Non-cooperative target clustering algorithm based on clonal selection

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Abstract. Orderly observation of non-cooperative targets for subsequent identification and control is one of the important prerequisites and key technologies of space on orbit service. Restricted by the limited number of ground observation equipment, the visible time window of each non-cooperative target, and the different types of targets, it is increasingly difficult to observe the transit non-cooperative targets and plan the observation tasks. In this paper, the fuzzy clustering algorithm based on clonal selection is used to cluster the non-cooperative targets which are about to cross the border according to their own characteristics, physical characteristics, geometric characteristics, orbital characteristics and other different attributes. Considering the urgency of the task, the importance and priority of each non-cooperative target relative to the observation task are formed, it can provide effective input for the subsequent task planning of non-cooperative target observation, reduce the problem complexity of orderly observation of non-cooperative target, and improve the efficiency of problem solving.

1. Introduction
With the development of space industry, the number of spacecraft is increasing, and the space environment is becoming more and more complex. Each country in order to maintain the space environment, and grasp the space situation, as well as make the spacecraft stable and controllable in the complex space, space on orbit service has become the focus of space research.

The target spacecraft of space on orbit service system is generally divided into cooperative target and non-cooperative target. Cooperative target refers to spacecraft with specially designed docking mechanism and specially designed cooperative target marker, non-cooperative targets generally refer to those spacecrafts that are not equipped with transponder or other sensors, including satellites that are not equipped with cooperative interfaces, satellites that are installed with cooperative interfaces but fail or run out of fuel, space debris of failed satellites and enemy spacecraft[1]. At present, the on orbit service technology of space non-cooperative target is much more difficult than that of cooperative target, which is an urgent problem to be solved in the field of space technology. It is an important premise and one of the key technologies to realize space on orbit service to observe the non-cooperative target in a planned way for subsequent identification, manipulation and classification.
Since non-cooperative targets include not only ordinary satellites in orbit, but also all kinds of failed satellites, space debris and space garbage, autonomous observation of non-cooperative targets can not be separated from the ground observation equipment of space system. Ground observation equipment is expensive and occupies a large area, so it is impossible to build it without limitation. In this case, the contradiction between the limited ground observation resources, the increasing number of non-cooperative targets, the different transit time of each non-cooperative target and the growing observation demand due to the development of space industry is increasing, which increases the complexity of task scheduling and planning for non-cooperative target observation.

At present, there is little research on the observation task scheduling of non-cooperative targets by scholars at home and abroad. Most scholars propose various solutions to the complexity of multi-Satellite TT&C resource scheduling (MSTCRS), which can be referred here. National Aeronautics and Space Administration (NASA) and Air Force Institute of technology\cite{2-4} put forward a constraint planning method which can accurately describe the MSTCRS problem. However, the constraints considered in this method are very complex. In practical application, this method undoubtedly increases the difficulty and complexity of non-cooperative target observation task. (formerly) School of equipment command technology, National University of Defence Technology\cite{5} proposed to use agent technology to solve MSTCRS. Compared with ant colony algorithm\cite{6-11} or genetic algorithm proposed by Xi’an Satellite Control Center and Jiangsu Normal University, this technology has higher solving efficiency. Applying this kind of method to the planning of non-cooperative target observation mission will alleviate the complexity of the problem to a certain extent.

