

Research Article

An Information-Entropy-Based Hierarchical Serialization Allocation Method for UAV Tracking in 6G Networks

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Unmanned aerial vehicles (UAVs) play an important role in future 6G networks, which can be used to assist cellular networks in setting up temporary networks to provide communication services when network access demand is intense. It is critical to design a UAV tracking method with high efficiency and high precision under active sensor radiation control to build a reliable network of UAVs. Multisensor cooperative multitarget tracking for UAVs with high accuracy is an alternative solution to meet the performance requirements of 6G. In this paper, an information-entropy-based multisensor to multitarget allocation method under low-radiation control is proposed for UAV tracking. Specifically, the knowledge-map-based demand assessment of integrated track detection is first present; and then, fuzzy-decision-tree-based generation of sensor management plan is given; the next, the basic linear programming model for multitarget to multi-UAV allocation is utilized based on cooperative tracking under radiation control; finally, extensive experiments are conducted, and the experimental results show that the proposed method has a good performance.

1. Introduction

With the rise of emerging technologies, e.g., AI [1–3], unmanned aerial vehicle (UAV) communication [4, 5], and D2D communication [6, 7], the future 6G network is expected to connect everything and meet different communication needs [8, 9]. Actually, UAVs play an important role in future 6G networks, which can be used to assist cellular networks in setting up temporary networks to provide communication services when network access demand is intense. It is critical to design a UAV tracking method under active sensor radiation control to build a reliable network of UAVs [10]. Sensor-based detection and tracking is one of the mainstream UAV tracking approaches, which can realize the tasks of formation coordination to build a reliable UAV network [11–13].

Through the cooperative action of two or three unmanned aerial vehicles (UAVs) equipped with passive detection sensors in formations, coordinated target position-

ing and silent attack can be realized. Under the premise of high precision for tracking targets, the coordinated guidance and tracking of the active and passive sensors of the UAVs can reduce the electromagnetic radiation time, power, and airspace of the active sensors and improve the overall performance of UAV communication. In addition, it is possible to realize decentralized optimization and coordinated control of heterogeneous multimotion platforms through the coordination of aircraft formations with active and passive sensors. However, there are two main constraints for sensor cooperative tracking. The first constraint is the capability of a single sensor. In a complex battlefield environment, each sensor unit can only track a limited number of targets with fixed detection accuracy. The second constraint is the resources contained in a single aircraft. Limited by transmission bandwidth and computing power, a single aircraft can only fuse and process measurement information from a small number of sensors. Therefore, it is necessary to focus on solving the problem of optimal pairing of sensors and

targets, rather than choosing as many sensors as possible. Moreover, it is also necessary to select the optimal sensor combination for each target and select the optimal tracking object for each sensor, so as to achieve the optimal tracking performance of multisensor to multitarget.

In this paper, a multi-UAV multitarget assignment method based on low-radiation control active sensors is proposed to meet the performance requirements of the tracking task. In the method, a mathematical model of multi-UAV to multiobjection allocation decision is established, in which, one sensor is equipped on one UAV. First of all, the interval between active sensors' radiation duration periods is calculated. According to the current situation of active sensors, it is divided into two modes: active and passive coordinated tracking and passive sensor coordinated tracking. Then, based on the information entropy and target threat degree, a multi-UAV cooperative allocation scheme for multitarget tracking is given. To verify the effectiveness of the multitarget and multisensor allocation method in this paper, the simulation experiments are carried out according to the following scenarios. A single UAV platform with multiple sensors is used to track four target UAVs. The experimental result demonstrates that our method has a high efficiency and high accuracy.

2. Related Work

Regarding target allocation, many scholars have conducted research, mainly focusing on multi-UAV (unmanned aerial vehicle) task allocation as the research background [14]. In recent years, the research on the model of multisensor to multitarget allocation mainly includes two aspects: one is the target-priority, and the other is the matching algorithm of the sensors (or combination) to the targets [15–17]. Among them, the matching algorithm is difficult to express with a specific mathematical formula, and most of them use the method of directly assigning values to the existing parameter table. However, such methods cannot quantify the matching algorithm scientifically and reasonably, making the allocation result inaccurate. In [18], a sensor management method is proposed based on the efficiency function, in which, the efficiency function is established through the pairing function of the sensor and the target and the target priority function to realize the reasonable allocation of sensor resources.

