Hindawi
Journal of Sensors
Volume 2022, Article ID 7919808, 13 pages
https://doi.org/10.1155/2022/7919808

Research Article

Multisensor Dynamic Alliance Control Problem Based on Fuzzy Set Theory in the Mission of Target Detecting and Tracking

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Received 8 March 2022; Revised 1 July 2022; Accepted 30 August 2022; Published 22 September 2022

Academic Editor: Xueliang Xiao

A multisensor alliance is established by the activation of tasks or occurrences. It is also characterized as a multisensor dynamic alliance since it originates with mission development and disintegrates with task accomplishment. To overcome the constraint that a single sensor can only gather a one-sided, little amount of erroneous target information, each sensor in the dynamic alliance has diverse information collection capabilities and implements a cooperative methodology to complete the target mission. This paper emphasizes on alliance formation in multisensor dynamic alliance control under diverse missions. To begin with, we investigate the problem at the sensor recognition level for each target feature, delving into the concepts of alliance formation, renewal, and dissolution and emphasizing the fuzzy relationship in the multisensor dynamic alliance for multitarget. Moreover, dynamic alliance models are constructed using the fuzzy set calculation algorithm, which is powered by target detection, recognition, and tracking tasks in that sequence. Last but not least, simulation experiments demonstrated that the proposed model and algorithm outperform the existing models and algorithms. We may achieve the optimal alliance scheme by introducing the fuzzy set calculation algorithm into the dynamic alliance establishment process, which completely nullifies information redundancy and enhances the monitoring capabilities of the sensor network.

1. Introduction

Multisensor networks are widely applied in medical [1, 2], agriculture [3, 4], forest [5, 6], vehicle and ocean [7, 8] monitoring, and other fields. In particular, the application of multisensor networks in intelligent transportation systems has become a current research hotspot. In the research process, many practical problems need to use a series of measurement data of sensor networks to estimate the system's state. One of the most important information sources in an intelligent transportation system is the sensor. Sensors can be installed on vehicles or as part of infrastructures such as bridges, roads, or traffic signs [9, 10], providing information about weather and traffic conditions and improving the driving process. A sensor network consists of several microcomputers (nodes) that are outfitted with sensors and work together to complete a certain mission [11]. These nodes offer special sensing and wireless communication capabilities and perform various ad hoc networking without the need for a predefined physical infrastructure or centralized administration. Currently, the resource scheduling issue between sensors and targets is to eliminate sensor network resource occupancy while guaranteeing sensor monitoring efficiency for multiple targets. Selecting appropriate sensors to detect and track targets is a multisensor scheduling problem [12, 13], a research hotspot for many years, and is the core of this paper.

The multisensor scheduling problem is usually complex, multidimensional, and NP-hard. It mainly refers to reasonably scheduling various sensor resources in the sensor network to meet the requirements of multitarget detection and tracking in a certain time interval according to specific optimization criteria to achieve the comprehensive optimization of some or some indicators. The solving process of the multisensor scheduling problem is generally two steps. The first step is to establish the multisensor scheduling model, that is, to construct the objective function according to certain constraints. The second step is to find the optimal solution for the model by designing an optimization algorithm or exhaustive method to obtain the multisensor scheduling scheme. As a global optimization problem, the multitarget sensor scheduling problem needs to compute the simultaneous interpreting of all possible sensor management actions on different sensors. When the scale of the multisensor system is large, the global combinatorial optimization problem needs much computation, so it is necessary to design an optimization algorithm to solve the multisensor scheduling scheme. The solution to the scheduling problem of large-scale systems mainly uses a swarm intelligence algorithm. Swarm intelligence algorithm is primarily divided into centralized algorithms, such as Harris hawk algorithm (HHO) [14], whale algorithm (WOA) [15], slime mold algorithm (SMA) [16], bee colony algorithm (BCO) [17], and particle swarm optimization algorithm (PSO) [18]. In addition, auction algorithm (AA) [19] and contract network algorithm (CNA) [20] are distributed algorithms. The centralized algorithm transmits all data to the fusion center to calculate the optimal solution with more time and energy. Each sensor can be regarded as an agent with computing power in the distributed algorithm, exchanging information with adjacent sensors with fast computing speed and low energy consumption.

After a comprehensive review of the above references, we may infer that the multisensor dynamic alliance control problem based on fuzzy set theory still has three issues to be solved.

(1) First of all, while investigating the detection probability of the sensor to the target, most research papers frequently utilize the overall detection probability without considering whether the target's specific features are correctly detected, which could also contribute to information redundancy

(2) More significantly, the established sensor alliance may fail to recognize a certain target characteristic, causing the combat to be delayed. Moreover, sensor monitoring alters as the intended flight progresses. It should be considered to properly distribute sensor resources throughout activities to minimize redundancy and waste of sensor resources. Furthermore, in establishing multisensor alliances, the concerns of long solution time, low solution accuracy, and easily falling into local optimization of centralized and distributed algorithms should be highlighted

(3) As a result, this research demonstrates a fuzzy set and recommends a task-driven multisensor dynamic alliance model for multitarget, which can effectively minimize the information redundancy rate and resource occupancy rate to ensure the completion of target detection and recognition and tracking

Given the above analysis and summary, the following are the significant contributions of this paper.

(1) To begin, this paper explores the principles of the formation, renewal, and dissolution of the alliance and the problem at the level of sensor detection of each feature of the target to compensate for the shortcomings of previous research, which does not consider whether the specific qualities of the target are properly detected

(2) Meanwhile, establishing a dynamic alliance model driven by target detection, identification, and tracking tasks to tackle duplication and waste of sensor resources caused by unjustified sensor resource allocation when the task of sensor monitoring also varies in various stages of target flight

(3) Then, we implement fuzzy set theory [21–24] to solve the established dynamic alliance model, which is driven by target detection, recognition, and tracking tasks. Then, we generate multisensor alliance schemes driven by distinct goals to overcome the issues of long solution time and low solution accuracy in establishing multisensor alliances via centralized and distributed algorithms

The remainder of this paper is arranged as follows. Section 2 concentrates on the multisensor dynamic alliance mechanism and establishes the model driven by target detection, identification, and tracking tasks. Section 3 validates the methods and algorithms prescribed in this paper by utilizing example simulation. Section 4 summarizes the work of this paper.

2. Materials and Methods

2.1. Sensor Dynamic Alliance Mechanism

2.1.1. Definition of Multisensor Dynamic Alliance. The established sensors in the sensor network that perform early warning tasks are referred to as a multisensor dynamic alliance. In various scenarios of target assault, the pairing of sensors and targets is determined depending on monitoring (detection, identification, and tracking) tasks in various stages to establish a subsystem for each target, and each subsystem is dynamically updated, relying on mission alterations in various stages of target flight. Each alliance has 3 phases: formation, renewal, and disintegration.

2.1.2. Principles of Formation, Renewal, and Dissolution of the Alliance

(1) Alliance Formation. In the beginning, the sensor forms an alliance based on target identification and tracking mission. After gathering all of the target's characteristic information, it assesses the target's flight path (assuming that the sensor's prediction result is valid) and then forms an alliance based on the target tracking task.

(2) Alliance Renewal. When a sensor detects numerous targets, it must evaluate their priority and prioritize the targets with the highest priority to ally. When multiple sensors detect the same target, the relevance level of sensors in the sensor network must be considered, and the participating alliance with the lowest importance level must be chosen. The new alliance based on a target tracking task involves at least one sensor from the previous alliance discovered on

the target detection and recognition task to share target information with the sensor in the new alliance.

(3) Alliance Dissolution. When the target is demolished or delivered to the precision-guided weapon system, the sensors in the early warning system are no longer required to track it; the alliance could dismiss depending on the tracking mission.

