Approaching Intention Prediction of Orbital Maneuver Based on Dynamic Bayesian Network

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Abstract: The complexity of the modern space environment is increasing dramatically under the condition of informatization. Thus, it is difficult for ground operators to process a large amount of information and recognize the approaching intention of unknown objects in a short time. A dynamic Bayesian network model combined with fuzzy theory and experts' experience is designed to help operators recognize the approaching intention quickly and systemically. Compared with the static Bayesian network (SBN), the dynamic Bayesian network is more practical in recognizing the intention of multiple time slices and predicting the future trends through successive probabilities calculation, which is suitable for rapidly changing environment in space. Numerical examples show that the proposed method of intention prediction is feasible and effective.

Key words: dynamic Bayesian network; orbital maneuver; fuzzy set; intention prediction; satellite

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0 Introduction

Space facilities are facing fatal dangers from various flight objects, space debris, and so on. If they carry out orbital maneuver every time they detect danger, lots of fuel will be wasted and their orbital life can be shortened. Consequently, it becomes very important to recognize different intentions of approaching trajectory of satellites, and dodge real dangerous objects further. And, classifying approaching intention has come into being a hot topic.

Approaching intention refers to space flight planning which aims to achieve one specific goal, and it has great influence on operators' analysis and decision-making. But recognizing the approaching intention only by people is very subjective. Facing the large amount of orbit information in space, it is urgent to come up with an intelligent method to classify different risk factors and convert them to probability problem, so as to offer people data reference to evaluate the situation.

The existing research on intention recognition is mainly based on template matching, expert system, Bayesian network, neural network, deep learning, evidence theory and so on[1]. Li et al.[2] proposed a three-way decision-making model based on sequential intention recognition aiming at the temporal problem of air combat target intention recognition. Zhou et al.[3] introduced the rectified linear unit (ReLU) activation function and the adaptive moment estimation (Adam) optimization algorithm, and designed an intention recognition model based on deep neural network. Chen et al.[4] established a fuzzy system model based on integrated neural networks in which target property and the intention are used to train neural networks to obtain the degree of fuzzy membership and output functions of different intentions. Ou et al.[5] proposed an automatic tactical intention recognition model based on deep learning methods of stacked auto-encoder (SAE). Cao et al.[6] proposed a high-dimensional

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data similarity model and used the obtained high-dimensional data similarity to sequentially recognize intentions by means of the theory of D-S evidence. Yang et al.[7] analyzed the limitation of the multi-entities Bayesian network (MEBN) in expressing probabilistic transfer relation and sequence rule knowledge, and proposed the construction method of tactical intention recognition model based on extended multi-entities Bayesian network (EMEBN). However, the simulation results in Ref.[2] only represented the types of intentions in different time periods, but could not describe the data changes of various intentions over time. The methods in Refs.[3-4] were easy to make mistakes when the training data were insufficient. Ref.[5] was possible to make accumulated errors during the training of the model and affect the recognition effect because the input of the model contained the state information of the target at multiple times. Ref.[6] might lead to wrong conclusions if there was a strong conflict between the evidence.

Aiming at the above possible problems, this paper adopts the method of dynamic Bayesian network for intention recognition, which does not need a lot of empirical evidence input and training, and also simplifies the model establishing. Bayesian network is the product of the combination of probability theory and graph theory. It is an uncertain causal correlation model[8]. It not only intuitively shows the relationship among various risk factors in the process of space target approaching with the language of graph theory, but also builds the structure of related problems according to the rules of probability theory to reduce the complexity of orbit reasoning and analysis, which makes it especially suitable for solving the dynamic variability of space information.

At present, there are many literatures on recognizing the approaching intention of air targets by Bayesian network, but most of the researches on space targets are related to threat assessment or situational awareness. In this paper, a dynamic Bayesian network is used to achieve the intention recognizing of space targets in dealing with dynamic changes and unknown information of combat situation.

This paper adopts the method of combining fuzzy set theory and dynamic Bayesian network to process the data of the contemporary space battlefield, which is rational and advanced to some extent. The dynamic Bayesian model established in this paper innovatively sets time transfer probabilities on not only the parent node, but the child node whose values are not easy to obtain for data input. It ensures the authenticity and integrity of the satellite attributes determination and makes up for the situation that the membership function cannot be calculated. Through adding time element, the proposed method has the ability to update the recognition results in real time based on the successive orbital data and professional knowledge, and provide people with valuable combat operation references in probabilistic form. Apart from the approaching intention recognition, this method can also provide new ideas for collision evasion of space debris, which offers the basic evaluation for orbit transfer.

The rest of the paper is organized as follows. Firstly, the problem statement is described in Section 1. The scenario of target approaching is established, where the parameters of satellites and orbits are pointed out. Intention recognition steps and basics of orbit prediction and dynamics are also presented. Subsequently, Section 2 focuses on the introduction of Bayesian network, including various condition assumptions, use of membership function and probability transformation theory. Thirdly, a dynamic Bayesian network model is established according to the research content of this paper, each risk factor and its corresponding conditional probabilities are determined in Section 3. Finally, Section 4 realizes the simulation of intention recognition over continuous moments by inputting the prior probabilities and evidence obtained from the orbital data.

