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Adaptive resource management algorithm for target tracking in radar network based on low probability of intercept

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Abstract In this paper, a low probability of intercept (LPI) performance driven adaptive resource management algorithm for target tracking in a radar network is presented, where the radar network consists of a dedicated radar transmitter and multiple receivers. Firstly, the intercept probability for radar network systems is derived. Then, an adaptive resource management scheme based on LPI is proposed, in which a novel objective function for LPI performance is defined and minimized by optimizing the revisit interval, dwell time, and transmit power in radar networks to guarantee a specific target tracking accuracy with passive time difference of arrival and frequency difference of arrival cooperation. Numerical simulations demonstrate the superior performance of the proposed adaptive resource management scheme over other methods via Monte Carlo simulations.

Keywords Low probability of intercept (LPI) · Resource management · Intercept probability · Radar networks · Target tracking

1 Introduction

In recent years, distributed radar networks have received significant attention in a novel class of radar system, where the term radar networks refer to spatial distributed multiple-input multiple-output (MIMO) radar systems (Li and Stoica 2009; Pace 2009; Haimovich et al. 2008). Radar networks with widely separated antennas can capture information from different views of target's radar cross section (RCS) and employ spatial and signal diversities (Fisher et al. 2006). For a radar network architecture with M transmit antennas and N receiver antennas, the MN transmitter–receiver pairs observe different aspects of the target, while

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the conventional radar systems observe only one single aspect of the target. Thus, the radar networks can overcome deep fades other than the conventional radars (Shi et al. 2016b). Extensive research has been conducted into the potential use of radar networks for achieving system performance improvement owing to their advantage of spatial and signal diversities, including target detection (Fisher et al. 2006; Naghsh et al. 2013; Song et al. 2012b), target localization (Niu et al. 2010; Dogancay 2007), target tracking (Godrich et al. 2012b; Nguyen et al. 2014), waveform design (Chen et al. 2013; Shi et al. 2016b, e), sensor selection (Godrich et al. 2012a; Nguyen et al. 2015b; Shi et al. 2016c), parameter estimation (Shi et al. 2016c, e), and information extraction Song et al. (2012a). In Fisher et al. (2006), the authors introduce the concept of distributed MIMO radar and investigate the inherent performance limitations of both conventional phased array radars and the newly proposed radars. The problem of code design to improve the detection performance of multi-static radar in the presence of clutter is studied in Naghsh et al. (2013), where the information-theoretic criteria are used as design metrics. Niu et al. (2010) develop the localization and tracking algorithms for noncoherent MIMO radar systems, in which it is demonstrated that the noncoherent MIMO radar can provide a significant performance improvement over traditional monostatic phased array radar with high range and azimuth resolutions. In Nguyen et al. (2015a), the authors investigate the problem of target tracking in a multistatic radar system from the perspective of adaptive waveform selection, in which the transmitted waveform parameters are selected to minimize the target tracking covariance matrix.

Power management and mode control play a key role in industrial and military applications such as energy storage systems, power converters, sensor networks, etc. (Liu et al. 2016, 2017; Su et al. 2016, 2017). This paper focuses on the problem of adaptive transmitting resource management for radar networks. The objective of resource management is to optimize the LPI performance for network systems. The study of power allocation in distributed radar network architectures has received sizeable impetus, which has been extensively studied from various perspectives (Song et al. 2012a; Chavali and Nehorai 2012; Yan et al. 2015, 2016; Sun et al. 2014; Chen et al. 2015, 2016; Ma et al. 2014). Yan et al. (2015) extend the previous results in Chavali and Nehorai (2012) and propose a performance-driven power allocation strategy for Doppler-only target tracking in unmodulated continuous wave (UCW) radar network, where the Bayesian Cramer–Rao lower bound (BCRLB) is derived and utilized as an optimization criterion for the optimal power allocation scheme. The authors in Sun et al. (2014) and Chen et al. (2015) study the problem of optimal power allocation with the goal of maximizing the determinant of Bayesian Fisher information matrix (B-FIM) in distributed MIMO radar networks for target localization and tracking respectively, where it is formulated as a cooperative game and the Shapley value is exploited as the solution to the proposed scheme. Ma et al. (2014) presents a joint strategy of antenna subset selection and optimal power allocation for target localization in distributed MIMO radar sensor networks, and the authors develop a two-step suboptimal approach to tackle the optimization problem. The power management games for wireless sensor network localization with agent cooperation in both asynchronous and synchronous networks are analyzed in Chen et al. (2016), whose objective is to minimize the individual power-penalized cost function to achieve a better trade-off between target localization performance and power consumption for each agent. In Yan et al. (2016), a joint beam selection and power allocation algorithm is proposed for multiple target tracking in netted colocated MIMO radar system, and a fast two-step solution technique is developed to decide the assignment and transmit power of each radar. Overall, the previous studies lay a solid foundation for the problem of performance optimization in radar networks, and it should be pointed out that the target tracking performance improvement can be obtained with an increase of either the transmitted energy or the number of radar nodes.

Since the notion of low probability of intercept (LPI) design is an essential part of military operations in modern electronic warfare, LPI performance optimization is a primary issue that needs to be taken into account in designing radar system (Schleher 2006; Lynch 2004). An LPI radar is defined as a radar that uses a special emitted waveform intended to prevent a non-cooperative interceptor from intercepting, detecting and classifying its emission (Stove et al. 2004). In order to obtain good LPI performance, it is necessary to strictly control the radiation of radar system. Transmit power and dwell time management, ultra-low side-lobe antenna, waveform agility and selection are employed to guarantee the LPI performance. Hence, extensive research has been conducted in LPI optimization for radar system, and some of the noteworthy works include (Stove et al. 2004; Shi et al. 2016a; Chen et al. 2014; Narykov et al. 2013). In Shi et al. (2016a), the problem of LPI-based adaptive radar waveform design in signal-dependent clutter for joint radar and cellular communication systems is investigated, and three different criteria for radar waveform optimization are proposed to minimize the total transmitted power of radar by optimizing the multicarrier radar waveform with a given signal-to-interference-plus-noise ratio (SINR) constraint and a minimum required capacity for the communication systems. Chen et al. (2014) present a time difference of arrival (TDOA) cooperation based radar radiation control in multiple aircraft platforms, which utilizes the comparison of covariance and the predefined threshold to control the radar radiation state. The authors in Narykov et al. (2013) investigate the sensor scheduling algorithm of selecting and assigning sensors dynamically for target tracking, which can obtain a good trade-off between the target tracking accuracy and the LPI performance. Shi et al. (2014) address the problem of LPI optimization in radar networks for the first time, where it has been demonstrated that radar network architectures with multiple transmitters and receivers can provide remarkable LPI performance advantages over traditional monostatic radar system, and has triggered a resurgence of interest in radar networks. Later, LPI based robust waveform optimization schemes are proposed for distributed multiple-radar systems (Shi et al. 2016d), where SINR and mutual information (MI) are used as the metrics for target detection and information extraction, respectively. Panoui et al. (2014) presents a novel game theoretic approach for power allocation in a MIMO radar network. The aim of each clusters of radars in the network is to minimize the total transmitted power in the cluster while guaranteeing a specific target detection threshold. Zhang and Tian (2016); Zhang et al. (2016) study the radio frequency-based coordination strategy of opportunistic array radars for target tracking in clutter. Simulation results demonstrate that the presented strategies not only have excellent target tracking performance in clutter but also save much transmit power compared with other algorithms. Reference Deligiannis et al. (2016) models the interaction between the radar network and multiple jammers as a non-cooperative game. The goal of the radar network is to minimize the total power transmitted by the radars while achieving a predetermined detection performance for each of the targets, while the jammers have the ability to observe the radar transmitted power and consequently decide its jamming power to maximize the interference to the radars. However, almost all of those works focus on the single parameter optimization. On the basis of the research mentioned above, the problem of LPI based adaptive resource management for target tracking in radar network, which has not been considered, needs to be investigated.

This paper aims to investigate the problem of adaptive resource scheduling based on LPI for target tracking by a distributed radar network, wherein the radar network with one dedicated radar transmitter and multiple receivers is considered. Firstly, the intercept probability for distributed radar network systems is calculated. Then, a novel objective function is developed, which is minimized by optimizing the revisit interval, dwell time, and transmit power in radar networks to improve the LPI performance for a given target tracking accuracy with TDOA and frequency difference of arrival (FDOA) cooperation. We employ an interacting multiple model (IMM) algorithm incorporating extended Kalman filter (EKF) for target tracking. The proposed algorithm can be formulated as a two-step optimization problem: the outer one is for revisit interval control, and the inner one is for transmission parameters scheduling. Numerical simulation results show the effectiveness of the proposed algorithm. To the best of authors knowledge, no literature discussing the LPI based adaptive resource management in radar network was conducted prior to this study.

The remainder of this paper is organized as follows. Section 2 introduces the considered radar network system model. In Sect. 3, with the derived intercept probability for radar network, a novel adaptive resource management algorithm for target tracking based on LPI is formulated. The performance of the proposed algorithm is validated by Monte Carlo simulations in Sect. 5. Finally, conclusion remarks are drawn in Sect. 6.