2.1.3. Fuzzy Relation in Dynamic Alliance. Set up a sensor network with m sensors and n incoming targets. Since a sensor can participate in the dynamic alliance for multiple targets simultaneously, the classification of a sensor a_i in the n-th dynamic alliance $\{G_1, \cdots G_j, \cdots, G_n\}$ established for target $\{b_1, b_2, \cdots, b_j, \cdots, b_n\}$ in the sensor network $\{a_1, a_2, \cdots, a_i, \cdots, a_m\}$ is not the direct relationship of if $a_i \in G_i$, then $a_i \notin G_i$, but $a_i \in G_i$, or $a_i \in G_{i+1}$, this and other fuzzy relationship. Similarly, a target can be detected by multiple sensors; the classification of each target $\{b_1, b_2, \cdots, b_j, \cdots, b_n\}$ in the sensor set $\{O_{1,} O_2, \cdots, O_m\}$ is also an ambiguous relationship.

2.1.4. Target Priority Model. Target priority P is a mathematical number that indicates the target's threat level. When the target priority is high, it indicates that the target is highly dangerous. The sensor needle must prioritize allying with it to minimize the threat degree of the target.

Priority level elements b_j include attribute p_{j1}, type p_{j2}, speed p_{j3}, angle p_{j4}, height p_{j5}, distance p_{j6}, and situation p_{j7}. The factors listed above have varying effects on the target priority, and the weighting function is typically employed to establish the target priority level:

$$\varpi_1 + \varpi_2 + \varpi_3 + \varpi_4 + \varpi_5 + \varpi_6 + \varpi_7 = 1, \tag{1}$$

$$p_j = \varpi_1 p_{j1} + \varpi_2 p_{j2} + \varpi_3 p_{j3} + \varpi_4 p_{j4} + \varpi_5 p_{j5} + \varpi_6 p_{j6} + \varpi_7 p_{j7}, \tag{2}$$

where $\varpi_i (i = 1, 2, \cdots, 7)$ is the weight value of the factors mentioned above.

The priority of each objective among all objectives is expressed by normalization, that is,

$$P_j = \frac{p_j}{\sum_1^n p_j}. \tag{3}$$

2.1.5. Sensor Importance Level Model. Q is a mathematical number that indicates the sensor's relevance in the sensor network. When a sensor's relevance level is high, it performs an essential detecting task in the sensor network. When sensor resources are occupied, the sensor network's resource consumption is high.

Sensor performance q_{i1}, sensor deployment position q_{i2}, sensor detection area q_{i3}, sensor type q_{i4}, and sensor anti-interference ability q_{i5} are the main factors determining the second critical level of the i-th sensor.

When many sensors compete for the same goal in a sensor alliance, the sensors with the lowest relevance level join the alliance to reduce resource consumption in sensor networks.

$$\beta_1 + \beta_2 + \beta_3 + \beta_4 + \beta_5 = 1, \tag{4}$$

$$q_i = \beta_1 q_{i1} + \beta_2 q_{i2} + \beta_3 q_{i3} + \beta_4 q_{i4} + \beta_5 q_{i5}, \tag{5}$$

where $\beta_i (i = 1, 2, \cdots, 5)$ is the weight value of the factors mentioned above.

The priority of each objective among all objectives is expressed by normalization, that is,

$$Q_i = \frac{q_i}{\sum_1^m q_i}. \tag{6}$$

The target can be monitored when the linear distance between b_j and d_{ij} is less than the detection radius of the sensor r_{i0}, in which $r_{i0} \geq d_{ij}$.

Following the formation of a dynamic alliance for all targets, the sensor network must detect all features of all targets to the fullest degree possible. Each target requires seven feature identifications, b_j and v_j features are detected, which may be stated as follows:

$$\max \sum_{j=1}^{n} v_j. \tag{7}$$

Simultaneously, to reduce the total of the basic levels of sensors participating in the alliance, which may be stated as follows:

$$\min \sum_{j=1}^{n} Q_{j\text{occupy}}. \tag{8}$$

To eliminate the number of sensors involved in the alliance, that is,

$$\min \sum_{j=1}^{n} s_j. \tag{9}$$

2.2. Establishment of the Dynamic Alliance Model

2.2.1. Alliance Model Based on Target Detection and Recognition Task

(1) Constructing Fuzzy Sets. When taking the sensor's overall recognition degree to the target as the discussion item, the alliance process may result in information duplication, and more significantly, it may result in inadequate detection information. Assuming that each target characteristic accounts for 1/7 of the total elements, when the recognition degree of a_i to b_j is $\Omega_{ij} = 6/7$, which cannot recognize the speed of b_j, and the recognition degree $\Omega_{i+1j} = 5/7$ of a_{i+1} to b_j, which cannot identify the kind and speed of b_j, the two sensor partnerships did not increase the degree of target recognition. However, they resulted in information duplication and the waste of sensor resources.

In the operational scenario of a specific target attack, if there are only two results that a_i can recognize (state $o = 1$) and cannot recognize (state $o = 0$) for the k-th feature p_{jk} of b_j, it can be established that a sensor network can specify the domain, and the division of $O_1, O_2, \cdots, O_m$ on U is

$$O_1 = \frac{o_{11}^1}{P_{11}} + \frac{o_{12}^1}{P_{12}} + \cdots + \frac{o_{17}^1}{P_{17}} + \cdots + \frac{o_{j1}^1}{P_{j1}} + \frac{o_{j2}^1}{P_{j2}} + \cdots \frac{o_{j7}^1}{P_{j7}} + \cdots,$$
$$\cdots\cdots$$
$$O_i = \frac{o_{11}^i}{P_{11}} + \frac{o_{12}^i}{P_{12}} + \cdots + \frac{o_{17}^i}{P_{17}} + \cdots + \frac{o_{j1}^i}{P_{j1}} + \frac{o_{j2}^i}{P_{j2}} + \cdots \frac{o_{j7}^i}{P_{j7}} + \cdots,$$
$$\cdots\cdots$$
$$O_m = \frac{o_{11}^m}{P_{11}} + \frac{o_{12}^m}{P_{12}} + \cdots + \frac{o_{17}^m}{P_{17}} + \cdots + \frac{o_{j1}^m}{P_{j1}} + \frac{o_{j2}^m}{P_{j2}} + \cdots \frac{o_{j7}^m}{P_{j7}} + \cdots, \tag{10}$$

where $O_1, O_2, \cdots, O_m$ are the fuzzy sets corresponding to $a_1, a_2, \cdots, a_i, \cdots, a_m$; $o^i{}_{jk}$ represents the recognition effect of a_i the k-th feature b_j. Written in vector form, there are

$$O_1 = \begin{bmatrix} o_{11}^1 & o_{21}^1 & \cdots & o_{n1}^1 \\ o_{12}^1 & o_{22}^1 & \cdots & o_{n2}^1 \\ \cdots & \cdots & \cdots & \cdots \\ o_{17}^1 & o_{27}^1 & \cdots & o_{n7}^1 \end{bmatrix}, \cdots,$$
$$O_i = \begin{bmatrix} o_{11}^i & o_{21}^i & \cdots & o_{n1}^i \\ o_{12}^i & o_{22}^i & \cdots & o_{n1}^i \\ \cdots & \cdots & \cdots & \cdots \\ o_{17}^i & o_{27}^i & \cdots & o_{n7}^i \end{bmatrix}, \cdots, \tag{11}$$
$$O_m = \begin{bmatrix} o_{11}^m & o_{21}^m & \cdots & o_{n1}^m \\ o_{12}^m & o_{22}^m & \cdots & o_{n1}^m \\ \cdots & \cdots & \cdots & \cdots \\ o_{17}^m & o_{27}^m & \cdots & o_{n7}^m \end{bmatrix}.$$

(2) Alliance Establishment Steps. In general, all sensors can detect and identify several targets simultaneously, fulfilling the task requirements.

