A multi-platform sensor networking scheduling method

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Abstract. In order to make the sensor system accomplish the target tracking task and reduce the amount of electromagnetic radiation, a multi-platform active and passive sensor network scheduling method for target tracking task is studied. In this method, the radiation state of the active sensor is quantified by the influence of the radiation degree, and the radiation model based on the partial observable markov decision process is established. Then, according to the target tracking task requirements, considering the task requirements and tactical constraints, the objective optimization function is established, and finally the scheduling algorithm under the radiation control is given. Simulation results show that the algorithm is effective and reasonable.

1. Introduction
With the continuous improvement of science and technology, a variety of sensors as an important tool to obtain battlefield information are increasingly used in the military field. Through sensor scheduling, real-time allocation of sensor resources can be realized, so as to achieve the optimal performance of specific tactical indicators [1-4]. When acquiring the target measurement, the active sensor will continuously radiate electromagnetic wave to the target, and its signal is easy to be intercepted by the other party's detector, thus exposing its position. While the passive sensor does not radiate electromagnetic wave to the outside, it can only obtain Angle information. Active and passive sensors are often used in combat because of their advantages and disadvantages in measurement and radiation performance. Therefore, how to reasonably evaluate and control the radiation risk of the passive sensor system and conduct reasonable resource scheduling based on this has become a hot issue for scholars.

In [5-8], the radiation risk is quantified by the number of times which the active sensor is turned on. Its core idea is to prioritize the scheduling of passive sensors to reduce the startup times of active sensors and control the radiation times of active sensors under the condition of meeting the task requirements. However, this method does not quantify the specific radiation state of the sensor, and does not consider the difference of radiation risks of different sensors at different times. In [9], the radiation risk of the sensor is quantified as a fixed value, considering the prediction step target tracking error, target motion trend of predictive error and sensor radiation sensor scheduling model is constructed, the price 3 factors realized under the control of radiation to the target tracking, but in practice, as the growth of the boot time, sensors in each moment of radiation will change, but did not consider this method.

In [10] , the author deduces the interception probability factor model of schlichel by calculating parameters such as the echo power of active radar to target, receiver sensitivity of intercept, and coverage area of wireless beam, etc. On this basis, the evaluation of sensor radiometric cost is carried out, which improves the survival performance of radar platform. In [11-12] , the authors point out that only when multiple...
window functions overlap in the time domain can sensor radiation be intercepted. By calculating the window functions of sensors, target receivers and target monitoring systems at different times, the probability model of intercepted radiation signals is deduced. This kind of method is more reasonable, but in the actual situation, the parameters of the enemy target (such as the window function, receiver scanning area, etc.) are often not available, which brings difficulties to the practical application of this kind of method.

For target tracking problem A multi-platform active and passive sensor network scheduling method is proposed to control the radiation cost under the constraint of tracking accuracy. To solve the previous literature on the active sensor radiation risk to quantify the problem of inaccurate, considering practical application background, Emission Level Impact (ELI) [13] was used to quantify the radiation risk of active sensors. And set up based on Partially Observables Markov Decision Process (POMDP) radiation model; Then the objective function of the minimum radiation cost is constructed under the constraint of tracking accuracy. Finally, the optimal scheduling algorithm under radiation control is given. The simulation results show that the algorithm is effective.

2. Sensor radiation model

POMDP method is a theoretical method to study multi-stage decision-making in a random environment [14]. Due to the randomness and measurement uncertainty of the radiation quantity of sensors at each moment, POMDP method can be used to describe it. Based on POMDP theory, the mathematical description of the problem is as follows.

2.1. Sensor scheduling action

It is set that \( N \) sensor platforms are deployed in the 3d surveillance space to track a target, and each platform is equipped with an active sensor and a passive sensor. Define platform scheduling actions \( a_k = (a^n_k)_{N \times 1} \) \((n=1,2,\ldots,N)\), where \( a^n_k = 1 \) or \( a^n_k = 0 \) represents whether the sensor on the scheduling platform \( n \) tracks the target at time \( k+1 \). When \( a^n_k = 1 \), defining sensor scheduling actions \( b_k = (b^n_k)_{N} \), \( b^n_k = 1 \) or \( b^n_k = -1 \) respectively represent active or passive sensors tracking targets on scheduling platform \( n \) at time \( k+1 \). It is stipulated that each sensor can only track one target at the same time, and each target can only be tracked by one sensor.

