An adaptive dwell time scheduling model for phased array radar based on three-way decision

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Abstract: Real-time resource allocation is crucial for phased array radars to undertake multi-task with limited resources such as in the situation of multi-target tracking, in which targets need to be prioritized so that resources can be allocated accordingly and effectively. In this paper, a three-way decision-based model is proposed for adaptive scheduling of phased radar dwell time. Using the model, the threat posed by a target is measured by an evaluation function, and therefore, a target is assigned to one of the three possible decision regions, i.e., positive region, negative region, and boundary region. A different region has a various priority in terms of resource demand, and as such, a different radar resource allocation decision is applied to each region to satisfy different tracking accuracy of multi-target. In addition, the dwell time scheduling model can be further optimized by implementing a strategy for determining a proper threshold of three-way decision making to optimize the thresholds adaptively in real-time. The advantages and the performance of the proposed model has been verified by experimental simulations with comparison to the traditional two-way decision model and the three-way decision model without threshold optimization. The experiential results have demonstrated that the performance of the proposed model has a certain advantage in detecting high threat targets.

Keywords: phased array radar resource scheduling, three-way decision, threat assessment

1. Introduction

In recent years, phased array radar technology has achieved a rapid development. Compared with the traditional mechanically radars, this type of radar can flexibly change the direction of the emitted wave to select a target to be illuminated, and adjust the parameters such as transmit power, dwell time and beam width. These features provide the possibility to manage and optimize radar resources, so that radar resources, such as dwell time, revisit time and beam width, can be managed reasonably to save radar power, improve accuracy of measurement and tracking, and maximize the maximum number of tracking targets, save time and other effects. Therefore, in a situation where only limited radar resources are available, such as multi-target tracking, it is indispensable to properly schedule radar resources in order to enable phased array radars to track as many targets as possible with as less time resources as possible.

There have been some studies on radar resource management or optimization. Common methods include resource scheduling methods based on covariance

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control [1-4], resource management algorithms based on tracking and filtering algorithms [5-7], and radar resource scheduling methods based on the target threat[8-10]. The resource scheduling method based on covariance control is computationally complex with slow operation speed and high system computational resource consumption. Literatures [5][6] proposed an adaptive dwell time design method based on the IMMPDA (Interact Multiple Mode-Probability Data Association) tracking algorithm and IMMPF (Interacting multiple model particle filter) algorithm, respectively. In [7] a new method was proposed for calculating target revisit time based on IMM (Interacting Multiple Model) filtering algorithm. These three methods do not take into account factors such as target attributes and treat them equally. In contrast, radar resource scheduling methods based on the target threat do not have such problems. However, the target threat degree is mostly estimated and ranked according to ranking algorithms [11-13]. In the case of a large number of targets, it is difficult to efficiently and accurately manage each target separately. Therefore, in this paper， it is proposed to classify targets according to the degree of threat to solve the above problems.

Among the classification methods based on target threats, the two-way classification method [14] is simple, but the classification results have low accuracy and poor results. The method based on Bayesian network [15-17] can directly output the probability of a target in a certain category. However, this method requires a large amount of training data or expert knowledge to obtain the conditional probability of target attributes. Therefore, the method cannot obtain the result of the target threat classification conveniently and accurately. In order to solve the problems of the existing methods and better classify the targets, this paper introduces three-way decision theory [18-20].

Compared with the traditional two-way decision model with only two decision making options - a positive decision and negative decision - the three-way decision model has a third option: a boundary decision. The three-way decision theory is frequently used to solve the problem of information uncertainty in various fields, and the problem of target uncertainty information exists in the classification process of target threat assessment. Based on the three-way decision model, a target is assigned into one of the three regions, i.e., positive region, negative region, or boundary region. Compared with the Bayesian Network algorithm, the three-way decision does not require a large amount of training data in principle.

One of the major issues of the three-way decision is to determine an appropriate set of thresholds. In the application literature [21-23], the thresholds of the three-way decision are mostly set to some fixed values obtained based on the degree of Classification loss set by experience or expert. This method is relatively subjective, and the accuracy of the results is not high. It cannot effectively adapt to changes in the environment. Therefore, this paper will use dynamic adaptive thresholds, and consider toinclude radar resource utilization in a cost function to calculate the optimal threshold at each time moment, and continuously update them.

