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Airborne Sensor Resource Management in Air Battles based on Fuzzy Bayesian Networks

Abstract. *A method for air combat sensor resource management based on fuzzy Bayesian networks (FBN) is presented. Using the fuzzy value of target information gain, target threat level and pilot command, probabilistic reasoning among the networks is carried out. Simulation results indicate that FBN method performances better in the allocation of sensor resource compared to information gain (IG) method.*

Streszczenie. *W artykule przedstawiono zastosowanie sieci Bayes'a (ang. FBN) w zarządzaniu zasobem czujników w czasie walki powietrznej. Wykorzystując wartość rozmytą informacji o celu, poziom możliwego zagrożenia oraz komendy pilota, zbudowano sieć argumentowania probabilistycznego. Wyniki symulacyjne wykazują, że metoda FBN wykazuje lepsze właściwości alokacji zasobów niż metoda dywergencji Kullbacka-Leiblera (DKL, IG). (**Zarządzanie zasobem czujników w walce powietrznej z wykorzystaniem sieci Bayes'a FBN**).*

Keywords: fuzzy Bayesian networks (FBN); sensor management; target thread; information gain(IG)
Słowa kluczowe: sieć rozmyta Bayes'a FBN, zarządzanie czujnikami, zagrożenie celu, dywergencja Kullbacka-Leiblera (DKL, IG).

Introduction

In modern air combats, the detecting and tracking efficiency of airborne sensors are constrained by the number of targets as well as the flexibility, uncertainty and resource of airborne sensors. Therefore, the airborne sensor management is necessarily to effectively use the resource of sensors to fulfill the needs of target detecting and tracking.

There are some studies proposed several methods to manage sensor resource based on information theory, for example, assignment of sensor resource using comentropy in [1,2] and using targets threating weights in [3,4].

Compared to the previous methods, this paper proposes an airborne sensor resource management method based on fuzzy Bayesian networks (FBN) during air combats. This method achieves the assignment solution of sensor resource, which is based on FBN constructed by two aspects, the causality of the influence factors of the airborne sensor resource management in air battles and the probability reasoning using the gain of target information, target threatening and orders of pilots, etc.

Probability inference in FBN

Denoting $X_1 \ldots X_n$ as the variables of FBN, the joint probability distribution can be represented as follows:

$$P(X_1,\cdots,X_i)=\prod_{i=1}^{n}P(X_i\mid\pi(X_i)) \tag{1}$$

where $\pi(X_i)$ is a set of parent nodes of node X_i, and $P(X_i|\pi(X_i))$ can be determined by the conditional probability table.

The probability inference problem in this paper is mainly about posteriori distributions. Using known variables as the evidences, denoted by E, and e as its values. The posteriori distribution denoted by Q is an query variable. Thus, the posteriori probability is:

$$P(Q\mid E=e) \tag{2}$$

Using Bayes equation, we get

$$P(Q\mid E)=\frac{P(Q,E)}{P(E)}=\frac{P(Q,E)}{\sum_{Q}P(Q,E)} \tag{3}$$

$P(Q,E)$is the joint probability distribution of all the variables in a Bayes network. In FBN, all the variables are classified fuzzily. Thus, the values of those variables are not singular, but multiple values within fuzzy membership sets. Therefore, weights are introduced in the calculation of posteriori probability as follows;

$$P(Q\mid E)=\sum_{j=1}^{k}\frac{P(Q,E)}{\sum_{Q}P(Q,E)}\omega_j \tag{4}$$

where ω_j is the weight of the combination of status, and k is the total number of status combinations. Denoting i as the index of evidence nodes, which has m nodes in total. The number of fuzzy classification for each node is λ_i, then $k=\prod_{i=1}^{m}\lambda_i$. Denoting the status combination S_{ij}, then ω_j can be determined as follows:

$$\omega_j=\prod_{i=1}^{m}\alpha_{iS_{ij}}(E_i=e_i) \tag{5}$$

where $\alpha_{iS_{ij}}(E_i=e)$ is the fuzzy membership value while the value of the evidence node i is e_i and the status combination is S_{ij}.

