A belief-rule-based inference method for carrier battle group recognition

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Abstract. This paper proposes a method for carrier battle group recognition with over-the-horizon radar outputs. A newly developed belief-rule-based inference method is employed to deal with uncertainties in both radar outputs and domain knowledge. The recognition belief-rule base is constructed considering the constraints among sub-targets in the carrier battle group and subsequently the inference according to such hierarchical belief-rule base is implemented. Moreover, the parameters training method is designed to update the belief-rule base through accumulated historical data. The simulation results show that the belief-rule-based inference method is effective to address the uncertainties in carrier battle group recognition, and the method performs much better after parameters training.

Keywords: Belief-rule base • Carrier battle group • Over-the-horizon radar • Target recognition

1 Introduction

The carrier battle group (CVBG) consists of an aircraft carrier and its escorts (carrier-borne aircrafts and other warships), together comprising the combat formation [1]. The CVBG includes capabilities sufficient to accomplish a variety of combat tasks in war, and so the detection and recognition of CVBG become quite urgent for early warning. Over-the-horizon radar (OTHR), as important equipment in early-warning system, can detect beyond-the-horizon targets at ranges of thousands of kilometers [2]. Generally, the outputs of OTHR are target tracks and very limited attribute information can be obtained. However, it's believed that the sub-targets in CVBG usually satisfy some kinds of spacial and subordinate relation-

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ship and it's possible to recognize CVGB as a whole with higher reliability by mining the internal constraints among the sub-targets.

The CVGB recognition problem based on the outputs of OTHR faces many challenges as follows. Firstly, because of the vast sight scope, the clutters may be mistakenly detected as target and thus it makes the target tracks information with great probability uncertainty. Secondly, limited by radar's detecting accuracy, the target tracks information has great fuzzy uncertainty. Lastly, sometimes the experts' subjective information will be utilized when the target tracks information provided by radar is inadequate. As a result, an inference method that can address the information with both probability uncertainty and fuzzy uncertainty, as well as subjective information, is needed. Recently, a generic rule-based inference methodology using the evidential reasoning approach (RIMER) has been proposed [3], which provides a flexible and effective framework to represent not only precise data but also vagueness and ignorance in knowledge, as well as a rigorous inference procedure to deal with such hybrid uncertain information. It has been used for clinical guideline [4], nuclear safeguards evaluation [5], and new product development [6].

Motivated by above consideration, to support modelling and reasoning with radar outputs information and domain knowledge under uncertainties, we propose to employ RIMER for developing the CVGB recognition method. The belief-rule base (BRB) for CVGB recognition is constructed considering the constraints among sub-targets in CVGB and subsequently the inference based on such hierarchical BRB is implemented. Furthermore, the parameters training method is designed to update the BRB through accumulated historical cases in order to obtain higher recognition rate.

2 Outline of RIMER

In RIMER, BRB is used to model domain specific knowledge under uncertainty, and the evidential reasoning (ER) approach is employed for inference with BRB. In this section, we provide a brief introduction to BRB first, and then we outline the process of inference with BRB using the ER approach.

2.1 Modelling Domain Knowledge Using BRB

In order to model the uncertainty in domain knowledge, the belief rule extended from the traditional 'IF-THEN' rule with a belief structure can be described as

$$R_k: \text{If } x_1 \text{ is } A_1^k \wedge x_2 \text{ is } A_2^k \wedge \cdots \wedge x_M \text{ is } A_M^k$$
$$\text{then } \{(D_1, \beta_{1,k}), (D_2, \beta_{2,k}), \cdots, (D_N, \beta_{N,k})\} \quad (1)$$
$$\text{with a rule weight } \theta_k \text{ and attribute weight } \bar{\delta}_1, \bar{\delta}_2, \cdots, \bar{\delta}_M,$$

where $\beta_{j,k}$ ($j = 1, 2, \cdots, N$, $k = 1, 2, \cdots, L$) is the belief degree to which D_j is believed to be the consequent if, in the k th rule, the input $x = [x_1, x_2, \cdots, x_M]$ satisfies the antecedent referential value vector $A_k = [A_1^k, A_2^k, \cdots, A_M^k]$. θ_k is the relative weight of the k th rule and $\bar{\delta}_1, \bar{\delta}_2, \cdots, \bar{\delta}_M$ are the relative weights of the M antecedent attributes that are used in the k th rule.