Figure 1 shows the proposed radar time resource scheduling model. The key idea here is: based on the three-way decision model, a target is assigned to one of the three regions, and each region corresponds to a different tracking accuracy. Then, we determine dwell time based on the tracking accuracy. This model can optimize thresholds of the current time point according to the scheduling result of the radar time at the last time point to re-classify targets and re-allocate the dwell time. The model adjusts the dwell time allocation in real-time based on situational changes of a target.

The remainder of this paper is organized as follows. Section 2 presents the three-way decision model and the evaluation function for assigning a target into a proper region. Section 3 discusses in detail how to make adaptive adjustment of threshold and how the proposed scheduling method works. The analytical experiments and the relevant results obtained are given in Section 4, and finally, the concluding remarks are summarized in Section 5.

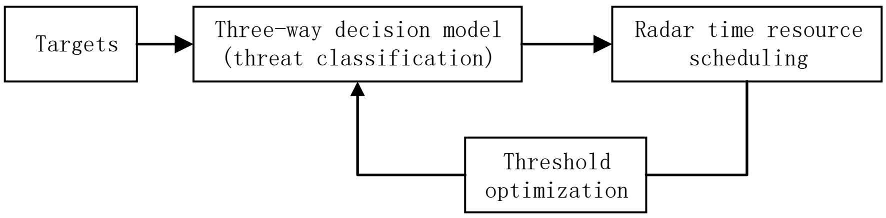

Fig. 1 Radar time resource scheduling model**.**

2. Target classification

In this paper, it is proposed to assign each target in a multiple-target tracking situation into an appropriate region of three possible regions before assigning radar resources. This Section describes in detail how to determine an evaluation function of a target and how to assign a target into one of the three decision regions according to the value of the evaluation function of a target.

2.1 Three-way decision model

The three-way decision was proposed by Yao in 2010 on the basis of decision-theoretic rough set [24], and it introduces a third option of decision-making, namely no commitment or delay so potentially losses caused by false rejection or false acceptance of decision-making could be avoided. In comparison, in the traditional two-way decision approach, only acceptance or rejection are considered.

In the three-way decision, there is a domain defined by a finite non-empty set **U**. Let *A* donate a finite set of condition attributes. Based on the condition set *A*, the main task of the three-way decision is to divide the entity set **U** into three disjoint regions, denoted as *POS*, *NEG* and *BND*, respectively, indicating positive region, negative region and boundary region.

In practical applications, it is indispensable to construct the evaluation function which reflects the extent to which an entity in the entity set **U** meets the condition set *A* and the specified thresholds for classification for three-way decision model [25].

Definition 1: Given a subset $X \subseteq \mathbf{U}$, an evaluation function $\mu(x)$ and a pair of thresholds α and β with $0 \leq \beta < \alpha \leq 1$, the positive region, boundary region and negative region are defined as follows:

$$\begin{aligned} POS(X) &= \{x \in U \mid \mu(x) \geq \alpha\} \\ BND(X) &= \{x \in U \mid \alpha < \mu(x) < \beta\} \\ \mathrm{NEG}(X) &= \{x \in U \mid \mu(x) \leq \beta\} \end{aligned} \quad (1)$$

It is assumed that there is a state space $\Omega = \{X, \neg X\}$. Let X denote high threat and $\neg X$ denote low threat. According to **Definition 1**, we can use an evaluation function for classification of targets. In this paper, we use the threat level of a target as the evaluation function to classify each target into one of the three possible decision regions: high threat region, low threat region and boundary region. Threat degree as an evaluation function is affected by many measures relating to the target, such as speed, distance, altitude, heading angle, and interference ability of a target. Therefore, each target can be represented by a feature vector $\boldsymbol{x}_i = \left(g_{i1}, g_{i2}, ..., g_{ij}, \cdots, g_{im}\right)$, where $g_{ij}\left(j=1,2,\cdots,m\right)$ represents the j^{th} feature of a target i affecting a threat. We can find a target threat $\mu\left(\boldsymbol{x}_i\right)$ by the feature vector $\boldsymbol{x}$ of a target. The specific algorithm is given in the next section. Based on an evaluation function $\mu\left(\boldsymbol{x}_i\right)$, if a pair of thresholds $0 \le \beta < \alpha \le 1$ is introduced, then options for decision-making are as follows:

If $\mu\left(\boldsymbol{x}_i\right) \ge \alpha$, choose to accept, $\boldsymbol{x}_i \in POS\left(X\right)$, belonging to high threat;

If $\mu\left(\boldsymbol{x}_i\right) \le \beta$, choose to reject, $\boldsymbol{x}_i \in NEG\left(X\right)$, belonging to low threat;

If $\beta < \mu\left(\boldsymbol{x}_i\right) < \alpha$, choose not to commit or delay the decision, $\boldsymbol{x}_i \in BND\left(X\right)$, belonging to the boundary region.

