (13), and (14), (11) can be rewritten as

$$G_k = \begin{bmatrix} \sum_{i=1}^{n} \frac{(y_k - y_i)^2}{\sigma_i^2(d_i^k)} & \sum_{i=1}^{n} \frac{(x_k - x_i)(y_k - y_i)}{\sigma_i^2(d_i^k)} \\ \sum_{i=1}^{n} \frac{(x_k - x_i)(y_k - y_i)}{\sigma_i^2(d_i^k)} & \sum_{i=1}^{n} \frac{(x_k - x_i)^2}{\sigma_i^2(d_i^k)} \end{bmatrix}$$  \hspace{1cm} (15)$$
The most important step of path scheduling is the choice of cost function that requires low real-time computation. To formulate an appropriate cost function, we use the determinant of FIM (product of the eigenvalues of FIM) as the cost function. In optimal experiments theory, it is referred to as D-optimal criterion [14]. A D-optimality design for parameters will minimise the volume of the uncertainty ellipsoid generated by CRLB. The determinant of the FIM is a widespread criterion used for path scheduling [18], and it is more comprehensive than the trace of the FIM [2] (A-optimality criterion) since it takes into account all the terms of FIM. The cost function at $k$ state based on FIM is

$$
\Psi_k(x_k, p^{\theta}_1, \ldots, p^{\theta}_q, \sigma, \ldots, \sigma) \triangleq \det(G_k)
$$

(16)

Note that the determinant of FIM, abbreviated as $\Psi$, is a function of the target state, the noise distribution, and the position of the sensors. As we assumed, the standard deviation of measurement noise $\sigma$ is a constant, the calculation of (16) only requires the knowledge of target location $x_k$, which in practice is approximated by the track estimate $\hat{x}_k$. In this paper, we use EKF to obtain the local estimate of the target by each tracking sensor, then the distributed fusion relationships (6) and (7) is employed to obtain the fused estimate $\hat{x}_k$.

3.2 Threats and sensor physics constraints

In electronic warfare environment, sensors need to avoid some threats because of a priori knowledge. Due to the inherent physical knowledge of target location optimality criterion) since it takes into account all the terms of the FIM is a widespread criterion used for path scheduling [18], and it is more comprehensive than the trace of the FIM [2] (A-optimality criterion) since it takes into account all the terms of FIM. The cost function at $k$ state based on FIM is

$$
\Psi_k(x_k, p^{\theta}_1, \ldots, p^{\theta}_q, \sigma, \ldots, \sigma) \triangleq \det(G_k)
$$

(16)

Note that the determinant of FIM, abbreviated as $\Psi$, is a function of the target state, the noise distribution, and the position of the sensors. As we assumed, the standard deviation of measurement noise $\sigma$ is a constant, the calculation of (16) only requires the knowledge of target location $x_k$, which in practice is approximated by the track estimate $\hat{x}_k$. In this paper, we use EKF to obtain the local estimate of the target by each tracking sensor, then the distributed fusion relationships (6) and (7) is employed to obtain the fused estimate $\hat{x}_k$.

4 Efficient strategy based on steepest descent

In this section, an efficient path scheduling strategy based on steepest descent is proposed and the computational complexity is also analysed. Fig. 2 is the flow chart of efficient path planning algorithm based on steepest descent for cooperative target tracking. Gradient controllers are at the core of our solution, which contains the modified cost function, the calculation of gradient, and turning angle constraints.

4.1 Path scheduling strategy based on steepest descent

The next position of moving sensors at time $k + 1$ is

$$
\xi_{k+1} = \xi_k + u_k
$$

(20)

where $u_k$ is the control input of moving sensors which include step size and their directions. As the number of cooperative sensors increase, obtaining the control input quickly would be very sophisticated. We propose a strategy based on steepest descent akin to [19] to solve the difficult problem, which implies that the update rule is

$$
\xi_{k+1} = \xi_k + \eta_k \frac{\partial \Psi_k^2(x_k)}{\partial \xi_k}
$$

(21)

where $\eta_k$ is a time varying step size, and the direction of each moving sensor is

$$
\frac{\partial \Psi_k^2(x_k)}{\partial \xi_k} = [\alpha_1, \alpha_2, \ldots, \alpha_k]
$$