BRB is a collection of belief rules as described by Eq.(1) [3]. Inference with BRB is implemented using the ER approach, and knowledge representation parameters including rule weights θ_k, antecedent attribute weights $\bar{\delta}_m$ and consequent belief degrees $\beta_{j,k}$ are usually given by domain experts.

2.2 Inference with BRB Using the ER Approach

The analytical format of the ER approach [7] used for inference with the BRB and the input data under uncertainties can be described as follows.

$$\beta_j = \frac{\mu \times \left[\prod_{k=1}^{L} \left(\omega_k \beta_{j,k} + 1 - \omega_k \sum_{j=1}^{N} \beta_{j,k} \right) - \prod_{k=1}^{L} \left(1 - \omega_k \sum_{j=1}^{N} \beta_{j,k} \right) \right]}{1 - \mu \times \left[\prod_{k=1}^{L} (1 - \omega_k) \right]}, \quad j = 1, \cdots, N \quad (2)$$

with

$$\mu = \left[\sum_{j=1}^{N} \prod_{k=1}^{L} \left(\omega_k \beta_{j,k} + 1 - \omega_k \sum_{j=1}^{N} \beta_{j,k} \right) - (N-1) \times \prod_{k=1}^{L} \left(1 - \omega_k \sum_{j=1}^{N} \beta_{j,k} \right) \right]^{-1} \quad (3)$$

where, $\beta_j (j = 1, \cdots, N)$ is the final belief degree attached to the j th consequent D_j after combining all activated rules in BRB; $\beta_{j,k}$ ($j = 1, 2, \cdots, N$, $k = 1, 2, \cdots, L$) is the original belief degree assigned to D_j in the k th belief rule, and ω_k is the k th rule's activation weight which can be calculated by

$$\omega_k = \theta_k \prod_{m=1}^{M} (\alpha_m^k)^{\bar{\delta}_m} \Bigg/ \left[\sum_{l=1}^{L} \theta_l \prod_{m=1}^{M} (\alpha_m^l)^{\bar{\delta}_m} \right] \quad (4)$$

where, α_m^k ($m = 1, 2, \cdots, M$) is the individual matching degree to which the input x_m belongs to A_m^k that is the referential value of the m th antecedent attribute used in the k th rule.

The final combined result generated by ER approach is represented by $\{(D_1,\beta_1),(D_2,\beta_2),\cdots,(D_j,\beta_j),\cdots,(D_N,\beta_N)\}$, where β_j ($j=1,2,\cdots,N$) is the final belief degree attached to the j th consequent D_j after combining all activated rules in the BRB.

3 CVBG Recognition Based on RIMER

3.1 Overview

The outputs of OTHR are series of target tracks within the surveillance area, which are used as the inputs of the inference system for CVBG recognition. It's believed that the most significant indication of CVBG is that the carrier-borne aircrafts and warship formation usually operate together. So, if the OTHR can detect both the carrier-borne aircrafts and warship formation in the same area, it can make the judgement of CVBG with high confidence. Further, the warship formation can be distinguished from other targets according to its velocity and parallel tracks. On the other hand, the carrier-borne aircraft can be distinguished from other targets according to its velocity and track that initiates and terminates at sea. As a result, the inference logics can be formulated based on the above constraints using the outputs of OTHR.

Besides, some external information, for example, the prior-known operation regulations, can be used as another source of evidence for CVBG recognition independent with the outputs of OTHR.

Remark 1. This paper emphasize on the construction of BRB for CVBG recognition and the inference implementation based on BRB, and the track processing procedures (such as the judgment of parallel tracks) are not discussed in detail here.

3.2 Construction of BRB for CVBG Recognition

According to the above analysis of the constraints among sub-targets in CVBG, the structure of BRB for CVBG recognition can be constructed as Fig. 1, which is composed of four sub-BRBs. This BRB system uses five input variables (X_3, X_6, X_7, X_8, X_9) and three intermediate variables (X_2, X_4, X_5) to predict X_1. For illustration purposes, each of these input variables and the output variable are defined in terms of qualitative linguistic values (high (H), medium (M), or low (L)).