2.2 Evaluation function model

In order to deal with any uncertain information of a target, such as the uncertainty of target situation information, and the uncertainty in the environment and meteorology, the evaluation function (threat degree) is usually obtained by an evaluation method based on intuitionistic fuzzy reasoning [26-28].

Definition 2: There exists a set of interval numbers $\left[a_{ij}^L, a_{ij}^U\right]$, $i=1,2,3,...,n$, $j=1,2,3,...,m$. There are two types of interval numbers: the benefit type (the bigger the better) and the cost type (the smaller the better). The algorithm for converting the interval numbers of the benefit and the cost type interval into intuitionistic fuzzy numbers is as follows:

For the benefit type:

$$\left[b_{ij}^L, b_{ij}^U\right] = \left[\frac{a_{ij}^L}{\max\limits_{1\le k\le n}\left(a_{kj}^U\right)}, \frac{a_{ij}^U}{\max\limits_{1\le k\le n}\left(a_{kj}^U\right)}\right] \tag{2}$$

For the cost type:

$$\left[b_{ij}^L, b_{ij}^U\right] = \left[\frac{\min\limits_{1\le k\le n}\left(a_{kj}^L\right)}{a_{ij}^U}, \frac{\min\limits_{1\le k\le n}\left(a_{kj}^L\right)}{a_{ij}^L}\right] \tag{3}$$

The membership degree of the interval number converted into an intuitionistic fuzzy number is:

$$\mu_{ij} = \gamma \frac{b_{ij}^U}{\max\limits_{1\le k\le n}\left(b_{ij}^U\right)} \tag{4}$$

and the non-membership degree is:

$$\upsilon_{ij} = 1 - \mu_{ij} - \frac{b_{ij}^U - b_{ij}^L}{b_{ij}^U + b_{ij}^L} \tag{5}$$

Definition 3: There exists a set of real numbers for benefit types x_{ij}, $i=1,2,3,...,n$, $j=1,2,3,...,m$, the membership degree and non-membership degree of the benefit type real number converted to the intuitionistic fuzzy number are:

$$\begin{cases} \mu_{ij} = \alpha \dfrac{x_{ij}}{\max\limits_{1\le k\le n}\left(x_{ij}\right)} \\ \upsilon_{ij} = \beta \dfrac{x_{ij}}{\max\limits_{1\le k\le n}\left(x_{ij}\right)} \end{cases} \tag{6}$$

The main steps of the evaluation function algorithm (threat degree) are as follows:

Suppose that there are n targets, and each target has m attributes.

Step 1: The target information, namely the target threat factor, is detected by the radar to obtain the target information matrix: $\boldsymbol{f}=(\boldsymbol{x}_i)_{n\times 1}=(g_{ij})_{n\times m}$, where $\boldsymbol{x}_i$ represents feature vector of the i^{th} target, and g_{ij} represents the value of the j^{th} attribute of the i^{th} target. The speed, distance, altitude and heading angle of the target are represented by an interval number $g_{ij}=\left[x_{ij}^L, x_{ij}^U\right]$, and the interference is represented by a real number $g_{ij}=x_{ij}$;

Step 2: For normalization, different types of data values need to be transformed into intuitionistic fuzzy numbers [29], and an intuitionistic fuzzy decision matrix $\boldsymbol{F}=(s_{ij})_{n\times m}$ is obtained from (4), (5), and (6), where $s_{ij}=(\mu_{ij},\nu_{ij})$, μ_{ij} represents the membership degree of the j^{th} attribute of the i^{th} target; and ν_{ij} represents the non-membership of the j^{th} attribute of the i^{th} target.

Step 3: Calculate the weights of target attribute $\boldsymbol{\omega}=\left[\omega_1, \omega_2, \ldots, \omega_j,\ldots,\omega_m\right]$ using the entropy method:

$$\omega_j=\frac{1-E_j}{m-\sum_{j=1}^{m}E_j}\ (\omega_j\geq 0 \text{ and} \sum_{j=1}^{n}\omega_j=1),$$

where E_j is the intuitionistic fuzzy entropy.