2 System model

2.1 Target tracking model

Consider a two-dimensional target tracking scenario. The target state is given by $\mathbf{X}(k) = [x(k), \dot{x}(k), y(k), \dot{y}(k)]^{\dagger}$, where $[x(k), y(k)]$ denotes the target position, $[\dot{x}(k), \dot{y}(k)]$ denotes the target velocity, and the superscript † represents matrix transpose. The target dynamic model can be described as:

$$\mathbf{X}(k) = \mathbf{F}\mathbf{X}(k-1) + \mathbf{N}(k-1), \tag{1}$$

where $\mathbf{F}$ is the transition matrix. The term $\mathbf{N}(k-1)$ in (2) represents the process noise of target motion, and is supposed to be an additive Gaussian noise vector with a known covariance matrix $\mathbf{Q}(k-1) = \mathcal{E}[\mathbf{N}(k-1)\mathbf{N}(k-1)^{\dagger}]$, where $\mathcal{E}[\cdot]$ denotes the mathematical expectation.

The nonlinear observation equation is given by:

$$\mathbf{Z}(k) = \mathbf{h}\left(\mathbf{X}(k)\right) + \mathbf{W}(k), \tag{2}$$

where $\mathbf{Z}(k)$ is the observation vector at time index k, $\mathbf{W}(k)$ stands for the observation error, and $\mathbf{h}(\cdot)$ is a vector of nonlinear transformation function.

2.2 Passive mode in radar networks

In this paper, we consider a distributed radar network consists of one dedicated radar transmitter and N_r receivers, which are located at different sites as depicted in Fig. 1. The radar network can work in two modes, i.e., passive mode and active mode. If the expected target tracking accuracy is satisfied, the radar networks work in passive mode, wherein the dedicated radar transmitter does not transmit any signals, and all the radar receivers in radar networks locate and track the target by receiving the signal $s(t)$ radiated from the target. Herein, it is supposed that the radar receivers in radar networks can receive the signals radiated from the target all the time, so that the passive TDOA and FDOA method (Wu et al. 2014) can be employed to locate and track the target. If the expected target tracking accuracy is not satisfied, the radar networks work in active mode. In this case, the dedicated radar transmitter transmits radar signals $x(t)$ and all the receivers in radar networks can receive and process the echoes $y_j(t)(j = 1, \ldots, N_r)$ that are reflected from the target. The estimates of target range, Doppler shift, and arrival angle can be obtained from all receivers, where target range and Doppler shift are estimated employing matched filters and square-law envelope detectors,

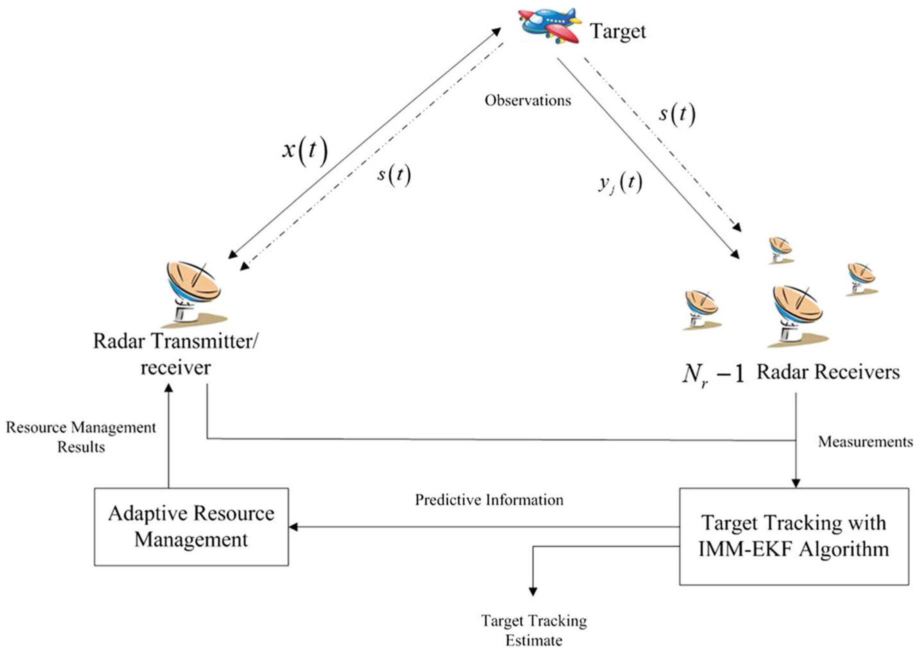

Fig. 1 Distributed radar network systems considered in paper

and arrival angle is estimated utilizing phased array antennas. Then, radar estimates are sent to the radar transmitter that incorporates a fusion processor to perform target tracking and resource management.

It is known to all that different modes have different observation vectors. Herein, we assume that the elevation angle is zero for concise description. In our case, N_r radar receivers are employed to track a single target with TDOA and FDOA method (Wu et al. 2014). In order to locate a 2D target, the TDOA and FDOA system should comprise three stations at least. The measurements received from all the receivers must be sent to the radar transmitter, where the time difference and the target position estimate are computed.

Without loss of generality, it is assumed that the dedicated radar transmitter is located at the origin $(x_1, y_1) = (0, 0)$km with a receiver colocated and the jth receiver is located at $(x_j, y_j)(j = 2, \ldots, N_r)$, respectively. The TDOA equations can be given by:

$$\begin{cases} r_j^2(k) = [x(k) - x_j]^2 + [y(k) - y_j]^2, \\ r_1^2(k) = x^2(k) + y^2(k), \end{cases} \tag{3}$$

where $r_1(k)$ denotes the range between the target and the radar transmitter, $r_j(k)$ denotes the range between the target and the jth receiver. Then, we can obtain:

$$\triangle r_{j,1}(k) = r_j(k) - r_1(k) = c \triangle t_{j,1}(k), \tag{4}$$

where c represents the speed of electromagnetic transmission. $\triangle t_{j,1}(k)$ stands for the corresponding time difference of $\triangle r_{j,1}(k)$:

$$\triangle t_{j,1}(k) = t_j(k) - t_1(k), \tag{5}$$

where $t_1(k)$ and $t_j(k)$ are the time when the targets radiated signal is received by the radar transmitter and recevier, respectively.

The time derivative of (3) shows the relationship between the range rate and target position parameters:

$$\begin{cases} \dot{r}_j^2(k) = \frac{(x(k)-x_j)\dot{x}(k)+(y(k)-y_j)\dot{y}(k)}{r_j(k)}, \\ \dot{r}_1^2(k) = \frac{x(k)\dot{x}(k)+y(k)\dot{y}(k)}{r_1(k)}. \end{cases} \tag{6}$$

To make use of FDOA measurements, taking the time derivative of the range difference $\triangle r_{j,1}(k)$ in (4), we can have its rate $\triangle \dot{t}_{j,1}(k)$ as follows:

$$\begin{aligned} \triangle \dot{r}_{j,1}(k) &= \dot{r}_j(k) - \dot{r}_1(k) \\ &= c \triangle \dot{t}_{j,1}(k) = \frac{c}{f_c} \triangle f_{j,1}^d(k), \end{aligned} \tag{7}$$

where f_c is the carrier frequency, and $\triangle f_{j,1}^d(k)$ is the corresponding frequency difference.

The observation vector of the passive mode can be described as:

$$\mathbf{Z}_{\mathrm{PM}}(k) = \begin{bmatrix} \triangle r_{2,1}(k) \\ \triangle \dot{r}_{2,1}(k) \\ \theta_{\mathrm{PM}}^2(k) \\ \vdots \\ \triangle r_{N_r,1}(k) \\ \triangle \dot{r}_{N_r,1}(k) \\ \theta_{\mathrm{PM}}^{N_r}(k) \end{bmatrix} = \begin{bmatrix} c(t_2(k) - t_1(k)) \\ c(\dot{t}_2(k) - \dot{t}_1(k)) \\ \arctan\left(\frac{y(k)-y_1}{x(k)-x_1}\right) \\ \vdots \\ c(t_{N_r}(k) - t_1(k)) \\ c(\dot{t}_{N_r}(k) - \dot{t}_1(k)) \\ \arctan\left(\frac{y(k)-y_{N_r}}{x(k)-x_{N_r}}\right) \end{bmatrix} + \mathbf{W}_{\mathrm{PM}}(k), \tag{8}$$

where $\theta_{\mathrm{PM}}^j(k)(j = 2, \ldots, N_r)$ denotes the passive arrival angle at the jth receiver, $\mathbf{W}_{\mathrm{PM}}(k)$ denotes the observation error with covariance $\mathbf{N}_{\mathrm{PM}}(k)$, and $\mathbf{h}_{\mathrm{PM}}(\cdot)$ denotes the nonlinear transformation from the target state vector of target position in Cartesian coordinates to the observation vector of time difference.

