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Game Theory Based Sensor Management in Reducing Target Threat Level Assessment Risk

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Abstract: Sensor management schemes are calculated to reduce target threat level assessment risk in this paper. Hidden Markov model and risk theory are combined to build the target threat level model firstly. Then the target threat level estimation risk is defined. And the sensor management schemes are optimized with the smallest target threat level assessment risk. What's more, the game theory is applied to calculate the optimal sensor management scheme. Some simulations are conducted to prove that the proposed sensor management method is effective.
Key words: target threat level assessment, sensor management, hidden Markov model, risk theory, game theory
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0 Introduction

There are various kinds of sensors, such as satellite and radars, in the space to monitor targets, such as missiles and aircrafts in the military. Once sensor resources are not made full use of, two defects can occur. On the one hand, sensor resources may be wasted when too many sensors are detecting one same target, and on the other hand, it may bring too much harm when one target is ignored and no sensors are tracking it. Thus, sensor management methods are important in the military to defend coming targets. Sensor management can be divided into three kinds, including sensor management on account of covariance theory[1-3], sensor management on account of information theory[4-6], and sensor management on account of risk theory[7-9]. In the mentioned three kinds of sensor management methods, target tracking performance is taken into account firstly in the first two kinds of method, no matter how much sensor resources have been used. However, in risk-based sensor resource management method, the sensor resource wasting risk and the target tracking risk are measured at the same time. That is to say, in the third sensor management method, if all sensor resources have been applied to track one target, but it cannot meet the tracking requirement, no sensors will be used to protect and save sensor resources.

After sensor management has been changed into a mathematic problem and sensor management models have been built, the most important event will obtain sensor management schemes based on sensor management models. There are usually two kinds of algorithms to calculate sensor management schemes, and they are centralization algorithms and distribution algorithms. As for centralization algorithms, the sensor management scheme is produced in a calculation center. The branch threshold algorithm has been used to obtain sensor management scheme in Refs. [10] and [11]. Reference [12] adopted the Hungary algorithm to seek for the best sensor management scheme. What's more, artificial intelligence algorithms represented by particle swarm optimization (PSO) algorithm, have been applied to calculate the optimal solution in sensor management. The advantage of centralization algorithm is mainly the high calculation accuracy at the sacrifice of communication pressure. As for the distribution algorithm, each single sensor can be seen as a calculation point. The sensor allocation process is seen as the auction process and the auction algorithm is applied to calculate the optimal solution in Ref. [13]. In Refs. [14] and [15], the contract net algorithm is applied to obtain the best solution. Different form the centralization algorithms, the advantage of distribution algorithm is the fast calculation speed. Its solution may not be the global optimization, but the local optimization. How to improve the solution quality and keep the high calculation speed in distribution algorithms has been a hot research topic.

In target tracking, target threat levels must be defined, which is called target threat level estimation. In the former researches, sensor management is seldom

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analyzed in target threat level estimation. Obviously, risk occurs once the target is taken as the wrong threat level. For example, a target with a high threat level is regarded as a target with a low threat level, and the defensed objective may be destroyed. So target threat assessment risk must be reduced in target tracking[17-18].

In this paper, the target threat level assessment model is built based on hidden Markov model (HMM) and risk theory. Then the target threat level assessment risk is defined, and the sensor management model is built to reduce target threat level assessment. What's more, the game theory is applied to calculate the optimal sensor management scheme. Some simulations are made to prove the effectiveness of the proposed sensor management method.

1 Problems Formulation

When targets move, their motion states estimated through expended Kalman filter (EKF) or interactive multiple mode filter (IMM) obey the distribution $N(\hat{\boldsymbol{X}}_{k|k}, \hat{\boldsymbol{P}}_{k|k})$[18], where the variable $\hat{\boldsymbol{X}}_{k|k} = (\boldsymbol{p}_k^t, \boldsymbol{v}_k^t) = (x_k^t, \dot{x}_k^t, y_k^t, \dot{y}_k^t)^{\mathrm{T}}$ denotes the motion state of target t at time instant k, and the matrix $\hat{\boldsymbol{P}}_{k|k}$ denotes the covariance matrix.

The threat of targets is usually taken as a function of the targets' motion states. For example, it can be calculated by Ref. [18]:

$$f_{\text{threat}}(\hat{\boldsymbol{X}}_{k|k}) = \exp\left(\frac{-[(x_k^t - x^0)^2 + (y_k^t - y^0)^2]}{2\left(1 - \dfrac{\theta(\boldsymbol{p}_k^t, \boldsymbol{v}_k^t)}{\pi}\right)^2 (k_0\|\boldsymbol{v}_k^t\| + m_0)^2}\right), \quad (1)$$

where, (x^0, y^0) is the coordinate of our defensed center; $\theta(\boldsymbol{p}_k^t, \boldsymbol{v}_k^t)$ is the azimuth angle of the target; k_0 and m_0 are the constants.

When $N(\hat{\boldsymbol{X}}_{k|k}, \hat{\boldsymbol{P}}_{k|k})$ is used to calculate the threat value of a target, the estimation of threat should not be a precise value, but obeys some mathematical distributions. To simplify the model but still effectively, the threat of a target is related to its distance to the defense center and velocity. The transmission from the target motion state to the threat value is shown in Fig. 1. Obviously, if only $\hat{\boldsymbol{X}}_{k|k}$ is used to estimate the threat value as before, there may be some errors which can be seen from Fig. 1. However, the threat equation is a nonlinear function of the motion states, and the distribution is difficult to obtain by mathematical deduction. In Ref. [16], sampling is used to calculate the variance of the threat distribution with large calculation, and the objective of sensor scheduling is just to make the estimation of target threat more precise by minimizing the variance. However, in this method, the calculation amount is too large to calculate in time.

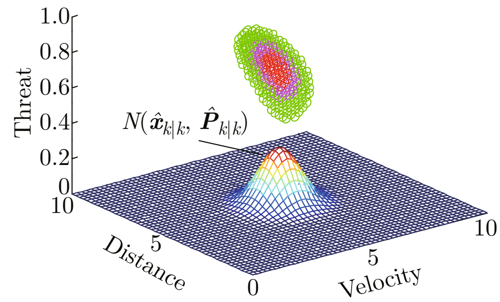


Fig. 1 Demonstration of threat distribution

2 System Model

In this section, to avoid the defects mentioned in Section 1, a target threat level based on HMM[19] is proposed first. Based on that, a sensor scheduling model is built to minimize the risk value in the target threat estimation.

2.1 Target Threat Level Information State Model Based on HMM

In this paper, the threat value of target t at time instant k is divided to three levels, and represented by the variable θ_k^t, where $\theta_k^t = 1$ denotes the low threat, $\theta_k^t = 2$ denotes the medium threat, and $\theta_k^t = 3$ denotes the high threat. The matrix $\boldsymbol{E}_k^t = (e_k^t(1), e_k^t(2), e_k^t(3))^{\mathrm{T}}$ denotes the information state of target t's threat at time instant k, where $e_k^t(i) = P(\theta_k^t = i)$ denotes the probability of the event that there is $\theta_k^t = i$.