Because of the complexity of ant colony algorithm and genetic algorithm, the solution effect is not very obvious. School of information system and management in National University of Defence Technology\cite{12} proposed to consider task clustering in satellite observation scheduling in order to improve observation efficiency under the condition of limited energy and time on the satellite in orbit. Inspired by the way of using task clustering to improve the efficiency of satellite observation in satellite observation scheduling, if the targets can be clustered according to the physical characteristics, geometric characteristics, orbital characteristics and other different characteristics of the target before the task planning of non-cooperative target observation, the targets can be clustered with similar characteristics. The targets with different similar characteristics are divided into different clusters, and then the target type and value are determined according to the target characteristics of each cluster. At the same time, considering the actual observation demand and the urgency of the task, the observation order of the targets is prioritized. In the result of ranking non-cooperative targets, the non-cooperative targets ranking the last can not be included in the observation planning according to the importance and urgency of the task, or observation can be carried out when the ground observation resources can be free, so as to improve the efficiency of observation planning for non-cooperative targets in practical application, reduce the complexity, and make the observation more targeted. To some extent, the contradiction between limited observation equipment and the increasing demand for non-cooperative targets is alleviated, which is the key research direction of future non-cooperative target observation task planning.

The space situation is complex and changeable. The non-cooperative target itself has no standard target recognizer, so it is difficult to obtain a unified feature attribute for multi-target, and the target movement changes quickly. In the complex space environment, it will be subject to a variety of interferences, so the acquired data is often noisy, which requires the clustering algorithm to have good noise robustness and adaptability. At the same time, it puts forward higher accuracy and real-time requirements for the algorithm.

In this paper, fuzzy clustering algorithm based on clonal selection (CSAFCM) is used to cluster non-cooperative targets. The algorithm is composed of fuzzy c-means algorithm (FCM) and clonal selection algorithm (CSA). Compared with the traditional K-means clustering algorithm, each data object can only be assigned to one of multiple clusters. FCM allows a data object to belong to multiple clusters, and gives the probability that each data belongs to each cluster. It introduces the concept of membership degree, and iterates the cluster center according to the iterative update of membership.
degree. It is a soft clustering algorithm, potential practical significance of more data can be fined. FCM algorithm is an iterative optimization algorithm [13]. Although each step of iteration is along a good direction, this FCM based on gradient descent is essentially a local search algorithm, which is easy to fall into local minimum [14]. CSA adopts the group search strategy, which adopts the parallel and random strategy in the process of searching the optimal solution, and carries on the random search according to certain rules near the feasible solution, which can make up for the defect that FCM is easy to fall into the local minimum to a great extent, and it is an algorithm with global search characteristics. Therefore, FCM in the framework of clonal selection algorithm can obtain clustering centers with higher accuracy, faster convergence speed and better noise robustness.

This paper is divided into five parts. The first part analyzes the application status of clonal selection based clustering algorithm in observation non-cooperative target task planning. The second part introduces the principle of FCM algorithm and clonal selection algorithm. In the third part, clonal selection strategy is applied to fuzzy clustering, and the process and key steps of fuzzy clustering algorithm based on clonal selection are given. In the fourth part, the proposed algorithm is applied to the non-cooperative target task planning problem, and the numerical simulation analysis is given. The fifth part makes a summary of the full text, and gives the further research direction.

2. Algorithm principle

2.1. FCM clustering algorithm

FCM clustering algorithm is one of the most widely used partition clustering models. It was first proposed by Dunn [15], and then extended by Bezdek et al [16]. Given a set of finite data sets:

$$X = \{x_1, x_2, \ldots, x_n\}$$

FCM clustering algorithm returns k clustering center:

$$c = \{c_1, c_2, \ldots, c_k\}$$

and membership fuzzy partition matrix $$U = [u_{ij}],$$ and $$i = 1, \ldots, n, j = 1, \ldots, k,$$ where each element $$u_{ij}$$ represents the probability of each sample $$x_i$$ belonging to cluster $$c_j.$$ The element $$u_{ij}$$ in the membership fuzzy partition aggregation matrix $$U = [u_{ij}]$$ satisfies:

- For any $$i, j, u_{ij} \in [0,1].$$
- For any $$i, \sum_{j=1}^{k} u_{ij} = 1.$$
- For any $$j, \sum_{i=1}^{n} u_{ij} < n.$$