Step 4: Calculate the weighted intuitionistic fuzzy matrix $\boldsymbol{R}=\left(\left[a_{ij}, b_{ij}\right]\right)_{n\times m}$,

where $$\begin{aligned}\left[a_{ij}, b_{ij}\right]&=\omega_j\square\left[\mu_{ij}, \upsilon_{ij}\right]\\&=\left[1-(1-\mu_{ij})^{\omega_j}, \upsilon_{ij}^{\ \omega_j}\right]\end{aligned}.$$

Step 5: Calculate the positive and negative ideal solutions of the weighted intuitionistic fuzzy matrix R. The positive ideal solution is the best solution of each attribute. Negative ideal solution is the worst solution of each attribute:

Positive ideal solution:

$$\boldsymbol{R}^+=\left(\left[a_1^+, b_1^+\right], \left[a_2^+, b_2^+\right], \cdots, \left[a_m^+, b_m^+\right]\right),$$

where $\left[a_j^+, b_j^+\right]=\left[\max_{1\leq i\leq n}a_{ij}, \min_{1\leq i\leq n}b_{ij}\right]$;

Negative ideal solution:

$$\boldsymbol{R}^-=\left(\left[a_1^-, b_1^-\right], \left[a_2^-, b_2^-\right], \cdots, \left[a_m^-, b_m^-\right]\right),$$

where $\left[a_j^-, b_j^-\right]=\left[\min_{1\leq i\leq n}a_{ij}, \max_{1\leq i\leq n}b_{ij}\right]$;

Step 6: Calculate the target threat degree: Calculate the Hamming distances D_i^+ and D_i^- of each target to the positive ideal and the negative ideal according to the distance formula

$$D(A,B)=\frac{1}{2m}\sum_{j=1}^{m}\left(|\mu_A-\mu_B|+|\upsilon_A-\upsilon_B|\right),$$ and

the threat degree is: $W_i=\frac{D_i^-}{D_i^+ + D_i^-}$. The evaluation function in three-way decision $\mu(\boldsymbol{x}_i)=W_i$.

3. Phased array radar resource scheduling method based on three-way decision

3.1 Thresholds adaptation

The three-way decision can produce a pair of thresholds according to a cost function. The cost function in the three-way decision is a function relating to the classification cost.

However, in practical applications, the cost function must consider not only the classification cost but also the cost of implementation of the decision rules [30].

This paper considers the cost of resource allocation of phased array radar after three-way classification, and therefore, the cost function of resource allocation cost_f is added to the cost function of the three-way classification cost_s : cost_s is related to the thresholds α, β and the factor γ between the thresholds; cost_f is expressed as the ratio of the sum of radar dwell time T_{ef} for each target to the working cycle time T of the phased array radar. Hence, the cost function can be expressed as

$$\mathrm{cost}=\mathrm{cost}_s+\mathrm{cost}_f=$$

$$\sum_{\mu(\boldsymbol{x}_i)\geq\alpha}\left(1-\mu(\boldsymbol{x}_i)\right)+\sum_{\beta<\mu(\boldsymbol{x}_j)<\alpha}\left(\begin{array}{l}\mu(\boldsymbol{x}_j)\cdot\dfrac{(1-\alpha)\cdot(\gamma-\beta)}{\gamma\cdot(\alpha-\beta)}\\+\left(1-\mu(\boldsymbol{x}_j)\right)\cdot\dfrac{\beta\cdot(\alpha-\gamma)}{\gamma\cdot(\alpha-\beta)}\end{array}\right)+\sum_{\mu(\boldsymbol{x}_k)\leq\beta}\mu(\boldsymbol{x}_k)\cdot\frac{1-\gamma}{\gamma}+\frac{\sum T_{ef}}{T} \tag{7}$$

The process of deriving the threshold is a typical problem of solving an optimization problem of a cost function. Simulated Annealing is one of the popular methods to solve this kind of problems. The basic principle of the approach is to start from an initial solution i and an initial value t of the control parameter (temperature), and repeat the following steps for the current solution: 1) Generate a new solution; 2) Calculate the difference in fitness function; and 3) Accept or discard the solution, while gradually attenuating the t value. The solution at the end of the algorithm results in an optimal approximate solution. The specific steps of solving the threshold are as follows:

Step 1: Determine the initial temperature T (sufficiently large), the lower limit temperature $T_{\min}$ (sufficiently small), and the number of iterations L for each T value. The fitness function of this paper is $\mathrm{cost}(\alpha,\beta,\gamma)$ according to (7).