2.3 Active mode in radar networks

When the radar networks work in active mode, the network systems can be broken into $1 \times N_r$ transmitter–receiver pairs each with a bistatic component contributing to the entirety of the radar network signal-to-noise ratio (SNR). We assume that the radar networks have a common precise knowledge of space and time. The total SNR in radar networks can be obtained by aggregating the SNR of each transmit–receive pair as follows:

$$\mathrm{SNR}_{\mathrm{net}} = \sum_{j=1}^{N_r} \frac{P_{\mathrm{t}} G_{\mathrm{t}} G_{rj} \sigma_{tj} \lambda^2 G_{\mathrm{RP}}}{(4\pi)^3 k T_0 B_{rj} F_{rj} R_{\mathrm{t}}^2 R_{rj}^2}, \tag{9}$$

where P_t is the transmit power of the dedicated radar transmitter, G_t is the transmitting antenna gain, G_{rj} is the jth receiving antenna gain, σ_{tj} represents the target's RCS for the dedicated radar transmitter and jth receiver, λ represents the transmitted wavelength, G_{RP} denotes the radar network processing gain, k and T_0 are Boltzmanns constant and the receiving system noise temperature respectively, B_{rj} denotes the bandwidth of the matched filter for the transmitted waveform at the jth receiver, F_{rj} denotes the noise factor for the jth receiver, R_t and R_{rj} are the distance from the dedicated radar transmitter to the target and the distance from the target to the jth receiver, respectively.

Moreover, the observation vector of the active mode includes target range measurement $r^j_{\mathrm{AM}}(k)$, Doppler-shift measurement $\nu^j_{\mathrm{AM}}(k)$, and arrival angle measurement $\theta^j_{\mathrm{AM}}(k)$ at each receiver, which can be written as:

$$\mathbf{Z}_{\mathrm{AM}}(k) = \begin{bmatrix} r^1_{\mathrm{AM}}(k) \\ \nu^1_{\mathrm{AM}}(k) \\ \theta^1_{\mathrm{AM}}(k) \\ \vdots \\ r^{N_r}_{\mathrm{AM}}(k) \\ \nu^{N_r}_{\mathrm{AM}}(k) \\ \theta^{N_r}_{\mathrm{AM}}(k) \end{bmatrix} = \begin{bmatrix} \sqrt{[x(k)-x_1]^2 + [y(k)-y_1]^2} \\ \frac{1}{\lambda}\left[\frac{\dot{x}(k)(x(k)-x_1)+\dot{y}(k)(y(k)-y_1)}{\sqrt{[x(k)-x_1]^2+[y(k)-y_1]^2}}\right] \\ \arctan\left(\frac{y(k)-y_1}{x(k)-x_1}\right) \\ \vdots \\ \sqrt{[x(k)-x_{N_r}]^2 + [y(k)-y_{N_r}]^2} \\ \frac{1}{\lambda}\left[\frac{\dot{x}(k)(x(k)-x_{N_r})+\dot{y}(k)(y(k)-y_{N_r})}{\sqrt{[x(k)-x_{N_r}]^2+[y(k)-y_{N_r}]^2}}\right] \\ \arctan\left(\frac{y(k)-y_{N_r}}{x(k)-x_{N_r}}\right) \end{bmatrix} + \mathbf{W}_{\mathrm{AM}}(k), \tag{10}$$

where $\mathbf{W}_{\mathrm{AM}}(k)$ represents the observation error with covariance $\mathbf{N}_{\mathrm{AM}}(k)$, and $\mathbf{h}_{\mathrm{AM}}(\cdot)$ is the nonlinear transformation from the target state vector of target position in Cartesian coordinates to the observation vector of range and azimuth angle.

2.4 IMM–EKF algorithm

The standard EKF is sufficient to track the target with a single target dynamic model. However, for the target with time-varying or multiple dynamic models, a single dynamic model cannot represent the actual target motion well. For that reason, we employ the IMM method which incorporates three standard EKFs in this paper.

The IMM algorithm can estimate the target state with multiple tracking filters running in parallel, where each tracking filter is responsible for a particular target dynamic model, and finally obtain a weighted combination of the state estimates and tracking covariances from individual tracking filters (Nguyen et al. 2015a). In this paper, we consider three target dynamic models: (1) a constant velocity model, (2) a coordinate turn model with positive turn rate, and (3) a coordinate turn model with negative turn rate.

The crucial feature of the resource management algorithm in radar network is that it must be predictive. The predictive error covariance matrix can gives us the ability to make decisions in advance based on current knowledge. Given the predicted target state $\widehat{\mathbf{X}}^i(k)$, model probability $u(k+1|k)$, and error covariance matrix $\mathbf{P}^i(k+1|k)$ at time index k, we can calculate the predictive error covariance matrix $\mathbf{P}^{\mathrm{IMM}}_{\mathrm{pre}}(k+1|k)$. For real time application, the combined target state can be calculated by:

$$\widehat{\mathbf{X}}^{\mathrm{IMM}}_{\mathrm{pre}}(k+1|k) = \sum_{i=1}^{3} \widehat{\mathbf{X}}^i(k+1|k)u^i(k+1|k). \tag{11}$$

Then, we can obtain the predictive error covariance matrix as follows:

$$\begin{aligned}\mathbf{P}^{\mathrm{IMM}}_{\mathrm{pre}}(k+1|k) = \sum_{i=1}^{3} u^i(k+1|k)\Big\{&\mathbf{P}^i(k+1|k) + \left[\widehat{\mathbf{X}}^i(k+1|k) - \widehat{\mathbf{X}}^{\mathrm{IMM}}_{\mathrm{pre}}(k+1|k)\right] \\ &\times \left[\widehat{\mathbf{X}}^i(k+1|k) - \widehat{\mathbf{X}}^{\mathrm{IMM}}_{\mathrm{pre}}(k+1|k)\right]^{\dagger}\Big\}.\end{aligned} \tag{12}$$

3 Problem formulation

In this section, the adaptive resource management strategy can be mathematically formulated as the problem of minimizing a novel objective function for LPI performance subject to a predetermined target tracking performance. With the derived intercept probability for radar network, we are then in a position to design and minimize the objective function in order to achieve effective LPI performance improvement in radar networks.

3.1 Intercept probability for radar network

In this paper, intercept probability is utilized to evaluate the LPI performance for radar network. Based on the discussions in Lynch (2004), intercept probability is a function of several variables. The transmit power of radar networks obviously is an important element (Shi et al. 2014); so are the illumination time of the interceptor by the radar network, or time-on-target, and the revisit interval.

Intercept probability is especially important in any situation in which a time-varying radar network is to be detected (Lynch 2004). Time variations may result from radar network platforms motion, antenna scanning, waveform on-time, and frequency variations. Given that the radar network presents (in some sense) the intercept receiver with an opportunity to detect it, the intercept probability is the likelihood that the intercept receiver system is both pointed in the right direction and tuned to the right frequency when that opportunity occurs.

For the sake of simplicity, it is supposed that the intercept receiver is carried by the target. Thus, the probability that the radar beam illuminates the interceptor location is 1, that is:

$$p_{\mathrm{s}} = 1. \tag{13}$$

In practice, frequency scanning and spatial scanning are carried out simultaneously. We assume that a radar system scans across the location of an intercept receiver so that the antenna beam remains pointed toward the receiver for T_{OT}, referred to as the time on target. During the time on the target, the interceptor will be able to listen to a total of N_{L} combinations of beam positions and frequency channels. Then, we have that:

$$N_{\mathrm{L}} = T_{\mathrm{OT}}/t_{\mathrm{L}}, \tag{14}$$

where t_{L} denotes the time that the interceptor listens in each beam position and frequency channel.

It is assumed that the interceptor scans a total of N_{Freq} frequency channels and N_{B} beam positions, one of which corresponds to the radar platform position and frequency. Thus, the time-frequency probability that an intercept occurs during the time T_{OT} can be expressed as:

$$p_{\mathrm{t}} \cdot p_{\mathrm{f}} \approx \min\left\{\frac{N_{\mathrm{L}}}{N_{\mathrm{Freq}} \cdot N_{\mathrm{B}}}, 1\right\}. \tag{15}$$

Furthermore, the intercept receiver total search time T_{I} can be defined as the time that it takes for the interceptor to scan through its set of beam positions and frequency channels, that is:

$$T_{\mathrm{I}} = N_{\mathrm{Freq}} \cdot N_{\mathrm{B}} \cdot t_{\mathrm{L}}.(T_{\mathrm{I}} \geq T_{\mathrm{OT}}) \tag{16}$$

Actually, the time on target T_{OT} is equal to the dwell time T_{d}. Therefore, the time-frequency probability (13) can be rewritten as follows:

$$p_{\mathrm{t}} \cdot p_{\mathrm{f}} \approx \frac{T_{\mathrm{d}}}{T_{\mathrm{I}}}. \tag{17}$$

The probability that the interceptor detects the radar transmitted signal when it is above the threshold of the intercept receiver is $p_{\mathrm{d}}^{'}$, which refers to the probability that radar network is detected assuming illumination and proper tuning. With the derivations in Liu et al. (2015) and Mahafza and Elsherbeni (2009), we can obtain:

$$p_{\mathrm{d}}^{'} = \frac{1}{2}\mathrm{erfc}\left(\sqrt{-\ln p_{\mathrm{fa}}^{'}} - \sqrt{\mathrm{SNR_O} + \frac{1}{2}}\right), \tag{18}$$

$$\mathrm{erfc}(z) = 1 - \frac{2}{\sqrt{\pi}}\int_0^z e^{-v^2}dv, \tag{19}$$

where $p_{\mathrm{fa}}^{'}$ represents the probability of false alarm at intercept receiver, $\mathrm{SNR_O}$ represents the SNR of a single pulse at the intercept receiver signal processor output.

