Air-Attack Weapon Identification Model of Weighted Naïve Bayes Based on SOA

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Abstract. Traditional Naïve Bayes algorithm exists the issues of low inefficiency for the Air-attack Weapon Identification. In order to solve this problem, Air-attack Weapon Identification model of Weighted Naïve Bayes Based on Seeker Optimization Algorithm is proposed. Firstly, the model reduces the dimension of the data samples using rough set theory. Secondly, Seeker Optimization Algorithm searches the best attribute weights of Weighted Naïve Bayes. Finally, Naïve Bayes classifier is structured with the best attribute weights to complete detection. The combination of the two algorithms can not only solve the feature redundancy problem of the traditional Navie Bayes algorithm, but also can optimize the strong independence between features. Through the experiments, prove that using this model for Air-attack Weapon Identification in air defense combat identification

1. Introduction

The modern air warfare, with air weapons combat style more diversified and air density increasing, the amount of information required to deal with the air also increases, so more and more important for recognition of air raid weapons effectively and accurately, help the commanders to make correct decisions, improve the air defense weapon system combat capability [1-2]. Study on the recognition of air strike weapons, currently is the most used BP neural network, BP neural network in classification requires a large number of training samples, and the slow convergence speed, easy to fall into local optimum, thus the training effect is not stable[3]; literature[4] constructs the recognition model of particle group average clustering, but the model is easy to appear larger convergence oscillation, the convergence speed is not fast; Paper [5] is established based on object recognition model Naïve Bayesian and target recognition model based on probabilistic neural network, and through the comparison of probabilistic neural network and Naïve Bayesian method in the accuracy of aerial target identification, found Naïve Bayesian model better recognition effect.

Naïve Bayes algorithm is widely applied, and has the characteristics of simple structure, fast computation speed and good classification effect [6], however, the classifier can get the optimal solution [7] only when it satisfies the class independent condition. In practical applications, there is a certain correlation between attributes and attributes. Therefore, the independence assumption of naive Bayes algorithm cannot be satisfied. In order to break through the shortcomings of Naïve Bayesian algorithm, weighted Harry et al [8-9] of Naïve Bayesian algorithm, the algorithm based on the attributes of the contribution of the classification of the different weights, so as to optimize the independence of the property, and get good results. Literature [10] uses the information gain as a
weight to improve the naive Bayes weight, but it does not solve the problem of inaccurate classification caused by the large correlation between attributes. Document [11] first introduces rough set to attribute reduction to the data set of naive Bias model, and obtains the simplest attribute set. Then it sets the weight of the condition by maximizing the logarithmic conditional likelihood estimation, and proposes a weighted rough naive Bias model. According to the distribution of feature items between classes and classes, combined with the correlation degree between feature items, document [12] calculates weights, which effectively improves the classification effect of naive Bayes. The above improvement method has certain subjective factors for the determination of the weight value, and it is difficult to get the optimal weight.

Based on the technology of air raid weapons reduction attribute set of rough set, and then use the weighted population Naive Bayesian algorithm attribute weights search algorithm for optimization calculation, the optimal weights according to the Bayesian recognition model of air raid weapons, thereby eliminating the human factors influence on the weight given, simulation results show that the recognition effect is better than the the model of other models.

2. Basic theories and related models

2.1. Rough set theory

Rough set theory is first proposed by Pawlak [13]-[14], is a new mathematical method for data dealing with imprecise, uncertain and incomplete problem, knowledge reduction method of rough set theory, is retained in the basic knowledge and basis to ensure constant ability of classification on the object attributes and eliminate repeated and redundant the value of knowledge and realize the compression and refining, the attributes of air raid weapons set reduction based on discernibility matrix.

**Definition 1:** Decision tables $IS = (U, A, V, F)$, $U = \{x_1, x_2, \ldots, x_n\}$ as the nonempty finite set of objects, also known as the universe of discourse. $A = RU D$ is the nonempty finite set of conditional attributes, $D = \{d\}$ is the set of decision attributes, $V$ represents the range of information functions, and $V_j$ is $a_j$ information function, $f$ represents the information function of $IS$, and $f_j$ is the $a_j$ attribute information function.