Step 2: Randomly generate the initial solution $\boldsymbol{x}_0=(\alpha_0,\beta_0,\gamma_0)$, as the current best solution $\boldsymbol{x}_{opt}=\boldsymbol{x}_0$, calculate the fitness function value $\mathrm{cost}(\boldsymbol{x}_{opt})$.

Step 3: Do Step 4-6 for $l=1,2,...,L$.

Step 4: Make random changes to the current best solution to generate a new solution $\boldsymbol{x}_k$, and then calculate the fitness function value of the new solution $\mathrm{cost}(\boldsymbol{x}_k)$ and the increment of the fitness function value $\Delta\,\mathrm{cost}=\mathrm{cost}(\boldsymbol{x}_k)-\mathrm{cost}(\boldsymbol{x}_{opt})$.

Step 5: When $\Delta<0$, accept the new solution as the current best advantage $\boldsymbol{x}_{opt}$; Otherwise accept the new solution as the current best advantage with a certain probability $P=\exp\left(-\dfrac{\Delta\,\mathrm{cost}}{T_i}\right)$.

Step 6: If the termination condition is satisfied ($l>L$ or several consecutive solutions have not been accepted), the current solution is outputted as the optimal solution to obtain the thresholds α and β, and the program is terminated.

Step 7: T is gradually reduced by the rules of $T_{i+1}=r\cdot T_i$ ($r=0.93$) and $T>T_{\min}$, then go to Step 3.

Here we set the constraint of the solution to $0.1 \le \beta \le \gamma \le \alpha \le 0.7$.

3.2 Phased array radar resource scheduling rules

This Section discusses different allocation rules for phased array radar resources allocation according to the three regions into which a target has been assigned. If a target has been detected[31-32], then certain radar resources should be allocated to the detected target to make it conform to a certain tracking accuracy - The greater the threat, the greater the tracking accuracy to be met; and in the meantime, certain resources should be allocated other undetected target so that it can be detected.

A radar detects, locates, and identifies the target based on the received echo energy. Assuming that the radar shares an antenna for transmitting and receiving targets, the echo power of a target with a distance R from the radar is:

$$P_r = \frac{P_t G_t^2 \lambda^2 \sigma}{(4\pi)^3 R^4 L_r} \tag{8}$$

where P_t is the transmit power, G_t is the antenna gain of radar, λ is the wavelength of the laser, σ is Radar Cross-Section, and L_r is the radar loss factor.

For phased array radar, the target echo power, which calculated by a single phased array cell, is multiplied by the power partition coefficient T_e of purpose unit, accordingly the echo power of the target unit is

$$P_r = \frac{P_t T_e G_t^2 \lambda^2 \sigma}{(4\pi)^3 R^4 L_r} \tag{9}$$

The power partition coefficient

$$T_e = \frac{T_{ef}}{C} \tag{10}$$

where C is the detection period coefficient.

The effective interference power spectral density is:

$$P_{jp} = \frac{P_j G_j G_t^{'} \lambda^2}{(4\pi)^2 R^2 L_j \Delta f_c} \tag{11}$$

where P_j is the interference power transmitted by the target aircraft, G_j is the antenna gain of the jammer, and Δf_c is the interference spectral density. Since $G_t^{'}=G_t$, the interference signal enters from the main lobe of the radar antenna.

Therefore, the signal-to-noise ratio is

$$SNR = \frac{P_r}{N_r + P_{jp}} \tag{12}$$

where N_r represents the sum of the total noise power such as the radar internal noise power and the background noise power.

The target detecting probability is

$$P_d = \frac{1}{2}\left(1 - erf\left(\sqrt{-\ln P_{fa}} - \sqrt{0.5 + SNR}\right)\right) \tag{13}$$

where $erf(z) = \frac{2}{\sqrt{\pi}} \int_0^z \exp(-x^2) dx$ is the error function, the false alarm probability P_{fa} is generally taken as 10^{-5} . A random number P_0 obeying the uniform distribution on the interval $[0,1]$ is generated, and if $P_0 \le P_d$, the condition for finding the target is met, and the radar can find the target.

This paper is mainly concerned with determining the radar dwell time of each target. The major steps are as follows:

Step 1: Determine the detection period coefficient factor C and the azimuth tracking accuracy δ_θ :

$$C=\begin{cases} a_1 & \text{High threat} \\ a_2 & \text{Intermediate domain} \\ a_3 & \text{Low threat} \end{cases},$$

$$\delta_\theta=\begin{cases} b_1 & \text{High threat} \\ b_2 & \text{Intermediate domain} \\ b_3 & \text{Low threat} \end{cases}$$

where a_1,a_2,a_3,b_1,b_2,b_3 are constants. C and δ_θ are determined according to the results of the three-way classifications: the greater the threat, the smaller C and δ_θ. Therefore, we have $a_1<a_2<a_3$, $b_1<b_2<b_3$.