Like K-means clustering algorithm, FCM is an iterative clustering algorithm, which generates the optimal partition by minimizing the sum of squares of weighted intra group errors $$J_m$$:

$$J_m = \sum_{i=1}^{n} \sum_{j=1}^{k} u_{ij}^m \|x_i - c_j\|^2$$

Where, $$m$$ can be any fuzzy weight index greater than 1, which is a real number, $$\|x_i - c_j\|^2$$ is the distance measure between data $$x_i$$ and the center $$c_j.$$ In FCM clustering algorithm, membership $$u_{ij}$$ and clustering center $$c_j$$ are updated iteratively, and the objective function is divided into two parts:

$$u_{ij} = \frac{1}{\sum_{l=1}^{k} \|x_i - c_l\|^2 \|x_i - c_j\|^{2m-1}}$$
\[ C_j = \frac{\sum_{i=1}^{n} u_{ij}^m * x_i}{\sum_{i=1}^{n} u_{ij}^m} \]  

(5)

When

\[ \max \left\{ \left| u_{ij}^{*+1} - u_{ij}^{*} \right| \right\} < \epsilon \]  

the iteration stops. \( \epsilon \) is the termination condition between 0 and 1, and \( t \) is the iteration step.

In reference[17], the value of fuzzy weight index \( m \) of FCM algorithm is studied. Experiments show that the best value range in practical application is \([1.5, 2.5]\). In this paper, the fuzzy weight index is 2.

2.2. Clone selection algorithm

Clone selection algorithm is a new method of artificial immune system\(^{[18]}\), which was proposed by de Castro LN and von Zuben f J in 2000\(^{[19,20]}\), and its inspiration comes from the principle of biological acquired immune clonal selection. Clone selection algorithm constructs a clonal operator suitable for artificial intelligence computation by means of antibody clonal selection mechanism of biological immune system. The core of the algorithm is clone operator and mutation operatori. According to the theory of antibody clonal selection, when the antigen invades the organism, the clonal selection mechanism of the biological immune system selects and recognizes the antibody (immune cell) that can destroy the corresponding antigen in the organism, and selects the antibody with higher adaptability and matching with the antigen, so that the antibody can be cloned and mutated to carry out the immune response of the organism. Finally, the antigen was eliminated. The essence of clonal immunity is that in the evolution of each generation, according to the degree of adaptation between antibody and antigen, a group of mutation solutions is generated near the feasible solution. At the same time, a group strategy is adopted to expand the search range of the optimal solution. It has the characteristics of global search and can obtain the optimal solution of the problem with a high probability\(^{[1]}\).

The traditional clonal selection algorithm can be described as follows:
- Randomly generates \( n \) antibodies in the problem definition space.
- \( n \) antibodies with high affinity to antigen were selected according to a certain proportion of \( p_1 \).
- \( n \) antibodies were cloned and mutated to select \( n \) antibodies with high affinity and replace \( n \) individuals with the worst antibody group.
- If the termination condition is satisfied, the calculation is stopped and the solution of the problem space is output, otherwise, repeat steps 2 and 3 until the stop condition is met.s

3. Fuzzy clustering algorithm based on clonal selection

The fuzzy clustering algorithm based on clonal selection introduces the population size iteration of clonal selection algorithm into FCM, and integrates the operations of clonal selection, antibody cloning, antibody mutation and antibody selection into the iterative calculation process of clustering algorithm.

The pseudo code of the algorithm is as follows:

**Algorithm 1: CSAFCM**

**Input:** Dataset data, Algorithm parameters

**Output:** Cluster result diagram and cluster centers

1. **Begin**
2. Make iteration counter \( t = 0; \)
3. Randomized data: `new_data`
4. Randomized sorting of records: `order`
5 Initialize the membership matrix $U$ , population ;