sensor resource allocation model based the FBN

The air combat sensor resource allocation is influenced by the increment of target information and the target threat level. There is such causal relationship: Increment of target information → Sensor resource, Target threat → Sensor resource. In the actual air combat, target threat is the outcome of the threat assessment, which is determined by battlefield situational factors. In addition, the pilot instruction can directly interfere the allocation of sensor resource. Thus, there is such causal relationship as well: Battlefield situation →Target threat, Pilot instruction→Sensor resource. "→" show the causal relationship between the adjacent nodes. Based on the above causal relationship and combined with the knowledge of expert system, a discrete fuzzy Bayesian network (FBN) can be obtained as shown in Figure 1. The meaning of each node of Figure 1, as shown in Table 1.

Table 1. Node meaning

SNS	The sensor resources allocated level
PO	The pilot task instruction level
INF	Information incremental level
TTR	Target threat level
TP	Target distance threat level
TS	Target approach speed threat level
TA	Target entry angle threat level
TT	Target type threat level
TM	Target weapons threat level
MM	Machine weapons guide demand level

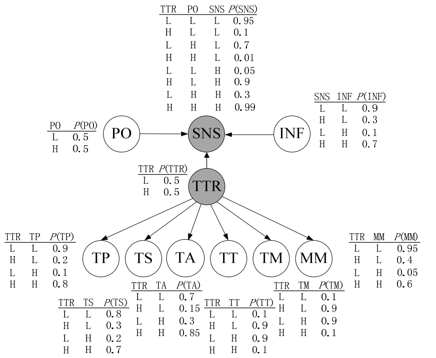

Fig. 1 sensor resource allocation discrete fuzzy Bayesian network

Each node is a binary semantic node, which is classified by fuzzy knowledge. *L* represents a low level and *M* indicates a high level. The conditional probability table of each node is shown in Table 1. The gray nodes are query nodes and the white ones are evidence nodes.

The precise value of the evidence must be stroked before the accurate values of the evidence nodes are calculated, then fuzzy processing could be done. The accurate value of the evidence nodes and the way to do fuzzy processing is shown as follows:

Nodes *INF\TP\TS\TA*

In the process of the airborne sensors achieving perception of battlefield, the precise value of the information increment (*INFp*) can be calculated based on the variation of the uncertain target is as follows:

(6) $$INF_P = \log[\frac{\sqrt{\|^c \ P(k/k-1)\,\|}}{\sqrt{\|^c \ P(k/k)\,\|}}]$$

Where: *P*(*k/k-1*) and *P*(*k/k*) are the prediction error covariance and the filtering error covariance of the targets before and after the measuring.

Target distance (TP_P), approaching speed (TS_P) and the exact value of the entry angle (TA_P) can be estimated directly by using the target state value of the filter system.

In the evidence nodes, the affect from the information increment, approaching speed and the entry angle to the fuzzy classification is benefit-like, which means that the lager the precise value is, the higher level of the fuzzy classification you will get. The fuzzy subordinate degree can be calculated through the increasing of Semi-Gaussian distribution function:

(7) $$\mu_H(x)\begin{cases} =0 & x \le a \\ =1-e^{-k(x-a)^2} & x > a, k > 0 \end{cases}$$

Target distance affection on the fuzzy classification is cost-like, which means that the lager the precise value is, the lower level of the fuzzy classification you will get. The fuzzy subordinate degree can be calculated through the decreasing of Semi-Gaussian distribution function:

(8) $$\mu_H(x)\begin{cases} =1 & 0 \le x \le a \\ =e^{-k(x-a)^2} & x > a, k > 0 \end{cases}$$

In (7) and (8), *α* is the discriminator threshold and *k* is the proportionality coefficient. They can be gained from the experts' experience, for example, the discriminator threshold α of target distance can be calculated by the related location between the target and the weapons launch envelope.