(22)

where $\alpha_k$ is the $k$th sensor direction at time $k$ and it take one of a set of finite values. To implement conveniently, we assume that the speed $v_i = [v_i^1, v_i^2, \ldots, v_i^n]^T$ of sensors is a constant, where $v_i^j$ is the speed of $i$th sensor at time $k$. Thus $\eta_k$ can be expressed as

$$
\eta_k = \frac{v_{i}^T}{\| \nabla \Psi_k^2(x_k) \|}
$$

(23)

Using (21) and (23), (20) can be rewritten as

$$
\xi_{k+1} = \xi_k + v_{i}^T \frac{\nabla \Psi_k^2(x_k)}{\| \nabla \Psi_k^2(x_k) \|} \| \nabla \Psi_k^2(x_k) \|
$$

(24)
steer themselves to the best course of \( N \) directions with respect to their current directions at each frame. Assuming that our approach calculating the trajectories of three sensors at each frame requires \( I_a \) addition operation and \( I_m \) multiplication operation, thus the total calculation is \( I_a + I_m \). However, the total calculation of grid-based search method is \( N (I_a + I_m) \), which calculates \( >10^3 \) values during each optimisation.

5 Simulation results

In this section, simulations are designed to verify the performance of the steepest descent strategy both in localisation of a stationary target and tracking a moving target. In order to better reflect the effectiveness, the method in [20] is provided for comparison and we define it as the grid-based search method. As shown in Fig. 3, we use three bearings, only sensors starting from \( p_i = [700 \text{ m}, 1700 \text{ m}]^T \), \( p_i = [750 \text{ m}, 1600 \text{ m}]^T \), \( p_i = [600 \text{ m}, 1650 \text{ m}]^T \), to track a stationary target \( x_i = [3500 \text{ m}, 0 \text{ m/s}, 2300 \text{ m}, 0 \text{ m/s}]^T \). The sensors are assumed to fly at a constant speed of \( v_i = 40 \text{ m/s} \). The covariance matrixes of measurement and process noise are, respectively, taken as \( R_1 = 5^3 \text{diag}(1,1,1,1) \) and \( Q_1 = 1 \text{e}^{-4} \text{diag}(1,1,1,1) \), where \( \text{diag()} \) is a square diagonal matrix with specified elements on its main diagonal. The EKF is initialised to \( x_i = [3525 \text{ m}, 0 \text{ m/s}, 2280 \text{ m}, 0 \text{ m/s}]^T \), \( P_i = 5I \).

Fig. 3 shows the trajectories of multiple moving sensors using the proposed strategy and the grid-based search method. From Fig. 3, we see that the three sensors move apart from each other from the initial locations and then close to the target gradually. We also find our method is relatively smoother than the grid-based search method, which indicate our technique is more feasible to actual flight. Moreover, we note that the sensors trajectories of our approach is almost identical to the grid-based search method; however, our strategy requires very little computation.

As shown in Fig. 4, the moving target moves from \((1700 \text{ m}, 1700 \text{ m})\) to the northeast at the speed of \(30 \text{ m/s}\) in \(x\)-axis and \(10 \text{ m/s}\) in \(y\)-axis. There are two threats \( X^1 = (1600 \text{ m}, 1450 \text{ m}) \) and \( X^2 = (1800 \text{ m}, 1300 \text{ m}) \) with threat intensities \( \rho_1 = \rho_2 = 50 \). The maximise turning angle \( \phi \) is 30°. Filter initial value is initialised to \( x_i = [1725 \text{ m}, 30 \text{ m/s}, 1680 \text{ m}, 10 \text{ m/s}]^T \) and \( P_i = 5I \). The initial position of the sensors is the same as Fig. 3. Fig. 4a shows typical trajectories of three cooperative sensors track a moving target. We see that cooperative sensors can avoid threats with smooth trajectories, by comparing Figs. 4a with Fig. 4b. That is because when the sensors are close to the threat, the cost function is penalised and the sensors are forced to move away from threats.