**Definition 2:** $a_i(x_i)$ is the value of the sample $x_i$ on the attribute of $a_i$. The resolution matrix of the system is defined as:

$$m_{ij} = \begin{cases} a_i \in A, a_i(x_i) \neq a_j(x_i) \wedge D(x_i) \neq D(x_j) \\ \emptyset, D(x_i) = D(x_j), i, j = 1, 2, \ldots, n \end{cases}$$

The D kernel of C is the sum of all the single elements in the matrix, that is:

$$M(S) = \bigcup m^*_i$$

**Definition 3:** The resolution function of the decision table is defined as follows:

$$f_{M(S)}(a_1, a_2, \ldots, a_n) = \cap\{\bigcup m^*_i, 1 \leq i < j \leq n, m^*_j \neq \emptyset\}$$

The reduction steps are as follows:

1) the decision table $IS$ is converted to the resolution matrix $m^*_{ij}$.

2) the resolution function $f_{M(S)}$ is obtained according to the resolution matrix.

3) for each conjunct minimal disjunctive form in function $f_{M(S)}$.

4) the output results of attribute reduction, and that each conjunctive minimal disjunctive form contains attributes.
2.2. Weighted Naive Bayes model  

**Definition 4:** From the decision table IS, A is the attribute VARIABLE A1, and the n-dimensional attribute sample X is used to express the measured value. Given the m class C. For an unknown sample X, when and only then \( p(C_i | X) = \frac{p(X | C_i) p(C_i)}{p(X)} \) \( i = 1, 2, \ldots, m \) is the prior probability of class C, \( s_i \) is the number of training samples in class \( C_i \), and \( s \) is the total number of training samples.

**Definition 5:** The simple Bias classification model is the \([8]\) in the class that divides the sample into the maximum posterior probability, and the model formula is:

\[
C(X) = \arg \max_{c_i \in C} P(x_j | C_i) \quad \tag{5}
\]

**Definition 6:** The attribute A variable is given to the weight value W, and the formula of the weighted naive Bayes model \([8]\): 

2.3. Seeker Optimization Algorithm

Seeker Optimization Algorithm (SOA), from human long life social experience through scientific analysis of human intelligent behavior in search activity, the intelligent search behavior is divided into egoism, altruism, pre dynamic behavior, uncertainty reasoning behavior, and the behavior modeling for computing search direction and step. In the iteration of the algorithm, the search direction and the step length are constantly updated to update the searcher's position, so as to get a better solution.

The algorithm flow is as follows:

Step 1: \( t \rightarrow 0 \).

Step 2: initialization, s initial positions are randomly generated in the feasible solution domain:

\[
\left\{ x_i(t) \mid x_i(t) = (x_{i1}, x_{i2}, \ldots, x_{is}) \right\}
\]

Among, \( i=1, 2, 3, \ldots, s; \ t=0 \)

Step 3: evaluate, calculate the fitness value for each position.

Step 4: calculate the search direction for each searcher \( i \) in the one dimension \( j \) Search direction \( d_{ij}(t) \) and the step length \( a_{ij}(t) \).

Step 5: update the location of the searcher according to the formula.

Step 6: \( t = t + 1 \).

Step 7: if the algorithm stops the condition, stop the search; otherwise, turn to Step 3.

3. Model architecture

3.1. model structure

This paper proposes a weighted naive Bayes air attack weapon recognition model based on crowd search algorithm. It can provide reliable information for tactical actions of next target threat assessment and target assignment by accurately and rapidly identifying air attack weapons. This model is divided into two stages, the data preprocessing stage and the crowd search algorithm search the optimal feature attribute weight phase.

In the data preprocessing stage, because the characteristics and attributes of air raid weapons are more, and include continuous and discrete data, in order to use rough set theory to process data, we need to discretize the original data. Then the rough set technique is used to reduce the feature set of the sample, and the optimal set is obtained. According to the formula (2), the posterior probabilities and priori probabilities of the attributes of the reduced attribute concentration are calculated. In the stage of
search for optimal weight, the position of the searcher is generated randomly, and the position of each searcher represents a weight value. The weights are taken into the type (5) for identification and detection, each of which corresponds to a recognition accuracy. The weight of the highest recognition accuracy is the global optimal value.

The best location of individual history is compared with the best location of the group's history to update its position, search step length and direction. By constantly updating the location of the searcher to get better solutions until the iteration value is set, the iteration is over, and the optimal weight is saved. According to the optimal weight obtained, the Bias classifier is constructed to complete the air attack weapon recognition.

3.2 SOA algorithm verification
This paper uses the Sphere test function to test the optimization performance of the SOA and PSO algorithms.