1 Problem Description of Approaching Intention Prediction

There are many possible intentions for an unknown space target to approach a satellite with prediction ability, as shown in Fig.1 by blue satellite and red satellite separately. Several potential intentions are included, such as on-orbit repairment, disassembly, attack, interference, etc. Generally, approaching to satellite is implemented by means of orbital maneuver, and intention prediction takes advantage of orbital prediction and relative attributes among satellites.

To describe approaching intention prediction, some parameters need to be declared:

(1) $d_{\min}$ is the minimum distance between two satellites of prediction satellite (PSat) and unknown satellite (USat), namely, the minimum distance between Orbit 1 and Orbit 2 in Fig.1.

(2) $d'_{\min}$ is the minimum distance between PSat's orbit and USat's new orbit that is generated from orbital maneuver at position M.

(3) Point M denotes the position where USat makes orbital maneuver.

(4) Point A denotes the position where the distance between Orbit 1 and Orbit 3 reaches the minimum value.

(5) Orbit 1 represents the orbit of the PSat, and Orbit 2 and Orbit 3 represent the orbits of the USat before and after maneuvering, respectively.

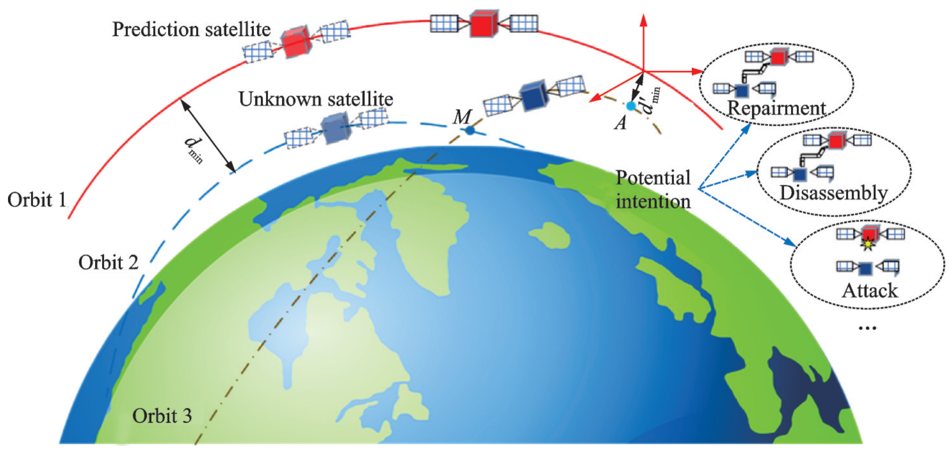

Fig.1 Scenario of satellite approaching intention prediction

The approaching intention prediction problem usually refers to determining the USat's approaching intention at the closest distance between two orbits and the position before and after maneuvering. These are the places where the intention is most obvious and likely to change. The prediction procedures are separated into five steps.

Step 1 Establish the motion model of satellite.

Step 2 Use the Runge-Kutta method to realize orbital prediction based on the motion model.

Step 3 Analyze various risk factors that affect intention recognition and build dynamic Bayesian network.

Step 4 Choose proper membership function and conditional probability for reasoning.

Step 5 Realize the approaching intention recognition.

Orbit prediction is to predict the position and velocity of a space target through kinematics equation or mathematical analysis under its current state[9]. Its essence is the process of solving the differential equation describing the motion of the space target.

When the perturbation force is not considered, the orbital dynamics model of the space target represents the two-body problem, which is shown as

$$\ddot{\boldsymbol{r}} = -\frac{\mu}{r^3}\boldsymbol{r} \tag{1}$$

where $\boldsymbol{r} = [x, y, z]^{\mathrm{T}}$ is the position of satellite in the equatorial inertial coordinate, $r = |\boldsymbol{r}|$ the geocentric distance and μ the geocentric gravitational constant, $\mu = 3.986\,005 \times 10^{14}\ (\mathrm{m}^3/\mathrm{s}^2)$.

When the perturbation force is considered, the motion equation is represented as

$$\ddot{\boldsymbol{r}} = -\frac{\mu}{r^3}\boldsymbol{r} + \boldsymbol{a} \tag{2}$$

where $\boldsymbol{a} = [a_x, a_y, a_z]$ is the sum of the perturbation acceleration, which includes the acceleration caused by the earth's non-spherical perturbation, the gravitational perturbation of the third body (sun, moon), the atmospheric drag perturbation, etc.