In practice, generally, no more than five sensors can detect b_j simultaneously. For b_j, the establishment process of the alliance B_j is as follows:

(a) When sensors detect the j-th target at the same time, the sensor alliance has $2^{m_j} - 1$ alliance schemes

(b) The f scheme lets the fuzzy sets corresponding to each sensor do the intersection operation of the fuzzy set $O_j^f = O_1^* \wedge O_2^* \wedge \cdots$, O_j^f is the final corresponding coalition operator, and the sum of the crucial levels of all sensors in the coalition is $Q_j^f = Q_1^* + Q_2^* + \cdots$

(c) If the j-th column element O_j^f satisfies $\sum_{k=1}^{7} o_k \geq 7$, the alliance can complete the task of identifying all the features b_j

(d) Suppose a total of e alliances meet the above requirements, then find min $\{Q_j^1, Q_j^2, \cdots, Q_j^e\}$, and the corresponding alliance scheme G_j^1 is the optimal scheme to establish an alliance for the target b_j

2.2.2. Alliance Model Based on the Target Tracking Task. After completing the target recognition and detection tasks, an alliance is formed based on the target tracking task.

Varying sensors have different tracking capacities (some can only track one target while others can interpret many targets simultaneously), complicating the problem analysis. When a_i can track K_i targets, in the dynamic alliance, the sensor may be viewed as K_i sensors with the same performance that can only track one target, and the sensor network can be regarded as m^* $(m^* \geq m)$ sensors that can only track one target. At this point, the sensor set is $\{a_1, a_2, \cdots, a_i, \cdots, a_{m^*}\}$.

(1) Classification Method. The track calculated by the sensor alliance in the detection and identification stage is l_j. The set of sensors intersecting within sensor networks is $G_j = \{a_1', a_2', \cdots, a_t'\}$, which has $l_j \in G_j$.

The sensors G_j^* are classified by fuzzy cluster analysis.

Step 1. Determine the calibration method of the fuzzy similarity coefficient.

If the detection field of a_i' is V_i and the detection field of a_{i+1}' is V_{i+1}, then the similarity coefficient between a_i' and a_{ii+1}' is

$$r_{ii+1} = \frac{V_i \cap V_{i+1}}{V_i \cup V_{i+1}}. \tag{12}$$

Step 2. Establish the fuzzy similarity coefficient matrix.

$$R = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1t} \\ r_{21} & r_{22} & \cdots & r_{2t} \\ \cdots & \cdots & \cdots & \cdots \\ r_{t1} & r_{t2} & \cdots & r_{tt} \end{bmatrix}. \tag{13}$$

Step 3. Given $\lambda \in [0, 1]$, get the relationship between λ and R_λ, and use R_λ to get the classification corresponding to *λ.(2) Alliance Establishment Steps.* According to priority, the sensors have been ranked from high to low. When the alliance $G_j^2$is established for b_j higher priority and lower priority, the selection range of sensors becomes $\{a_1, a_2, \cdots, a_{m^*}\} - G_j^2$.

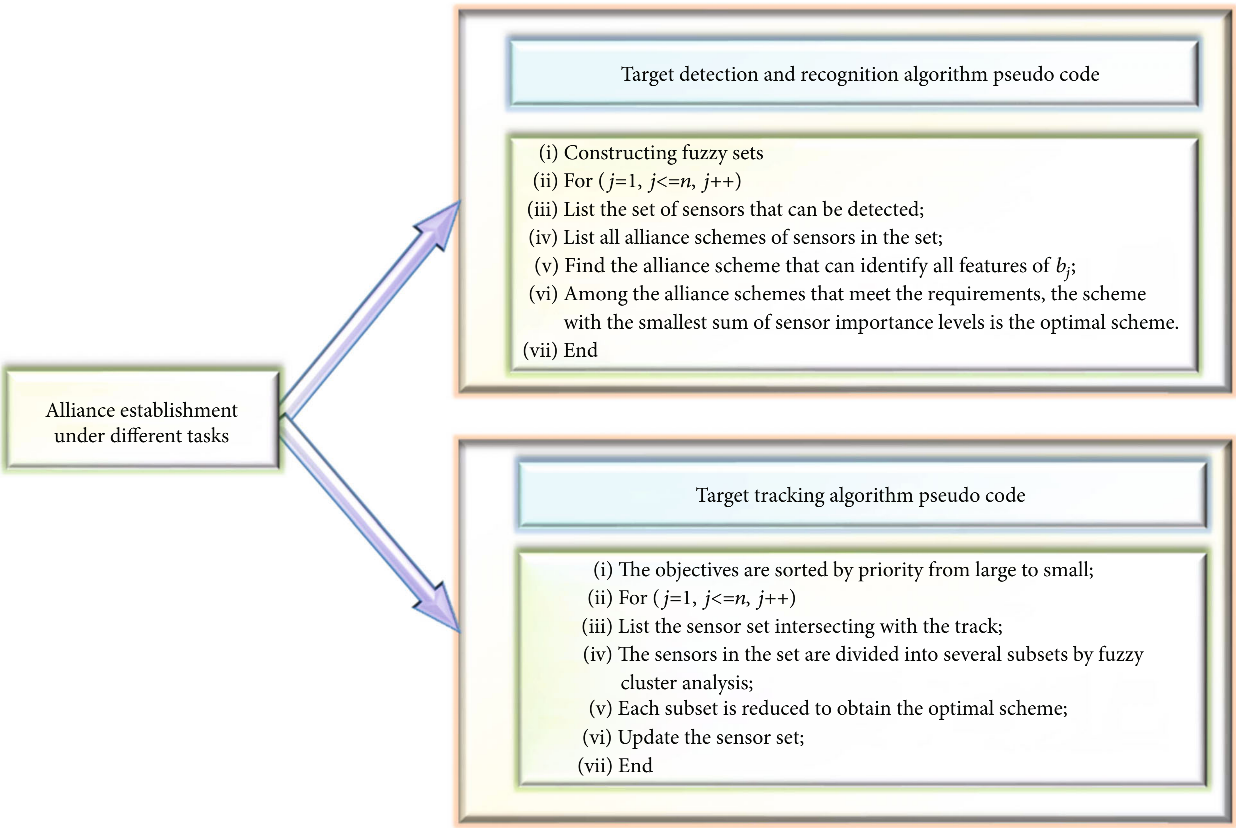


Figure 1: Pseudocode for two suggested algorithms.

For b_j, the establishment process of the alliance G_j^2 is as follows.

Step 1. Determine the sensor set $G_j = \{a_1', a_2', \cdots, a_t'\}$ where the updated sensor network intersects with the b_j target track.

Step 2. The sensors $G_j = \{a_1', a_2', \cdots, a_t'\}$ are classified by fuzzy cluster analysis, and the target tracks are also divided into corresponding subsets. The target tracks contained in the intersection of the two subsets are randomly assigned to any subset.

Step 3. Reduce the sensor subset to determine the alliance scheme that meets the tracking task and ensures the minimum sensor importance levels.

The reduction principle of the T-th subset $(G_j)_T$ of the set G_j is as follows.