In [19], the target-to-sensor allocation efficiency function is defined as a value function and a loss function in the target-to-sensor allocation model, but it does not consider the impact of the diversification of target characteristics on the efficiency. In [20], the target priority function and the sensor's effectiveness function are considered to establish a multisensor resource preallocation mathematical model, in which, the preallocation of the three tasks of target detection, target tracking, and target recognition is unified into one framework. Moreover, an improved Hungarian algorithm is used in [20] to solve the objective function. However, the disadvantage is that the task-based matching efficiency is not determined in the actual simulation. In [21], an allocation model is proposed based on the recon-

naissance resolution of the sensors, where the UAV carries and the constraints of the targets' appearance time window. A set of UAVs with different reconnaissance payload capabilities to conduct information reconnaissance in multiple mission areas in a mission scenario is studied in [22]. In [23], Spyridis et al. studied target tracking of mobile IoT devices at unknown locations with a set of UAVs equipped with received signal strength indicator (RSSI) sensors in 6G network. In the proposed method, it preserves the swarms that approach the radio frequency (RF) source more efficiently, removing the rest of the drones that return to base.

In [24], a distributed reinforcement learning (RL) approach is proposed with an algorithmic framework that relies on the possibility of drones exchanging some information through communication channels to achieve context awareness and implicitly coordinate the actions of UAV swarms. In [25], an end-to-end collaborative multiagent reinforcement learning (MARL) scheme is presented that enables UAVs to make intelligent flight decisions for collaborative target tracking based on the past and current state of the target. In [26], a multi-UAV intelligent maritime task assignment and route planning scheme is designed based on improved particle swarm optimization combined with genetic algorithm (GA-PSO). In the proposed scheme, the traditional particle swarm optimization (PSO) is improved by introducing partial matching crossover and quadratic transposition variation based on the simulation of the intelligent ship control system. Moreover, the improved GA-PSO is used in [26] to solve the stochastic task assignment problem of multiple UAVs and the two-dimensional path planning problem of a single UAV. In [27], a multitarget tracking algorithm is proposed, in which trajectories evolve over a special Euclidean group $SE(2)$. Applications include tracking ground targets using cameras on hovering multirotor drones. The method extends the recursive random sample consensus (R-RANSAC) algorithm to nonlinear motion models. Other related works also include security techniques for IoT and 6G [28–30] and AI for UAV communication [31–33].

In summary, these studies focus on the multiplatform and multitarget allocation of a single sensor without considering radiation control conditions. However, the development of formation coordination has not been analyzed, and the influence of these factors on target allocation has not been considered. It lacks comprehensive consideration of the influence of multiple factors such as formation coordination, active sensor low-radiation control, and heterogeneous multisensors.

3. Allocation Method Based on Information Entropy

According to the sensor scheduling instructions of the operator and the results received from the information fusion calculation, the sensor allocation results and management plans are generated, and the specific sensors are called to perform the actual measurement tasks.

First of all, it is necessary to carry out a comprehensive track detection requirements assessment, clarify the detection requirements, and then generate a sensor plan. On this basis, it is necessary to realize the sensor target pairing and dispatch the corresponding sensors. Due to the fact that the information gain in UAV allocation refers to the reduction of information entropy (uncertainty about target state) before and after each tracking [34], the UAV resources can be scheduled according to the value of the information gain, and then, the resource allocation and pairing of multitarget and multi-UAV can be completed.

3.1. Knowledge-Map-Based Demand Assessment of Integrated Track Detection. The integrated track detection demand assessment is to undertake the track information and track evaluation information from the information fusion system and make decisions to generate the current sensor task demand in combination with the actual task and aircraft platform status, including the demand for supplementing dimension detection when the target detection dimension is missing and the demand for improving target accuracy when the target accuracy is low. The sensor usage plan generation algorithm is utilized to obtain the usage and allocation of multisensor based on the detection requirements from the sensor detection requirements, as well as the sensor status, task, and carrier platform status.

Figure 1 shows the basic process of track integrated detection demand assessment. The track integrated detection demand assessment is mainly based on the system track quality assessment results and the actual task, platform status, and other information, making comprehensive decisions to generate the track integrated detection demand such as dimension supplement and accuracy improvement.