The indicator function \( \sigma(a^n_k, b^n_k) \) defining active sensor scheduling is:

\[
\sigma(a^n_k, b^n_k) = \begin{cases} 
1, & a^n_k b^n_k = 1 \\
0, & \text{others}
\end{cases}
\]

(1)

2.2. Radiation state

The radiation state of the sensor at time \( k \) is defined as \( E_k = [E_{p_k}, E_{a_k}]^T \). Where \( E_{p_k} = [E_{p_1}, E_{p_2}, \ldots, E_{p_N}]^T \) represents the radiation state of passive sensors on \( N \) platforms at time \( k \). Since the passive sensors do not radiate electromagnetic waves outwards, all elements in \( E_{p_k} \) are 0. \( E_{a_k} = [E_{a_1}, E_{a_2}, \ldots, E_{a_N}]^T \) represents the radiation state of active sensors on \( N \) platforms at time \( k \). In this paper, the radiation state of active sensor is quantified by ELI state, \( E_{a_k}^n \) is the ELI state of the active sensor on the platform \( n \) at moment \( k \), representing the accumulated amount of radiation of the sensor intercepted by the enemy by time \( k \) [13], which can be quantified into a finite positive integer set \( \{1,2,3,\ldots,E_{max}\} \) with length \( E_{max} \).
Combined with the scheduling action of the sensor, if the active sensor on the scheduling platform \( n \) is used at time \( k \), the sensor will radiate energy outward, and its ELI state may change. However, its state transition is a stochastic process, which is only related to the ELI state of the sensor at the previous moment. Therefore, the process of ELI state transition can be regarded as a Markov chain [13]. Therefore, state transition matrix \( T^n \) can be introduced to describe the transition process of ELI state, when active sensors on platform \( n \) are scheduled at time \( k \), defining \( T^n \) as:

\[
T^n = \left( t^n_{ij} \right)_{i,j \in \{1,2,3,\ldots,E_{\text{max}}\}}
\]

### 2.3. Observation of Radiation State

Define the observation set of the radiation state of the system at time \( k \) as \( Z_k = \left[ Z_{p_k}, Z_{a_k} \right]^{\top} \), where \( Z_{p_k} \) or \( Z_{a_k} \) represent the instantaneous radiation measurements of passive sensors or active sensors on all platforms. The value of \( Z_{p_k} = \left[ Z_{p_k}^1, Z_{p_k}^2, \ldots, Z_{p_k}^N \right]^{\top} \) is identically equal zero. \( Z_{a_k} = \left[ Z_{a_k}^1, Z_{a_k}^2, \ldots, Z_{a_k}^N \right]^{\top} \) can be quantified as a set of finite positive integers \( \{1,2,3,\ldots,L_{\text{max}}\} \), which is defined as the threat level of instantaneous observations and can be expressed by a set of observation probability matrices:

\[
U^n_{a_k} (Z^n_{a_k} = l) = \left( u^n_{ij} \right)_{i,j \in \{1,2,3,\ldots,E_{\text{max}}\}}
\]

Here, \( u^n_{ij} = p(Z^n_{a_k} = l | E_{a_k} = j, E_{a_{k-1}} = i) \) \( (l \in \{1,2,3,\ldots,L_{\text{max}}\}) \) denotes the probability that the instantaneous observation threat level is \( l \) when the ELI state of the sensor is transferred from \( i \) to \( j \).

### 2.4. Radiation cost

According to the knowledge of sensor scheduling, the ELI state of active sensor can not be predicted completely. In order to update the ELI state of active sensor at every moment, the belief state is introduced, which is a sufficient statistic about historical information and represents the probability distribution of all possible states[15].

The set of ELI belief states of active sensors at time \( k \) is defined as \( P_k = \left[ (p_k^1)^{\top}, (p_k^2)^{\top}, \ldots, (p_k^N)^{\top} \right] \). Assuming that active sensor on platform \( n \) is scheduled at time \( k \), and its instantaneous observation threat level is \( l \), then the Hidden Markov Model filter can be used to update its ELI belief state [13]:

\[
p^n_{k+1} = \frac{1^{\top} \left[ U^n_k (l) \otimes T^n \right] b^n_k}{1^{\top} \left[ U^n_k (l) \otimes T^n \right] b^n_k}
\]

Here, \( \otimes \) represents Hadamard tensor product, \( 1 \) is Unit Vector.

The radiation cost of the system at time \( k + 1 \) is defined as the expected sum of ELI values of all active sensors scheduled at time \( k + 1 \). According to the eq.(1) and eq.(4), the radiation cost of the system can be obtained as follows:

\[
Y_{k+1} = \sum_{n=1}^{N} \sigma \left( a^n_k, b^n_k \right) E \left( V^T p^n_{k+1} \right)
\]
Here, $E(\cdot)$ represents mathematical expectations, $V$ is column vector.