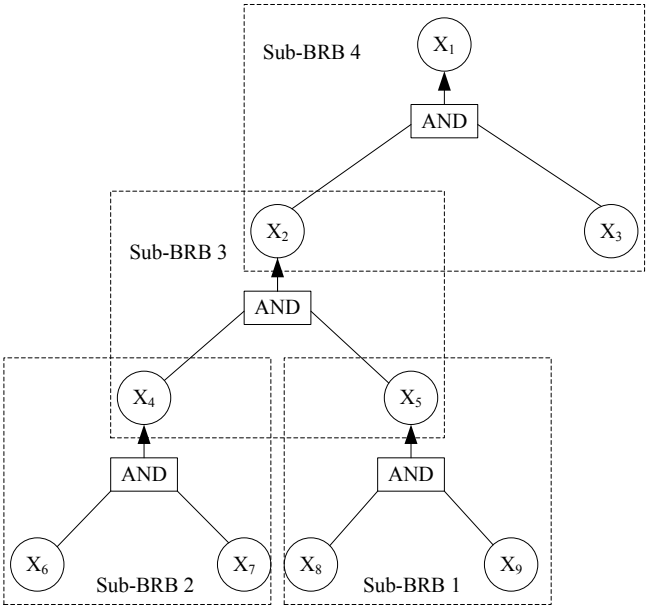

Fig. 1 The hierarchical BRB structure for CVBG recognition

In Fig. 1, the parameters are defined as follows.

- X_1 -- CVBG recognition confidence.
- X_2 -- CVBG recognition confidence based on OTHR outputs.
- X_3 -- CVBG recognition confidence based on operation regulations.
- X_4 -- Warship formation recognition confidence.
- X_5 -- Carrier-borne aircraft recognition confidence.
- X_6 -- warship formation recognition confidence based on velocity.
- X_7 -- warship formation recognition confidence based on parallel tracks.
- X_8 -- Carrier-borne aircraft recognition confidence based on velocity.
- X_9 -- Carrier-borne aircraft recognition confidence based on track that initiates and terminates at sea.

Based on the above hierarchical BRB structure, the CVBG recognition BRB, composed of 36 belief rules, can be constructed as Table 1, in which, the initial BRB parameters including rule weights, attribute weights and consequent belief degrees are usually given by domain experts.

3.3 Inference with Hierarchical BRB

From previous subsection, it can be seen that the CVBG recognition BRB has hierarchical structure. The inference based on this hierarchical BRB can be implemented form bottom to up using the single-level inference method revisited in Subsection 2.2. Specifically, the output of sub-BRB 1 (X_5) and the output of sub-BRB 2 (X_4) are taken as the input states to sub-BRB 3; the output of sub-BRB 3 (X_2) together with the independent input state X_3 are taken as the input states to get the final result X_1.

Noting that the input value are usually depicted as a single probability, before the inference can be started, input values need to be transformed and represented in terms of the referential values (low, medium, and high) with belief degrees. The rule-based transformation technique [8] is used for the quantitative data transformation. The equivalence rules are given as

1 is equivalently transformed to {(H, 1)};
0.5 is equivalently transformed to {(M, 1)};
0 is equivalently transformed to {(L, 1)}.

Hence,

0.95 is equivalently transformed to {(H, 0.9), (M, 0.1)};
0.6 is equivalently transformed to {(H, 0.2), (M, 0.8)};
0.4 is equivalently transformed to {(M, 0.8), (L, 0.2)};
0.1 is equivalently transformed to {(M, 0.2), (L, 0.8)}.

3.4 BRB Training

Practically, it is difficult to accurately determine the parameters of a BRB entirely subjectively, particularly, for a large-scale BRB with tens or even hundreds of rules. An initial BRB can be trained using historical data to improve its ability for representing domain knowledge.