Fig. 5 depicts the performance comparison of the proposed steepest descent strategy, the grid-based search method, and random search method. Fig. 5a shows the cost of our strategy is close to the grid-based search method, and they are far superior to random search method. We also note that the determinant of the FIM curve increases monotonously, which means cooperative sensors gradually take more valuable information. Fig. 5b depicts the proposed algorithm takes almost 0.45 ms to solve the optimisation problem for each frame, while exhaustive search spends almost 55 ms, which verifies the effectiveness of our method. Fig. 6 shows the root-mean-squared position error comparison under the three methods. We see that the proposed strategy exhibit an acceptable performance loss with respect to the grid-based search method but a significant performance gain over random search method.

6 Conclusion

In this paper, we have studied the path scheduling problem for cooperative target tracking by multiply sensors with bearings only measurements. First, we derived a closed-form expression of the determinant of the FIM as the cost function, which contains the knowledge of the target and the locations of sensors. Next, we introduce a penalty function for threats avoidance and employ

\[
\begin{align*}
I_a & = 5^3 \text{diag}(1,1,1,1), \\
I_m & = 1 \text{e}^{-4} \text{diag}(1,1,1,1), \\
\text{diag()} & = \text{a square diagonal matrix with specified elements on its main diagonal.}
\end{align*}
\]

\[
\begin{align*}
X^1 & = (1600 \text{ m}, 1450 \text{ m}) \text{ and } X^2 = (1800 \text{ m}, 1300 \text{ m}) \text{ with threat intensities } \rho_1 = \rho_2 = 50, \\
\text{maximise turning angle } \phi \text{ is 30°. Filter initial value is initialised to } x_i & = [1725 \text{ m}, 30 \text{ m/s}, 1680 \text{ m}, 10 \text{ m/s}]^T, \\
P_i & = 5I. 
\end{align*}
\]

\[
\begin{align*}
\text{Fig. 3} & \text{ Trajectories of multiple sensors track a stationary target} \\
(a) & \text{Steepest descent strategy, (b) Grid-based search method. The target location and final sensors locations are marked with pink star, green circle, red circle and blue circle, respectively.}
\end{align*}
\]

\[
\begin{align*}
\text{Fig. 4} & \text{ Trajectories of multi-sensor track a moving target} \\
(a) & \text{The trajectories of cooperative sensors without constraints, (b) The trajectories of cooperative sensors under threats constraints and physics constraints. The final target location and sensors locations are marked with pink star, green circle, red circle and blue circle, respectively}
\end{align*}
\]

\[
\begin{align*}
\text{Fig. 5} & \text{ Performance comparison of three methods versus time} \\
(a) & \text{The cost functions of three methods, (b) The time cost of three methods}
\end{align*}
\]

\[
\begin{align*}
\text{Fig. 6} & \text{ Position RMSE comparison under different methods}
\end{align*}
\]
turning angle constraints to limit the directions of sensors. Then, an efficient strategy based on steepest descent is proposed to solve the optimisation problem. Finally, we have evaluated the performances of the proposed algorithm both in localisation of a stationary target and tracking a moving target. The results highlight that the proposed strategy exhibit an acceptable performance loss with respect to the grid-based search method but a significant performance gain over random search method with less computational complexity.

7 Acknowledgments
This work was supported in part by the Chang Jiang Scholars Program, in part by the 111 Project No. B17008, in part by the National Natural Science Foundation of China under Grant no. 61771110, in part by the Fundamental Research Funds of Central Universities under Grant ZYGX2016J031, and in part by the Chinese Postdoctoral Science Foundation under Grant no. 2014M550465 and Special Grant no. 2016T90845.