In this paper, the orbital dynamic model is established based on J_2-perturbed model, which means only the J_2 perturbation is considered besides the gravity of the earth and is shown as

$$\begin{cases} \ddot{\boldsymbol{r}} = -\dfrac{\mu}{r^3}\boldsymbol{r} + \boldsymbol{a} \\ a_x = -\dfrac{\mu}{r^3}\left[1 - J_2\left(\dfrac{R_e}{r}\right)^2\left(7.5\dfrac{z^2}{r^2} - 1.5\right)\right]x \\ a_y = -\dfrac{\mu}{r^3}\left[1 - J_2\left(\dfrac{R_e}{r}\right)^2\left(7.5\dfrac{z^2}{r^2} - 1.5\right)\right]y \\ a_z = -\dfrac{\mu}{r^3}\left[1 - J_2\left(\dfrac{R_e}{r}\right)^2\left(7.5\dfrac{z^2}{r^2} - 4.5\right)\right]z \end{cases} \tag{3}$$

where R_e is the equatorial radius of the earth[10].

The USat is selected as the space target that may maneuver potentially, and the fourth-order Runge-Kutta method is used to achieve orbit prediction.

2 Description of Bayesian Network

Bayesian network, also known as belief network or directed acyclic graphical model, is a probabilistic graph model which consists of nodes representing variables and directed lines connecting these nodes. The directed lines between nodes represent the relationship between them (from the parent node to its child nodes). Conditional probability is used to express the relationship strength, and prior probability is used to express information if there is no parent node[11].

The Bayesian network model of a single time slice is called the static Bayesian network (SBN). The dynamic Bayesian network is based on SBN, on which the time factor is added to make the event reasoning process continuous and be able to calculate the intention probabilities of multiple time slices.

Assume the time-varying node set is $X=\{X_1, X_2, \cdots, X_n\}$, and $X_i[t]$ indicates the state value of the ith variable at moment t, which is a random variable of set $X[t]$. A dynamic Bayesian network can be defined as $(B_0, B_\rightarrow)$, where B_0 represents the initial Bayesian network and $B_\rightarrow$ the transfer network[12].

It is assumed that the Markov chain model is satisfied in the whole change process, namely, that the state at moment t is only affected by that at moment $t-1$, shown as

$$P(X[t+1]|X[0],\cdots,X[t]) = P(X[t+1]|X[t]) \tag{4}$$

And it is assumed that the whole process is static, which means that the transition probability $P(X[t+1]|X[t])$ is independent of time t.

The joint probability distribution of dynamic Bayesian network on $X[0], X[1], \cdots, X[t]$ is

$$P(X[0],\cdots,X[t]) = P(X[0])\prod_{t=0}^{t-1}P(X[t+1]|X[t]) \tag{5}$$

It can be seen that the dynamic Bayesian network can well reflect the time-series relationship among the characteristics of variables by establishing a mathematical model[13].

Bayesian network is based on the probability theory, so the probability values of different variables are the key to intention recognition. The traditional Bayesian network model generally only describes discrete random variables, and the state of variables is limited. However, the reasoning problem of continuous variables also needs to be considered in some cases. Therefore, the concept of fuzzy set is used to classify each variable, and the membership function can be used to express the membership degree to different state attributes of each continuous variable.

In the Bayesian network of intention recognition, each variable corresponds to a risk factor that affects intention recognition, and each risk factor can be classified to several state attributes according to a fuzzy set A. As for continuous variables, the approaching velocity of USat is chosen to be an example which can be fuzzily divided into two attributes: "fast" and "slow" and is assigned to a specific value in all research situations, namely, $X_i[t]=x$. By using the membership functions $A(x)$ corresponding to different attributes, the membership degrees to these two fuzzy subsets can be obtained[14]. The use of fuzzy set classifications can reduce the subjective definition of standards in the process of artificial grading. As for discrete variables, whether to take 0 or 1 as the probability value of their state attribute is completely determined by the observation results.

Commonly used types of membership function include Gaussian, triangular and trapezoidal. At present, there is no definite method to select the specific membership function, and no general theorem or formula to follow. In practice, it is often selected according to the characteristics of specific problems.

It is noted that the membership degree can not be directly applied to Bayesian network based on probability calculation. Therefore, it is necessary to introduce the probability conversion formula through which membership degree can be converted into probability value[15].

Assume $U=\{u_1,u_2,\cdots,u_n\}$ is a discrete finite set, and X is a variable in U. $p(u_i)$ represents the probability when $X=u_i$, $\mu_A(u)$ is the membership function of the fuzzy set A and α indicates the satisfaction degree of the consistency condition of probability conversion, $0<\alpha<1$[16]. Then the probability conversion formula can be represented as

$$p(u_i)=\mu(u_i)^{\frac{1}{\alpha}}\Big/\sum_{k=1}^{n}\mu(u_k)^{\frac{1}{\alpha}} \tag{6}$$

Therefore, for the observed values of continuous variables, when the membership degree of each fuzzy set is obtained, it can be converted into the probability information that can be applied by Bayesian network through the formula above, and the Bayesian network reasoning problem with continuous variables can be solved.

3 Establishment of Dynamic Bayesian Network

The approaching intention of the USat is mainly determined by analyzing and judging various risk factors of the satellite in combination with the characteristics of space situation and operational environment[17]. The approaching intentions of the USat mainly include hover, capture, attack, approach, etc.