The core of the track integrated detection demand assessment is to build a knowledge map generated by the detection demand. Based on the map, the demand reasoning is carried out to generate the basic sensor use requirements, which is the basic constraint for the next multitarget and multisensor allocation. Figure 2 shows the entity relationship diagram of airborne sensor detection demand knowledge map, which describes the association relationship between airborne sensor detection demand entities. Here, the macro association relationship is described, and only the possible coupling relationship between entities is described.

The track integrated detection demand entity, as the output node, combined with the system cross-linking relationship, concludes that the track integrated detection demand entity has a direct one-step inference relationship with the fusion situation, basic task type, and sensor equipment. There is a direct one-step inference relationship between the aircraft platform and the sensor equipment, which represents the sensor load configuration of a specific flight platform. There is a direct one-step inference relationship between the aircraft platform and the fusion situation, which is used to express the relationship between the attitude of the aircraft platform and the fusion situation. The indirect relationship between flight platform and track integrated detection demand entity is multistep inference, which indicates the impact of different aircraft platform states on detection

demand generation, such as health status. There is a direct one-step inference relationship between the basic task type and the sensor equipment, which indicates the constraints of different task types and stages on the available sensor modes, parameters, etc. In addition to the direct relationship between the basic task type and the sensor equipment, there is also an indirect relationship through multistep inference of the sensor equipment. The knowledge map should be continuously expanded and improved based on experience and knowledge.

3.2. Fuzzy-Decision-Tree-Based Generation of Sensor Management Plan. By receiving the integrated detection demand generated from the track integrated detection demand estimation, combined with the mission stage information, platform status information, etc., the comprehensive decision-making is how to generate specific parameters to guide the sensor work and generate the sensor management plan.

On the basis of obtaining the demand of track integrated detection, considering that the types of airborne sensors, multisensor control methods, and controllable parameters are basically clear, and the requirements for real-time decision-making are relatively high, the fuzzy decision tree method is selected to generate specific sensor equipment types and sensor control parameter sequences. The construction of fuzzy decision tree is to introduce fuzzy inference system (FIS) into the structure of traditional decision tree to form a fuzzy tree structure and fuzzify the fixed rule parameters, so that it has the ability to be optimized, and it is convenient to optimize the parameters of decision tree on its basis.

The purpose of the sensor management plan generation technology is to effectively use the existing sensor resources to collect information, meet the requirements of targets and scanning space, and effectively perform specific tasks. Its core problem is to determine which sensor to choose to monitor and track the target of concern, as well as the type, configuration, working mode, parameters, and measurement process of sensors according to certain rules or optimization criteria (such as track accuracy and detection probability). Mutual cooperation among sensors, etc., because different sensors have different characteristics, undertake different tasks, have different requirements for sensors, and have more practical information requirements, the generation of sensor management plan usually includes the following contents.

- (i) *Switch State Management.* When the active sensor emits energy, it will expose itself and then be attacked. In order to hide or protect itself, it is necessary to control the switch state of the active sensor and reduce the radiation times of the sensor. On the premise of meeting the basic task, the active sensor should be in a silent state as far as possible. For the sensor with limited energy, controlling the switch state of the sensor can also prolong the working time and service life of the sensor