Step 2: Take $T_{ef0}=T_{ef\min}$, $T_{ef\min}$ is the minimum value of the retention time T_{ef} .

Step 3: Calculate expected SNR and detecting probability P_d .

T_e is calculated by (10), and the signal-to-noise ratio and the probability of discovery are obtained by (9), (11), (12) and (13), successively. If $P_d<P_{d,\min}$, increase the dwell time

$$T_{efi}=T_{efi}+c \tag{14}$$

where c is a constant, to recalculate the SNR and P_d , until $P_d\geq P_{d,\min}$ is met, and then proceed to the next step. If the maximum value of the dwell time still does not meet the limit value of the detecting probability, proceed directly to the next step.

Step 4: Select a proper dwell time.

The azimuth tracking accuracy is determined according to the classification result of the three-way decision on the target threat degree. Then calculate the azimuth standard deviation $\sigma_{\Delta\theta}$ according to formula $\sigma_{\Delta\theta}=\dfrac{\theta_{0.5}}{1.89\sqrt{2SNR}}$ and compare it with the set azimuth tracking accuracy δ_θ . If $\sigma_{\Delta\theta}\leq\delta_\theta$, save the time in an array and go to the next step, or increase the dwell according to (7), and return to Step 3. If the maximum time of the dwell time is still not met, take the minimum dwell time and go directly to the next step.

Step 5: Calculate the total dwell time of all targets.

Step 2 to Step 4 are repeated to obtain the dwell times corresponding to the respective targets and add them.

Step 6: Calculate the threshold based on according to Section 3.1.

Step 7: Reclassify the target based on the updated threshold and return to Step 1.

4. Simulation and analysis

This Section provides experimental simulations to demonstrate the adaptive scheduling process of phased array radar dwell time in a multi-target environment based on the proposed model in Section 1. The process includes radar detection classification and dwell time allocation of multi-target. This experiment testifies the effectiveness of the adaptive model based on the three-way decision on phased array radar dwell time scheduling when phased array radar detects and tracks multiple targets.

In the experiment, a ground-radar model was established and 10 different maneuvering targets in the air were considered, each of which was conducting self-defense jamming to avoid the detection by the phased array radar. Earth-fixed coordinate system with ground-radar as the origin was established. The target status is shown in Table 1.

Table 1. Status of an air target

Target	Initial position （km）	Initial speed (m/s)	Maneuver	Maneuvering Direction (relative to radar)	Self-defence jamming (W)
1	(100, 80, 4)	（-250, -100, 0）	varying acceleration	close	300
2	(55,105,5.5)	（-250, -250, 0）	varying acceleration	close	100
3	(95, 50, 2.5)	（0, 200, 0）	varying acceleration	away	10
4	(70, -90, 2.5)	（-150,-200, 0）	varying acceleration	away	50
5	(-300, 120, 3.5)	（200,-200, 0）	varying acceleration	close	50
6	(-85, 218, 2.75)	（100,-250, 0）	varying acceleration	close	100
7	(-70,-250, 3.25)	（280, 200, 0）	uniform speed	close	10
8	(110,100, 3)	（-250, -200, 0）	uniform speed	close	200
9	(130, 95, 5.5)	（150, 250, 0）	varying acceleration	away	150
10	(200, -100, 4.5)	（200, 200, 0）	varying acceleration	away	120

It is known from Step 1 in Section 2.2 that the distance, speed, and angle of the target are expressed by interval values. This involves measurement errors of a radar. Interval values are obtained by superimposing error signals on the basis of real values, and these errors satisfy White Gaussian Noise.

The standard deviation of the radar distance error is

$$\sigma_{\Delta R} = \frac{c}{2} \cdot \frac{\tau}{2\sqrt{SNR}} \tag{15}$$

where c is the speed of light and τ is the pulse width.

If the pulse doppler identification is used to measure the speed, the standard deviation of the speed error is

$$\sigma_{\Delta v} = \frac{\lambda}{2} \cdot \frac{0.39\Delta f}{\sqrt{SNR}} \tag{16}$$

where Δf is the resolution of the doppler frequency.