The signal power available at the intercept receiver from the radar system is:

$$P_i = \frac{P_{\mathrm{t}}G_{\mathrm{t}}^{'}G_{\mathrm{i}}\lambda^2 G_{\mathrm{IP}}}{(4\pi)^2 R_{\mathrm{t}}^2}, \tag{20}$$

where $G_t^{'}$ is the gain of the radars transmitting antenna in the direction of the interceptor, G_i is the gain of the interceptors antenna, G_{IP} is the interceptor processing gain. Here, the intercept receiver detects the radar main lobe, then $G_t^{'} = G_t$. In addition, the sensitivity in the interceptor is:

$$S_{\mathrm{I}} = kT_0 B_{\mathrm{I}} F_{\mathrm{I}}(\mathrm{SNR_I}), \tag{21}$$

where B_{I} denotes the bandwidth of the intercept receiver, F_{I} denotes the intercept receiver noise factor, and $\mathrm{SNR_I}$ denotes the SNR at the intercept receiver signal processor input. Thus, the SNR of a single pulse at the intercept receiver signal processor output is given by:

$$\mathrm{SNR_O} = \frac{P_i}{kT_0 B_{\mathrm{I}} F_{\mathrm{I}}} = \frac{P_t G_t^{'} G_i \lambda^2 G_{\mathrm{IP}}}{(4\pi)^2 R_{\mathrm{t}}^2 kT_0 B_{\mathrm{I}} F_{\mathrm{I}}}, \tag{22}$$

For any fixed value of the probability of false alarm $p_{\mathrm{fa}}^{'}$, (16) can be derived as:

$$p_{\mathrm{d}}^{'} = \frac{1}{2}\mathrm{erfc}\left(\sqrt{-\ln p_{\mathrm{fa}}^{'}} - \sqrt{\frac{P_{\mathrm{t}}G_{\mathrm{t}}G_{\mathrm{i}}\lambda^2 G_{\mathrm{IP}}}{(4\pi)^2 R_{\mathrm{t}}^2 kT_0 B_{\mathrm{I}} F_{\mathrm{I}}} + \frac{1}{2}}\right), \tag{23}$$

From the above all, the intercept probability for radar network can be obtained as follows:

$$\begin{aligned} p_{\mathrm{I}} &= p_{\mathrm{s}} \cdot p_{\mathrm{t}} \cdot p_{\mathrm{f}} \cdot p_{\mathrm{d}}^{'} \\ &= \frac{T_{\mathrm{d}}}{2T_{\mathrm{I}}}\mathrm{erfc}\left(\sqrt{-\ln p_{\mathrm{fa}}^{'}} - \sqrt{\frac{P_{\mathrm{t}}G_{\mathrm{t}}G_{\mathrm{i}}\lambda^2 G_{\mathrm{IP}}}{(4\pi)^2 R_{\mathrm{t}}^2 kT_0 B_{\mathrm{I}} F_{\mathrm{I}}} + \frac{1}{2}}\right). \end{aligned} \tag{24}$$

3.2 LPI based resource management algorithm

Herein, the objective function for LPI performance is defined as a quotient of the intercept probability p_{I}, divided by the revisit interval $\triangle T$ for one step horizon:

$$L(k) = \frac{p_{\mathrm{I}}(k)}{\triangle T(k+1)}, \tag{25}$$

where $p_{\mathrm{I}}(k)$ is the intercept probability for radar network at time step k, and $\triangle T(k+1)$ is the expected time after the measurement at time step k. In this case, we can observe that the objective function $L(k)$ is related to the intercept probability for radar network and the revisit interval. Intuitively, minimization of the objective function means better LPI performance for radar network. Thus, the objective function (23) can provide guidance to the problem of resource management for radar network architecture.

In this paper, we concentrate on the LPI based adaptive resource management for radar network, whose purpose is to minimize the objective function by optimizing the revisit interval, dwell time, and transmit power with passive TDOA and FDOA cooperation for a given target tracking accuracy, such that the LPI performance is met on the guarantee of tracking performance. Consequently, the underlying resource management problem for radar network can be developed as:

$$\min_{\triangle T(k+1), T_{\mathrm{d}}(k), P_{\mathrm{t}}(k)} \quad L(k), \tag{26a}$$

$$s.t.: \begin{cases} \mathrm{SNR}(k) \geq \mathrm{SNR}_{\min}, \\ \delta \cdot \mathbf{P}_{\mathrm{d}} - \mathbf{P}_{\mathrm{pre}}^{\mathrm{IMM}}(k+1|k) \geq \mathbf{0}, \\ 0 \leq P_{\mathrm{t}}(k) \leq \overline{P_{\max}}, \\ T_{\mathrm{r}} \leq T_{\mathrm{d}}(k) \leq \frac{c\tau}{2\nu}. \end{cases} \tag{26b}$$

where $\mathrm{SNR}(k)$ denotes the achieved SNR in radar network at step k, $\mathrm{SNR}_{\min}$ denotes the SNR threshold for target detection performance, $\delta \cdot \mathbf{P}_{\mathrm{d}}$ is the expected covariance matrix, and the scalar $\delta(0 < \delta < \infty)$ is defined as radar radiation control factor (RRCF), which can be used to control target tracking accuracy. The transmit power of the dedicated radar transmitter at step k is constrained by a maximum value $\overline{P_{\max}}$ and a minimum value 0, T_{r} represents the pulse repetition interval, τ is the pulse width, and ν is the target radial velocity.

In what follows, we approach the problem of LPI based resource management as a two-step optimization problem: the outer one is for revisit interval control, and the inner one is for transmitting parameters scheduling. This way the problem of resource management in radar network is designed as a set of problems for individual parameters. The general LPI optimization strategy is detailed as follows.

3.2.1 Revisit interval control with TDOA and FDOA cooperation

One can notice from (10) that there exists a restrictive relationship between the predictive error matrix $\mathbf{P}_{\mathrm{pre}}^{\mathrm{IMM}}(k+1|k)$ and the revisit interval $\triangle T(k+1)$. Specifically, increasing the revisit interval $\triangle T(k+1)$ leads to enlarging the trace of $\mathbf{P}_{\mathrm{pre}}^{\mathrm{IMM}}(k+1|k)$, which in turn results in the degradation of target tracking performance. Then, a new measurement needs to be scheduled as soon as the tracking accuracy degrades to a predefined level.

It is notable that the term $\mathbf{P}_{\mathrm{pre}}^{\mathrm{IMM}}(k+1|k)$ in (10) implies the feedback information from the tracker to radar network, based on which the adaptive resource management scheme can be implemented. Herein, we can utilize (10) to generate a so-called uncertainty ellipse, which describes the spatial variance distribution of an efficient target estimate (Yan et al. 2015).

Generally, the uncertainty ellipse of $\mathbf{P}_{\mathrm{pre}}^{\mathrm{IMM}}(k+1|k)$ would be contained in the uncertainty ellipse of $\delta \cdot \mathbf{P}_{\mathrm{d}}$, which denotes the lower bound on the error covariance of the estimation of the target position and velocity, if the expected target tracking accuracy is satisfied. Hence, it is sufficient for us to use $\left[\delta \cdot \mathbf{P}_{\mathrm{d}} - \mathbf{P}_{\mathrm{pre}}^{\mathrm{IMM}}(k+1|k)\right]$ as a criterion for the revisit interval control strategy. In other words, we can judge whether $\mathbf{P}_{\mathrm{pre}}^{\mathrm{IMM}}(k+1|k)$ meets the requirement of $\delta \cdot \mathbf{P}_{\mathrm{d}}$ according to whether $\left[\delta \cdot \mathbf{P}_{\mathrm{d}} - \mathbf{P}_{\mathrm{pre}}^{\mathrm{IMM}}(k+1|k)\right]$ is positive semi-definite or not. The radar network will work in active mode only when the expected target tracking accuracy is not satisfied, which means that the dedicated radar transmitter will be used to radiate radar signals at time slot $k+1$ only when $\mathbf{P}_{\mathrm{pre}}^{\mathrm{IMM}}(k+1|k)$ meets the following constraint:

$$\delta \cdot \mathbf{P}_{\mathrm{d}} - \mathbf{P}_{\mathrm{pre}}^{\mathrm{IMM}}(k+1|k) < \mathbf{0}. \tag{27}$$

To be specific, if $\delta \cdot \mathbf{P}_{\mathrm{d}} - \mathbf{P}_{\mathrm{pre}}^{\mathrm{IMM}}(k+1|k) \geq \mathbf{0}$, the expected target tracking accuracy is satisfied. The radar network works in passive mode, and all the netted radars locate and track the target with TDOA and FDOA method. While if $\delta \cdot \mathbf{P}_{\mathrm{d}} - \mathbf{P}_{\mathrm{pre}}^{\mathrm{IMM}}(k+1|k) < \mathbf{0}$, the expected target tracking accuracy is not satisfied, and the radar network works in active mode. The dedicated radar transmitter transmits radar signals and all the receivers in radar networks can receive and process the echoes that are reflected from the target.