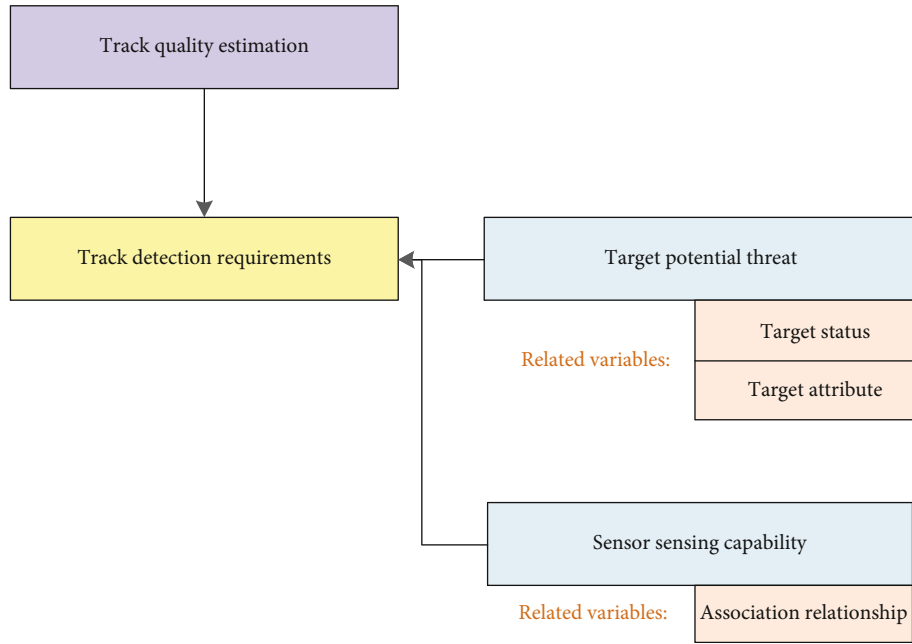


FIGURE 1: Flowchart of track integrated detection demand assessment.

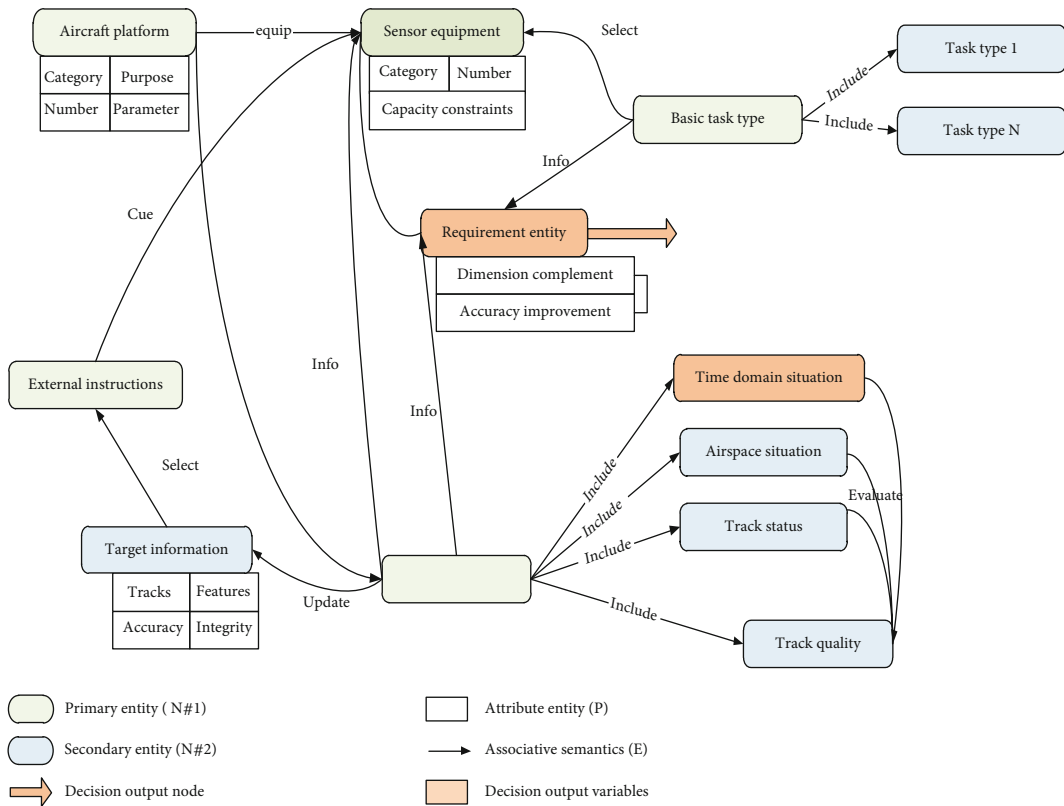


FIGURE 2: Schematic diagram of entity relationship of sensor detection demand knowledge map.

(ii) *Working Mode Management*. Some sensors have different working modes. Choosing different working modes can complete different tasks, and the working modes of sensors can be flexibly selected according to task requirements

(iii) *Working Parameter Control*. The working parameters of some sensors can be controlled, which will affect the task execution of the sensor. For example, for radar, the main operating parameters include operating carrier frequency, transmission power,

beam direction, and revisit frequency. By controlling these parameters, the target detection and tracking performance of radar can be optimized