Let $(G_j)_T = \{a_i, a_{i+1}, \cdots\}$ have m_t sensors in total, which are responsible for the tracking task of a track segment b_j. The sensors have $2^{m_t} - 1$ alliance schemes, and the alliance of the f-th strategy is $[a_1^*, a_2^*, \cdots]$. If $l_{jT} \in [a_1^*, a_2^*, \cdots]$ $[a_1^*, a_2^*, \cdots]$ can complete the tracking task l_{jT}, the sum of the elementary levels of all sensors in the alliance is $Q_j^f = Q_1^* + Q_2^* + \cdots$.

Let e kinds of alliances meet the above requirements, then find $\min\{Q_j^1, Q_j^2, \cdots, Q_j^e\}$; the corresponding alliance scheme G_j^T is the optimal scheme for l_{jT} tracking. Find the optimal scheme in all subsets, and then, get the alliance scheme G_j^2 driven by the tracking task.

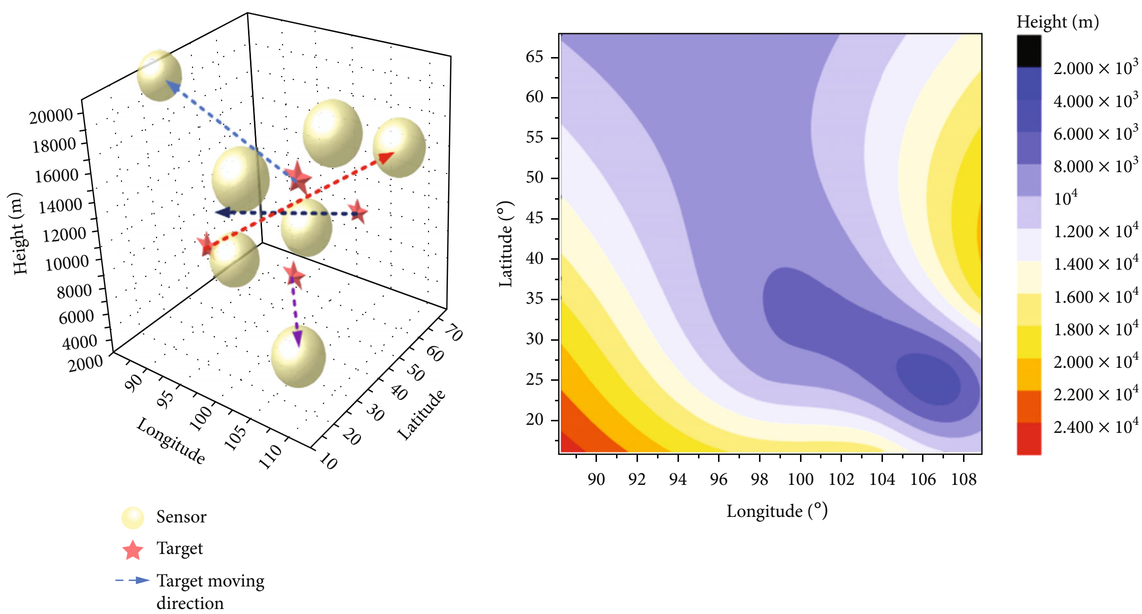
The running pseudocodes of the two algorithms are displayed in Figure 1.

2.2.3. Analysis of Algorithm Complexity. The algorithm in the alliance model based on the task of detection and recognition of the target must be performed n times, so its complexity is $O(n)$, and the algorithm in the alliance model based on the task of tracking the target must also be run n times, so its complexity is likewise $O(n)$.

3. Simulation

3.1. Parameter Settings. Figure 2 depicts the deployment of the sensor network in the region. Four targets enter the sensor network at a specified time. Table 1 illustrates the essential level information for each sensor in the sensor network. Table 2 displays the sensor's detection of each target characteristic.

Figure 2(a) depicts sensor and target deployment information; the yellow ball represents the sensor, the red pentagram represents the target, and the dashed line with arrows represents the target's motion direction; additionally, because the detailed position information of the target and



(a) (b)

FIGURE 2: Sensor network and target situation map. (a) Sensor and target deployment information. (b) Performance indicators of each sensor and target.

TABLE 1: Sensor parameters.

Sensor	Important level	Number of detectable	Number of traceable
S_1	0.17	≥8	4
S_2	0.15	≥8	4
S_3	0.19	≥8	3
S_4	0.26	≥8	5
S_5	0.08	≥8	3
S_6	0.11	≥8	5
S_7	0.04	≥8	2

TABLE 2: The number of target features detected by sensors.

Parameter	T_1	T_2	T_3	T_4
Detecting sensor number	4, 5, 6	2, 3, 5, 6, 7	1, 2, 6	1, 7
Attribute	4, 5	2, 5, 7	2, 3	2
Type	6, 7	3, 6	1, 5	5
Speed	3, 4	1, 4	2, 6	3
Angle	2, 5	2, 4	4, 5	6
Height	4, 6	2, 3	6, 7	1
Distance	3, 7	4, 7	3, 6	2
Situation	5, 6	5, 6	2, 7	4
Priority	0.3	0.5	0.2	0.4

sensor is not accessible in the figure, Figure 2(b) provides the position information of the target and sensor as supplementary images.

The essential level properties of each sensor and the number of targets that each sensor can detect and track can be seen in Table 1 in the simulated experiments described in the paper. Table 2 depicts the specific features of each target to be recognized by the sensors in the same way. The table includes the sensor's serial number used to identify each target and the sensor's serial number that detects the target's features.

The similarity coefficients between sensors are written in the form of the matrix:

$$\begin{bmatrix} 1 & 0.063 & 0 & 0 & 0 & 0 & 0 \\ 0.063 & 1 & 0.077 & 0 & 0 & 0 & 0 \\ 0 & 0.077 & 1 & 0.136 & 0.153 & 0.200 & 0.364 \\ 0 & 0 & 0.136 & 1 & 0.250 & 0.250 & 0.667 \\ 0 & 0 & 0.153 & 0.250 & 1 & 0.273 & 0.455 \\ 0 & 0 & 0.200 & 0.250 & 0.273 & 1 & 0.499 \\ 0 & 0 & 0.364 & 0.667 & 0.455 & 0.499 & 1 \end{bmatrix}. \tag{14}$$

3.2. *Task Alliance Scheme Based on Target Detection and Recognition Task*

3.2.1. *Multisensor Alliance Scheme Based on Fuzzy Set Theory.*

First, establish the universe $U = \{A_1, A_2, A_3, A_4, A_5, A_6, A_7\}$ and write the corresponding fuzzy sets as follows:

$$O_1 = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}, O_2 = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}, O_3 = \begin{bmatrix} 0 & 1 & 1 & 1 \\ 0 & 0 & 1 & 1 \\ 0 & 0 & 1 & 0 \\ 0 & 1 & 1 & 1 \\ 0 & 1 & 1 & 0 \\ 0 & 0 & 1 & 1 \\ 0 & 0 & 1 & 1 \end{bmatrix}, O_4 = \begin{bmatrix} 0 & 1 & 1 & 0 \\ 0 & 1 & 1 & 1 \\ 0 & 1 & 1 & 1 \\ 0 & 1 & 1 & 1 \\ 0 & 0 & 1 & 1 \\ 0 & 1 & 1 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}, O_5 = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}, O_6 = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 1 & 1 & 0 & 0 \\ 1 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 1 & 1 & 0 & 0 \end{bmatrix}, O_7 = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 1 & 0 & 1 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 1 & 0 & 1 & 0 \\ 1 & 0 & 0 & 0 \\ 1 & 0 & 1 & 0 \end{bmatrix}. \tag{15}$$

Table 3: Multisensor alliance scheme.

	Target 1	Target 2	Target 3	Target 4
Sensor number	2, 3, 5, 7	1, 3, 5, 6	1, 2, 3 , 5, 7	1, 2, 3, 4, 5

According to the fuzzy sets obtained above, the optimal solution to the multisensor alliance scheme is shown in Table 3.