However, in the actual sensor scheduling process, the instantaneous observation threat level cannot be obtained directly at any time, which can be obtained according to historical information

$$
p\left(Z_{a_{k+1}}^{n} \mid p_{k}^{n}\right) = \sum_{E_{k+1}=1}^{E_{\text{max}}} \sum_{E_{k+1}=1}^{E_{\text{max}}} p\left(Z_{a_{k+1}}^{n} \mid E_{a_{k+1}}^{n}, E_{a_{k+1}}^{n}, p_{k}^{n}\right) = \sum_{E_{k+1}=1}^{E_{\text{max}}} \sum_{E_{k+1}=1}^{E_{\text{max}}} p\left(Z_{a_{k+1}}^{n} \mid E_{a_{k+1}}^{n}, E_{a_{k+1}}^{n}, p_{k}^{n}\right) p\left(E_{a_{k+1}}^{n} \mid p_{k}^{n}\right)\]

$$

$$
n = \sum_{E_{k+1}=1}^{E_{\text{max}}} \sum_{E_{k+1}=1}^{E_{\text{max}}} p\left(Z_{a_{k+1}}^{n} \mid E_{a_{k+1}}^{n}, E_{a_{k+1}}^{n}, p_{k}^{n}\right) p\left(E_{a_{k+1}}^{n} \mid p_{k}^{n}\right)
$$

Turn into matrix

$$
p\left(Z_{a_{k+1}}^{n} \mid p_{k}^{n}\right) = \mathbf{1}^{T} \left[\mathbf{U}_{k}^{n} \left(Z_{a_{k+1}}^{n}\right) \odot \mathbf{T}^{n}\right] p_{k}^{n}
$$

Therefore, the predictive belief state of the scheduled active sensor is

$$
\hat{p}_{k+1}^{n} = \sum_{E_{k+1}=1}^{E_{\text{max}}} \left[\mathbf{U}_{k}^{n} \left(Z_{a_{k+1}}^{n}\right) \odot \mathbf{T}^{n}\right] p_{k}^{n} = \left(\left[\sum_{E_{k+1}=1}^{E_{\text{max}}} W_{k}^{n} \left(Z_{a_{k+1}}^{n}\right)\right]^{T} \odot \left(\mathbf{T}^{n}\right)^{T}\right) p_{k}^{n}
$$

Then the radiation cost of the system at is:

$$
Y_{k+1} = \sum_{n=1}^{N} \sigma \left(a_{k}^{n}, b_{k}^{n}\right) E\left(V^{T} \hat{p}_{k+1}^{n}\right) = \sum_{n=1}^{N} \sigma \left(a_{k}^{n}, b_{k}^{n}\right) V^{T} \left(\mathbf{T}^{n}\right)^{T} p_{k}^{n}
$$

3. Scheduling algorithm

3.1. Objective function

The purpose of this paper is to select the optimal sensor scheduling action so that the overall radiation cost of the sensor system can be minimized under the specified tracking accuracy constraints. According to eq.(9), the objective optimization function is as follows:

$$
\min Y_{k} = \sum_{n=1}^{N} \sigma \left(a_{k}^{n}, b_{k}^{n}\right) V^{T} \left(\mathbf{T}^{n}\right)^{T} p_{k-1}^{n}
$$

s.t.

$$
\rho_{k}^{m} \leq \rho_{k}^{m}, m = 1,2,\ldots,M
$$

Here, $\rho_{k}^{m}$ represents predictive value of covariance matrix for tracking target at time $k$, which can be found by using cubature kalman filter [15]. $\rho_{k}^{m}$ represents tracking accuracy threshold of task requirements.

3.2. Algorithmic flow

Considering the constraints of target tracking accuracy and the radiation cost of sensor system, a multi-platform active and passive sensor scheduling algorithm under radiation control is proposed. The flow chart is as follows:

Step 1 Obtain the initial motion state of each target at time $k$.

Step 2 Use nonlinear filtering method to calculate the prediction value of tracking accuracy error of each sensor at time $k+1$.

Step 3 By comparing the error prediction value with the tracking accuracy threshold, the sensor set $\Omega$ which meeting the accuracy requirements generated. If $\Omega$ is an empty set, go to step 6.
Step 4 According to eq.(9), calculating the radiation cost of different sensor combinations in set $\mathbf{\Omega}$ at time $k + 1$. Update the ELI belief status of each active sensor according to eq.(8).

Step 5 Solution eq.(11) to obtain the optimal sensor scheduling action, then the algorithm is over.

Step 6 When $\mathbf{\Omega}$ is an empty set, the sensor with the smallest tracking error is scheduled, then the algorithm is over.