- (iv) *Time Management.* In a multisensor system, for different tasks or observation objects, only a part of the sensors may be required to work at a certain time. Therefore, it is necessary to plan the tasks of each sensor in the time series. In addition, when some sensors or certain things in the target environment maintain synchronization or relationship in time (such as moving target detection, track loss, etc.), it is required to manage the time of sensor operation
- (v) *Space Management.* The main task of space management is to determine the spatial direction of each sensor, so as to better complete the detection and tracking tasks of single target and multitarget. In addition, many sensors do not work in an omnidirectional way, which requires that the spatial orientation of multiple sensors can ensure the coverage of the entire airspace and the continuity of task execution, such as the indication and handover of sensors to targets, while requiring time and space management
- (vi) *Sensor Task Coordination.* Multiple sensors in sensor networks usually need different sensing capabilities and can obtain different sensing information. By realizing information sharing among sensors, they can cooperate with the tasks of each sensor on this basis, drive the actions of sensors with tasks, and enable multisensor cooperation to complete battlefield sensing tasks. Through the decomposition of the above management purpose, the whole multisensor information fusion system becomes a closed-loop system, so that the working state and tasks of the sensors can be adjusted in real time according to the needs of the task and the changes of the target and environment, so as to give full play to the advantages of each sensor, better complete the target and environment sensing tasks, improve performance, improve their own viability, automate the process, and reduce the burden of operation

As shown in Figure 3, the decision tree based on tree structure is suitable for most of the clear correspondence between input and output and can give more accurate prior expert knowledge. It can express the related knowledge through the multitree structure, expand the knowledge conveniently through the construction of subtree, and realize the reasoning ability with fuzzy attributes or Bayesian probability by setting the fuzzy system on the tree node or the state transition probability on the opposite side. On the basis of prior expert knowledge, genetic algorithm and small neural network can be used to optimize the combination relationship of knowledge structure and even the parameters in knowledge structure, which can produce more reasonable and high-quality decisions.

On the basis of obtaining the demand of track integrated detection, considering that the multisensor control mode is basically clear, the fuzzy decision tree method is selected to generate specific sensor equipment types and sensor control parameter sequences. The construction of fuzzy decision tree is to introduce fuzzy inference system (FIS) into the structure of traditional decision tree to form a fuzzy tree structure and fuzzify the fixed rule parameters, so that it has the ability to be optimized, and it is convenient to optimize the parameters of decision tree on its basis.

As shown in Figure 3, by obtaining the time domain situation, airspace situation, measurement dimension requirements, and measurement performance requirements with the detection demand assessment, two state measurement nodes can be set: (1) situation assessment node and (2) status evaluation node. Note that, the situation assessment node completes the measurement parameter demand analysis of all targets in the airspace within a certain period; and the status evaluation node completes the performance demand analysis of all measured parameters. These two state nodes correspond to two decision points, which are sensor type decision and sensor working parameter decision.

The fuzzy reasoning mode based on fuzzy inference engine is suitable for the knowledge expression mode of tree structure. By introducing the fuzzy reasoning system into the decision tree node, it has the ability of generalization and optimization under the guidance of certain prior knowledge and has a wide range of applications. As shown in Figure 4, taking radar mode management as an example, drawing on the knowledge of domain experts, multiple target attribute values and corresponding radar mode selection results are selected as training samples to learn the fuzzy decision tree and establish the fuzzy decision tree of radar mode management. The established fuzzy decision tree is used as the reasoning rule, and the real-time target is used as the test data to reason and classify it. The classification results are expressed with confidence as the real-time radar mode management results. For fuzzy decision tree, the most important reasoning mechanism depends on the design of fuzzy system. The membership function and the design of membership function are introduced. For details of the fuzzy attribute membership values of enemy target attributes, please refer to Table 1.

As shown in Figure 5, the selection of the attribute with the smallest fuzzy information entropy among all attributes to be the current test attribute node and the specific tree building algorithm is as follows.

Let the data set (e.g., instance set) $D = \{e_1, e_2, \dots, e_N\}$ be the example set defined on the discrete value universe x , the fuzzy attribute set be $\{A_1, A_2, \dots, A_M\}$, the attribute value of attribute A_i be $T(A_i) = \{a_{i_1}, a_{i_2}, \dots, a_{i_k}\} (1 \leq i \leq M)$, and the class $C = \{C_1, C_2, \dots, C_K\}$ to be divided. In the i example, the value of e_i about the j attribute is represented by the corresponding membership degree μ_{ij} , which is a fuzzy subset defined on $T(A_i)$. If the attribute A_i is a symbolic value attribute, the value of μ_{ij} is 0 or 1. Let D^{C_k} be the data subset of category C_k , and $|D|$ be the cardinality of D .