Table 3 demonstrates that the sensors detect all four targets, but the number of detected sensors differs per target: targets 1 and 2 correspond to four sensors, while targets 3 and 4 belong to five sensors. This is owing to the preceding section's discussion of the multisensor detection model based on fuzzy sets, and the table also reveals that sensors 1, 2, 3, and 5 are committed to detection.

The detection impact change curve of each target is depicted in Figure 3, assuming that the relevance of each target feature in the overall target feature is 1/7.

Figure 3 depicts the degree of detection of several sensors corresponding to each target, with sensors 1, 2, and 5 having the lowest degree of detection and sensors 3 and 4 having the highest degree of detection. When paired with Table 4, it is clear that, while sensors 1, 2, and 5 participate in target detection the most frequently, their actual contribution is less when compared to sensors 3 and 4. The relevance of the sensors in the early conditions is the primary reason for this circumstance.

3.2.2. Multisensor Alliance Schemes under Different Algorithms. To verify the effectiveness of the proposed algorithm, we compared the centralized intelligent algorithm (particle swarm optimization algorithm (PSO) [17], bee colony optimization algorithm (BCO) [18]) and distributed intelligent algorithm (auction algorithm (AA) [19]) as the comparison algorithm.

The auction algorithm is highlighted here. The auction algorithm belongs to the search tree algorithm and is a fast and efficient multiagent coordination mechanism with strong operational features. There are two agents in the auction algorithm: auction agent A and bidding agent B. Auction agent A performs as an agent for the auctioned task, whereas bidding agent B bids depending on its resources and task characteristics. Through the auction, Auction agent A chooses all the successful bids based on the concept of the highest price, and the winners could collaborate to complete task T, therefore fulfilling the mapping between agents and tasks, i.e., completing the multiple agents. Thus, task allocation across several agents is accomplished.

The sensor alliance schemes under different algorithms are given in Table 5.

Table 5 demonstrates the advantages of the algorithm based on the fuzzy set theory described in this paper for solving the multisensor alliance scheme. The utilization of sensors in the detection and recognition process of each target is relatively balanced in the scheme generated by the algorithm based on fuzzy set theory, and each target has 4-5 sensors for detection and recognition; nevertheless, it is also noted that the utilization rate of sensors in the scheduling schemes generated by other comparison algorithms is unbalanced. For instance, in the centralized swarm intelligence algorithm (PSO, BCO), the utilization rate of sensor resources is poor during the detection and tracking of a target. In contrast, the distributed intelligence algorithm (AA) consists of sensor resources at a higher rate than the centralized intelligence algorithm. However, the solvent impact is lesser than that of the fuzzy set theory algorithm.

The basic reason for this situation is the difference in how centralized and distributed algorithms perform. Although the centralized algorithm attains the best result by employing global information, which is computationally precise, the solution time is sluggish, putting a significant strain on the sensor network's connection. The distributed algorithm utilizes parallel computing to obtain a faster convergence rate and reduces the communication load on the system. Although the sensors in the sensor network are involved in the detection frequency, the real sensor utilization rate is low due to the centralized algorithm's time-consuming and onerous operational mechanism, demonstrating a high sensor use rate.

The time diagrams of sensor detection and recognition targets in the multisensor alliance are solved by different algorithms in Figure 4 to highlight further the efficacy and rationality of the multisensor alliance scheme solved based on the fuzzy set theory algorithm paper.

Figure 4 illustrates that the temporal graphs of multisensor detection and recognition targets solved by different algorithms have some discrepancies. Figure 4(a) exhibits a fuzzy set theory-based multisensor detection and recognition of the target sequence diagram. Its effect is superior to that of other comparison algorithms. Through simultaneous interpretation, each target may accomplish continuous detection among different sensors. There is no blank detection stage, and the sensor network's burden is minimal. Figures 4(b) and 4(c) demonstrate the time charts of multisensor detection and identification of targets acquired by the centralized algorithm; each sensor conducts detection and tracking tasks, the number of targets is generally balanced, and there is no frequent switching of sensors.

In comparison to the algorithm conducted in this paper, the PSO algorithm can complete the detection of each target, but there is a blank section of detection and tracking in the latter stages of detection, which enhances the risk of missing targets. The BCO algorithm employs a single sensor to detect and identify targets; this puts significant strain on the sensor, and we can see from the diagram that the sensors in the alliance can identify targets compared to the centralized approach's sensor alliance results. Although the impact is superior to that of the centralized algorithm, the sensor alliance's solution quality is still inferior to the algorithm suggested in this paper.

Figure 5 shows the running time and utilization rate of sensor resources under different algorithms in the mission of target detecting.

Figure 5(a) reveals that the proposed algorithm in this paper has a lower running time than other algorithms. Furthermore, we may conclude that the proposed algorithm has

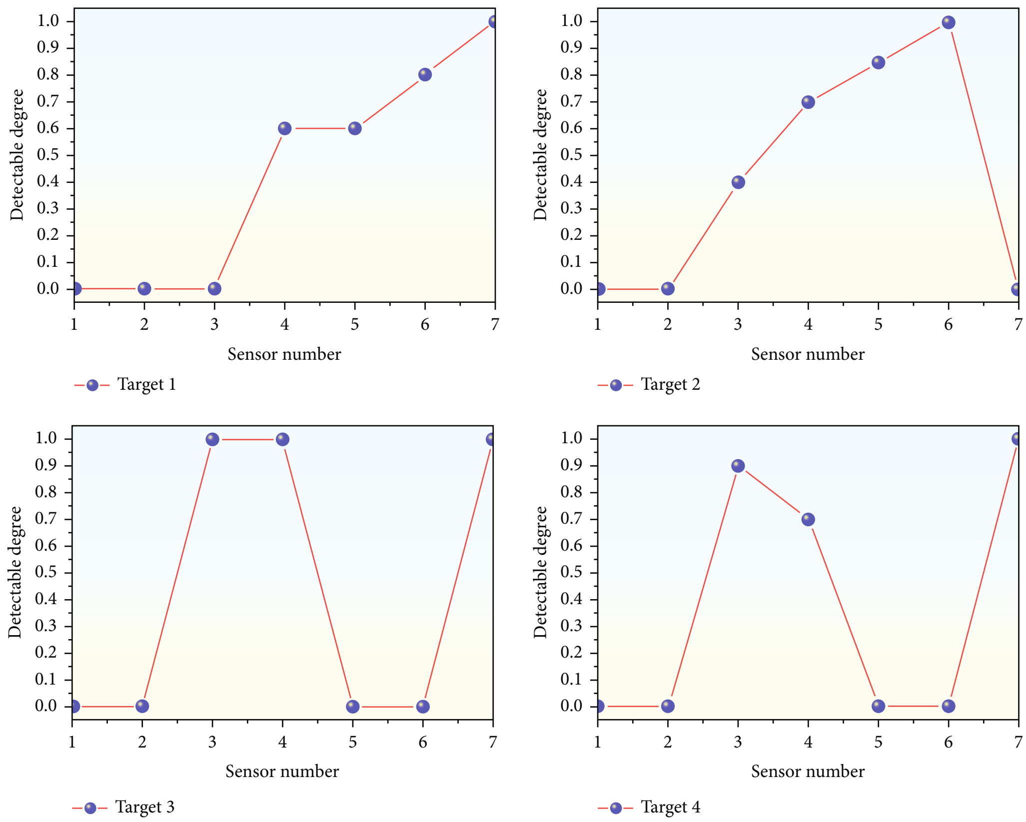


Figure 3: Detectability curve of the sensor to target.