8 References
[1] Win, M.Z., Conti, A., Mazuelas, S., et al.: ‘Network localization and navigation via cooperation’, IEEE Commun. Mag., 2011, 49, (5), pp. 56–62
[2] Passerieux, J.M., Van Cappel, D.: ‘Optimal observer maneuver for bearings-only tracking’, IEEE Trans. Aerosp. Electron. Syst., 1998, 34, (3), pp. 777–788
[3] Oshman, Y., Davidson, P.: ‘Optimization of observer trajectories for bearings-only target localization’, IEEE Trans. Aerosp. Electron. Syst., 1999, 35, (3), pp. 892–902
[4] Krishnamurthy, V.: ‘Algorithms for optimal scheduling and management of hidden Markov model sensor’, IEEE Trans. Signal Process, 2002, 50, (6), pp. 1382–1397
[5] Ragi, S., Chong, E.K.P.: ‘UAV path planning in a dynamic environment via partially observable markov decision process’, IEEE Trans. Aerosp. Electron. Syst., 2013, 49, (4), pp. 2397–2412
[6] Fawcett, J.A.: ‘Effect of course manoeuvres on bearings-only range estimation’, IEEE Trans. Acoust. Speech. Signal Process, 1988, 36, (8), pp. 1193–1199
[7] Le Cadre, J.P., Jaffre, C.: ‘Discrete time observability and estimability analysis for bearings-only target motion analysis’, IEEE Trans. Aerosp. Electron. Syst., 1997, 33, (1), pp. 178–201
[8] Sinha, A., Kirubarajan, T., Bar-Shalom, Y.: ‘Autonomous ground target tracking by multiple cooperative UAVs’. Proc. Int. Conf. Aerospace, Big Sky, MT, USA, March 2005, pp. 892–902
[9] Hernandez, M.L.: ‘Optimal sensor trajectories in bearings-only tracking’. Proc. 7th Int. Conf. Information Fusion, Stockholm, Sweden, June 2004, pp. 893–900
[10] Pire, R.R., Li, X.R., Delbazo, R.: ‘UAV route planning for joint search and track missions-an information-value approach’, IEEE Trans. Aerosp. Electron. Syst., 2012, 48, (3), pp. 2551–2565
[11] Koohifar, F., Kambhar, A., Guvenc, I.: ‘Receding horizon multi-UAV cooperative tracking of moving RF source’, IEEE Commun. Lett., 2016, 21, (6), pp. 1150–1166
[12] Hoffmann, G.M., Tomlin, C.J.: ‘Mobile sensor network control using mutual information methods and particle filters’, IEEE Trans. Autom. Control, 2009, 55, (1), pp. 32–47
[13] Wang, X., Ristic, B., Himed, B., et al.: ‘Joint passive sensor scheduling for target tracking’. Proc. 20th Int. Conf. Information Fusion, Xi’an, China, July 2017, pp. 1–7
[14] Morbidi, F., Mariotti, G.L.: ‘Active target tracking and cooperative localization for teams of aerial vehicles’, IEEE Trans. Control. Syst. Technol., 2013, 21, (5), pp. 1694–1707
[15] Dogancay, K.: ‘UAV path planning for passive emitter localization’, IEEE Trans. Aerosp. Electron. Syst., 2012, 48, (2), pp. 1150–1166
[16] Bar-Shalom, Y., Fortman, T.E.: ‘Tracking and data association’ (Academic Press, San Diego, CA, 1988)
[17] Van Trees, H.L.: ‘Detection, estimation, and modulation theory part I’ (Wiley, New York, 1968)
[18] Meng, W., Xie, L., Xiao, W.: ‘Communication aware optimal sensor motion coordination for source localization’, IEEE Trans. Instrum. Meas., 2016, 65, (11), pp. 2505–2514
[19] Chung, T.H., Burdick, J.W., Murray, R.M.: ‘A decentralized motion coordination strategy for dynamic target tracking’, Proc. Int. Conf. Robotics and Automation, Orlando, FL, USA, May 2006, pp. 2416–2422
[20] Wang, X., Cheng, X., Morelande, M., et al.: ‘Bearings-only sensor trajectory scheduling using accumulative information’. Proc. 12th Int. Conf. Radar Symp., Leipzig, Germany, October 2011, pp. 682–688