6 Calculating population affinity: fitness using Eq. 8 and Eq. 3

7 The antibody best with the largest fitness value in the current population was output

8 While $\max \|u^{t+1}_{ij} - u^{t}_{ij}\| < \varepsilon$ do

9 $t = t + 1$

10 Clonal population antibodies by Eq. 9

11 Mutate Population Antibodies by Eq. 14

12 One iteration update of FCM by Eq. 4 and Eq. 5

13 Select high quality antibodies Eq. 16

14 Update antibody population

15 ending

3.1. Antibody coding

One of the important operations of fuzzy clustering algorithm based on clonal selection is the generation of antibody coding. The clonal selection algorithm and clustering algorithm are combined to solve the clustering problem of non-cooperative target attribute data set $X$. The data with high similarity are clustered into one cluster, while the data with low similarity are clustered into another cluster. According to the clonal selection principle, the antibody represents the feasible solution of the problem to be solved in the clonal selection algorithm. Therefore, in the clonal selection based fuzzy clustering algorithm, each antibody is composed of the cluster center of the data set $X$ to be clustered. For antibody coding, real vector coding is usually used. Each antibody is encoded by a real vector representing the coordinates of the cluster center.

In the initial stage of antibody, it is assumed that each antibody $a_i$ is composed of $k$ cluster centers $\{c_1, c_2, ..., c_k\}$, which can be expressed as real number coding with length of $k \times d$:

$$a_i = \{a_{i1}, a_{i2}, ..., a_{id}, ..., a_{i1}, a_{i2}, ..., a_{id}\}$$ (7)

Where $d$ is the dimension of data in non-cooperative target attribute data set $X$.

3.2. Antibody affinity

The antibody antigen affinity of the clone selection algorithm based on artificial immune system is a function to characterize the binding strength of antibody and antigen. The input of the function is the antibody individual (feasible solution), and the output is the result of affinity evaluation. The higher the affinity of antibody antigen, the better the binding of antibody to antigen, the better the quality of feasible solution. The fuzzy clustering algorithm based on clonal selection performs the iterative operation of clustering algorithm under the framework of clonal selection algorithm’s group search strategy, and searches the cluster center corresponding to the most effective index value by continuously optimizing the appropriate clustering effectiveness index. For the clustering of different data sets, reference[14] proposed many clustering validity indexes in clustering analysis. In this paper, the attributes of non-cooperative targets are clustered based on the square sum error criterion $J_m$. The definition of antibody antigen affinity is as follows:

$$\text{affinity}(a_i) = \frac{1}{1 + J_m}$$ (8)

Where $a_i$ is the $i$th antibody of antibody group $A_{\{N\}}$, and $N$ is the number of antibodies in antibody group.
3.3. Clone operation

When the antigen invades the body, the antibody is cloned to increase the number of antibodies, which provides quantitative support for the subsequent antibody mutation and selection, and ultimately eliminates the antigen. The antibody population $A(t)$ obtained by cloning the $t$ generation antibody population can be expressed as:

$$A(t) = T^C_c(A(t)) = \{a_{i_1}(t), \ldots, a_{i_{N_i}}(t)\}$$

Where

$$T^C_c(a_i(t)) = I_i \times a_i(t)$$

$i = 1, 2, \ldots, N$, and $I_i$ are vectors of dimension $q_i$. There are $q_i$ clones of antibody $a_i$ in the antibody pool. $q_i(t)$ is expressed as:

$$q_i(t) = g(N_c, \text{affinity}(a_i(t)))$$

$\text{affinity}(\ast)$ is the antibody antigen affinity defined in equation (5) and $N_c$ is the number of antibodies cloned from the antibody population. In general, $q_i(t)$ is given by equation (8):

$$q_i(t) = \ln(\frac{\text{affinity}(a_i(t))}{\sum_{j=1}^{N_c} \text{affinity}(a_j(t))}), i = 1, 2, \ldots, N$$

Where $\ln(x)$ returns the smallest integer greater than or equal to $x$. For an antibody, the proportion of the antibody to be cloned is adjusted according to the antibody affinity. The larger the affinity, the larger the scale of cloned antibody, and vice versa.