The information state of target threat is regarded as Markov chain. The information state $\boldsymbol{E}_k^t$ transmits to $\boldsymbol{E}_{k+1}^t$ from time instant k to $k+1$ according to the transmission matrix:

$$\boldsymbol{A}^t = [a_{ij}^t]_{3\times 3} = [P(e_{k+1}^t = j | e_k^t = i)]_{3\times 3}, \quad (2)$$

where $a_{ij}^t = P(e_{k+1}^t = j | e_k^t = i)$ denotes the probability of $e_{k+1}^t = j$ when $e_k^t = i$. In this paper, all targets share the same transmission matrix.

The variable d_k^t is noted as the distance between the target t and the defensed center at time instant k, and is divided into three kinds, where $d_k^t = 1$ denotes the near distance, $d_k^t = 2$ denotes the medium distance, and $d_k^t = 3$ denotes the far distance. Similarly, the variable v_k^t denotes the target t's velocity with three levels, and there are $v_k^t = 1$, $v_k^t = 2$ and $v_k^t = 3$ respectively.

At time instant $k+1$, the observation values on the distance and velocity are noted as $o_{k+1}^w, w \in \{v, d\}$. The observation matrix is

$$\begin{aligned}\boldsymbol{B}_l^w = [b_{l,ij}^w]_{3\times 3} = \\ [P(o_{k+1}^{tw} = l | e_k^t = i, e_{k+1}^t = j)]_{3\times 3}, \\ w \in \{v, d\}, \quad l \in \{1, 2, 3\},\end{aligned} \quad (3)$$

where $b_{l,ij}^w = P(o_{k+1}^{tw} = l | e_k = i, e_{k+1} = j)$ denotes that the observation of variables is $o_{k+1}^{tw} = l$ at time instant

$k+1$ when $e^t_{k+1}=j$ and $e^t_k=i$. In this paper, all sensors share the same observation matrix.

At time instant k, the estimation of $\boldsymbol{E}^t_k$ can be represented by

$$\hat{\boldsymbol{E}}^t_{k|k}=(\hat{e}^t_{k|k}(1),\hat{e}^t_{k|k}(2),\hat{e}^t_{k|k}(3))^{\mathrm{T}}, \tag{4}$$

where $\hat{e}^t_{k|k}(i)=P(\hat{\theta}^t_{k|k}=i|O^{tv}_{1:k},O^{td}_{1:k})$ is the conditional probability of $\hat{\theta}^t_{k|k}=i$ on the condition of velocity and distance observation sequences $O^{tv}_{1:k}=\{o^{tv}_1,o^{tv}_2,\cdots,o^{tv}_k\}$ and $O^{td}_{1:k}=\{o^{td}_1,o^{td}_2,\cdots,o^{td}_k\}$.

The prediction of $\boldsymbol{E}_{k+1}$ at time instant k can be calculated by

$$\bar{\boldsymbol{E}}^t_{k+1|k}=(\bar{e}^t_{k+1|k}(1),\bar{e}^t_{k+1|k}(2),\bar{e}^t_{k+1|k}(3))^{\mathrm{T}}=\left(\sum_{i=1}^{3}\hat{e}^t_{k|k}(1)a^t_{i,1},\sum_{i=1}^{3}\hat{e}^t_{k|k}(2)a^t_{i,2},\sum_{i=1}^{3}\hat{e}^t_{k|k}(3)a^t_{i,3}\right)^{\mathrm{T}}. \tag{5}$$

At time instant $k+1$, once the observation o^{tv}_{k+1} and o^{td}_{k+1} are obtained, based on Bayesian theory, the $\hat{\boldsymbol{E}}^t_{k+1|k+1}$ can be updated by

$$\hat{\boldsymbol{E}}^t_{k+1|k+1}=(\hat{e}^t_{k+1|k+1}(1),\hat{e}^t_{k+1|k+1}(2),\hat{e}^t_{k+1|k+1}(3))^{\mathrm{T}}, \tag{6}$$

$$\begin{aligned}\hat{e}^t_{k+1|k+1}(j)&=P(\hat{\theta}^t_{k+1|k+1}=j|\hat{e}^t_{k|k},O^{tv}_{1:k+1},O^{td}_{1:k+1})=\\&\frac{P(\hat{\theta}^t_{k+1}=j,O^{tv}_{1:k+1},O^{td}_{1:k+1},\hat{e}^t_{k|k})}{P(O^{tv}_{1:k+1},O^{td}_{1:k+1}|\hat{e}^t_{k|k})}=\\&\frac{P(o^{tv}_{k+1},o^{td}_{k+1}|\hat{\theta}^t_{k+1}=j,\hat{e}^t_{k|k})P(\hat{\theta}^t_{k+1}=j|\hat{e}^t_{k|k})}{P(o^{tv}_{k+1},o^{td}_{k+1}|\hat{e}^t_{k|k})}=\\&\frac{P(o^{tv}_{k+1},o^{td}_{k+1}|\hat{\theta}^t_{k+1}=j,\hat{e}^t_{k|k})P(\hat{\theta}^t_{k+1}=j|\hat{e}^t_{k|k})}{\sum_{m=1}^{3}P(o^{tv}_{k+1},o^{td}_{k+1}|\theta^t_{k+1}=m,\hat{e}^t_{k|k})}=\\&\frac{\sum_{i=1}^{3}\hat{e}^t_{k|k}(i)a^t_{i,j}b^{tv}_{i,j,o^v_{k+1}}b^{td}_{i,j,o^d_{k+1}}}{\sum_{i=1}^{3}\sum_{m=1}^{3}\hat{e}^t_{k|k}(i)a_{i,m}b^{tv}_{i,m,o^v_{k+1}}b^{td}_{i,m,o^d_{k+1}}}.\end{aligned} \tag{7}$$

2.2 Information Fusion Based on Evidence Theory

At $k+1$ instant, if there are n_{k+1} targets detecting target t at the same time, the information fusion rule[20] is

$$e^{*,t}_{k+1|k+1}(w)=M_{\oplus}(A)=\frac{\sum\limits_{\substack{A_1\cap A_2\cap\cdots\cap\\ A_{n(k+1)}=A}}M_1(A_1)M_2(A_2)\cdots M_{n(k+1)}(A_{n(k+1)})}{1-K}, \tag{8}$$
$$A\in\{1,2,3\},$$

$$K=\sum_{\substack{A_1\cap A_2\cap\cdots\cap\\ A_{n_{k+1}}=\emptyset}}M_1(A_1)M_2(A_2)\cdots M_{n_{k+1}}(A_{n_{k+1}}), \tag{9}$$

where the variable K is the conflicting probability between different evidences and it shows the conflicting degree between evidences.