3.2.2 Transmitting parameters scheduling

When the radar network works in active mode to track a single target during the time T_{d}, several pulses will be scattered from the target. The process of summing up all the radar echoes available from a target can significantly improve the SNR for radar network. Here, we employ the coherent integration method.

If N_{p} pulses, all of the same SNR, are perfectly integrated by an ideal lossless integrator, the integrated SNR would be exactly N_{p} times that of a single pulse, that is:

$$\mathrm{SNR}_{\mathrm{c}} = N_{\mathrm{p}} \cdot \mathrm{SNR}_{\mathrm{s}}, \tag{28}$$

where $\mathrm{SNR}_{\mathrm{s}}$ denotes the SNR of a single pulse, and $\mathrm{SNR}_{\mathrm{c}}$ denotes the integrated SNR of N_{p} pulses. Then, we can obtain:

$$\mathrm{T}_{\mathrm{d}} = N_{\mathrm{p}} \cdot \mathrm{T}_{\mathrm{r}}. \tag{29}$$

Substituting (26) into (27), one can observe that:

$$\mathrm{SNR}_{\mathrm{c}} = \frac{\mathrm{T}_{\mathrm{d}}}{\mathrm{T}_{\mathrm{r}}} \cdot \mathrm{SNR}_{\mathrm{s}}. \tag{30}$$

Thus, (28) can be calculated as follows:

$$\mathrm{SNR}_{\mathrm{c}} = \frac{\mathrm{T}_{\mathrm{d}}}{\mathrm{T}_{\mathrm{r}}} \cdot \sum_{j=1}^{N_r} \frac{P_{\mathrm{t}} G_{\mathrm{t}} G_{rj} \sigma_{tj} \lambda^2 G_{\mathrm{RP}}}{(4\pi)^3 k T_0 B_{rj} F_{rj} R_{\mathrm{t}}^2 R_{rj}^2}. \tag{31}$$

It is assumed that each transmitter–receiver pair combination in radar network is the same. Rearranging terms in (29) yields:

$$\mathrm{SNR}_{\mathrm{c}} = \frac{\mathrm{T}_{\mathrm{d}}}{\mathrm{T}_{\mathrm{r}}} \cdot \frac{P_{\mathrm{t}} G_{\mathrm{t}} G_{\mathrm{r}} \lambda^2 G_{\mathrm{RP}}}{(4\pi)^3 k T_0 B_{\mathrm{r}} F_{\mathrm{r}} R_{\mathrm{t}}^2} \sum_{j=1}^{N_r} \frac{\sigma_{tj}}{R_{rj}^2}. \tag{32}$$

When the target signals arrive at an angle ϕ with respect to the normal direction, the corresponding main lobe gain of phased array radar can be calculated as:

$$G_{\mathrm{t}} = \eta N \pi \cos\phi, \tag{33}$$

where η is antenna efficiency, and N is the number of elements. Substituting (31) into (30), the SNR equation for radar network can be simplified as follows:

$$\mathrm{SNR_c} = \frac{T_\mathrm{d} P_\mathrm{t} (\cos\phi)^2}{T_\mathrm{r} B_\mathrm{r} R_\mathrm{t}^2} C_1 \sum_{j=1}^{N_r} \frac{\sigma_{tj}}{R_{rj}^2}, \tag{34}$$

where

$$C_1 = \frac{(\eta N \pi)^2 \lambda^2 G_\mathrm{RP}}{(4\pi)^3 k T_0 F_\mathrm{r}}, \tag{35}$$

It is known to us all that transmitting energy is the minimum if the achieved SNR in radar network at each time index is equal to the predetermined SNR threshold. Then, we have:

$$\frac{T_\mathrm{d} P_\mathrm{t} (\cos\phi)^2}{T_\mathrm{r} B_\mathrm{r} R_\mathrm{t}^2} C_1 \sum_{j=1}^{N_r} \frac{\sigma_{tj}}{R_{rj}^2} = \mathrm{SNR_{min}}. \tag{36}$$

Rearranging terms yields:

$$P_\mathrm{t} = \mathrm{SNR_{min}} \frac{T_\mathrm{r} B_\mathrm{r} R_\mathrm{t}^2}{T_\mathrm{d} P_\mathrm{t} (\cos\phi)^2 C_1} \sum\nolimits_{j=1}^{N_r} \frac{R_{rj}^2}{\sigma_{tj}}. \tag{37}$$

Substituting (35) into (22), (22) can be rewritten as:

$$\begin{aligned} p_\mathrm{I} &= p_\mathrm{s} \cdot p_\mathrm{t} \cdot p_\mathrm{f} \cdot p_\mathrm{d}^{'} \\ &= \frac{T_\mathrm{d}}{2T_\mathrm{I}} \mathrm{erfc} \left(\sqrt{-\ln p_\mathrm{fa}^{'}} - \sqrt{\mathrm{SNR_{min}} \frac{T_\mathrm{r} B_\mathrm{r} C_2}{T_\mathrm{d} C_1 \cos\phi} \sum_{j=1}^{N_r} \frac{R_{rj}^2}{\sigma_{tj}} + \frac{1}{2}} \right). \end{aligned} \tag{38}$$

where

$$C_2 = \frac{\eta N \pi G_\mathrm{i} \lambda^2 G_\mathrm{IP}}{(4\pi)^2 k T_0 B_\mathrm{I} F_\mathrm{I}}. \tag{39}$$

Let us define $a = \sqrt{-\ln p_\mathrm{fa}^{'}}$, $b = \mathrm{SNR_{min}} \frac{T_\mathrm{r} B_\mathrm{r} C_2}{C_1 \cos\phi} \sum_{j=1}^{N_r} \frac{R_{rj}^2}{\sigma_{tj}}$, $x = T_\mathrm{d}$, $c = T_\mathrm{I}$, then (36) can be described as:

$$p_\mathrm{I}(x) = \frac{x}{2c} \mathrm{erfc} \left(a - \sqrt{\frac{b}{x} + \frac{1}{2}} \right). \tag{40}$$

After basic algebraic manipulations in Chen et al. (2014), we can obtain:

$$\frac{\mathrm{d}^2 p_\mathrm{I}}{\mathrm{d}x^2} < 0, x \in [T_\mathrm{r}, \overline{T_\mathrm{max}}]. \tag{41}$$

Therefore, it can be concluded from (39) that the intercept probability is upper convex with respect to the dwell time. Intuitively, the optimal point is always at the boundary, i.e., $T_\mathrm{d} = \overline{T_\mathrm{max}}$, or $T_\mathrm{d} = T_\mathrm{r}$. That is to say, the minimum intercept probability can be obtained at the boundary, that is, $\min\{p_\mathrm{I}(T_\mathrm{r}), p_\mathrm{I}(\overline{T_\mathrm{max}})\}$. Moreover, the transmit power can be calculated in (35) with the obtained T_d. To be specific, if $T_\mathrm{d} = \overline{T_\mathrm{max}}$, the corresponding LPI strategy is called the minimum power strategy, in which case the radar transmitter transmits at minimum power at all times and use maximum signal integration. The intent is always to stay below the intercept receiver threshold (Lynch 2004). While if $T_\mathrm{d} = T_\mathrm{r}$, the LPI strategy is known as the

Table 1 Radar transmitter and receivers locations

Radar	Locations
Radar transmitter	[0, 0] km
Receiver 1	[0, 0] km
Receiver 2	[8, 6] km
Receiver 3	[−8, 6] km
Receiver 4	[0, 10] km

Table 2 Radar network parameters

Parameter	Value	Parameter	Value
N	2000	τ	1×10^{-6} s
η	0.9	B_{r}	1 MHz
σ_{tj} $(\forall j)$	30 m^2	F_{r}	3 dB
G_{RP}	40 dB	λ	0.03 m
T_{r}	5×10^{-4} s	f_c	10 GHz
$\overline{P_{\max}}$	12 KW	$\mathrm{SNR}_{\min}$	16.2 dB

Table 3 Intercept receiver parameters

Parameter	Value	Parameter	Value
p'_{fa}	10^{-8}	G_{IP}	2 dB
F_{r}	6 dB	T_{I}	2 s
G_{I}	0 dB	B_{I}	1 GHz

minimum dwell strategy, which is to keep the exposure time as short as possible. This means that the radar transmitter should be in its high power mode for the minimum time possible. Generally, the revisit interval, dwell time, and transmit power should be optimized based on the real-time status information in hostile environment, such that the LPI performance in radar network can be enhanced.