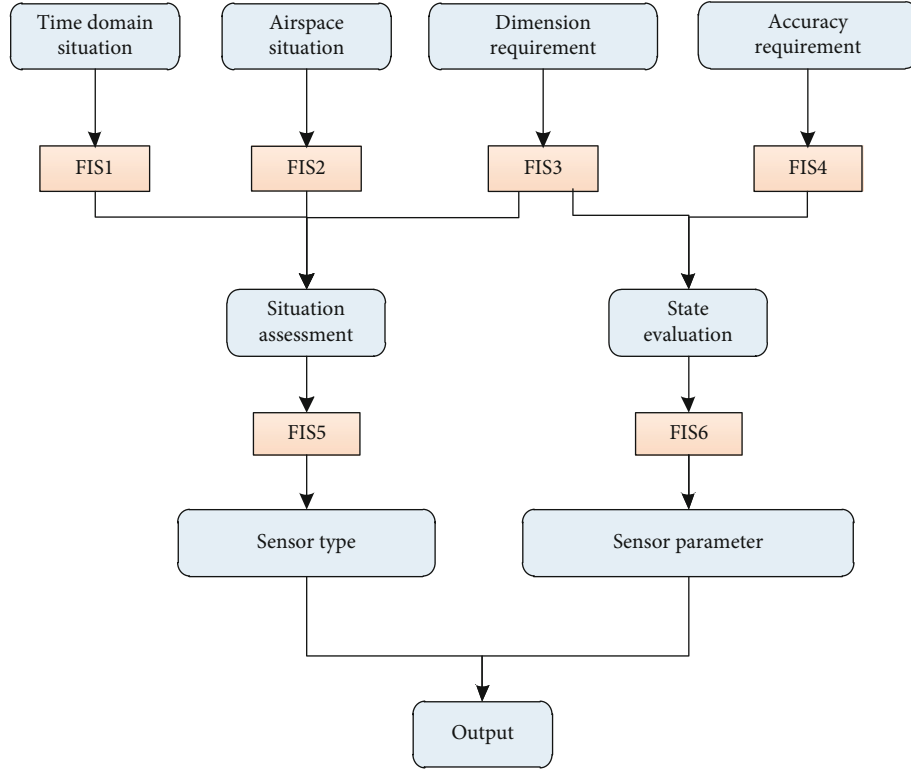


FIGURE 3: Decision tree model with fuzzy inference system.

Step 1. Initialize and create a root node.

Step 2. The node is a leaf node, if the current node meets one of the following conditions.

- (1) All attributes are used up
- (2) $D^C_k/D > \theta$
- (3) $|D| < \beta$

Among them, θ is the level of importance, and β is the confidence level.

Step 3. If the current node does not meet the above conditions, perform fuzzy segmentation on the node. The segmentation steps are as follows.

- (1) Calculate the information gain $G(A_i, D)$ of each attribute, and select the attribute A_{\max} with the largest information gain as the test attribute of the current node
- (2) Divide d according to the fuzzy attribute value of A_{\max} , get a new fuzzy subset D_1, D_2, \dots, D_m , and generate a new node t_1, t_2, \dots, t_m
- (3) Replace d with D_1, D_2, \dots, D_m in turn, and return to Step 2 for iteration

Using the above method, the attribute with the largest information gain is selected as the test attribute each time, and the data set is divided, so as to generate a fuzzy decision tree. The resulting decision leaf node is not a unique class, but a class calibrated by trust. Thus, a reference fuzzy decision tree for radar air mode management can be obtained, as shown in the above figure, in which $M_1 \sim M_5$ represent different RD working modes, including passive detection mode, side scan tracking mode, continuous tracking mode, follow-up detection mode, and active jamming mode. Reasoning based on the fuzzy decision tree is constructed above. The target data searches down multiple branches with its confidence (membership) of each branch (fuzzy subset) of the corresponding test attribute and finally reaches multiple leaf nodes and then calculates the confidence of each mode. The specific calculation process is as follows.

Step 1. Path confidence calculation. Fuzzificate the current target data, obtain the confidence of the target data to each branch of the fuzzy subset of the test attribute, and calculate the path confidence with the minimum operator. As shown in Figure 5, if the leftmost path has distance $\rightarrow F(\mu_F = 0.8)$, and Entry angle $\rightarrow H(\mu_H = 0.5)$, the confidence of the path is $\min(\mu_F, \mu_H) = \min(0.8, 0.5) = 0.5$.