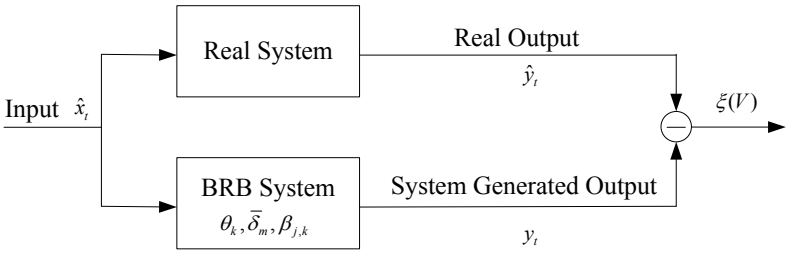

Fig. 2 The flow chart for BRB system parameters training

The training process is implemented through minimizing the discrepancy between BRB results and sampled data. Assuming there are T cases in a training sample, and the input–output pairs of the T cases are $(\hat{x}_t, \hat{y}_t)$ ($t = 1, \cdots, T$), the process of learning from these T datasets can be depicted as in Fig. 2, where y_t is produced by the BRB system, the real output $\hat{y}_t$ is observed by experts or acquired by instruments, and $\xi(V)$ represents the difference between the real output and the system output with $V = [\theta_k^z, \bar{\delta}_i^z, \beta_{j,k}^z]^T$. In the BRB optimization model, the objective function is to minimize $\xi(V)$, and the constraints define what the knowledge representation parameters of a BRB system should follow.

Considering the initial BRB for CVBG recognition displayed as Table 1 (columns 1-4), the input $\hat{x}_t = [X_3^t, X_6^t, X_7^t, X_8^t, X_9^t]^T$, the output $\hat{y}_t = [X_1^t]$ and $\hat{y}_t$ is a numerical value representing the target is CVBG ($y_t = 1$) or not ($y_t = 0$).

For certain input $\hat{x}_t$, the CVBG recognition BRB system can get the following output after inference

$$y_t = \{(D_j, \beta_j(t)), \quad j = 1, 2, \cdots, N\}. \tag{5}$$

For comparison, it's necessary to transform the above belief-degree structure into average utility as follows.

$$y_t = \sum_{j=1}^{N} \mu(D_j)\beta_j(t) \tag{6}$$

where, $\mu(D_j)$ the utility (or score) of an individual consequent D_j and for this problem, the values of $\mu(D_j)$ can be set as

$$\mu(D_j) = \begin{cases} 1, & \text{if } D_j = H \\ 0.5, & \text{if } D_j = M \\ 0, & \text{if } D_j = L \end{cases}. \tag{7}$$

So, the objective function in Fig.2 can be developed as

$$\xi(V) = \frac{1}{T}\sum_{t=1}^{T}(y_t - \hat{y}_t)^2 \tag{8}$$

The constraints are constructed according to the requirements of the application and if there is no additional requirement, the basic constraints can be given as follows.

$$\begin{cases} 0 \le \theta_k^z \le 1, & k = 1, 2, \cdots L_z,\ z = 1, 2, \cdots Z \\ 0 \le \bar{\delta}_i^z \le 1, & i = 1, 2, \cdots M_z,\ z = 1, 2, \cdots Z \\ 0 \le \beta_{j,k}^z \le 1, & j = 1, 2, \cdots N_z,\ k = 1, 2, \cdots L_z,\ z = 1, 2, \cdots Z \\ \sum_{j=1}^{N_z} \beta_{j,k}^z = 1, & k = 1, 2, \cdots L_z,\ z = 1, 2, \cdots Z \end{cases} \tag{9}$$

where, Z is the number of sub-BRBs; L_z is the number of belief rules in z th sub-BRB; M_z is the number of antecedent attributes in z th sub-BRB; N_z is the number of possible consequents in z th sub-BRB. The BRB training is therefore a nonlinear optimization problem with $S_1 = \sum_{z=1}^{Z}(L_z + M_z + N_z \times L_z)$ variables and $S_2 = \sum_{z=1}^{Z}(2L_z + M_z + N_z \times L_z)$ constraints, and can be solved using existing optimization software packages.

4 Numerical Simulations

In this section, we would like to evaluate the proposed CVBG recognition method through some numerical simulations. To support BRB training and algorithm evaluation, a set of 50 scenarios of the over-the-horizon radar outputs is simulated with some scenarios having CVBG and other scenarios only containing false targets (airliners or freighters). The simulated dataset is randomly divided into two groups (45 scenarios and 5 scenarios) as the training dataset and test dataset, respectively.