So far, we have completed the formulation of LPI based adaptive resource management strategy for target tracking in distributed radar network systems. In the following, some numerical simulations are dedicated to show the effectiveness of our presented method.

4 Numerical results

In this section, numerical simulation results are provided to verify the accuracy of the theoretical derivations as well as demonstrate the enhancement of the LPI performance brought by our proposed adaptive resource management scheme. A distributed radar network with one dedicated radar transmitter and $N_r = 4$ spatially distributed receviers is considered. Herein, the locations of radar transmitter and receivers are shown in Table 1. We set the system parameters as shown in Tables 2 and 3.

The IMM–EKF algorithm is employed in the simulation with three target dynamic models: (1) a constant velocity model F_{CV}, (2) a coordinate turn model F_{CT} with positive turn rate $\omega = \pi/180$, and (3) a coordinate turn model F_{CT} with negative turn rate $\omega = -\pi/180$.

$$F_{\mathrm{CV}} = \begin{bmatrix} 1 & T & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & T \\ 0 & 0 & 0 & 1 \end{bmatrix}, \tag{42}$$

$$F_{\mathrm{CT}} = \begin{bmatrix} 1 & \frac{\sin(\omega T)}{\omega} & 0 & \frac{\cos(\omega T)-1}{\omega} \\ 0 & \cos(\omega T) & 0 & -\sin(\omega T) \\ 0 & \frac{1-\cos(\omega T)}{\omega} & 1 & \frac{\sin(\omega T)}{\omega} \\ 0 & \sin(\omega T) & 0 & \cos(\omega T) \end{bmatrix}, \tag{43}$$

where T is the time interval between successive frames. For all the models, the covariance matrix of the process noise is set to be:

$$\mathbf{Q}(k-1) = \sigma^2 \begin{bmatrix} \frac{T^4}{4} & \frac{T^3}{2} & 0 & 0 \\ \frac{T^3}{2} & T^2 & 0 & 0 \\ 0 & 0 & \frac{T^4}{4} & \frac{T^3}{2} \\ 0 & 0 & \frac{T^3}{2} & \frac{T^4}{2} \end{bmatrix}, \tag{44}$$

where $\sigma^2 = 0.04^2$. The covariance matrices of the measurement errors:

$$\mathbf{N}_{\mathrm{AM}}(k) = \mathrm{diag}\,\underbrace{\{\sigma_{\mathrm{r}}^2, \sigma_{\nu}^2, \sigma_{\theta}^2, \ldots, \sigma_{\mathrm{r}}^2, \sigma_{\nu}^2, \sigma_{\theta}^2\}}_{3\times N_r}, \tag{45}$$

$$\mathbf{N}_{\mathrm{PM}}(k) = \mathrm{diag}\,\underbrace{\{\sigma_{\mathrm{TDOA}}^2, \sigma_{\mathrm{FDOA}}^2, \sigma_{\theta}^{'2}, \ldots, \sigma_{\mathrm{TDOA}}^2, \sigma_{\mathrm{FDOA}}^2, \sigma_{\theta}^{'2}\}}_{3\times (N_r-1)}, \tag{46}$$

where $\sigma_{\mathrm{r}} = 0.1$ km, $\sigma_{\nu} = 0.1$ Hz, $\sigma_{\theta} = 0.001^{\mathrm{o}}$, $\sigma_{\mathrm{TDOA}} = 1.5$ km, $\sigma_{\mathrm{FDOA}} = 5$ Hz, and $\sigma_{\theta}^{'} = 0.2^{\mathrm{o}}$.

The expected covariance matrix $\mathbf{P}_{\mathrm{d}}$ is set to be:

$$\mathbf{P}_{\mathrm{d}} = \begin{bmatrix} 0.1 & 0 & 0 & 0 \\ 0 & 0.1 & 0 & 0 \\ 0 & 0 & 0.1 & 0 \\ 0 & 0 & 0 & 0.1 \end{bmatrix}, \tag{47}$$

The initial model probabilities are 0.95 for the target to be in the constant velocity model, 0.025 for the target to be in the coordinate turn model with positive turn rate, and 0.025 for the target to be in the coordinate turn model with negative turn rate. The initial model transition probability matrix is set to be:

$$\mathbf{P}_{\mathrm{t}} = \begin{bmatrix} 0.98 & 0.01 & 0.01 \\ 0.01 & 0.98 & 0.01 \\ 0.01 & 0.01 & 0.98 \end{bmatrix}, \tag{48}$$

The simulated target trajectory is illustrated in Fig. 2. The initial position and velocity of the simulated target are [100, 80] km and [0.20, 0.15] km/s, respectively. The target takes a right turn between 30 and 110 s, and takes a left turn between 140 and 200 s. The time interval between successive frames is $T = 2$ s, and a sequence of 100 frames are utilized in the simulation.

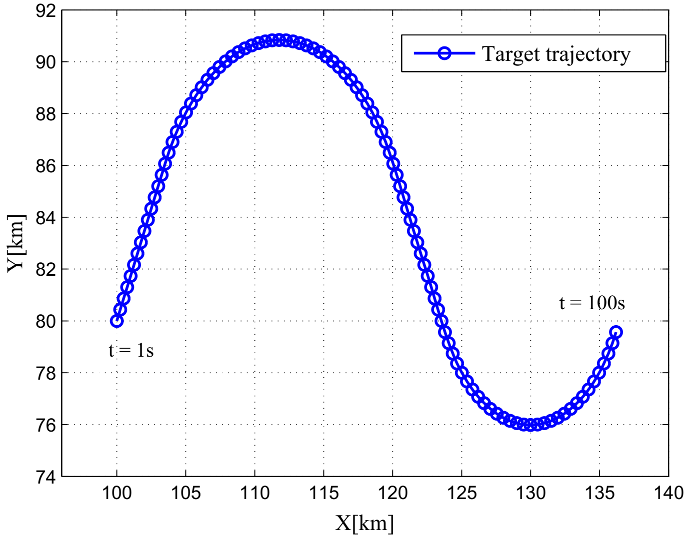

Fig. 2 Simulated target trajectory

4.1 Simulation example 1: target tracking performance

To better show the optimality of our proposed strategy, Figs. 3 and 4 illustrate the root mean square error (RMSE) and the average root mean square error (ARMSE) of the whole target tracking process, respectively. The RMSE at the kth tracking interval can be calculated as:

$$\mathrm{RMSE}(k) = \sqrt{\frac{1}{N_{\mathrm{MC}}} \sum_{n=1}^{N_{\mathrm{MC}}} \left\{[x(k) - \hat{x}_n(k|k)]^2 + [y(k) - \hat{y}_n(k|k)]^2\right\}}, \tag{49}$$

where N_{MC} is the number of Monte-Carlo trials, and $[\hat{x}_n(k|k), \hat{y}_n(k|k)]$ is the target state estimate at the nth trial. The ARMSE is defined as follows:

$$\mathrm{ARMSE} = \frac{1}{N_{\mathrm{T}}} \sum_{k=1}^{N_{\mathrm{T}}} \mathrm{RMSE}(k), \tag{50}$$

where N_{T} is the total frames in the simulation. The target tracking performance, in terms of RMSE of different RRCFs, has been compared in Fig. 3 averaged over 500 Monte Carlo trials. It can be clearly observed in Fig. 3 that the target tracking performance degrades as expected with the increase of RRCF. This is due to the fact that the expected error covariance matrix $\delta \cdot \mathbf{P}_{\mathrm{d}}$ is increased as the RRCF goes up, which demonstrates that there exists a restrictive relationship between the RRCF and the target tracking accuracy. In addition, there is sudden increase in all errors both between 30 and 110 s and between 140 and 200 s, which are the results of the targets turns during those periods. It is worth to mention that the proposed algorithm can recover significantly fast from the target-turning event.

The comparisons of various target tracking algorithms are shown in Fig. 4. As depicted in Fig. 4, the target tracking performance of the standard IMM–EKF algorithm is the best, which exhibits the smallest ARMSE in target tracking. This is because that the dedicated radar transmitter is scheduled to radiate the maximum energy in each time index. Moreover, it is worth pointing out that the covariance control methods utilized in Chen et al. (2014)