The fusion result can be denoted as

$$\hat{\boldsymbol{E}}^{*,t}_{k+1|k+1}=(\hat{e}^{*,t}_{k+1|k+1}(1),\hat{e}^{*,t}_{k+1|k+1}(2),\hat{e}^{*,t}_{k+1|k+1}(3))^{\mathrm{T}},$$

where the element $\hat{e}^{*,t}_{k+1|k+1}(j), j\in\{1,2,3\}$ is calculated by Eq. (8).

2.3 Target Threat Level Model Based on Risk Theory

The matrix

$$\mathbf{CM}=\begin{array}{c}\\1\\2\\3\end{array}\begin{array}{c}\begin{array}{ccc}1&2&3\end{array}\\\begin{bmatrix}0&c_{12}&c_{13}\\c_{21}&0&c_{23}\\c_{31}&c_{32}&0\end{bmatrix}\end{array},$$

is the cost matrix. Its row represents the true threat level of target t, and its column stands for the estimation; the variable $c_{f,g}$ stands for the cost when the true value is f while the estimation is g; in this paper, there is

$$\mathbf{CM}=\begin{array}{c}\\1\\2\\3\end{array}\begin{array}{c}\begin{array}{ccc}1&2&3\end{array}\\\begin{bmatrix}0&1&2\\2&0&1\\3&2&0\end{bmatrix}\end{array}.$$

If when the threat level of target t is estimated according to the observations from sensor s^i, the estimation is $\hat{\theta}^{i,j}_{k+1|k+1}=g$ with the risk value

$$r^{i,t}_{k+1}(g)=\sum_{f=1}^{3}c_{f,g}\hat{e}^t_{k+1|k+1}(f),$$

where the variable $\hat{e}^t_{k+1|k+1}(f)$ is the element of the set $\hat{\boldsymbol{E}}^t_{k+1|k+1}$ in Eq. (6). The detection risk in the estimation of the target threat level of target t is defined as

$$r^{i,t}_{k+1}=\min\{r^{i,t}_{k+1}(1),r^{i,t}_{k+1}(2),r^{i,t}_{k+1}(3)\},$$

and the estimation result of the threat level of target t is seen as

$$\hat{\theta}^{i,t}_{k+1}=\arg r^{i,t}_{k+1}.$$

When two or more sensors are detecting the same one target meanwhile, the estimation is

$$\hat{\theta}^{i,j}_{k+1|k+1}=g,$$

with the risk value

$$r_{k+1}^{i,t}(g) = \sum_{f=1}^{3} c_{f,g}\hat{e}_{k+1|k+1}^{*}(f),$$

where the variable $\hat{e}_{k+1|k+1}^{*,t}(f)$ is the element of the set $\hat{\boldsymbol{E}}_{k+1|k+1}^{*,t}$ which is the fusion result from the evidence theory (Eqs. (8) and (9)). The detection risk in the estimation of the target threat level of target t is defined as

$$r_{k+1}^{*,t} = \min\{r_{k+1}^{*,t}(1), r_{k+1}^{*,t}(2), r_{k+1}^{*,t}(3)\},$$

and the estimation result of the threat level of target t is seen as

$$\hat{\theta}_{k+1}^{*,t} = \arg r_{k+1}^{*,t}.$$

3 Sensor Scheduling Model in Target Threat Level Assessment

3.1 Local Risk Function Model

At time instant $k+1$, sensor s^i is used to detect target t^j, the local risk value in sensor s^i is defined as $R_{k+1}^{i,j}$, and its calculation method is

$$R_{k+1}^{i,j} = \tau_{k+1}^{i} + r_{k+1}^{i,j} = p_{k+1}^{i}c_s^i + r_{k+1}^{i,j}, \qquad (10)$$

where, the variable τ_{k+1}^{i} is the radiation interception risk when sensor s^i emits radiation to detect target t^j at time instant $k+1$; the variable c_s^i is the cost due to the interception and it is equal to the importance degree of the sensor; the variable p_{k+1}^{j} is the sensor interception probability in an observation interval of sensor s^i, and the calculation method is introduced in Ref. [21]; the variable $r_{k+1}^{i,j}$ is the estimation risk in the threat level from sensor s^i, and the calculation method can be seen in Section 2.

3.2 Global Risk Function Model

When m sensors are applied to detect n targets, at time instant $k+1$, the sensor scheduling can be seen as an $m \times n\boldsymbol{U}_{k+1}$, where when there is $u_{k+1}^{i,j} = 1$, the sensor s^i is used to detect target t^j at time instant $k+1$, or when there is $u_{k+1}^{i,j} = 0$, the sensor s^i is not used to detect target t^j at time instant $k+1$.

The optimal sensor scheduling scheme is the scheme with the minimum risk value and it can be seen as the following objective function:

$$\min\left\{\sum_{i=1}^{m}\sum_{j=1}^{n} u_{k+1}^{i,j}p_{k+1}^{i}c_s^i + \sum_{j=1}^{n} r_{k+1}^{*,j}\right\}, \qquad (11)$$

where the variable $r_{k+1}^{*,j}$ is the estimation risk when multiple sensors are detecting the target t^j at the same time to estimate its threat level, and there is

$$r_{k+1}^{*,j} = \min\{r_{k+1}^{*,j}(1), r_{k+1}^{*,j}(2), r_{k+1}^{*,j}(3)\} = \min\left\{\sum_{f=1}^{3} c_{f,1}\hat{e}_{k+1|k+1}^{*,j}(f), \sum_{f=1}^{3} c_{f,2}\hat{e}_{k+1|k+1}^{*,j}(f), \sum_{f=1}^{3} c_{f,3}\hat{e}_{k+1|k+1}^{*,j}(f)\right\},$$

where the variable $\hat{e}_{k+1|k+1}^{*}(f)$ is the element of the set $\hat{\boldsymbol{E}}_{k+1|k+1}^{*t}$ which is the fusion result from the evidence theory (Eqs. (8) and (9)).

The objective function subjects to:

(1) Each target is detected by one sensor at least and there is $\sum_{i=1}^{m} u_k^{i,j} \geqslant 1$.

(2) Each sensor can detect $\varDelta$ targets mostly at the same time; that is to say, for sensor s^i, if it can detect $\varDelta^i$ targets mostly at the same time, then there is $\sum_{j=1}^{m} u_k^{i,j} \leqslant \varDelta^i$.

3.3 Approximate Solution of Model

At time instant k, there is no observations of targets at time instant $k+1$, and when calculating the sensor scheduling scheme, the prediction is taken place of the observation. At time instant k, the predicted probability that the observation is l of target t at time instant $k+1$ can be calculated by

$$o_{k+1}^{w}(l) = \sum_{j=1}^{3}\sum_{i=1}^{3} \hat{e}_{k|k}^{*,t}(i)a_{i,j}b_{i,j,l}^{w}, \qquad (12)$$
$$w \in \{v, d\}, \quad l \in \{1,2,3\},$$

where $\hat{e}_{k|k}^{*,t}(i)$ belongs to the set.