First, the first group dataset is taken to train the BRB. Usually, the difference among weights of antecedent attributes is little, so for simplicity, it's assumed that $\bar{\delta}_i^z = 1$ ($i = 1, 2, \cdots M_z$, $z = 1, 2, \cdots Z$). After parameter training using Eq.(8) and Eq.(9), we can get the trained CVBG recognition BRB as shown in Table 1 (columns 5-6).

Second, for comparison, the test dataset is used to conduct the inference based on the initial BRB and trained BRB respectively, and the results are shown in Table 2, in which, columns 2-6 are the inputs of BRB, columns 7-8 are the inference results (conference / decision result) based on the initial BRB and trained BRB respectively, and column 9 gives the real result.

From the simulation results in Table 2, it can be seen that

- Overall, the recognition rate can improve efficiently (from 60% to 100%) through BRB training.
- As for the second dataset, actually the antecedent attribute X_3 is not reliable, but in the initial BRB, X_3 and X_2 are treated with same importance, while in the trained BRB, X_2 is more importance than X_3. So, when the confidence input for X_3 is high and the confidence input for X_2 is low, the wrong inference result will be obtained based on the initial BRB.
- As for the fifth dataset, the input confidence is high for X_6 and X_8, and low for X_7 and X_9, in which case, the targets are single airliner and single freighter for the real scenario. Noting that, after BRB training, the antecedent attributes X_7 and X_9 that reflect the track parallelity, initiation and termination constraints in-

formation, are much more important than X_6 and X_8, inference based on trained BRB will not make mistake.