Step 2. Confidence calculation of each mode. Calculate the trust degree of each mode on all leaf nodes with the product operator, as shown in the leftmost leaf node in Figure 5. The trust degree of $D = M_1 = 0.83 \cdot \min(\mu_F, H) = 0.83 \cdot 0.5 =$

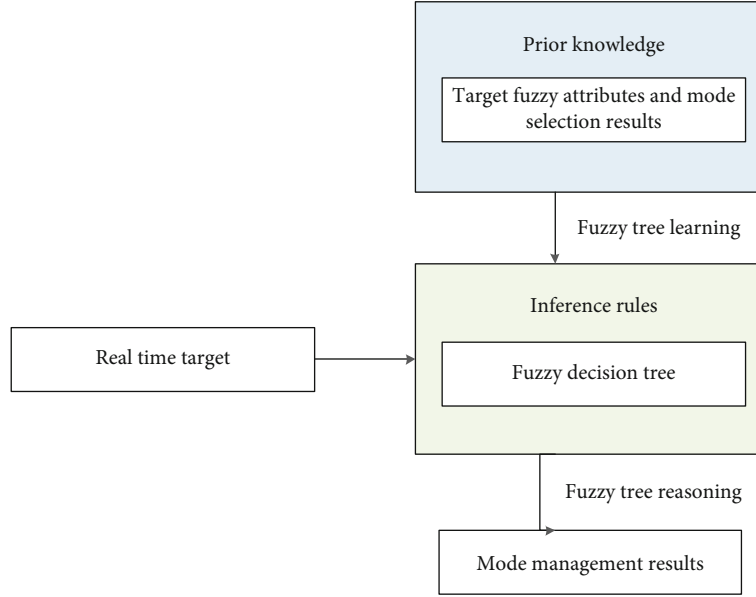


FIGURE 4: Radar mode management system based on fuzzy decision tree.

TABLE 1: Fuzzy attribute membership value table of target attribute.

Fuzzy attribute	Attribute value
Target distance	Far (F), middle (M), and near (N)
Target entry angle	Head on (H) and tail rear (T)
Lock status	Lock (L) and unlock (U)

0.415. And then, combine the confidence of the same mode on all leaf nodes and calculate with the maximum operator. If the confidence of $D = M_1$ of each leaf node is $\{0.42, 0.8, 0.6, 0.36, 0.92, 0.5, 0.83\}$, the confidence of $D = M_1$ after combination is $\mu_D = M_1 = \max(0.42, 0.8, 0.6, 0.36, 0.92, 0.5, 0.83) = 0.92$; finally, normalize the confidence of the merged model as follows.

$$\bar{\mu}_D = \frac{\mu_D = M_i}{\sum_{j=1}^5 \mu_D = M_j}. \quad (1)$$

The confidence of each mode obtained in the above steps is used as the reasoning result to characterize the demand degree of RD for each mode. When nonnumerical reasoning results are needed, the mode with the greatest confidence is selected as the result of RD empty mode management. In addition, for the fuzzy membership parameters of fuzzy tree, genetic algorithm can be constructed to form genetic fuzzy tree for parameter optimization, and then, the decision-making process can be optimized more carefully and flexibly.

3.3. Basic Linear Programming Model for Multitarget to Multi-UAV Allocation Based on Cooperative Tracking. Generally, we assume that a sensor-to-target pairing system includes a set of basic sensors $\{s_1, s_2, \dots, s_n\}$ and a set of targets $\{tar_1, tar_2, \dots, tar_m\}$, where n and m , respectively, refer to the numbers of sensors and targets. For n

basic sensors are able to form $2^n - 1$ sensors' combinations which are named tracking unit. The basic sensors are signed from 1 to n , and the combinations are signed from $n + 1$ to $2^n - 1$. Therefore the m targets are tracked by $2^n - 1$ sensors' combination. Here, the symbol S_i is used to present the combinations. For an example, 3 sensors are able to form a set of 7 tracking units named, contained $S_1 = \{s_1\}$, $S_2 = \{s_2\}$, $S_3 = \{s_3\}$, $S_4 = \{s_1, s_2\}$, $S_5 = \{s_2, s_3\}$, $S_6 = \{s_1, s_3\}$, $S_7 = \{s_1, s_2, s_3\}$.