At time instant $k+1$, the target t is detected, and the mean probability that the target threat level is j can be calculated by

$$\mathrm{Mean}(\hat{e}_{k+1|k+1}^{t}(j)) = \sum_{h=1}^{3}\sum_{l=1}^{3}[o_{k+1}^{v}(h)o_{k+1}^{d}(l)] \times \frac{\sum_{i=1}^{3} \hat{e}_{k|k}^{*,t}(i)a_{i,j}b_{i,j,o_{k+1}^{t,v}}^{v} b_{i,j,o_{k+1}^{t,d}}^{d}}{\sum_{i=1}^{3}\sum_{m=1}^{3} \hat{e}_{k|k}^{*,t}(i)a_{i,m}b_{i,m,o_{k+1}^{v}}^{v} b_{i,m,o_{k+1}^{d}}^{d}} = \bar{e}_{k+1|k}^{t}(j), \qquad (13)$$

where $\mathrm{Mean}(\cdot)$ is the calculation of mean value, and the calculation result is

$$\bar{\boldsymbol{E}}_{k+1|k}^{t} = (\bar{e}_{k+1|k}^{t}(1), \bar{e}_{k+1|k}^{t}(2), \bar{e}_{k+1|k}^{t}(3))^{\mathrm{T}}.$$

The mean value of the risk can be calculated by

$$\mathrm{Mean}(r_{k+1}^{t}(j)) = \sum_{i=1}^{3} c_{ij}\mathrm{Mean}(\hat{e}_{k+1|k+1}(i)).$$

The mean value of the risk value is defined as

$$\mathrm{Mean}\{\bar{r}^i_{k+1}\} = \min\{\mathrm{Mean}(r^t_{k+1}(1)), \mathrm{Mean}(r^t_{k+1}(2)), \mathrm{Mean}(r^t_{k+1}(3))\}.$$

Therefore, there is the local risk value in Eq. (1) predicted as

$$\bar{R}^t_{k+1} = p^i_k c^i_s + \mathrm{Mean}(\bar{r}^t_{k+1}). \tag{14}$$

The overall objective function in Eq. (11) can be changed into

$$\min\left\{\sum_{i=1}^{m}\sum_{i=j}^{m} u^{i,j}_{k+1} p^i_{k+1} c^i_s + \sum_{j=1}^{n}\mathrm{Mean}(\bar{r}^t_{k+1})\right\}. \tag{15}$$

4 Optimization Algorithm Based on Game Theory

A distributed optimization algorithm based on the game theory is proposed in this paper. The basic idea is to regard the process of multi-sensor multi-target allocation as a process of gaming[22] between sensors, and the problem of global risk function optimization is regarded as a problem of a single sensor local risk function optimization. When the local risk optimal function values of each sensor get to the best points, the global risk can achieve the optimal function values.

4.1 Sensor Gaming Model

In the process of sensor gaming, when the sensor group used to detect target t is built, there are two strategies that each sensor can select, and they are: C (which stands for "cooperative") and D (which stands for "non-cooperative"), where C stands for the cooperative strategy that the sensor is used to detect target t, and D stands for the non-cooperative strategy that the sensor refuses to detect target t.

In the gaming model, the sensor s_a and sensor s_b are the gaming players. When there is $s_a = s^i$, that is to say, the local risk value is calculated from the perspective of sensor s_a, the variable s_b stands for the sensor group of all sensors in the sensor network except the sensor s_a, and there is $s_b = \{s_1, s_2, \cdots, s_m\} - s^a$, called the "virtual sensor". As any one from s_b detects target t, it can be seen that the sensor group s_b adopts to the strategy C. When all sensors from s_b adopt to the strategy D, it can be seen that the sensor group s_b adopts to the strategy D.

When sensor s_a and sensor s_b are gaming at time instant $k+1$, four cases in the perspective of sensor s_a are as follows:

(1) When sensor s_b is adopting to strategy C, sensor s_a also adopts to strategy C; its local risk value is $R^{a,t}_{k+1|k+1} = p^i_{k+1}c^i_s + r^{*,t}_{k+1|k+1}$, where the variable $r^{*,t}_{k+1|k+1}$ is the estimation risk when both sensor s_a and sensor s_b are both detecting target t; there is

$$r^{*,t}_{k+1|k+1} = \min\{r^{*,t}_{k+1|k+1}(1), r^{*,t}_{k+1|k+1}(2), r^{*,t}_{k+1|k+1}(3)\} = \min\left\{\sum_{f=1}^{3} c_{f,1}\hat{e}^*_{k+1|k+1}(f), \sum_{f=1}^{3} c_{f,2}\hat{e}^*_{k+1|k+1}(f), \sum_{f=1}^{3} c_{f,3}\hat{e}^*_{k+1|k+1}(f)\right\},$$

where there is

$$\hat{e}^*_{k+1|k+1}(f) \in \hat{\boldsymbol{E}}^{*,t}_{k+1|k+1} = (\hat{e}^{*,t}_{k+1|k+1}(1), \hat{e}^{*,t}_{k+1|k+1}(2), \hat{e}^{*,t}_{k+1|k+1}(3))^{\mathrm{T}},$$

which is the fusion result from the evidence theory (Eqs. (8) and (9)).

(2) When sensor s_b is adopting to strategy C, sensor s_a adopts to strategy D, and sensor s_a till obtains information about the target through communication after sensor s_b detects the target and transmits the information to sensor s_a. At this time, the local risk value of sensor s_a can be defined as $R^{a,t}_{k+1|k+1} = r^{b,t}_{k+1|k+1}$, where the variable $r^{b,t}_{k+1|k+1}$ is the estimation risk value when only sensor s_b is used to detect target t.

(3) When sensor s_b is adopting to strategy D, sensor s_a adopts to strategy C, and the local risk value of sensor s_a is defined as $R^{a,t}_{k+1|k+1} = p^a_{k+1}c^a_s + r^{a,t}_{k+1|k+1}$, where the variable $r^{a,t}_{k+1|k+1}$ is the estimation value when only sensor s_a is used to detect target t.

(4) When sensor s_b is adopting to strategy D, sensor s_a also adopts to strategy D. At this time, the constraint 1 in Section 3.2 is not satisfied, and assume that there is $R^{a,t}_{k+1|k+1} = \eta$, where the variable η is a constant, and is too bigger than any values in the three cases above in order to ensure that each target can be detected when the game is over.

Through the above analysis, the gaming matrix of sensor s_b is

$$\begin{array}{cc} & \begin{array}{cc} \mathrm{C} & \mathrm{D} \end{array} \\ \begin{array}{c} \mathrm{C} \\ \mathrm{D} \end{array} & \begin{bmatrix} p^i_{k+1}c^i_s + r^{*,t}_{k+1|k+1} & p^a_{k+1}c^a_s + r^{a,t}_{k+1|k+1} \\ r^{b,t}_{k+1|k+1} & \eta \end{bmatrix} \end{array}, \tag{16}$$

where the row is the gaming strategy of sensor s_a, and the column is the gaming strategy of sensor s_b.