Table 1 BRB for CVBG recognition

Rule No.	Antecedent	Initial BRB		Trained BRB	
		W	Consequent	W	Consequent
1	X_8 is H∧X_9 is H	1	X_5 is {(H,1)}	1	X_5 is {(H,1)}
2	X_8 is H∧X_9 is M	1	X_5 is {(H,0.5), (M,0.5)}	1	X_5 is {(H,0.2), (M,0.8)}
3	X_8 is H∧X_9 is L	1	X_5 is {(M,1) }	0.5	X_5 is {(M,0.3), (L,0.7)}
4	X_8 is M∧X_9 is H	1	X_5 is {(H,0.5), (M,0.5)}	0.8	X_5 is {(H,0.5), (M,0.5)}
5	X_8 is M∧X_9 is M	1	X_5 is {(M,1)}	1	X_5 is {(M,1)}
6	X_8 is M∧X_9 is L	1	X_5 is {(M,0.5), (L,0.5)}	0.8	X_5 is {(M,0.1), (L,0.9)}
7	X_8 is L∧X_9 is H	1	X_5 is { (M, 1) }	0.5	X_5 is {(H,0.2), (M,0.2), (L,0.6)}
8	X_8 is L∧X_9 is M	1	X_5 is {(M,0.5), (L,0.5)}	0.8	X_5 is {(M,0.4), (L,0.6)}
9	X_8 is L∧X_9 is L	1	X_5 is {(L,1)}	1	X_5 is {(L,1)}
10	X_6 is H∧X_7 is H	1	X_4 is {(H,1)}	1	X_4 is {(H,1)}
11	X_6 is H∧X_7 is M	1	X_4 is {(H,0.5), (M,0.5)}	1	X_4 is {(H,0.3), (M,0.7)}
12	X_6 is H∧X_7 is L	1	X_4 is {(M,1) }	1	X_4 is {(H,0.3), (M,0.7)}
13	X_6 is M∧X_7 is H	1	X_4 is {(H,0.5), (M,0.5)}	1	X_4 is {(H,0.4), (M,0.6)}
14	X_6 is M∧X_7 is M	1	X_4 is {(M,1)}	0.4	X_4 is {(M,1)}
15	X_6 is M∧X_7 is L	1	X_4 is {(M,0.5), (L,0.5)}	1	X_4 is {(M,0.1), (L,0.9)}
16	X_6 is L∧X_7 is H	1	X_4 is { (M, 1) }	0.2	X_4 is {(H,0.1), (M,0.3), (L,0.6)}
17	X_6 is L∧X_7 is M	1	X_4 is {(M,0.5), (L,0.5)}	1	X_4 is {(M,0.3), (L,0.7)}
18	X_6 is L∧X_7 is L	1	X_4 is {(L,1)}	1	X_4 is {(L,1)}
19	X_4 is H∧X_5 is H	1	X_2 is {(H,1)}	1	X_2 is {(H,1)}
20	X_4 is H∧X_5 is M	1	X_2 is {(H,0.5), (M,0.5)}	0.6	X_2 is {(H,0.4), (M,0.6)}
21	X_4 is H∧X_5 is L	1	X_2 is {(M,1) }	1	X_2 is {(H,0.2), (M,0.3), (L,0.5)}
22	X_4 is M∧X_5 is H	1	X_2 is {(H,0.5), (M,0.5)}	0.6	X_2 is {(H,0.2), (M,0.8)}
23	X_4 is M∧X_5 is M	1	X_2 is {(M,1)}	0.6	X_2 is {(M,1)}
24	X_4 is M∧X_5 is L	1	X_2 is {(M,0.5), (L,0.5)}	1	X_2 is {(M,0.2), (L,0.8)}
25	X_4 is L∧X_5 is H	1	X_2 is { (M, 1) }	1	X_2 is {(H,0.1), (M,0.2), (L,0.7)}
26	X_4 is L∧X_5 is M	1	X_2 is {(M,0.5), (L,0.5)}	1	X_2 is {(M,0.2), (L,0.8)}
27	X_4 is L∧X_5 is L	1	X_2 is {(L,1)}	1	X_2 is {(L,1)}
28	X_2 is H∧X_3 is H	1	X_1 is {(H,1)}	1	X_1 is {(H,1)}
29	X_2 is H∧X_3 is M	1	X_1 is {(H,0.5), (M,0.5)}	0.2	X_1 is {(H,0.3), (M,0.7)}
30	X_2 is H∧X_3 is L	1	X_1 is {(M,1) }	0.8	X_1 is {(H,0.1), (M,0.3), (L,0.6)}
31	X_2 is M∧X_3 is H	1	X_1 is {(H,0.5), (M,0.5)}	1	X_1 is {(H,0.2), (M,0.8)}
32	X_2 is M∧X_3 is M	1	X_1 is {(M,1)}	0.4	X_1 is {(M,1)}
33	X_2 is M∧X_3 is L	1	X_1 is {(M,0.5), (L,0.5)}	1	X_1 is {(M,0.3), (L,0.7)}
34	X_2 is L∧X_3 is H	1	X_1 is { (M, 1) }	1	X_1 is {(H,0.1), (M,0.2), (L,0.7)}
35	X_2 is L∧X_3 is M	1	X_1 is {(M,0.5), (L,0.5)}	1	X_1 is {(M,0.2), (L,0.8)}
36	X_2 is L∧X_3 is L	1	X_1 is {(L,1)}	1	X_1 is {(L,1)}

Table 2 Recognition results (X_{1I}—Initial BRB based, X_{1T}—Trained BRB based, X_{1R}—Real)

Dataset	X_3	X_6	X_7	X_8	X_9	X_{1I}	X_{1T}	X_{1R}
1	0.6	0.9	0.8	0.9	0.8	0.9022/ **1**	0.8098/ **1**	**1**
2	0.8	0.3	0.2	0.3	0.2	0.5061/ **1**	0.1501/ **0**	**0**
3	0.3	0.5	0.3	0.5	0.2	0.0638/ **0**	0.2852/ **0**	**0**
4	0.5	0.8	0.8	0.2	0.2	0.4867/ **0**	0.1438/ **0**	**0**
5	0.5	0.9	0.3	0.9	0.3	0.5015/ **1**	0.2767/ **0**	**0**

5 Conclusions

The recognition of CVBG is critical for early warning. This paper proposes a belief-rule-based inference method for CVBG recognition with over-the-horizon radar outputs under uncertainty. The BRB for CVBG recognition is constructed considering the constraints among sub-targets in CVBG and subsequently the inference according to such hierarchical BRB is implemented. Moreover, the parameters training method is designed to update the BRB through accumulated historical cases. The simulation results show efficiency of the proposed method to address the uncertainties in both radar outputs and domain knowledge, and the method performs much better after BRB training.

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