4. Simulation results

Assuming that in the three-dimensional surveillance space, we deploy three sensor platforms to track an enemy target. The target moves in a uniform straight line with an initial position of (4,4,3) km and an initial velocity of (160,150,5) m/s. The ELI state of active sensor is quantified as $\{1, 2, 3\}$ and the threat level of instantaneous observation is quantified as $\{1, 2, 3\}$. The specific measurement parameters of the sensor platform are shown in Table 1. Here, $\delta_r$, $\delta_\theta$, $\delta_\phi$ represent standard standard deviations of the oblique distance, azimuth angle and altitude angle of the sensor respectively. The ELI state transition matrix of each active sensor is as follows:

$$
T_1 = 
\begin{bmatrix}
0.7 & 0.2 & 0.1 \\
0.5 & 0.3 & 0.2 \\
0.3 & 0.3 & 0.4 \\
\end{bmatrix},
T_2 = 
\begin{bmatrix}
0.6 & 0.3 & 0.1 \\
0.4 & 0.5 & 0.1 \\
0.1 & 0.2 & 0.7 \\
\end{bmatrix},
T_3 = 
\begin{bmatrix}
0.5 & 0.3 & 0.2 \\
0.2 & 0.4 & 0.3 \\
0.1 & 0.1 & 0.8 \\
\end{bmatrix}
$$

Table 1. Sensor measurement parameter.

| Platform number | Position | Measurement parameters of active sensors | Measurement parameters of passive sensors |
|-----------------|----------|------------------------------------------|------------------------------------------|
| 1               | (0,0,0) km | $\delta_r = 150$m, $\delta_\theta = \delta_\phi = 10$mrad | $\delta_\theta = \delta_\phi = 5$mrad |
| 2               | (4,4,0) km | $\delta_r = 150$m, $\delta_\theta = \delta_\phi = 5$mrad | $\delta_\theta = \delta_\phi = 5$mrad |
| 3               | (10,5,0) km | $\delta_r = 100$m, $\delta_\theta = \delta_\phi = 2$mrad | $\delta_\theta = \delta_\phi = 5$mrad |

In order to verify the effectiveness of the proposed method (PM), five common scheduling methods are compared.

1) Fixed Scheduling Method [4], scheduling platform 1 to track target and recording it as FSM 1.
2) scheduling platform 3 to track target and recording it as FSM2.
3) Precision Priority Scheduling Method (PPSM) [6].
4) Closest Scheduling Method (CSM)[16].
5) Random Scheduling Method [16].

In order to verify the effectiveness of the algorithm in target tracking, Root Mean Square Error (RMSE) and Root Time Average Square Error (RTAMSE) are introduced as the indexes to measure tracking accuracy.

(a) RMSE Curve of Target with Threshold of 40m   (b) RMSE Curve of Target with Threshold of 60m

Figure 1. Target position RMSE curve
Throughout the simulation time, the RMSE of target location under different methods is shown in Fig. 1, and the normalized radiation cost under different methods is shown in Fig. 2. Combining with Fig. 1 and Fig. 2, it can be seen that the radiation cost of FSM-1 method is the lowest, but it can't satisfy the restriction of tracking threshold and the requirement of tracking task. FSM-2 method can schedule the active sensors with the highest accuracy, so it can obtain higher tracking accuracy, but its radiation cost is the highest in the method, which is not conducive to the survival of the sensor system. It is a good balance between tracking accuracy and radiation cost, because it is also a single platform scheduling method in essence, and the number of sensors it can choose at any time is small, so when passive sensor does not meet the threshold requirements, it chooses too many active sensors; RSM method does not consider radiation cost and threshold constraints, and can not adapt radiation control according to different task requirements. Compared with the target RMSE of PPSM, the tracking error of this method is slightly larger than that of PPSM, but the radiation cost of this method is smaller. This is because this method can predict the next radiation cost when dispatching active sensors, and then select the active sensor with the lowest radiation cost, which proves that this method can achieve better results. Effective radiation control for mission requirements.

![Figure 2. Normalized radiation values](image)

5. Conclusion
Aiming at the background of target tracking task, the scheduling problem of multi-platform active and passive sensors is studied in this paper. Firstly, the radiation state model of sensor based on POMDP is established. In view of the shortcomings of other literatures, the time-varying radiation state of sensor is quantified, and the radiation cost prediction formula of sensor system is established through belief state. Then, the objective function is established, and the optimal scheduling algorithm under radiation control is given. In the simulation experiment, by comparing with several common scheduling methods, it is verified that the proposed method can self-adaptively schedule the sensor to control radiation under different tracking tasks, so as to reduce the risk of the sensor platform being hit.

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