4.2 Game Strategy Updating Rules Based on Optimal Response Dynamics

The gaming strategy of each sensor is adjusted by the optimal response dynamic theory. The learning and strategy adjustment mode described by the optimal response dynamic is that the gaming players can compare and evaluate different strategy results, then adjust their own strategies accordingly. In other words, given the previous game outcomes, each player is able to find and adopt the best response strategy for the other players in the previous gaming.

Denote the sequence $\{1, 2, \cdots, f, \cdots, F\}$ as the gaming process.

At the fth time gaming, for sensor s_a, assume that the number of sensors playing with sensor s_a and adopting to strategy C is $x_a(f)$, where the value of $x_a(f)$ is 0 or 1. Therefore, the number of sensors playing with sensor s_a and adopting to strategy D is $1-x_a(f)$, whose value may be also 0 or 1.

At the fth time gaming, the risk value when sensor s_a adopts to strategy C is

$$q_a(\mathrm{C}) = x_a(f)(p^i_{k+1}c^i_s + r^{*,t}_{k+1|k+1})+ (1 - x_a(f))(p^a_{k+1}c^a_s + r^{a,t}_{k+1|k+1}). \tag{17}$$

At the fth time gaming, the risk value when sensor s_a adopts to strategy D is

$$q_a(\mathrm{D}) = x_a(f)r^{b,t}_{k+1|k+1} + \eta(1 - x_a(f)). \tag{18}$$

Comparing the value of $q_a(\mathrm{C})$ and the value of $q_a(\mathrm{D})$, the strategy with lower risk vale is selected as the gaming strategy at the $(f + 1)$th time gaming.

(1) When there is $x_a(f) = 0$, there must be $q_a(\mathrm{C}) = (p^a_{k+1}c^a_s + r^{a,t}_{k+1|k+1}) < q_a(\mathrm{D}) = \eta$, and sensor s_a must adopt to strategy C at the $(f + 1)$th time gaming. Therefore, there is (C, D) which is the Nash equilibrium in order to ensure that each target is detected by one sensor at least.

(2) When there is $x_a(f) = 1$, there are $q_a(\mathrm{C}) = p^i_{k+1}c^i_s+r^{*,t}_{k+1|k+1}$ and $q_a(\mathrm{D}) = r^{b,t}_{k+1|k+1}$. For the reason that the value of $q_a(\mathrm{C})$ and the value of $q_a(\mathrm{D})$ cannot be compared in theory, there are two kinds of Nash equilibrium and they are (C, C) and (C, D). When there is $p^i_{k+1}c^i_s + r^{*,t}_{k+1|k+1} > r^{b,t}_{k+1|k+1}$, sensor s_a can adopt to strategy D at the $(f + 1)$th time gaming, and when there is $p^i_{k+1}c^i_s + r^{*,t}_{k+1|k+1} < r^{b,t}_{k+1|k+1}$, sensor s_a can adopt to strategy C at the $(f + 1)$th time gaming.

4.3 Calculation Steps

The distributed optimization algorithm based on game theory is adopted to determine the sensor group detect target t. The number of sensors is m. Denote the variable f as the gaming time of sensors. Denote the variable $G(1) = \{g_1(1), g_2(1), \cdots, g_m(1)\}$ as the set of sensors' gaming strategies. Denote the variable $Q(f) = \{q_1(f), q_2(f), \cdots, q_m(f)\}$ as the set of sensors' local risk values. Denote the variable $Z(f) = \{z_1(f), z_2(f), \cdots, z_m(f)\}$ as the set of the sensor' gaming matrixes.

The calculation steps are as follows:

Algorithm initialization: At time $f = 1$, the gaming strategy set of m sensors is $G(1) = \{g_1(1), g_2(1), \cdots, g_m(1)\}$.

Step 1 At the fth gaming time, calculate the predicted information states of targets according to Eqs. (12) and (13), and the result is $\bar{\boldsymbol{E}}^t_{k+1|k} = (\bar{e}^t_{k+1|k}(1), \bar{e}^t_{k+1|k}(2), \bar{e}^t_{k+1|k}(3))^{\mathrm{T}}$.

Step 2 Calculate the local estimation risk values of sensors $Q(f) = \{q_1(f), q_2(f), \cdots, q_m(f)\}$ according to Eq. (14).

Step 3 Sensors calculate their gaming matrixes $Z(f) = \{z_1(f), z_2(f), \cdots, z_m(f)\}$ according to Eq. (16).

Step 4 Sensors adjust their gaming strategies according to the rule of the optimal response dynamics. That is to say, each sensor obtains the original coordinates and velocities of targets which are shown in Table 1. The velocity is divided into three kinds: low velocity (0—5 km/min), medium velocity (5—10 km/min) and high velocity (> 10 km/min). The distance of targets and sensors is divided into three kinds: near (0—200 km), medium (200—400 km) and far (> 400 km).

Table 1 Information of target states

Target	Original coordinates/km	Velocity/(km · min^{-1})
1	(400, 0)	(2, 0)
2	(400, 400)	$(-9, -9)$
3	(0, 500)	$(0, -4)$
4	$(-400, 0)$	(4, 0)
5	$(-400, -400)$	(12, 12)
6	(300, −300)	$(-4, 5)$

Sensors' gaming strategy set $G(f)$ compares the two predicted cases where it adopts to the strategy C and the strategy D according to Eqs. (17) and (18) to make a decision whether it takes in the C strategy or the strategy D at the $(f + 1)$th gaming time. The calculation result is noted as the set $G(f + 1) = \{g_1(f + 1), g_2(f + 1), \cdots, g_m(f + 1)\}$.

Step 5 Judge if the final iteration time is achieved. If not, set $f = f + 1$ and go back to Step 2; otherwise, end the iteration.

The calculation map can be shown in Fig. 2.

In the multi-sensor multi-target allocation, the sensor groups of n targets are carried out at the same time, and when all gaming and allocation processes are completed, the sensor management scheme $\boldsymbol{U}_{k+1}$ is obtained.

5 Simulations

In simulation situation, there are 3 sensors $\{s^1, s^2, s^3\}$ used to detect target, and their coordinates are: (50, 0) km, $(0, -50)$ km and $(-50, 0)$ km. Their radiation interception probabilities in an observation internal are 0.05, 0.04 and 0.01. The importance degrees of sensors are 1, 2 and 3. Each sensor can detect 5 targets mostly at the same time.