The standard deviation of angle error is

$$\sigma_{\Delta \theta} = \frac{\theta_{0.5}}{1.89\sqrt{2SNR}} \tag{17}$$

where $\theta_{0.5}$ is the half-power width of the antenna beam.

A random number l obeying $N(0,\sigma)$ is generated. The interval number of target measurement information is expressed as $[x-|l|, x+|l|]$, where σ is the standard deviation of each error, and x is the real value of targets.

In order to demonstrate the effect of the three-way decision and the selection of the threshold, the performance of the phased array radar has been compared in the following three modes of radar resource scheduling:

1. Using the three-way decision threshold model in Section 3.1 to realize threshold adaptive change, the targets are assigned into three regions under the real-time threshold:
    - The positive region (high threat) with a required azimuth tracking accuracy 0.1;
    - The boundary region with a tracking accuracy of 0.2; and
    - The negative region (low threat) with a tracking accuracy of 0.3;
2. The three-way decision classifies the

target at a fixed threshold (0.6, 0.4), which requires the azimuth tracking accuracy to be the same as 1;

3. Under the traditional two-way decision, the targets are simply assigned into high threat and low threat according to the threshold of 0.5, and the standard deviation of the tracking angle error was required to be 0.1 and 0.3, respectively.

During the 120-second simulation, we assumed that the radar transmit peak power was 16MHz, the radar center frequency was 3GHz, the antenna gain was 35dB, the loss factor L_r and L_j were 4 and 3. Dwell time met $0.01 \le T_{ef} \le 0.2$, and the increment of adjusting was 0.01 *s*.

Fig. 2 shows the adaptive change of the three-way decision thresholds in Mode 1:

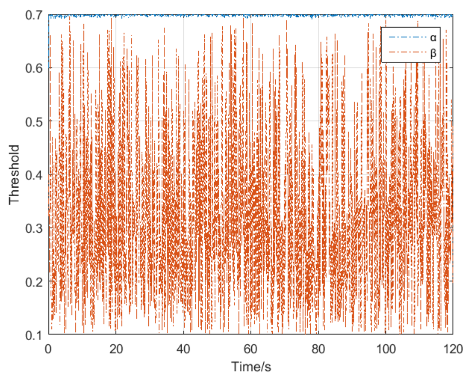

Fig. 2 The change of Three-way decision thresholds.

Then, a comprehensive comparison can be made with regard to the working efficiency of the radar from various aspects including the cumulative detection probability of the target and the utilization of the radar resources under three-way decision and traditional two-way decision, and exploring the effect of threshold on three-way decision, the necessity of resource management allocation and the feasibility of the allocation method.

For the situation of target detection, the time taken for the cumulative detection probability of the target to be 1 was used as the judgment standard, due to the large simulation time. Fig. 3 shows the result.

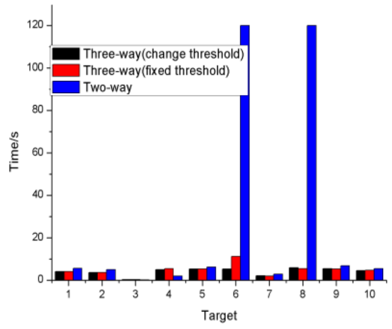

Fig. 3 The time taken for the cumulative detection probability to be 1 in three modes.

The total dwell time reflects the scheduling situation of radar time resources. The results in the three Modes are shown in Fig. 4.

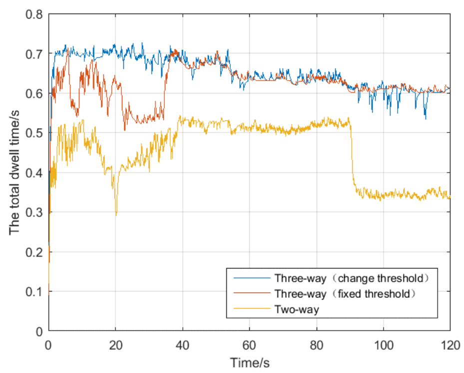

Fig. 4 The utilization of radar time resources in three modes.

As shown in Fig. 3, in addition to Target 4, the time taken for the cumulative detection probability of the target to be 1 was longer and the target detection and tracking had a poor effect under the two-way decision for the other targets. Fig. 4 shows that the radar dwell time of the two decisions was much less than that of the three-way decision. To summarize, the results have indicated that the radar dwell time scheduling method under the two-way decision could have problem in that it can’t allocate enough resources to the target, and the radar time resource cannot be effectively utilized, which would be harmful to the tracking and interception of the target under the two-way decision.