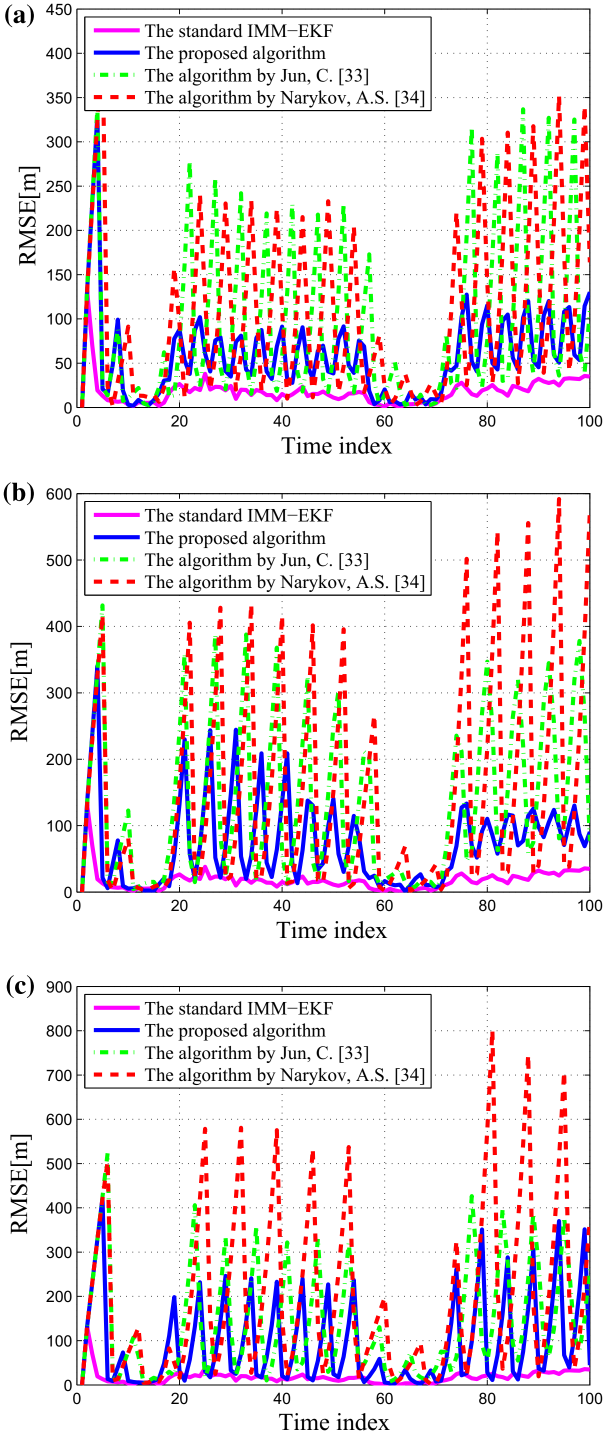

Fig. 3 Target tracking RMSE for various algorithms with different RRCFs. **a** $\delta = 1$, **b** $\delta = 2$, **c** $\delta = 3$

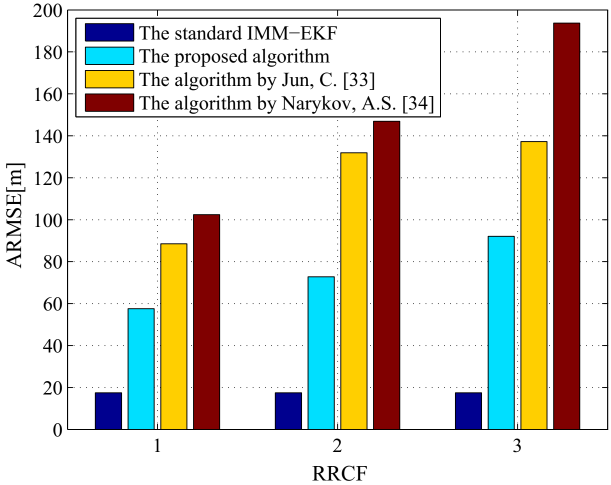

Fig. 4 Target tracking performance of various algorithms

and Narykov et al. (2013) do not perform well compared to our proposed algorithm. This is due to the fact that the proposed algorithm can obtain the best trade-off between the target tracking accuracy and the LPI performance in radar network. In other words, the uncertainty ellipse of the predictive error covariance matrix $\mathbf{P}_{\text{pre}}^{\text{IMM}}(k+1|k)$ may be not contained in the uncertainty ellipse of the expected error covariance matrix $\delta \cdot \mathbf{P}_{\text{d}}$ even though the trace of $\mathbf{P}_{\text{pre}}^{\text{IMM}}(k+1|k)$ is much smaller than that of $\delta \cdot \mathbf{P}_{\text{d}}$. This demonstrates the superior target tracking performance of the proposed algorithm.

4.2 Simulation example 2: LPI performance

In order to disclose the effects of our proposed algorithm on the LPI performance in radar network, Figs. 5, 6, and 7 illustrate the LPI performance for various algorithms with different RRCFs. As can be seen, the intercept probability utilizing our proposed LPI based adaptive resource management scheme is significantly smaller than those of other algorithms, which confirms the remarkable LPI performance enhancement by exploiting the presented scheme in radar network. Furthermore, taking Fig. 5 for example, the last two subplots in Fig. 5a show the values of dwell time and transmit power, from which we observe that at each step the radar radiation parameters, in terms of the revisit interval, transmit power, and dwell time, are adaptively optimized to minimize the objective function in (23), resulting in the best LPI performance for radar network.

Figure 8 shows the comparisons of the total times of radar radiation with different RRCFs. Analyzing the results provided in Fig. 8 reveals that higher target tracking accuracy can be obtained by decreasing of the RRCF, and so more measurements are needed to guarantee the accuracy during the target tracking process. It should be noted that the total times of radar radiation exploiting the covariance control algorithms proposed in Chen et al. (2014) and Narykov et al. (2013) are much smaller, but they exhibit worse target tracking accuracy. At last, as illustrated in Fig. 9, we depict the ratio of radiation times to ARMSE for various algorithms with different RRCFs, from which it can be concluded that the presented strategy achieves the best trade-off between the target tracking accuracy and the LPI performance in radar networks.

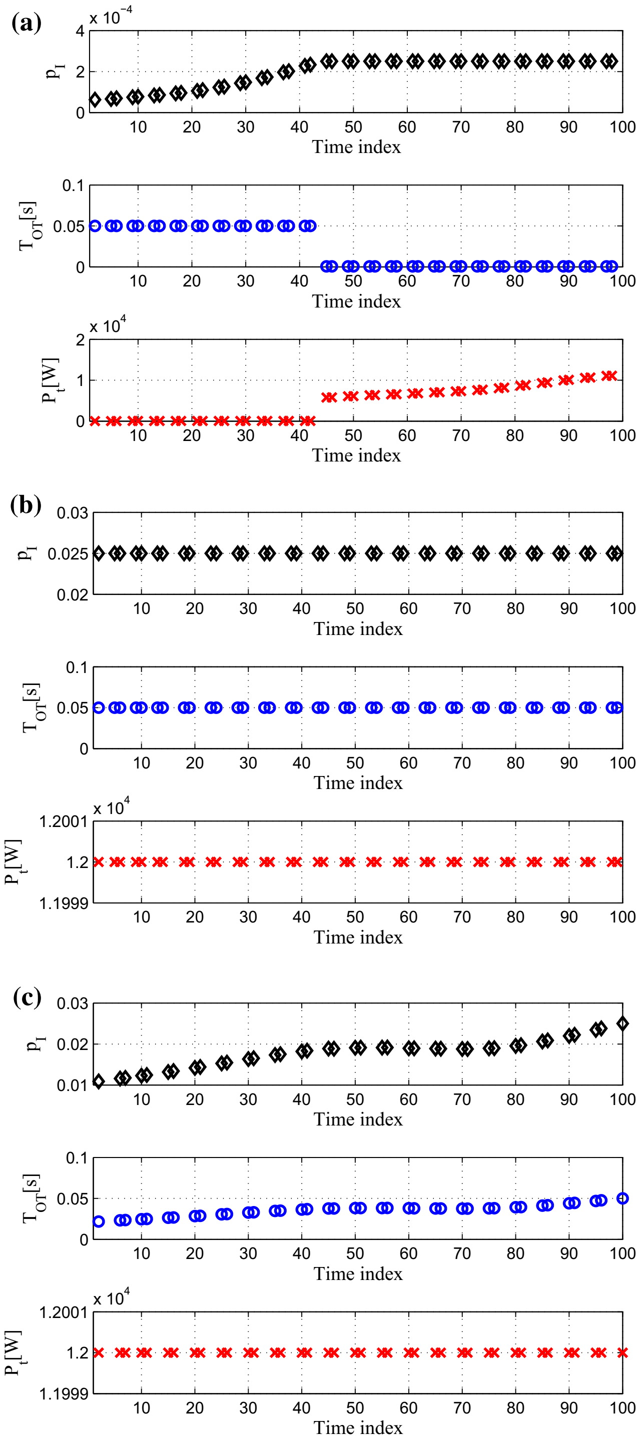

Fig. 5 LPI performance for various algorithms with $\delta = 1$. **a** The proposed algorithm, **b** the algorithm proposed by Jun, C., **c** the algorithm proposed by Narykov, A.S.