The low level subordinate degree of each node can be determined based on $\mu_H(x)$:

(9) $$\mu_L(x) = 1 - \mu_H(x)$$

Nodes *TT\TM\MM\PO*

All of the target types, the target weapons state, local machine weapons state, pilot task instructions are qualitative factors, which means all of the evidence values (e.g. TT_P, TM_P, MM_P, *and POP*) is qualitative collection of the exact values:

$TT_P \in$ { Bomber，Fighter，UCAV，…},

$TM_P \in$ { Hang up，Offline，Guidance，…},

$MM_P \in$ { Hang up，Offline，Guidance，…},

$PO_P \in$ { Silent，Interference，Attack，…},

When being fuzzed the above evidences can be assigned by the fuzzy subordinate degree assignment based on experts experience directly.

According to the probabilistic reasoning method of Bayesian network and the sensor resource allocation model based on the discrete fuzzy Bayesian network, the steps of the sensor management algorithm is as follows:

Step1：At time *t*, there are *i* kinds of sensor types of executable tasks, namely M_1, $M_2, \cdots M_i$; T_j is the current target. The evidence nodes in the FBN can be calculated by the formula form (6) to (9). Noise may cause some of the evidences unavailable, thus we set the current evidence value equal to the value of the moment *t*-1; if the value of the moment *t*-1 is still not available, and then set the current evidence value equal to the value of the moment *t*-2, and so on. If the initial evidence value is not available, we manually set $\mu_L(x) = \mu_H(x) = 0.5$.

Step2：Based on the evidence node values from step1, the target threat posterior probability can be calculated by the formula (2) to (5): $P(TTR{=}H/E_{TP},E_{TS},E_{TA},E_{TT},E_{TM},E_{MM})$, Then make $\mu_H(TTR_P) = P(TTR{=}H/E_{TP},E_{TS},E_{TA},E_{TT},E_{TM},E_{MM})$,

The posterior probability of the sensor resource assignment level can be calculated by the formula (2) to (5):

$P(SNS{=}H/E_{INF},E_{PO},E_{TTR},E_{TP},E_{TS},E_{TA},E_{TT},E_{TM},E_{MM})$

Step3：Use the task execution conditions to classify the target. The posterior probability of the sensor resource assignment level of T_j is P_j. When $P_j > \varepsilon_i$, do the mission M_i to T_j; When $P_j \leqslant \varepsilon_i$, do not do the mission M_i to T_j; The ε_i is the determine threshold to do the mission M_j, the value of M_j is the mission execute level. Generally, the bigger ε_i is, the more sensor resource requires. When multiple missions satisfy the execution conditions at the same time, do the mission with the biggest determine threshold.

Step4: The algorithm will stop when the simulation meets the preset limit. Otherwise, do the moment t+1 calculation.

Simulation experiment and result analysis

In this simulation, we assume that the aircraft is uniformly flying along a straight line, and an aerial attacker flies towards this aircraft. After a straight line uniformly flying for a period of time, the aerial attacker changes 50 degrees on roll angle and flies towards our aircraft, in order to attack. The attacking failed and the aerial attacker withdraws from the war zone. The entire simulation process lasts for 150 seconds, which is divided into four stages specifically:

Stage 1: from the simulation outset time to the 50th second, the aerial attacker approaches our aircraft with a uniform speed along a straight line;

Stage 2: from the 50th second to the 75th second, the aerial attacker enters the war zone, makes a turn to fly to our aircraft, and implements track locks;

Stage 3: from the 75th second to the 100th seconds, the aerial attacker gives up attacking;

Stage 4: from the 100th second to the end of the simulation, the aerial attacker evacuates from the war zone with a uniform speed along a straight line.

We suppose that our aircraft airborne radar supplies four kinds of patterns (i.e. M_1, M_2, M_3 and M_4) to process the tracking of the aerial attacker. We establish the four kinds of patterns to advantage the simulation analysis, which have the model fixed sampling interval as 0.5, 1, 2 and 4 seconds respectively in advance. Based on this patterns condition, we carry on 100 Monte-Carlo simulations separately using two methods, which are *IG* and *FBN*, and apply to a Kalman filtering model. Denoting the process noise covariance matrix as $Q_1=Q_2=1$, the observation noise covariance matrices are $R_1=10$, $R_2=5$. By using *FBN*, the pilot gets the instruction of silent and attack separately in the stage of T2 and T3.