The USat often shows different flight velocities when it conducts different space operations, so the relative velocity between USat and PSat is a factor that needs to be considered. In addition, the speed direction of USat, which stands for heading, and the relative distance between USat and PSat which reflects the flight trend jointly determine the relative position. In space environment, whether the position of USat is within our threat range can exert a significant impact on the approaching intention recognition. Generally, if the USat is beyond our threat range, its intention will be more likely to be approach, otherwise, it is more inclined to attack or hover. Moreover, the maneuver situation of the USat is also a main influencing factor of its approaching intention. If one or more maneuver behaviors occur at a certain time, its intention will be likely to change greatly, which may be manifested as approach and hovering. Therefore, combined with the experience of experts, the risk factors of this paper mainly include: relative velocity, relative distance, heading, location and maneuver situation. In addition, considering that the approaching intention of the USat at the last moment will directly affect the judgement at the next moment, time is also regarded as a potential influencing factor in the dynamic Bayesian network.

According to the factors mentioned above, the established dynamic Bayesian network model is shown in Fig.2. In the dynamic Bayesian network model of intention recognition, the relative velocity node and relative distance node are regarded as continuous variables, while approaching intention node, maneuver node, heading node and location node are regarded as discrete variables whose state attributes can be classified in fuzzy set. For example, the maneuver situation is divided into maneuver and non-maneuver, the location is divided into inside and outside of the threat range, and the heading is measured by the angle between the speed vectors of the USat and PSat ranging from 0 to 110 degrees and greater than 110 degrees. For continuous variables, the relative velocity is classified as “fast” and “slow”. Similarly, the relative distance is classified as “far” and “near”.

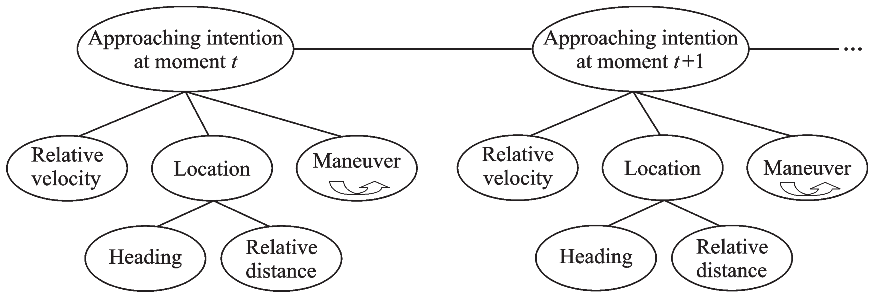

Fig.2 Established dynamic Bayesian network model

In order to obtain the probability evidence of continuous variables at different moments, the first step is to substitute the observed values into the corresponding membership functions. Considering that the relative velocity and the relative distance both change continuously with time, Gaussian membership function commonly used in fuzzy sets is selected to evaluate their state attributes, which is shown as

$$f(x;\varepsilon,\sigma)=\exp\left[-\frac{1}{2}\left(\frac{x-\varepsilon}{\sigma}\right)^2\right] \tag{7}$$

where ε represents the center of the membership function; and σ determines the width of the membership function. The values of these two parameters vary with the selected state attributes. Substituting the observed values as x into the function, the membership degrees of different state attributes can be obtained. Moreover, by using the probability conversion formula in Eq.(6), the membership degrees obtained before can be converted into probability forms.

For discrete variables, whether there is orbital maneuver of the USat or not corresponds to the membership value of 1 or 0. Similarly, after monitoring the velocity vectors of the USat and PSat at a certain moment, the membership degree of heading can also be assigned the value of 1 or 0. These values can be directly used as probability evidence.

Besides, the selection of basic model parameters is also the key to the intention recognition, which means determining the conditional probabilities of each node in the network and the state transition probabilities between time slices, by means of sample learning, creating from the knowledge base or getting advice from experts dedicated to related fields[18]. The conditional probabilities in the model reflect the dependence relationship of each variable and the state transition probabilities represent the probability changes of approaching intentions between successive time slices. In addition, since whether the USat will continue to maneuver in a short time after last maneuvering or not is unclear, this paper also sets another transition probabilities for the "maneuver" node, which is used to calculate the subsequent maneuvering evidence of the USat. In this paper, the conditional probabilities and the transition probabilities are presented by experts' experience.

The conditional probabilities of different variables in the dynamic Bayesian network are shown in Table 1 and Table 2. The probabilities of state transition between successive time slices of dynamic Bayesian network are shown in Table 3[19]. And the transition probabilities for "maneuver" node are shown in Table 4.