3.4. Clone mutation

The mutation of clonal antibody group $A_c(t)$ is a random mapping from antibody space to itself, which can be expressed as:

$$T^m_m : S^L \rightarrow S^L$$

The function of the operator in clonal selection algorithm is to make the antibody change its own gene randomly. The smaller the affinity is, the higher the mutation rate is, and the higher the affinity is. In this mutation mode, the diversity of antibody population is enhanced, and the local search in the neighborhood is realized. The antibody mutation is expressed by the following function:

$$T^m_m(a_k) = a_k + \text{rand()} \times \text{affinity}(a_k)$$

$a_k$ is the $k$-dimension value of antibody $a_i$, $\text{affinity}(a_i)$ is the affinity function of antibody $a_i$, $\text{rand()}$ is a random number generator, and random sequences can be generated by uniform distribution, Gaussian distribution and Cauchy distribution. In this paper, Gaussian distribution is used.

3.5. Clone selection

The best antibody with the highest affinity will be retained in the new antibody group with the probability of $p_i^j$, after mutation operation. The best antibody $b_j(t)$ was preserved as follows:

$$b_j(t) = \left\{ a_{i_j}(t) \bigg| j = \arg\left( \max_{i=1}^{N} \left[ \text{affinity}(a_{i_j}(t)) \right] \right) \right\}$$

The probability $p^j$ of new antibody $b_j(t)$ replacing antibody $a_i(t)$ is defined as:
Where $\beta > 0$ is a constant.

4. Non-cooperative target clustering based on clonal selection

4.1. Problem description

In order to reduce the complexity of task scheduling and planning for space non-cooperative target observation, and to alleviate the contradiction between the limited ground observation resources, the increasing number of non-cooperative targets, the different transit time of each non-cooperative target and the growing observation demand due to the development of space industry. Inspired by the way of using task clustering to improve satellite observation efficiency in satellite observation scheduling, this paper uses clonal selection fuzzy clustering algorithm with global search ability to cluster non-cooperative targets according to their related attributes before the observation tasks. Cluster analysis is carried out for non-cooperative targets to obtain the attribute information. According to the physical, geometric and orbital characteristics of attribute information, the non-cooperative targets with similar characteristics are clustered, and the targets with different characteristics are divided into another cluster. According to the cluster center data characteristics of each cluster, the target types belonging to which cluster are determined. At the same time, considering the observation needs of actual users and the urgency of tasks, the value of targets and the observation order are prioritized from multiple perspectives. Under this priority ranking result, the lower ranking targets can be excluded from the observation planning according to the importance and urgency of the task, so that the observation targets can be more controllable and targeted in different tasks and needs. To a certain extent, the contradiction between the limited observation equipment and the growing observation demand for non-cooperative targets can be alleviated.

4.2. Data preparation

In order to carry out the clustering analysis of non-cooperative targets, the first step is to obtain their relevant attribute information. In practical applications, space non-cooperative targets are not equipped with feature blocks and cooperative markers, neither equipped with specially designed docking interfaces, and they can not actively transmit their attitude information \(^1\), so it is more difficult to obtain the attribute information of non-cooperative targets than cooperative targets, and the acquired data information is often missing. The data in this paper are generated manually. The attributes of five non-cooperative targets are: own spacecraft / non-own spacecraft, spacecraft orbit height (km), spacecraft orbit half axis a (km), spacecraft load type and load accuracy (m).

Considering the different types of tasks performed by users, the decision of whether the non-cooperative target is its own spacecraft or not is one of the important attributes of non-cooperative target clustering analysis. In order to grasp the space situation and maintain the space security environment, the observation value of non-own spacecraft is greater than that of own spacecraft. According to the value of other attributes of the non-cooperative target, the attribute value is set as 1000 when the target belongs to the non-cooperative spacecraft, and 0 when the target belongs to the cooperative spacecraft.