Table 4: Addition of sensor and target tracks.

Sensor	Target 1	Target 2	Target 3	Target 4
Sensor number	2, 3, 4, 5 , 6, 7	1, 2, 3, 4, 5, 6, 7	1, 3, 5 , 6, 7	4, 5, 6, 7

Table 5: Multisensor alliance schemes under different algorithms.

Target	Different algorithm: Proposed algorithm (fuzzy set theory)	Particle swarm optimization (PSO)	Bee colony optimization (BCO)	Auction algorithm (AA)
	Sensor number			
T_1	2, 3, 5, 7	1, 2 , 5	2, 3	1, 4, 6
T_2	1, 3, 5, 6	2, 4	3, 6, 7	2, 3, 5
T_3	1, 2, 3, 5, 7	1, 4, 6	4	1, 4, 7
T_4	1, 2, 3 , 4, 5	2, 7	1, 5	2, 5, 6

better convergence than the other three algorithms. At the same time, it demonstrates that the centralized method has a longer running time than the distributed algorithm. The fundamental issue is that the centralized algorithm sends all data to the fusion center, which takes more time and energy to determine the ideal solution. Each sensor may be seen as an agent with computing power in the distributed algorithm, sharing information with nearby sensors at high computation speed and low energy usage.

Figure 5(b) indicates that the efficiency of sensor resources varies between alliance patterns generated by different algorithms. The algorithm in this paper produces the maximum utilization rate of sensor resources in the alliance, and there is minimal variation in the utilization rate of sensor resources in the alliance formed for each target. The resource utilization rates of the other two algorithms, on the other hand, are low, with a minimum of 14.29%.

3.3. Alliance Scheme Based on the Target Tracking Task

3.3.1. Multisensor Alliance Scheme Based on Fuzzy Set Theory. Due to the different tracking capabilities of each sensor, in the alliance, the sensor network can be equivalent to 18 sensor combinations that can only participate in one

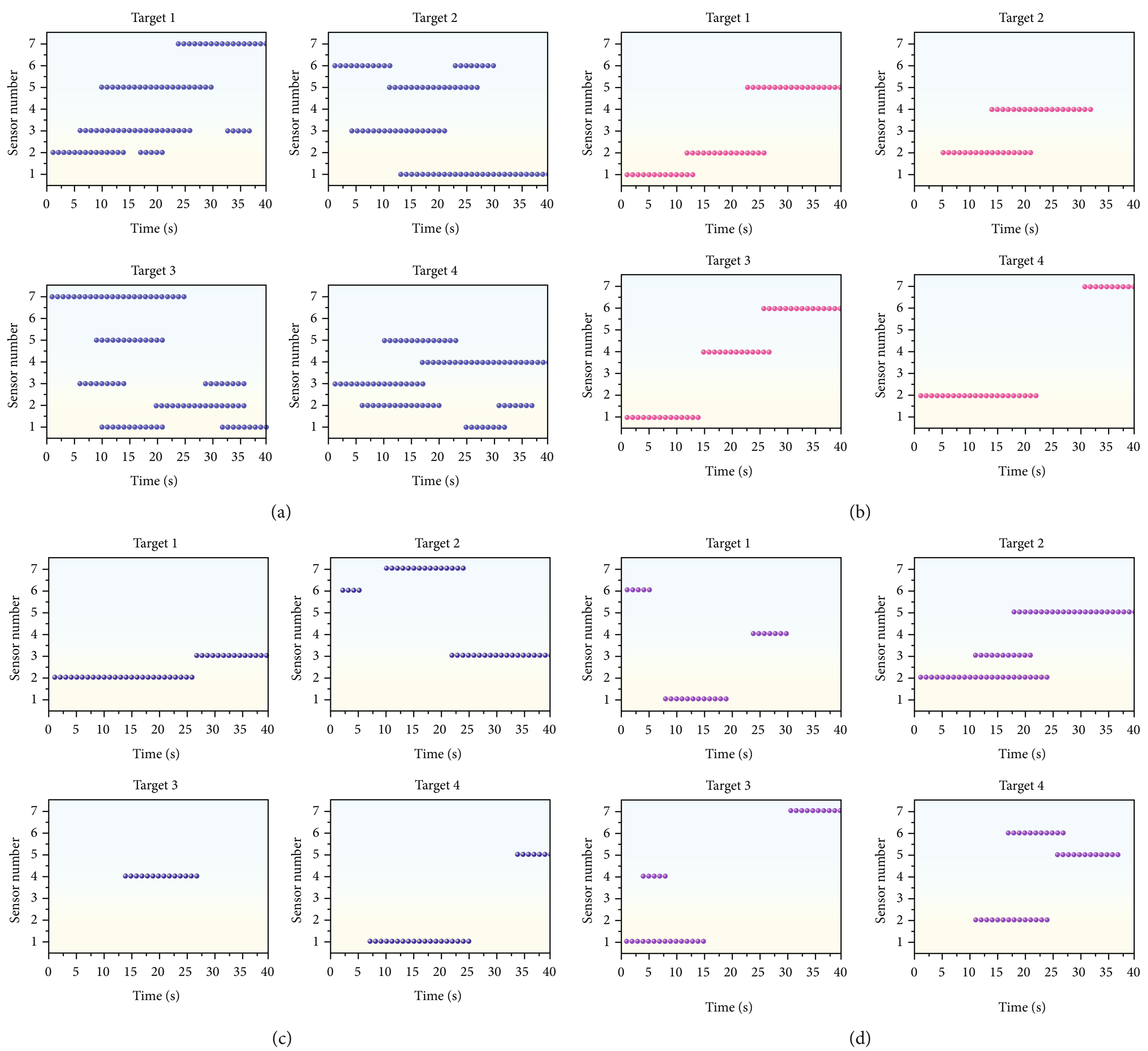


Figure 4: Timing diagrams of sensor detection and recognition targets in the multisensor alliance under different algorithms: (a) fuzzy set theory; (b) PSO; (c) BCO; (d) AA.

alliance $\{a_{11}, \cdots, a_{14}, a_{21}, \cdots, a_{24}, a_{31}, \cdots, a_{35}, a_4, a_{51}, a_{52}, a_{53}, a_{61}, a_{62}, a_{63}, a_7\}$, which is $\{a_1, a_2, \cdots, a_{18}\}$.

(1) The sensor sets intersecting four target tracks are calculated, which a_{11}, a_{12} have the same tracking effect on all sensors. The sensor sets intersecting with four target tracks are represented in Table 4

(2) Given $\lambda = 0.1$, the sensors intersecting each target track are grouped. The sensor groups of each target track intersection are indicated in Table 6

(3) According to the reduction rules, each alliance is reduced. The sensor groups of each target track intersection are indicated in Table 7

3.3.2. Multisensor Alliance Scheme under Different Algorithms. To verify the effectiveness of the algorithm proposed in this paper, we compare the centralized intelligent algorithm (PSO [17], BCO [18]) and distributed algorithm (AA [19]) as the comparison algorithm. Further, it analyzes the effectiveness of the alliance scheme based on target tracking tasks obtained by using the fuzzy set theory in this paper.

The sensor alliance schemes under different algorithms are given in Table 8.