In the entire simulation procedure with the previous two methods, the sampling interval and the target location mean error (*RMS*) changes simultaneously, which are shown in Figure 2 and Figure 3. The comparison of the performance with the previous two methods is shown in Table 2, 3.

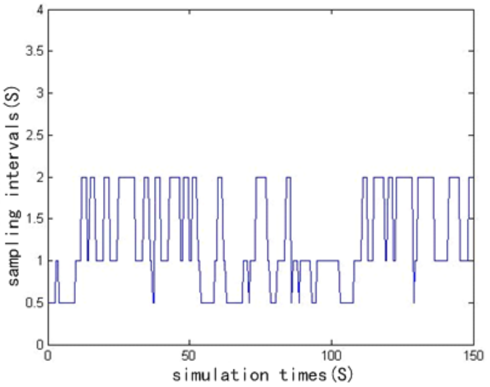

Fig. 2 IG sampling interval change

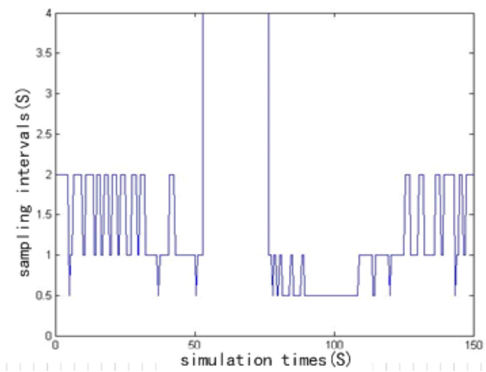

Fig. 3 FBN sampling interval change

Table 2 IG simulation performance parameter

	T1	T2	T3	T4
Number of sampling times	49.50	32.02	26.03	48.33
Sampling intervals(S)	1.27	0.98	1.22	1.34
Position variance(M)	5.07	6.36	5.52	5.88

Table 3 FBN simulation performance parameter

	T1	T2	T3	T4
Number of sampling times	51.19	1.29	60.17	47.12
Sampling intervals(S)	1.19	10.97	0.62	1.75
Position variance(M)	4.98	12.20	2.97	6.51

According to the simulation results, the target sampling intervals of both *IG* and *FBN* are only depend on the influence of filtering models, the performance of the two methods is close, because the targets have no manoeuvring and electronic countermeasure no simultaneously in the T1 stage in simulation; In stage T2, since the aerial attacker was turning its direction and implemented track locking to our aircraft at the same time, the threat of the aerial attacker to our aircraft dramatically increased. To meet the demand of silence of the *FBN* method, the sampling frequency of our aircraft should be decreased sharply. Compared to the *IG* method, the sampling frequency only dropped slightly because it is only influenced by the aerial attacker manoeuvre, which cannot fulfil the silence need under the attack threaten. Similarly, in stage T3, the *FBN* method can react according to the aerial attacker's threat and the attack demand to increase the target sampling number; however the *IG* method only showed a small change. In stage T4, because the aerial attacker evacuated from the war zone and the threat to our aircraft becoming smaller, the *FBN* method reduced the sampling number to the target (fewer than that in stage T1). But the sampling number of *IG* method is still almost the same as that in stage T1, which cannot manifests the influence on the sampling number from the threat change of the aerial attacker.

Conclusion

According to kinds of influence factor of the sensor resource distribution in air battles, this paper proposed a method of air battle sensor resource management based on the fuzzy Bayesian networks (*FBN*). In this method, *FBN* is set up based on the influence factor causal relation in the sensor resource management. The increasing of target information, the aerial attacker threat and the pilot instructions are the evidence variables to be considered to carry on the probability inference and acquire the sensor resource assignment. An auto-adapting sampling intervals strategy is proposed in this paper. The simulation experiment compared with a traditional method, it had been proven that the method in this paper is able to react according to the aerial attacker threat and the pilot instruction, to manage the sensor resource in different stages of an air battle to meet the operational need.

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