In Modes 1 and 2, the results of the target threat assessment under the three-way decision are shown in Fig. 5 and Fig. 6, where the threat degree of 0 means that the target was lost at that moment:

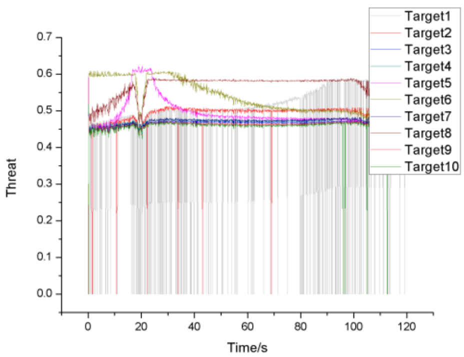

Fig. 5 Target threat in Mode 1.

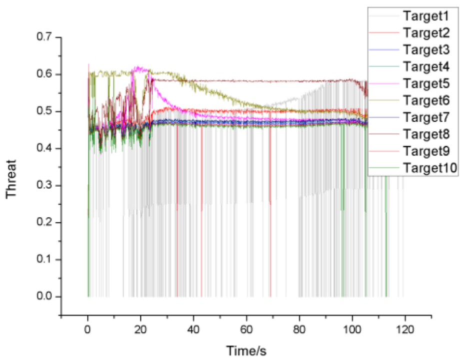

Fig. 6 Target threat in Mode 2.

We compare Mode 1 and Mode 2 to explore the role of thresholds in the three-way decision. As can be seen in Fig. 4, the change of radar dwell time under the three-way decision with adaptive thresholds change was stable. However, the radar dwell time curve under the three-way decision with fixed thresholds was a bit turbulent within 0-40 seconds, and then the radar dwell time curve tended to be smooth. This is because the classification results for targets were different in the two Modes: In Mode 1, the adaptive optimization of the threshold can find the optimal threshold in real time to classify targets and allocate the dwell time reasonably, so that the radar can track the target stably. In Mode 2, as shown in Fig. 6, the targets were divided into three regions according to the threshold (0.6, 0.4), and the detection and tracking of the targets was unstable within 0-40s. After 40 seconds in the simulation, all targets were in the boundary region due to the change of threat degrees, and the target tracking is more stable, so the dwell time curve was relatively smooth. The above analyses show that the selection of the thresholds will affect the classification of targets and the radar dwell time allocation, and this consequently will affect the target tracking.

In addition, comparing the dwell time curves under Mode 1 and Mode 2 in Fig. 4, it is apparent that in 0-40 seconds, the dwell time used in Mode 2 is significantly less than the time used in Mode 1. The key to seizing the initiative in modern warfare is the right to information, so it is crucial to get effective information quickly in the early stages. As shown in Fig. 3, in Mode 1 and Mode 2, there was no significant difference in terms of the time taken for the cumulative detection probability of the target to be 1 except for Target 6 that needs more time in Mode 2. Fig. 5 shows that Target 6 has the greatest threat within 0-20s. It can be seen that Mode 1 can make full use of time resources to enable the radar to quickly detect targets in the early stage, especially the targets with high threats, and facilitate the rapid acquisition of the initiative on the battlefield, so the adaptive optimization of thresholds has a certain advantage in detecting and tracking high threat targets.

In summary, the algorithm proposed in this paper can make full use of radar time resources to make phased array radar detect and track targets more stably and efficiently, especially for high-threat targets. Therefore, the simulation results in all the three Modes have collectively illustrated the effectiveness of the proposed phased array radar dwell time scheduling model proposed.

5. Conclusions

This study aims to address the problem of dwell time scheduling of phased array radar in target tracking, and a phased array radar dwell time scheduling model based on three-way decision has been proposed. Compared with the traditional two-way decision, the proposed model can potentially avoid waste of resources and/or insufficient of radar time resource scheduling, so that the radar can track targets better and prevent the target from being lost. In order to further optimize the dwell time of phased array radar, an adaptive optimization model of three-way decision thresholds has also been established, which implements real-time scheduling of phased array radar dwell time. In addition, the adaptive optimization of thresholds has a certain advantage in detecting high threat targets. The simulation results have shown that the model can improve the accuracy of phased array radar dwell time scheduling in multi-target tracking effectively.

Note that, compared with the method in Mode 2, the proposed algorithm has no obvious advantage for the detection and tracking of the target with less threat. Further improvements, such as the improvement of the threshold solving algorithm, will be made to improve performance in the future.

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