The suggested algorithm based on fuzzy set theory offers advantages in solving the multisensor alliance scheme, as shown in Table 8. The sensors in the tracking process of each target are uniformly distributed in the scheme developed by the algorithm based on fuzzy set theory, and each

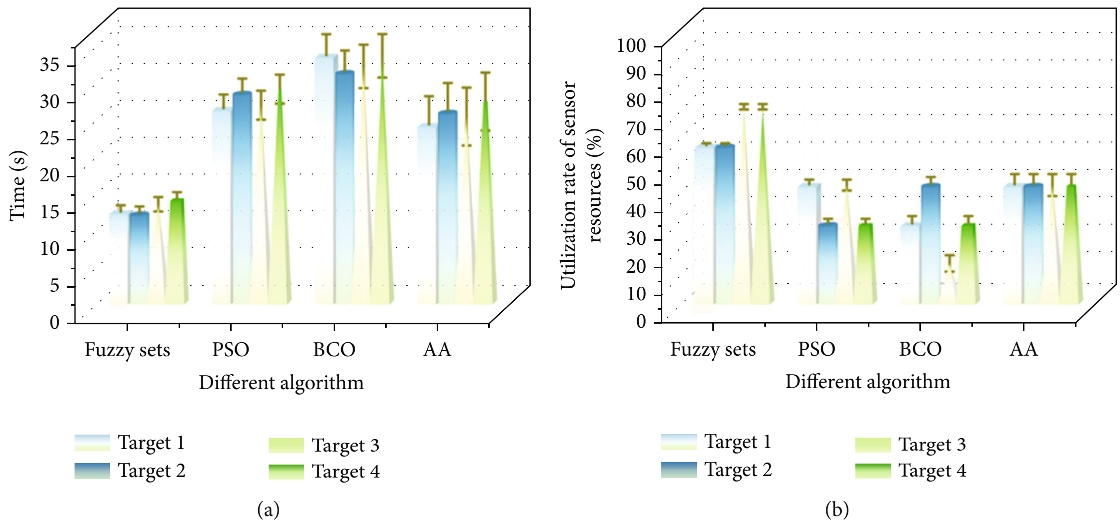


Figure 5: Running time and utilization rate of sensor resources under different algorithms in target detecting mission. (a) Running time under different algorithms. (b) Utilization rate of sensor resources under different algorithms.

Table 6: Classification results of sensors.

Sensor		Target 1	Target 2	Target 3	Target 4
	Group 1	2, 3, 4	1, 2, 3	1, 3, 5	4
Sensor number	Group 2	5, 6	4, 5	6	5, 6
	Group 3	7	6, 7	7	7

Table 7: Classification results of sensors.

Sensor		Target 1	Target 2	Target 3	Target 4
	Group 1	2, 3	1, 2	1, 5	4
Sensor number	Group 2	5	4	6	5
	Group 3	7	6	7	7

Table 8: The sensor alliance schemes under different algorithms.

Target	Different algorithm: Proposed algorithm (fuzzy sets)	Particle swarm optimization (PSO)	Bee colony optimization (BCO)	Auction algorithm (AA)
	Sensor number			
T_1	2, 3, 5, 7	1, 3, 4	4, 6	2, 3, 4
T_2	1, 2 , 4, 6	3, 6	2, 5, 6	1, 4, 5
T_3	1, 5, 6, 7	2, 4, 5	2, 3	3, 5
T_4	4, 5, 7	1, 5	4	4, 6

target includes 3-4 sensors for tracking. At the same time, we can see that the sensor dispersion in the centralized swarm intelligence algorithm (PSO, BCO) target tracking process is not uniform. The distributed intelligence algorithm (AA) is superior to the centralized intelligence algorithm, but its solution impact is inferior to that based on fuzzy set theory. The uniform sensor distribution of the centralized algorithm is due to the two algorithms' profoundly different operation mechanisms, which have been analyzed in the simulation experiment findings in Section 3.2.2 for the significant disparities in the two algorithms' operation mechanisms.

In centralized sensor networks, the centralized algorithm is usually utilized sensor scheduling. The sensor nodes provide observation data to the information fusion center, which analyzes it using relevant data, completes the target state estimate, and outputs the sensor scheduling scheme for the next observation moment. The information fusion center delivers control instructions to the sensor nodes, which they use to monitor the goal condition. Distributed algorithms are generally utilized in sensor scheduling in distributed sensor networks, and they are based on the notions of distributed computing and multiagent theory. Each sensor is viewed as an agent with autonomous decision-making capabilities to achieve distributed dynamic sensor action adjustment. Each agent determines the response protocol under the sensor management mechanism and then performs the calculation, reasoning, and decision-making on its own in the sensor management process.

Based on the preceding theory and the simulation experiments described in this section, we may infer that the multisensor multitarget allocation scheme of the distributed algorithm is more uniform than the scheme of the centralized algorithm. Similarly, we may conclude that the distributed algorithm's sensor usage rate is higher than that of the centralized algorithm.

Figure 6 depicts the sequence diagrams of sensor tracking targets in the multisensor alliance solved by different algorithms to highlight further the efficacy and rationality of the multisensor alliance scheme in solving target tracking based on the fuzzy set theory algorithm.

Figure 6 indicates discrepancies in the temporal graphs of multisensor tracking targets addressed by different methods. Figure 6(a) depicts the multisensor tracking target's time sequence diagram, translated utilizing the fuzzy set theory algorithm described in this paper. The graph demonstrates that each sensor may achieve steady target monitoring during the target tracking process via the handover