Table 1 Conditional probabilities of different distance

Variable of nodes	p (Heading/Location)		p (Relative distance/Location)	
	0°—110°	Greater than 110°	Far	Near
Within the threat range	0.7	0.3	0.3	0.7
Outside the threat range	0.3	0.7	0.7	0.3

Table 2 Conditional probabilities of different states

Variable of nodes	p (Rel-velocity/Intention)		p (Location/Intention)		p (Maneuver/Intention)	
	Fast	Slow	Within the threat range	Outside the threat range	Maneuver	Non-maneuver
Hover	0.5	0.5	0.8	0.2	0.8	0.2
Attack	0.7	0.3	0.7	0.3	0.6	0.4
Capture	0.4	0.6	0.6	0.4	0.7	0.3
Approach	0.3	0.7	0.7	0.3	0.5	0.5

Table 3 State transition probabilities

$p(t+1/t)$	Hover	Attack	Capture	Approach
Hover	0.7	0.1	0.1	0.1
Attack	0.1	0.7	0.1	0.1
Capture	0.1	0.1	0.7	0.1
Approach	0.1	0.1	0.1	0.7

Table 4 Transition probabilities for maneuver node

$p(t+1/t)$	Maneuver	Non-maneuver
Maneuver	0.3	0.7
Non-maneuver	0.7	0.3

Assume that there is no intelligence information in advance, and the prior probability of each approaching intention is equal, which means that the probabilities of different approaching intentions at the initial moment are the same. When the probability evidence of risk factors as well as the probabilities shown in the above three tables is substituted into the dynamic Bayesian network, the approaching intention recognition can be performed by the GeNIe software. Fig.3 shows a flow chart of intention recognition when the USat is observed to be approaching.

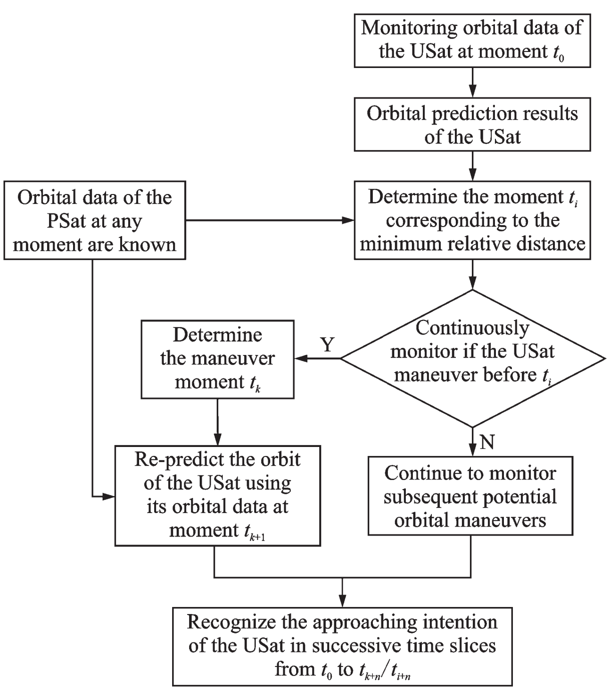

Fig.3 Flow chart of approaching intention recognition

4 Simulation

Assume that the position and velocity information of the USat at a certain time is monitored in inertial coordinate system and set this time as the initial moment t_0. The orbital data of the USat at the subsequent moments can be predicted by the Runge-Kutta method, shown in Table 5. Set the time interval as five minutes and the satellite operation period as one month for data reference. Take some time points as examples. The PSat's orbital data are known at the same time, as shown in Table 6. The relative velocity of two satellites at moment t_0 is

$$v_0=\sqrt{(\Delta v_x)^2+(\Delta v_y)^2+(\Delta v_z)^2}=0.003\,67(\text{km/s})$$

Table 5 Orbit prediction results of the USat

Moment	t_0	t_1	t_2	…	t_{10}
x/km	−37 799.2	−38 198.9	−38 580.3	…	−40 953.3
y/km	18 685.7	17 854.4	17 014.5	…	10 036.9
z/km	38.814 34	37.089 10	35.346 12	…	20.864 90
v_x/(km•s^{-1})	−1.362 42	−1.301 80	−1.240 56	…	−0.731 76
v_y/(km•s^{-1})	−2.756 22	−2.785 37	−2.813 18	…	−2.986 23
v_z/(km•s^{-1})	−0.005 72	−0.005 78	−0.005 84	…	−0.006 20

Table 6 Orbital data of the PSat

Moment	t_0	t_1	t_2	…	t_{10}
x/km	−37 821.3	−38 220.0	−38 600.4	…	−40 965.2
y/km	18 640.7	17 808.9	16 968.5	…	9 987.9
z/km	38.720 51	36.992 30	35.246 39	…	20.743 54
v_x/(km•s^{-1})	−1.359 16	−1.298 51	−1.237 23	…	−0.728 23
v_y/(km•s^{-1})	−2.757 91	−2.786 98	−2.814 72	…	−2.987 17
v_z/(km•s^{-1})	−0.005 73	−0.005 79	−0.005 85	…	−0.006 21

According to the selected membership function in Eq.(7), when the state attribute of velocity is "slow" or "fast" respectively, set $\{\varepsilon,\sigma\}$ as $\{0.000\,10, 0.013\,99\}$ or $\{0.030\,83, 0.013\,99\}$. The chosen values of ε are the minimum and maximum values that can be achieved by the relative velocity between the USat and PSat within the operation period. The value of σ is the average relative velocity within the operation period. Therefore, by substituting the relative velocity between two satellites at moment t_0 to the membership function, the membership degrees of "slow" and "fast" are calculated as 0.968 and 0.152, respectively.