There are 6 targets $\{t^1, t^2, t^3, t^4, t^5, t^6\}$ needed to be

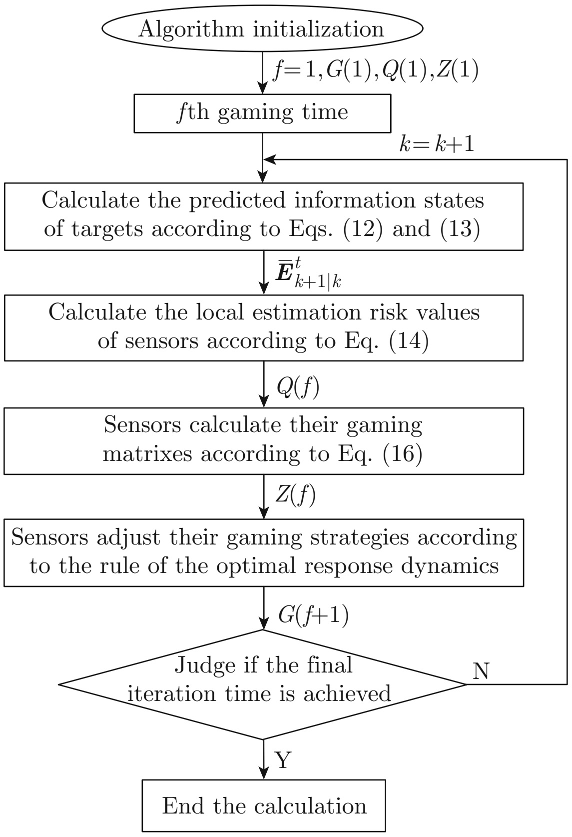


Fig. 2 Algorithm Process

detected, and they move approximately along straight lines.

The combat situation is seen in Fig. 3.

The transition matrix of target threat level is set to

$$\boldsymbol{A} = \begin{bmatrix} 0.6 & 0.3 & 0.1 \\ 0.3 & 0.5 & 0.2 \\ 0.1 & 0.2 & 0.7 \end{bmatrix}.$$

At time instant $k = 0$, the original threat levels of targets are set to

$$\hat{\boldsymbol{E}}_0^1 = (0.1, 0.5, 0.4)^{\mathrm{T}},$$
$$\hat{\boldsymbol{E}}_0^2 = (0.1, 0.5, 0.4)^{\mathrm{T}},$$
$$\hat{\boldsymbol{E}}_0^3 = (0.1, 0.5, 0.4)^{\mathrm{T}},$$
$$\hat{\boldsymbol{E}}_0^4 = (0.1, 0.5, 0.4)^{\mathrm{T}},$$
$$\hat{\boldsymbol{E}}_0^5 = (0.1, 0.5, 0.4)^{\mathrm{T}},$$
$$\hat{\boldsymbol{E}}_0^6 = (0.1, 0.5, 0.4)^{\mathrm{T}}.$$

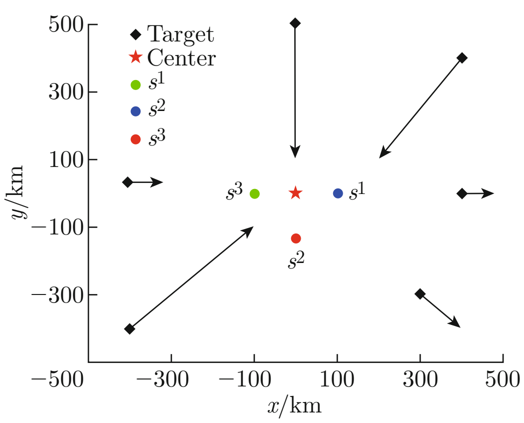
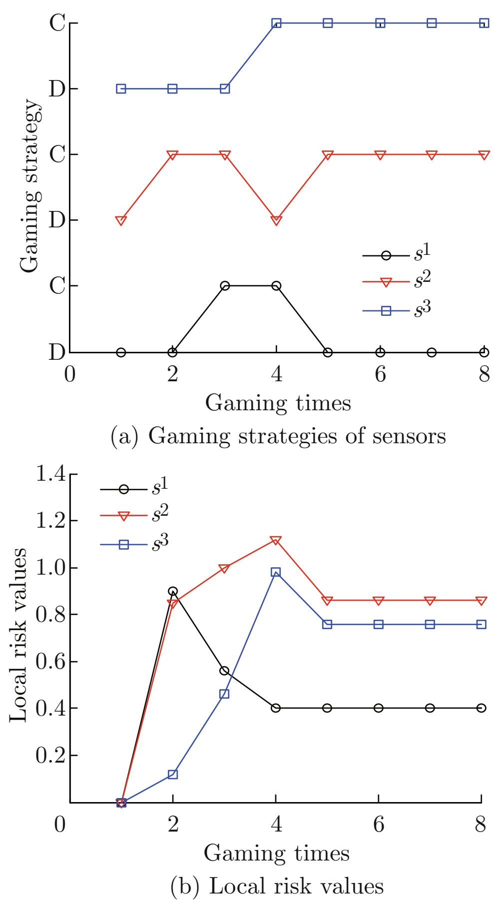


Fig. 3 Sketch of Combat Situation

5.1 Simulation on the Gaming Process

Taking tracking target t^4 as an example, the gaming process of sensors is shown in Fig. 4.



(a) Gaming strategies of sensors

(b) Local risk values

Fig. 4 Game process of sensors

Figure 4(a) shows the changes of targets' strategies in gaming. At the end of the gaming, sensor s^2 and sensor s^3 have taken the cooperation strategy C, and sensor s^1 has adopted to the non-cooperation strategy D, which indicates that sensor s^2 and sensor s^3 are allocated to target t^4, and sensor s^1 refused to track the target. Figure 4(b) shows the changes of sensors' risk values in gaming. When the gaming ends, the risk values of sensors will not change and all sensors have found their most suitable gaming strategies.

5.2 Simulations on Sensor-Target Allocation

In the optimization algorithms, compared with the distributed algorithm, the centralized algorithm has better solution quality, but more time consumption. And the Hungary algorithm can find the theoretical optimization. Thus this paper compares the proposed game-based algorithm with other distributed algorithm to show its fast convergence rate, and with centralized algorithm to check it solution quality. For the distributed algorithm, we use the auction algorithm to compare, and for the centralized algorithm, we use the artificial bee colony algorithm, the PSO algorithm, and the Hungary algorithm.

The proposed game-based algorithm (Algorithm 1), auction algorithm (Algorithm 2), artificial bee colony algorithm (Algorithm 3), PSO algorithm (Algorithm 4), and Hungary algorithm (Algorithm 5) were used to calculate the sensor management schemes respectively.

The parameters of algorithms are given in Table 2.

Table 2 Parameters of algorithms

Algorithm	Iteration times	Others
Algorithm 1	20	All sensors take in strategy D, and the number of sensors participating in the gaming is 3
Algorithm 2	20	The number of sensors participating in the auction is 3
Algorithm 3	50	Total number of bees is 30, and the minimum iteration times in a local optimization are 10
Algorithm 4	50	Total number of particles is 30
Algorithm 5	—	—

Here, 100 Monte Carlo experiments are conducted. The algorithm iteration processes are shown in Fig. 5.