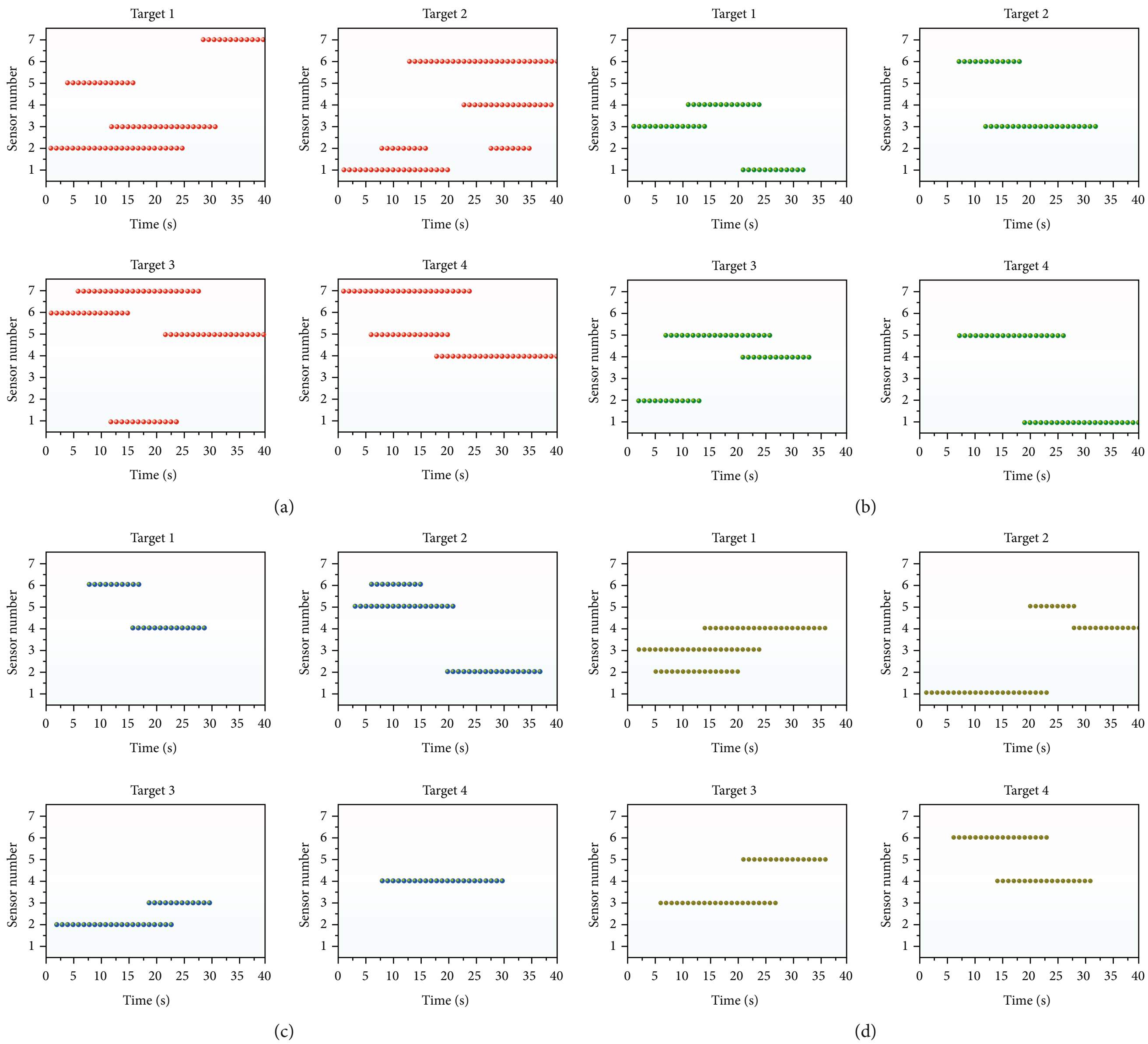


Figure 6: Timing diagrams of sensor tracking targets in the multisensor alliance under different algorithms: (a) fuzzy set theory; (b) PSO; (c) BCO; (d) AA.

task window. Furthermore, employing sensor resources minimizes the likelihood of target loss throughout the tracking process; Figures 6(b) and 6(c) reveal time charts of multisensor tracking targets acquired by the centralized method (PSO and BCO).

The PSO algorithm can perform the target tracking procedure compared to this paper's algorithm. The BCO algorithm employs a single sensor to track the target, resulting in sensor resource redundancy. At the same time, there are blank parts in the sensor working range, increasing the chance of losing the target; Figure 6(d) depicts the distributed algorithm's target tracking sequence diagram (AA). The figure illustrates that, compared to the tracking effect of the centralized algorithm, the sensors in the alliance can monitor the target throughout the process, but the tracking impact is still poor compared to the method proposed in this paper.

Figure 7 depicts the running duration and utilization rate of sensor resources under various algorithms in the target tracking mission.

As illustrated in Figure 7(a), the algorithm in this paper has a shorter running time than other algorithms. At the same time, we can conclude that the centralized algorithm's running time is longer than that of the distributed algorithm, which is determined by the operation mode of the centralized algorithm and the distributed algorithm; we can also conclude that the proposed algorithm's convergence is better than those three algorithms. Figure 7(b) demonstrates that different methods' efficiency rate of sensor resources in the alliance system varies.

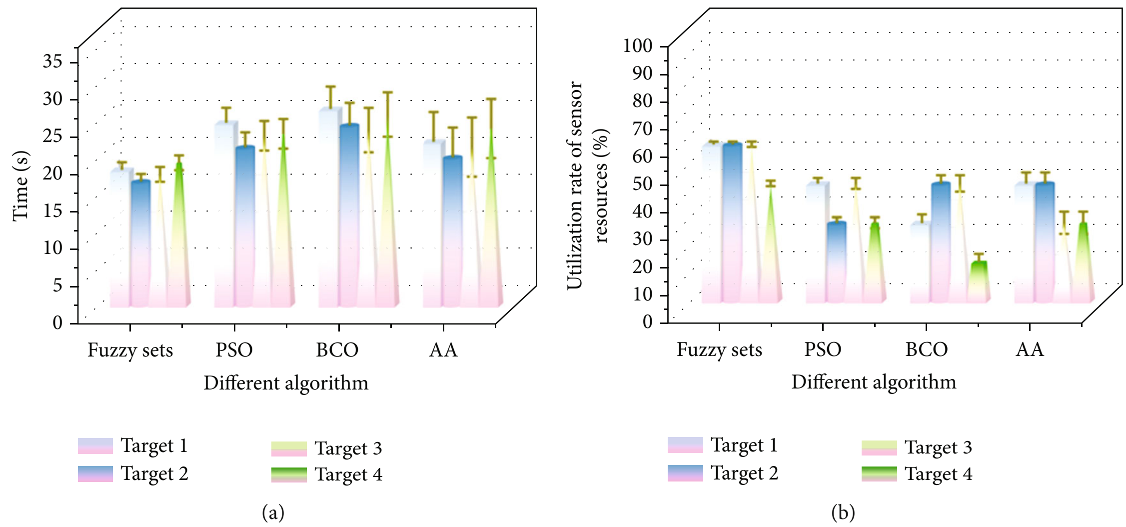


Figure 7: Running time and utilization rate of sensor resources under different algorithms in target tracking mission. (a) Running time under different algorithms. (b) Utilization rate of sensor resources under different algorithms.

The algorithm in this paper has the highest utilization rate of sensor resources in the alliance, whereas the other two algorithms have poor resource utilization. Furthermore, it minimizes sensor resource utilization in target tracking than in target detection and recognition. The fundamental reason for this is that target detection and monitoring are ongoing processes. The algorithm in this paper has accomplished the continual detection of targets in the early phase of target detection and recognition; in the follow-up tracking process, we can acquire the sensor alliance scheme by employing the reduction principle to avoid the waste of sensor resources.

4. Conclusions

This paper investigates and utilizes multisensor dynamic alliance control based on fuzzy set theory to target detection and tracking assignments. This paper evaluates the fuzzy relationship in multisensor dynamic alliance for multitarget and stimulates a task-driven dynamic alliance model utilizing a fuzzy set calculation algorithm. The simulation results suggest that the model and algorithm implemented in this paper have certain advantages over other models and algorithms, and we may reach several conclusions concurrently.

In the beginning, by incorporating the fuzzy set calculation methodology into establishing a dynamic alliance, the ideal alliance scheme can be brought, effectively decreasing information redundancy. The sensor network's monitoring capability can be enhanced. Moreover, dynamic alliance models driven by target detection, recognition, and tracking tasks are investigated, which is valuable in optimizing sensor resource utilization and avoiding sensor waste and redundancy. Meanwhile, when comparing the multisensor scheduling scheme designed by this algorithm to other clever algorithms, this algorithm's solution scheme outperforms the others. Simultaneously, the comparison experiment reveals that the multisensor alliance scheme solved by the distributed algorithm outperforms the centralized algorithm. The simulation results further demonstrate that the proposed method can monitor and track different sensors simultaneously for each target, with a low strain on sensor networks.

Further in-depth research on multisensor alliances could be conducted in the following research.

(1) Design optimization algorithms that focus on solving the current problems that the utilization of sensor resources is insufficient, and the tracking effect is insufficient in the process of alliance formation and updating

(2) The algorithm design may also consider further optimization of the alliance formation and updating methodology based on the fuzzy set theory provided in this research. As a new multisensor coalition control technique, the fuzzy set theory can perform target recognition and tracking tasks by strengthening its fuzzy clustering mechanism

(3) During the simulation tests, attention can also be devoted to the selection of comparison algorithms in order to validate the efficacy of the design algorithm by comparing current research hot algorithms

Data Availability

The data used to support the findings of this study have been deposited in the references [13, 17–23] in the paper.

Conflicts of Interest

The authors declare no conflict of interest.

Authors' Contributions

All authors contributed significantly to the manuscript's writing and final editing. Jiahao Xie conceived the ideas of theory and finally edited the paper. Shucai Huang, Daozhi Wei, and Zhaoyu Zhang checked and corrected the paper.

Acknowledgments

This research was funded by the National Natural Science Foundation of China, grant number 61703424.

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