Set the satisfaction degree α as 0.5 in Eq.(6). The membership degrees of "slow" and "fast" can be converted into probability information for Bayesian reasoning by probability conversion formula, which is 0.976 and 0.024, separately.

Similarly, the relative distance between the USat and the PSat at moment t_0 is

$$r_0=\sqrt{(\Delta r_x)^2+(\Delta r_y)^2+(\Delta r_z)^2}=50.134\,0(\mathrm{km})$$

When the state attribute of distance is "near" or "far" respectively, set $\{\varepsilon,\sigma\}$ as $\{0.044\,9,\ 191.904\,1\}$ or $\{423.015\,2,\ 191.904\,1\}$. Similarly, the chosen values of ε are the minimum and maximum values that can be achieved by the relative distance of the USat and PSat within the operation period; the value of σ is the average relative distance within the operation period. Repeat the above progress, the membership degrees of "near" and "far" are calculated as 0.967 and 0.151, and the corresponding probability evidence is 0.976 and 0.024, respectively.

At moment t_0, no maneuvering is detected by the USat from the ground station according to the results of orbit prediction and real orbital data, so the probability information of "maneuver" and "non-maneuver" is determined as 0 and 1, respectively.

According to the velocity vectors of the USat and PSat at moment t_0, the respective flight directions can be determined, and the angle between the velocity vectors of the two satellites can be calculated as follows

$$\theta_0=\arccos\left(\frac{\boldsymbol{v}_{\mathrm{Sat1}}\cdot\boldsymbol{v}_{\mathrm{Sat2}}}{|\boldsymbol{v}_{\mathrm{Sat1}}\|\boldsymbol{v}_{\mathrm{Sat2}}|}\right)=1(°)$$

It can be seen that the headings of the two satellites are nearly parallel, so the probability evidence of "0°—110°" and "greater than 110°" is set as 1 and 0, separately.

Above all, the probability information of each risk factor at moment t_0 is obtained, which is used as the evidence input of Bayesian network, as shown in Table 7.

Table 7 Probability evidence of risk factors at the moment t_0

Relative velocity	Relative distance	Maneuver	Heading
(Fast, Slow)	(Near, Far)	(Maneuver, Non-maneuver)	(0°—110°, greater than 110°)
(0.024, 0.976)	(0.976, 0.024)	(0, 1)	(1, 0)

From the initial moment, the USat is monitored every five minutes, and the evidence input at different moments can be calculated using the above calculation process. The dynamic Bayesian network model is established according to Fig.2, as shown in Fig.4.

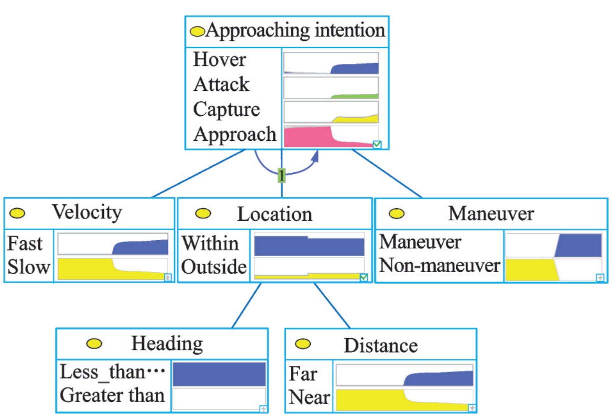

Fig.4 Dynamic Bayesian network model

Assuming that there is no intelligence information in advance, the prior probability of each approaching intention is equal. Substitute the prior probabilities and conditional probabilities of the state attributes to the dynamic Bayesian network model as the known conditions and input the evidence to determine its approaching intention probability values at every moment. Especially, once an orbital maneuver occurs, "maneuver" evidence should still be input as 1 at one or two moments after maneuvering of the USat to ensure the continuity and authenticity of data calculation. And then the "maneuver" evidence will be calculated and input according to Table 4 until the USat maneuvers in orbit again. Choose moment t_0 to t_{25} as the monitoring period of simulation. The complete dynamic Bayesian network is shown in Fig.5.

Fig.5 Complete dynamic Bayesian network of the monitoring period

According to the predicted orbital data of the USat and PSat at t_0, if the two satellites follow original orbits, the minimum value of relative distance $d_{\min}$ between them will be reached after two months. However, after continuous monitoring at fixed time points, assume that the orbital maneuver of the USat is detected at moment t_{13}, when the approaching intention of the USat is likely to change greatly and needs to be paid attention to. Probabilistic evidence for intermediate moments is not presented here. The specific information before and after the maneuver moment is shown emphatically below.