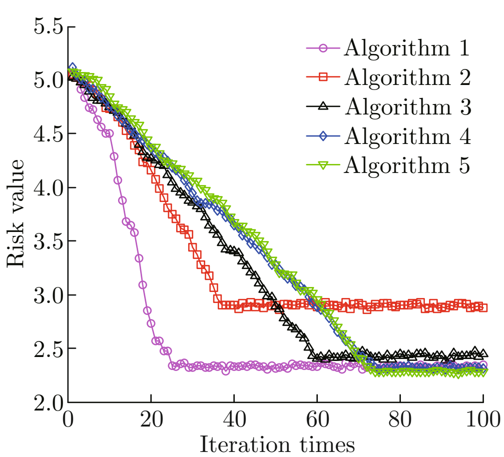


Fig. 5 Comparison of different algorithms in sensor-target allocation

In the process of calculation, the running time of the algorithm is recorded as: the game-based algorithm proposed in this paper (22.78 s), the auction algorithm (24.92 s), the artificial bee colony algorithm (52.14 s), the PSO algorithm (68.23 s), and Hungary algorithm (72.12 s), respectively. The game-based algorithm proposed in this paper and the auction algorithm are distributed algorithms, and have faster computing speed, but the game-based algorithm even outperforms the auction algorithm on convergence rate and solution quality. The artificial bee colony algorithm, the PSO algorithm and the Hungary algorithm belong to the centralized algorithm, and their calculation time is longer; especially, the artificial bee colony algorithm has struck into a local optimal solution. While the solution quality of the Hungary optimization algorithm is the best and the theoretical optimization, but its computation time is more than 1 min which is the observation period; so under the high real-time situation of battlefield, the algorithm cannot run effectively. The PSO algorithm has the same problem.

Above all, the game-based algorithm proposed in this paper has the best performance in terms of the solution speed and quality as well as the adaptability to the battlefield conditions.

5.3 Simulation on Target Detection

The game-based algorithm proposed in this paper, the auction algorithm, the artificial bee colony algorithm, the POS algorithm and the Hungary algorithm are used to calculate sensor management schemes within 0—50 observation intervals respectively. When the observation interval is 1 min, the iterative processes of the algorithms are shown in Fig. 6.

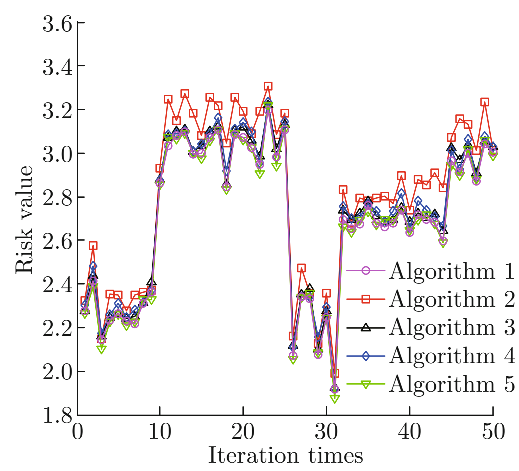


Fig. 6 Comparison of different algorithms in target detection when observation interval is 1 min

The game-based algorithm proposed in this paper, the auction algorithm, the artificial bee colony algorithm, the particle swarm optimization algorithm and the Hungary algorithm are used to calculate sensor management schemes within 0—50 observation intervals respectively. When the observation interval is 30 s, the iterative processes of the algorithms are shown in Fig. 7.

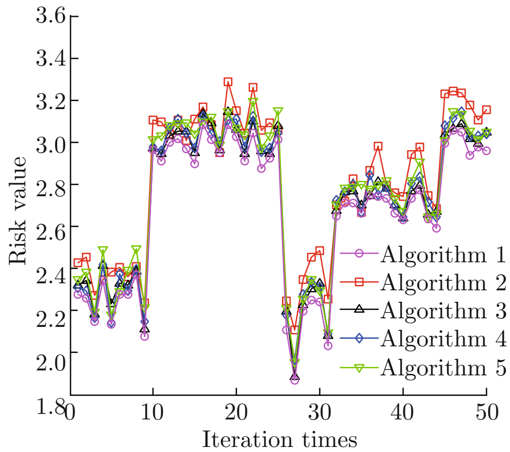


Fig. 7 Comparison of different algorithms in target detection when observation interval is 30 s

In Fig. 6, the algorithm proposed in this paper maintains a good solution quality in the whole time period. Although its solution quality at some moments is not as good as that of the Hungary algorithm, its strong distributed computing ability can greatly conserve the computing time. In Fig. 7, when the time interval becomes shorter, the operational situation tends to be urgent and changes rapidly, and the solution quality of the algorithm in this paper is at the optimal level. The centralized algorithm loses its computing advantage under the limitation of time, for the reason that they consume more time to obtain the optimization, while the algorithm in this paper can still process a greater advantage, with the advantage of a fast convergence rate.

5.4 Comparisons of Different Threat Assessment Methods

5.4.1 *Simulations on Threat Level Assessment*

At time instant $k = 0$, there is $\hat{\boldsymbol{E}}_0^3 = (0.3, 0.3, 0.4)^{\mathrm{T}}$. At time instant $k = 1$, sensor s^2 is used to detect target t^3, and the observations are $O_1^v = 1$, $O_1^d = 1$ and $O_1^c = 3$, The observation matrix of sensor s_1 is

$$B_1^v = \left\{ \begin{bmatrix} 0.5 & 0.2 & 0.3 \\ 0.2 & 0.7 & 0.1 \\ 0.8 & 0.1 & 0.1 \end{bmatrix}, \begin{bmatrix} 0.2 & 0.6 & 0.2 \\ 0.1 & 0.6 & 0.3 \\ 0.1 & 0.4 & 0.5 \end{bmatrix}, \begin{bmatrix} 0.1 & 0.1 & 0.8 \\ 0.1 & 0.4 & 0.5 \\ 0.2 & 0.2 & 0.6 \end{bmatrix} \right\},$$

$$B_1^d = \left\{ \begin{bmatrix} 0.5 & 0.2 & 0.3 \\ 0.2 & 0.7 & 0.1 \\ 0.8 & 0.1 & 0.1 \end{bmatrix}, \begin{bmatrix} 0.2 & 0.6 & 0.2 \\ 0.1 & 0.6 & 0.3 \\ 0.1 & 0.4 & 0.5 \end{bmatrix}, \begin{bmatrix} 0.1 & 0.1 & 0.8 \\ 0.1 & 0.4 & 0.5 \\ 0.2 & 0.2 & 0.6 \end{bmatrix} \right\},$$

$$B_1^c = \left\{ \begin{bmatrix} 0.5 & 0.2 & 0.3 \\ 0.2 & 0.7 & 0.1 \\ 0.8 & 0.1 & 0.1 \end{bmatrix}, \begin{bmatrix} 0.2 & 0.6 & 0.2 \\ 0.1 & 0.6 & 0.3 \\ 0.1 & 0.4 & 0.5 \end{bmatrix}, \begin{bmatrix} 0.1 & 0.1 & 0.8 \\ 0.1 & 0.4 & 0.5 \\ 0.2 & 0.2 & 0.6 \end{bmatrix} \right\}.$$