The orbit height and semi major axis attributes of spacecraft are also related to the type of mission they perform. Table 1 shows the classification of low orbit satellites(LOS), medium orbit satellites(MOS) and high orbit satellites(HOS). Spacecraft with important reconnaissance mission needs to observe the ground more clearly, so its orbit height is generally in the middle and low orbit. Most of the high orbit deep space satellites are used for communication. Then, due to the limitations of the ground observation equipment, it has little demand for the observation of HOS.
Table 1. Division of LOS, MOS and HOS.

| Satellite type | Orbit altitude (km) | Operation period (h) | Operation period |
|----------------|---------------------|----------------------|------------------|
| LOS            | 200-1200            | 2-4                  | RECS\textsuperscript{1} |
| MOS            | 20000               | 12                   | NAVS\textsuperscript{2} |
| HOS            | 35786               | 24                   | COMS\textsuperscript{3} |

The type and accuracy of the payload carried by the spacecraft are also closely related to the importance of the spacecraft itself and the value order for observation. The payload types carried by different spacecraft are different. For example, the payload types carried by reconnaissance satellites include visible light film camera, visible light CCD camera, radar information signal receiver (channelized receiver, direction finding receiver), antenna array and large format measurement camera. The payload carried by satellites used for communication mainly includes communication transponder and antenna. The payload of remote sensing satellite is mainly camera. The payload of navigation satellite includes satellite clock, navigation data memory and data injection receiver. In the aspect of load accuracy, the load accuracy of the different types of satellites is different according to the importance and value of the satellite itself. Generally speaking, the importance and value of spacecraft itself is directly proportional to the accuracy of the load it carries, and inversely proportional to the value of the load accuracy.

4.3. Experimental results and analysis

In this paper, 150 5-Dimensional human datasets with Gauss white noise are generated based on the sequence of five attributes, including the satellite's own/non-own spacecraft, the spacecraft's orbital altitude (km), the spacecraft's semi-major axis (km), the spacecraft's load type and the load accuracy (m). Then, the attribute datasets of non-cooperative targets are clustered using fuzzy clustering algorithm based on clonal selection, fuzzy c-means clustering algorithm and K-means clustering algorithm. Compared with fuzzy c-means clustering algorithm and K-means clustering algorithm, the result of fuzzy clustering algorithm based on clonal selection is more accurate. It is more suitable for pre-planning clustering of non-cooperative target observation tasks.

4.3.1. Targets clustering. In this paper, fuzzy clustering algorithm based on clonal selection is used to cluster non-cooperative target artificial data set, and the three cluster centers are:

\[
C = \begin{bmatrix}
    c_1 &=& [1000, 9561.62, 183.8, 79.19, 111], \\
    c_2 &=& [1000, 10293.13, 4282.78, 302.6, 148], \\
    c_3 &=& [0, 20957.33, 10300.87, 298.83, 19]
\end{bmatrix}
\]  

(17)

Combined with the characteristics of non-cooperative target attribute data and the cluster center of clustering results, it can be seen that most of the non-cooperative targets divided into cluster center belong to non-own spacecraft, and their orbit semi major axis height is low, which belongs to LEO satellites, and the representative satellite types are reconnaissance satellites. At the same time, the load precision of this type of satellite is small, which indicates that the load precision of satellite is high, and this type of spacecraft is more likely to perform important tasks than other types of spacecraft. Therefore, in the task of observing non-cooperative targets, the target that is divided into cluster center has the highest value of observation, and the higher the priority of observation, it can be determined as priority \([\text{the most important}].\)

\begin{itemize}
  \item \textsuperscript{1} Reconnaissance Satellite
  \item \textsuperscript{2} Navigation Satellite
  \item \textsuperscript{3} Communication Satellite
\end{itemize}
Similarly, observing cluster center
\[
c_2 = [1000, 10293.13, 4282.78, 302.6, 148]
\] (19)
most of the targets that are divided into cluster centers belong to non-own spacecraft. According to the orbital semi major axis and orbital height values, this type of satellite belongs to medium and low orbit satellites, and its payload precision is medium, and its observation value is also high. Therefore, the observation priority of the target that belongs to cluster center is determined as the secondary important].