The monitoring orbital data of the PSat and the USat at moment t_{12} are shown in Table 8. According to the above calculation process, the probability evidence at moment t_{12} can be obtained, as shown in Table 9.

Table 8 Orbital data at moment t_{12}

t_{12}	x/km	y/km	z/km	v_x/(km•s^{-1})	v_y/(km•s^{-1})	v_z/(km•s^{-1})
USat	−41 353.1	8 235.954	17.127 16	−0.600 44	−3.015 39	−0.006 26
PSat	−41 362.8	8 186.477	17.000 95	−0.596 87	−3.016 17	−0.006 27

Table 9 Probability evidence at moment t_{12}

Relative velocity	Relative distance	Maneuver	Heading
(Fast, Slow)	(Near, Far)	(Maneuver, Non-maneuver)	(0°—110°, greater than 110°)
(0.042,0.958)	(0.979,0.021)	(0,1)	(1,0)

The orbit prediction results of the USat and the orbital data of PSat at moment t_{13} are shown in Table 10. Re-predict the new orbit of the USat with moment t_{13} as the initial moment, re-select the parameters in the membership function and repeat the calculation process to get the probability evidence at moment t_{13}, which are shown in Table 11.

Table 10 Orbital data at moment t_{13}

t_{13}	x/km	y/km	z/km	v_x/(km•s^{-1})	v_y/(km•s^{-1})	v_z/(km•s^{-1})
USat	−41 521.8	7 337.830	15.229 60	−0.534 99	−3.027 76	−0.006 29
PSat	−41 532.0	7 279.672	15.117 00	−0.530 75	−3.028 51	−0.006 29

Table 11 Probability evidence at moment t_{13}

Relative velocity	Relative distance	Maneuver	Heading
(Fast, Slow)	(Near, Far)	(Maneuver, Non-maneuver)	(0°—110°, greater than 110°)
(0.490,0.510)	(0.502,0.498)	(1,0)	(1,0)

The partial recognition results of dynamic Bayesian network are shown in Figs. 6—8, including the approaching intention at initial moment, the last moment, and the moments before and after the maneuver. The transition of "maneuver" evidence input can be seen in Fig.7 and Fig.8.

According to the recognition results of twenty-five consecutive moments in Fig.5, the change curve of intentions of the USat during the approaching process is obtained, as shown in Fig.9. The abscissa is the continuous moments, where T represents the number of five-minute interval from the current moment to the initial moment, and the ordinate is the probability values corresponding to every five-minute.

According to the recognition results, it can be seen that the main approaching intention of the USat has changed a lot before and after the maneuver. At

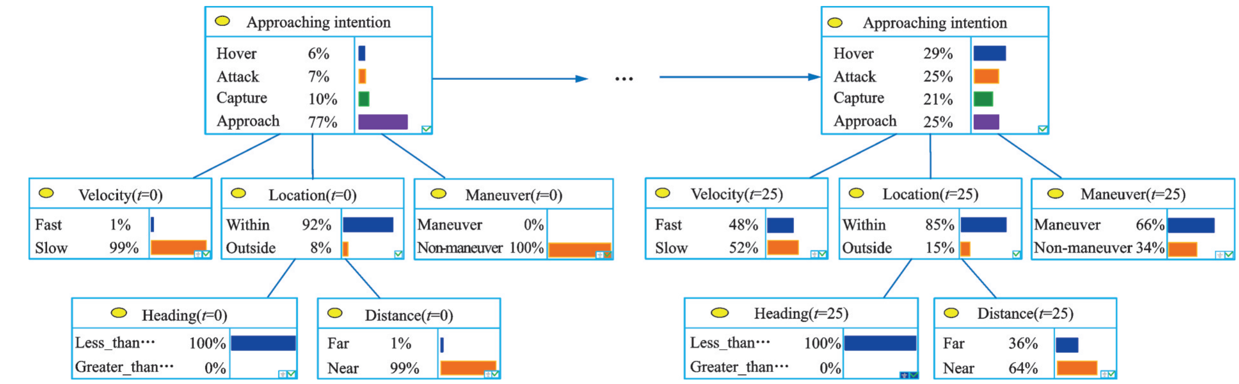

Fig.6 Recognition results of approaching intention of USat at moment t_0 and t_{25}

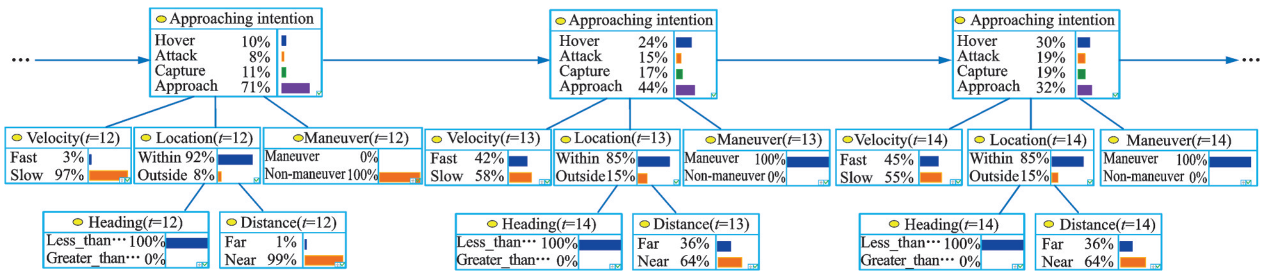

Fig.7 Recognition results of approaching intention of USat from moment t_{12} to t_{14}