The target threat level states are estimated as

$$\hat{e}_{1|1}(1) = \frac{\sum_{i=1}^{3} \hat{e}_{0|0}(i) a_{i,1} b_{i,1,o_{k+1}^v}^v b_{i,1,o_{k+1}^d}^d b_{i,1,o_{k+1}^c}^c}{\sum_{i=1}^{3} \sum_{m=1}^{3} \hat{e}_{0|0}(i) a_{i,m} b_{i,m,o_{k+1}^v}^v b_{i,m,o_{k+1}^d}^d b_{i,m,o_{k+1}^c}^v} = 0.66,$$

$$\hat{e}_{1|1}(2) = \frac{\sum_{i=1}^{3} \hat{e}_{0|0}(i) a_{i,2} b_{i,2,o_{k+1}^v}^v b_{i,2,o_{k+1}^d}^d b_{i,2,o_{k+1}^c}^c}{\sum_{i=1}^{3} \sum_{m=1}^{3} \hat{e}_{0|0}(i) a_{i,m} b_{i,m,o_{k+1}^v}^v b_{i,m,o_{k+1}^d}^d b_{i,m,o_{k+1}^c}^v} = 0.12,$$

$$\hat{e}_{1|1}(3) = \frac{\sum_{i=1}^{3} \hat{e}_{0|0}(i) a_{i,3} b_{i,3,o_{k+1}^v}^v b_{i,3,o_{k+1}^d}^d b_{i,3,o_{k+1}^c}^c}{\sum_{i=1}^{3} \sum_{m=1}^{3} \hat{e}_{0|0}(i) a_{i,m} b_{i,m,o_{k+1}^v}^v b_{i,m,o_{k+1}^d}^d b_{i,m,o_{k+1}^c}^v} = 0.22.$$

When the risk levels of the target are 1, 2 and 3, the risk values are

$$r_{t,1}^{1,3}(1) = \sum_{f=1}^{3} c_{f,1} \hat{e}_{1|1}(f) = 0.56,$$

$$r_{t,1}^{1,3}(1) = \sum_{f=1}^{3} c_{f,2} \hat{e}_{1|1}(f) = 1.10,$$

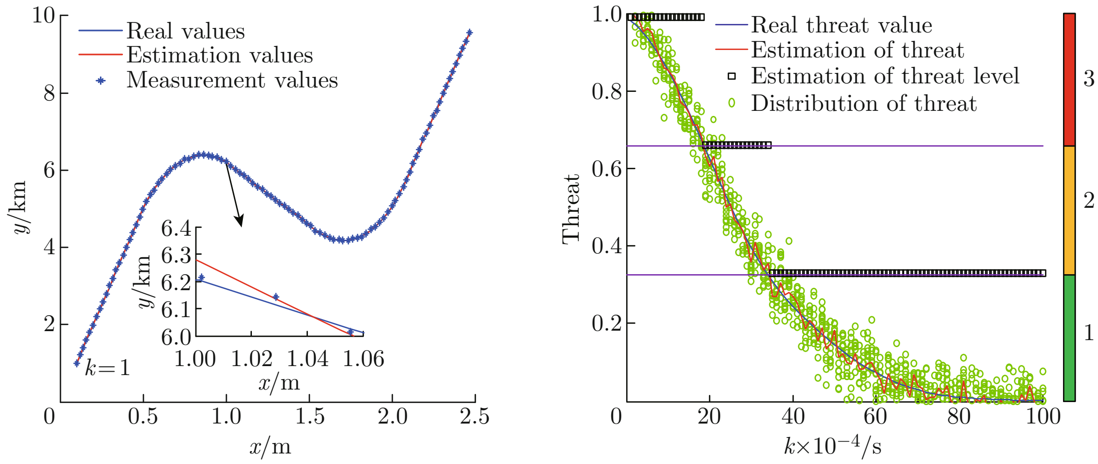
$$r_{t,1}^{1,3}(3) = \sum_{f=1}^{3} c_{f,3} \hat{e}_{1|1}(f) = 1.44.$$

Then the estimation of the target threat level is 1.

5.4.2 *Comparisons of Threat Level Estimation Methods*

The actual target threat degree values are calculated by Eq. (1). The relationship of target threat degree and the threat level should be defined first, and there is: when there is $f_{\text{threat}}(\boldsymbol{X}_k) \in (0, 1/3)$, the threat level is "1"; when there is $f_{\text{threat}}(\boldsymbol{X}_k) \in (1/3, 2/3)$, the threat level is "2"; when there is $f_{\text{threat}}(\boldsymbol{X}_k) \in (2/3, 1)$, the threat level is "3".

The differences between the target threat assessment methods in Ref. [17] and the method proposed in this paper are compared. Within 0—10^6 s, the change of target threat level and threat degree over time is shown in Fig. 8.



(a) Target's motion trajectory (b) Estimation to the target's threat level

Fig. 8 Comparisons of different threat-estimation methods

As the motion state of target obeys the Gaussian distribution $N(\hat{\boldsymbol{X}}_{k|k}, \hat{\boldsymbol{P}}_{k|k})$, the threat value calculated using the estimated target motion state through the target threat degree model should also approximately obey the distribution of the Gaussian distribution rather than an accurate value in fact. At this point, there must exist errors if only the mean value of the motion state is used to calculate the threat degree. In addition, the threat degree model in Ref. [17] obviously even did not consider the influence of the target classification on the target threat degrees, which increases the uncertainty of threat judgment.

However, using the threat level based on HMM and proposed in this paper as the criterion to judge the threat level of target can eliminate the estimation inaccuracy caused by measurement error and model error to a large extent. The reason is that the target threat level model based on HMM estimates the states of target not only depending on the observation, but also on the acquired knowledge, and allows that the observation is inaccurate. It doesn't concentrate on the specific values of threat degree, but the threat level directly, avoiding transmitting the observation error and model error from the target's motion states to the threat level twice, which is from the target' motion states to the threat degree, and from the target threat degree to the target threat level finally.

6 Conclusion

To reduce the observation error and model error in previous threat estimation models, this paper proposes a target threat level model based on HMM. First, the model of target threat level based on HMM and risk theory is established. Second, the local risk model and global risk model of sensor management are established to achieve the minimum risk of target threat level assessment and sensor radiation interception risk. Then a distributed optimization algorithm based on game theory is proposed to obtain sensor scheduling schemes from the sensor scheduling model. Finally, simulations are implemented and the results show that compared with the previous distributed algorithm and centralized algorithm; the game-based algorithm proposed in this paper has a faster calculation speed and solutions of higher quality. Compared with the previous target threat degree assessment model, the proposed threat level assessment method in this paper can effectively eliminate the observation error and model error, and make effective estimations of target threat level. The threat level assessment method proposed in this paper is based on the prior information, and the accuracy of the prior information directly affects the final result of estimation. How to obtain the prior information which is much closer to the reality and make the model more accurate will be the next research direction.

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