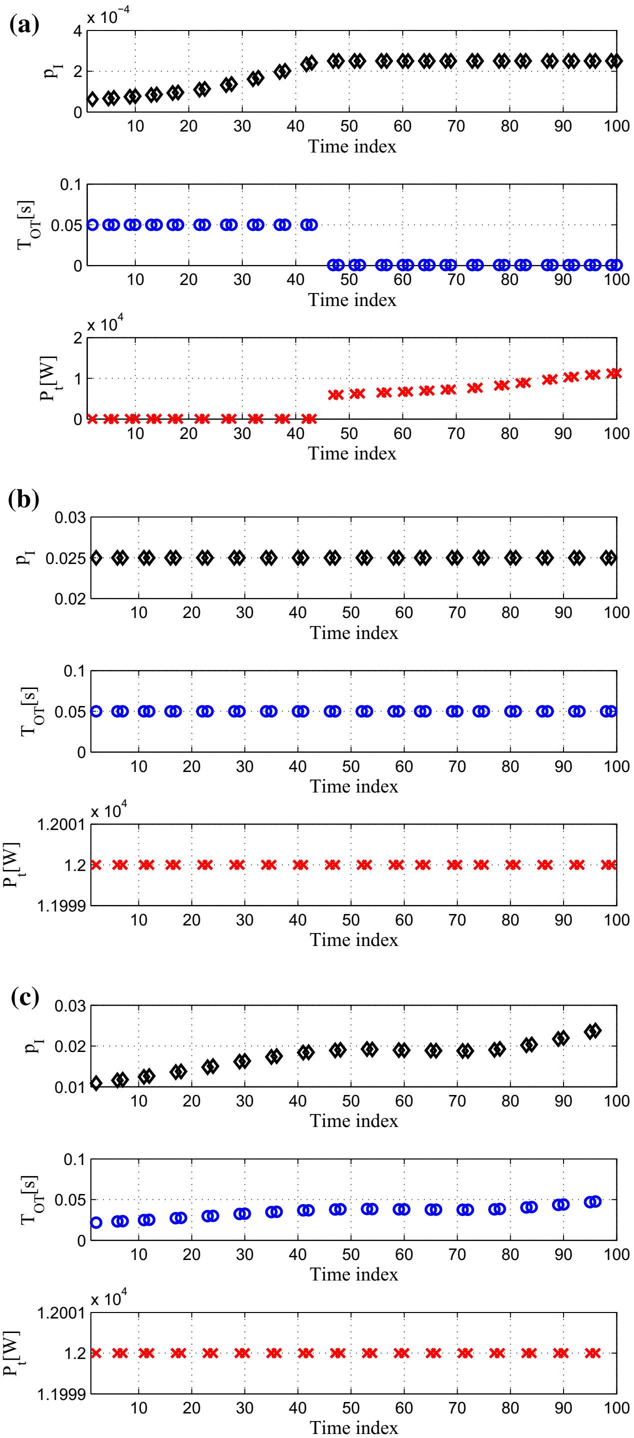

Fig. 6 LPI performance for various algorithms with $\delta = 2$. **a** The proposed algorithm, **b** the algorithm proposed by Jun, C., **c** the algorithm proposed by Narykov, A.S.

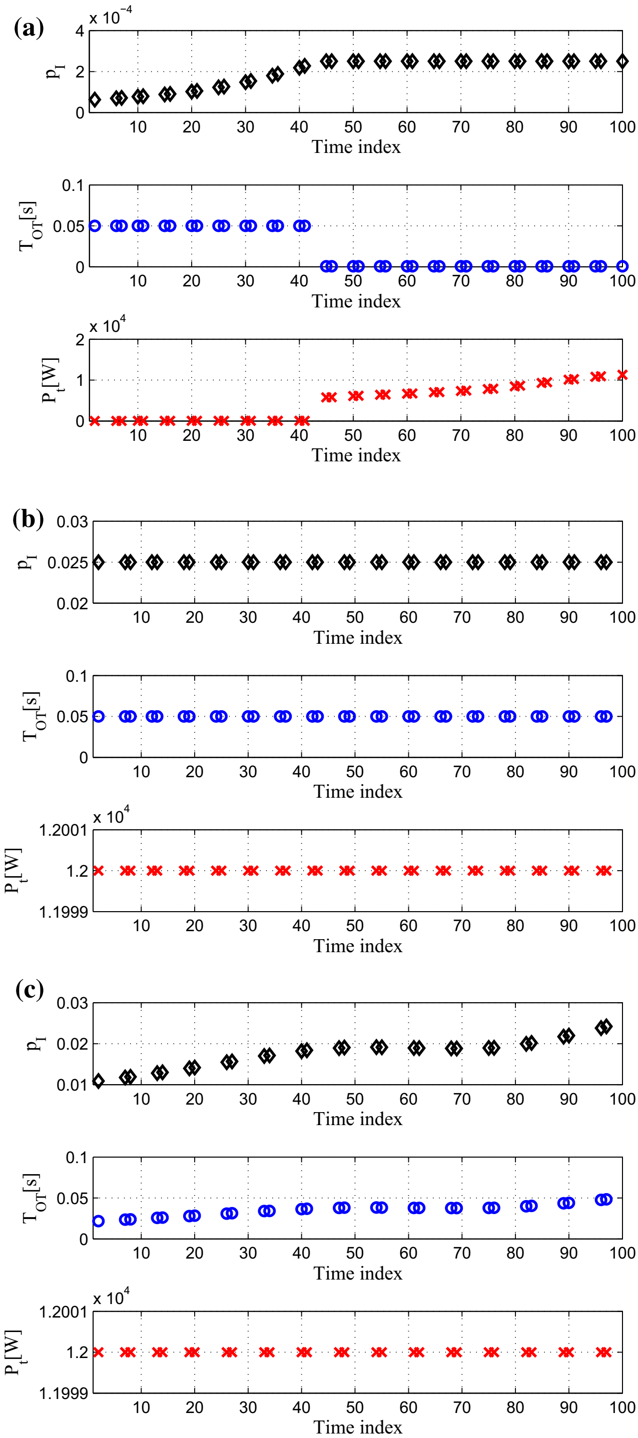

Fig. 7 LPI performance for various algorithms with $\delta = 3$. **a** The proposed algorithm, **b** the algorithm proposed by Jun, C., **c** the algorithm proposed by Narykov, A.S.

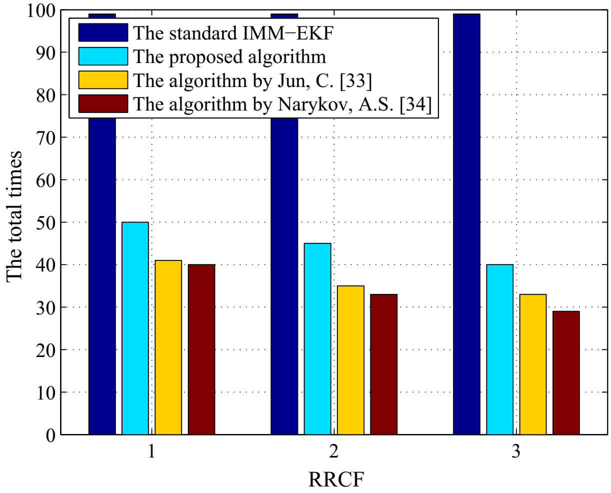

Fig. 8 The total times of radar radiation for various algorithms with different RRCFs

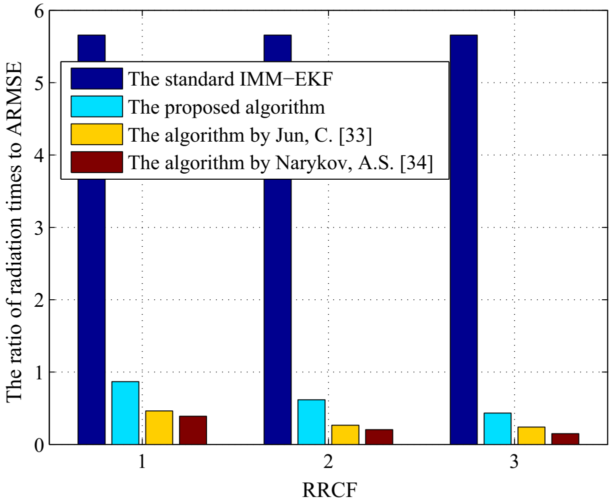

Fig. 9 The ratio of radiation times to ARMSE for various algorithms with different RRCFs

5 Conclusions

In this paper, the problem of adaptive resource management based on LPI in radar network is investigated, in which the objective function for LPI performance is minimized by optimizing the revisit interval, dwell time, and transmit power for a specific target tracking performance with TDOA and FDOA cooperation. Simulation results are provided to demonstrate that the proposed scheme not only provides excellent target tracking accuracy, but also has better LPI performance comparing with other algorithms. It should be noted that only single target is considered in this paper. Nevertheless, it is convenient to be extended to multiple-target scenario, and the conclusions obtained in this study suggest that similar LPI benefits would be achieved for the multiple targets case.

In future work, we will extend our analysis to multiple-target scenario. We will utilize real radar data for target tracking to validate the effectiveness of the presented algorithm. Furthermore, we will extend this strategy to the problem of selecting the optimal radar transmitter/receiver for radar network. Finally, we will employ the proposed objective function for other radar network problems including radar task scheduling.

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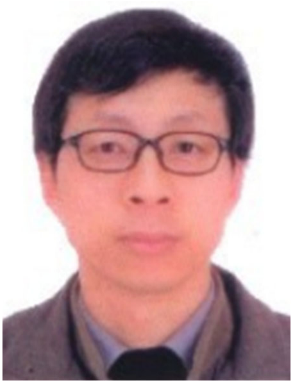

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