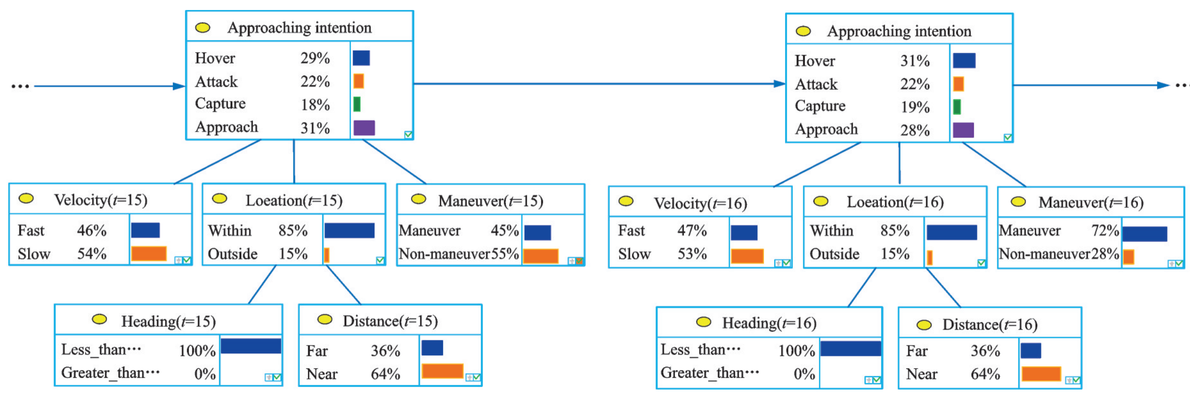

Fig.8 Recognition results of approaching intention of USat from moment t_{15} to t_{16}

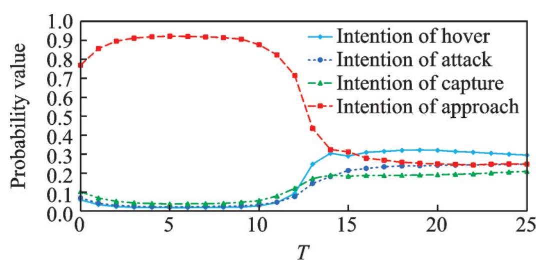

Fig.9 Approaching intention change curves of the USat

moment t_{12}, the probability of "Approach" begins to decrease greatly, while the probability of "Hover" gradually increases until the moment t_{16} when the intention of "Hover" becomes the main approaching intention after the maneuver of the USat. Compared with Tables 7, 9 and 11, it can be seen that when the chosen interval of each moment is short enough and no maneuver of satellite is detected, there are not big changes in the state attributes such as relative velocity, relative distance and heading, so that the approaching intentions of two consecutive moments are roughly the same, which can also be seen in Fig. 9. However, when the USat makes one or more maneuvers at some moments, the probability curve may fluctuate greatly, which indicates that its approaching intention starts to change. And then, when the maneuvering evidence input is completed, the variation of recognition results tends to be stable, in which stage the clear data reference can be offered to operators and the subsequent intention recognition can proceed. Therefore, taking multiple time slices and proper time-step to monitor in dynamic Bayesian network is of great significance to the real-time update of the USat's orbit and recognition results, which can provide ground operators with the latest and specific battlefield information to map out effective strategies.

5 Conclusions

Aiming at the problem that the approaching intention of unknown targets in space battlefield is dynamic and multifactorial, this paper introduces the prediction method of approaching intention using space relative motion model, and establishes a dynamic Bayesian network model for recognition. From the simulation results, different types of approaching intentions are given in probabilistic form and the change curve can be seen clearly, which are important references of decision-making for ground operators to carry out corresponding evasion operations. This method, which can be applied to the space battle scene to realize the tactical intention reasoning of enemy's targets in continuous time slices, is verified to be feasible and effective.

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基于动态贝叶斯网络的轨道机动接近意图预测

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摘要:在信息化条件下,现代空间环境的复杂性急剧增加,地面操作人员难以在短时间内处理大量信息并识别未知目标的接近意图。本文将模糊理论与专家经验相结合,设计了一种可以帮助操作者快速、系统地识别接近意图的动态贝叶斯网络模型。与静态贝叶斯网络(Static Bayesian network, SBN)相比,动态贝叶斯网络在识别多个时间片内意图和通过连续计算概率预测未来趋势两方面更加实用,适用于快速变化的空间环境。众多算例表明,本文所提出的意图预测方法可行有效。

关键词:动态贝叶斯网络;轨道机动;模糊集;意图预测;卫星