![Fitness curve comparison of SOA and PSO algorithms](image)

**Figure 1.** Comparison of the variation trend of the fitness value of SOA and PSO algorithm

The fitness curve of Figure 1 shows that the SOA algorithm converges faster than the PSO algorithm. According to the figure 1, it can be seen that the convergence accuracy of the SOA algorithm is higher and the robustness is better. It is proved that the optimization performance of the SOA algorithm is better than that of the PSO algorithm. Therefore, the use of SOA algorithm to optimize the weight of attributes is feasible and effective.

4. Experimental verification
According to the activity rules of air attack weapons, they can be divided into 5 categories: ballistic missiles, heavy weapons (including bombers, fighters, and fighter bombers, etc.), light weapons (including air to surface missiles, anti radiation missiles and cruise missiles, etc.), armed helicopters and bait. The feature attribute parameters are divided as shown in Table 1.

| Flight height (H) m | >27000,27000-150,<150 |
|--------------------|------------------------|
| Target distance (R) km | >250,<250 |
| Flight speed (V) m/s | >1800,1800-400, 400-200, <200 |
| Route features (Y) | Equal high flying, climbing or subduction, subduction, bifurcation |
| Target attack angle (C) °C | 0-30, 30-60,60-90 |
| Target interference ability (Y) | Strong, medium, weak, no |
| The incoming weapons (D) | Ballistic missiles, heavy weapons, light weapons, armed helicopters, bait |

The characteristic parameters of the discrete air attack weapons are shown in Table 2.
Table 2. Characteristic parameters of air raid weapons after discretization

| Flight height (H) m | Target discovery distance (R) km | Flight speed (V) m/s | Route features (Y) | Target attack angle (C) °C | Target interference ability (Y) | The incoming weapons (D) |
|--------------------|---------------------------------|---------------------|-------------------|---------------------------|-------------------------------|------------------------|
| 1, 2, 3            | 0, 1                            | 1, 2, 3, 4          | 1, 2, 3, 4        | 1, 2, 3                    | 1, 2, 3, 4, 5               |

The attribute reduction is carried out according to the formula (3), and the attributes of the incoming target are calculated, and the attributes of R, Y and L are redundant. The set of feature attributes after reduction is shown in Table 3.

Table 3. Sample data table after reduction

| U | H | V | C | D |
|---|---|---|---|---|
| 1 | 1 | 2 | 1 |   |
| 2 | 1 | 3 | 1 |   |
| 3 | 2 | 3 | 1 |   |
| 4 | 2 | 4 | 3 | 3 |
| 5 | 3 | 4 | 3 | 4 |
| 6 | 2 | 2 | 2 | 3 |
| 7 | 2 | 3 | 1 | 2 |
| 8 | 3 | 4 | 1 | 4 |
| 9 | 2 | 3 | 3 | 5 |

Figure 2 is the comparison chart of recognition and detection results based on attribute weighted naive Bias classification algorithm (WNB), improved weighted naive Bias classification algorithm (DWNB) and PSO-WNB algorithm in document [11] based on [10]. The recognition rate of the four algorithms for tactical ballistic missiles, bait and armed helicopters is generally high, but the recognition rate of two incoming weapons for heavy weapons and light weapons is relatively low. The recognition accuracy of DWNB model is higher than that of WNB model, because DWNB removes redundant attributes from the samples to be classified by rough set technology, avoiding the interference of redundant attributes to classification. The recognition effect of the SOA-WNB model is better than that of DWNB, because on the basis of eliminating redundant attributes, the weights found using SOA are better than those given by DWNB. After testing and testing, the average detection rate of the SOA-WNB model constructed in this paper is 94.08%, and the average detection rate of the model built by PSO-WNB is 92.15%, which validates the validity of the SOA-WNB model. The simulation experiments show that the model is not only effective, but also superior to other models.

5. Conclusion
This paper presents a search algorithm based on population weighted Naive Bayesian air raid weapons recognition model, model firstly by using rough set theory attribute reduction of the sample set, to solve the problem of air combat weapon of the redundant attributes, attribute weights and then use the population search algorithm optimization weighted naive Bayes Juliu algorithm, thus solving the insufficiency of traditional Naive Bayesian attributes the assumption of independence, according to the identification of the optimal weights obtained improved Naive Bayesian classifier and the air

Figure 2. Algorithm result contrast diagram
attack weapons. It is proved by the experiment that the recognition effect of this model is better than that of other classification models, and the target of improving the recognition rate of air attack weapons is achieved. In the experiment, the most important influence on the accuracy of recognition is the attributes of weapons. In this paper, only 6 attributes of air raid weapons are involved. In order to improve the accuracy of recognition, we need to further explore other attributes of air raid weapons.

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