The satellites that are divided into cluster center
\[
c_3 = [0, 20957.33, 10300.87, 298.83, 19]
\] (20)
are more likely to belong to their own spacecraft. According to the orbit semi major axis and orbit height of the satellite, it can be determined that this type of satellite belongs to high orbit satellite, which carries out many communication tasks. At the same time, due to the performance limitation of ground observation equipment, it is not possible to observe this type of target, so it is not important to determine its observation priority.

T-sne dimension reduction method is used to reduce and visualize the attribute data of non-cooperative targets in the clustering results of fuzzy algorithm based on clonal selection. The two-dimensional data clustering results are shown in Figure 1:

![Figure 1. Result diagram of non-cooperative targets clustering using CSAFCM.](image)

The green, yellow and red points in the clustering result graph represent the \( c_1 \), \( c_2 \), \( c_3 \) clusters of the artificial data set from the non-cooperative target attributes, and the pentagram in the center of each cluster is its clustering center.

4.3.2. Algorithm advantage. In this paper, K-means algorithm, fuzzy c-means algorithm and fuzzy clustering algorithm based on clonal selection are used to cluster the attribute data of non-cooperative targets, and the common internal evaluation index Calinski Harabase(CH) and contour coefficient, external evaluation index Adjusted Rand Coefficient(ARI), Adjusted Mutual Information Index(AMI), are clustered Accuracy(ACC) is used to compare the clustering results. As Table 2:

| Algorithms | CH     | contour coefficient | ARI  | AMI  | ACC  |
|------------|--------|---------------------|------|------|------|
| CSAFCM     | 226.803| 0.469               | 0.716| 0.725| 91.333|
| FCM        | 224.855| 0.455               | 0.619| 0.661| 84.667|
| K-Means    | 223.948| 0.599               | 0.398| 0.566| 85.33 |
CH index is a measure based on the sample distance and the matrix of cluster distance difference. It belongs to the internal evaluation index of clustering algorithm. The larger the CH index is, the smaller the distance in the cluster that represents the clustering results, and the greater the distance between clusters, the better the clustering results. The contour coefficient is in the range of $[-1,1]$, -1 represents the wrong cluster, 1 represents the high density cluster, and the overlapping clustering near 0, so the closer the contour coefficient is better. The range of ARI is $[-1,1]$. The larger ARI means the higher the similarity between predicted cluster vector and real cluster vector, and ARI is close to 0, indicating that cluster vector is randomly allocated, and ARI is negative number to represent very poor prediction cluster vector. AMI is based on the mutual information score between predicted cluster vector and real cluster vector to measure its similarity. The higher the similarity of AMI, the closer AMI is to 0, the cluster vector is randomly allocated.

It can be seen from the data in the table that the fuzzy clustering algorithm based on clonal selection has better clustering effect than k-means algorithm and fuzzy c-means algorithm in the application of non-cooperative target clustering.

5. Conclusions

This paper aims to reduce the complexity of task planning when observing non-cooperative satellites. The fuzzy clustering algorithm based on clonal selection is used to cluster the relevant attributes of non-cooperative satellites. Based on the clustering results and clustering center value, the priority of non-cooperative target observation is determined, which satellite is observed at which time for the observation equipment to save time. In practical application, the number and type of attributes can be added and adjusted according to the actual situation and demand on the basis of the non-cooperative target attributes selected in this paper. At the same time, other related constraints such as the urgency of the task can be taken into consideration to determine the final non-cooperative target priority, it makes the clustering of non-cooperative targets more comprehensive and practical.

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