An integer set $J(b) = \{j | s_b \in S_j\} (b = 1, 2, \dots, n)$ refers to the numbers of the tracking unit which the b^{th} basic sensor belongs to. The assignment decision mathematical model of target tracking under low radiation control can be expressed as a multiobjective optimization linear programming model with multiple constraints. The objective functions are composed of total tracking benefit and active sensors' radiation interval. The first optimal solution set D_1 is obtained for maximizing for the active sensor radiation interval, and the second optimal solution set D_2 is obtained for maximizing the total tracking benefit. The total tracking benefit can be expressed as a function of target tracking priority index, tracker coordination coefficient, information gain, and sensor-target pairing matrix. The objective functions are as follows

$$\max \begin{cases} C = \sum_{i=1}^m \left(R_j \cdot \left(\sum_{i=1}^{2^n-1} F_i \cdot I_{ij} \cdot X_{ij} \right) \right), \\ \Delta t_k, \end{cases} \quad (2)$$

$$\text{s.t.} \sum_{i \in J(b)} \sum_j X_{ij} \leq \tau_b, b = 1, 2, \dots, n, \quad (3)$$

$$\sum_{i=1}^{2^n-1} X_{ij} = 1, j = 1, 2, \dots, m, \quad (4)$$

$$X_{ij} \in \{0, 1\}, \forall i, j, \quad (5)$$

$$P(k) = f(\Delta t_k, R[P_T(k), T_{OT}(k)], POF) \leq P_{ex}. \quad (6)$$

In Eq. (2), the first equation refers to the maximum matching matrix C of the total tracking benefit of the sensor and target pairing. In this equation, R_j refers to the priority indicators for tracking targets. From [35, 36], we have the following property: the larger R_j is, the higher the priority indicator of the target j is. F_i refers to the coefficient of the i^{th} tracking unit which is according to the sensor coefficient function. I_{ij} refers to the information gain between the i^{th} tracking unit and the j^{th} target. X_{ij} is an element of the solution matrix, whose value is only 0 or 1. If the value of X_{ij} is 1, the i^{th} tracking unit tracks the j^{th} target, and if the value is 0, the i^{th} unit does not track the j^{th} target. Δt_k represents the covariance of the track filter and the recurrence rate of the active sensors' radiation discontinuity required to achieve the specified tracking accuracy.

In constraints, τ_b in Eq. (3) refers to the maximum number of tracking targets of the b^{th} basic sensor. Eq. (4) ensures that the number of targets tracked by the tracking unit will not exceed the maximum tracking number of each basic sensor. Equation (5) ensures that one target is tracked by one tracking unit at most. In Eq. (6), $P(k)$ is the targets' state covariance matrix at the moment t_k and related to the sensor measurement noise covariance function $R(\cdot)$. P_{ex} is the given expected covariance matrix which is the specified target tracking accuracy of the sensors, and the value of P_{ex} can be selected according to different control measurements.

3.4. Multitarget and Multi-UAV Allocation Method for Cooperative Tracking. In order to solve the model introduced in Section II-A, a hierarchical sequence optimization method is proposed in this paper. First, the stealth control model is solved by taking the active sensor radiation time as the target and the coordinated tracking accuracy as the constraint. Then, on the basis of this solution set, the allocation optimization model is solved by taking the synergy coefficient and the target priority to weight the information entropy as the goal. The hierarchical sequence optimization effectively reduces the dimensionality of the optimization problem and the probability of falling into a local optimum. According to the output state estimation and covariance estimation of the active and passive sensors' cooperative tracking algorithm, the predicted covariance is compared with the previous covariance to control the radar radiation. When the predicted covariance is less than the threshold which means $P_{k|k-1} \leq P_{ex}$, the radar does not radiate; when the predicted covariance exceeds the threshold, the radar radiates, where $P_{k|k-1}$ refers to the predicted position error for the moment k at the moment $k-1$.

3.5. UAV and Target Pairing Algorithm Based on Information Entropy. Pseudocode based on multi-aircraft cooperative tracking sensor and target pairing algorithm is proposed by using traversal target list method to achieve. Consider a scenario that there is a formation networked sen-

sor system with S sensors, and the number of tracked targets is N . At the moment k , it needs to be tracked according to the estimated accuracy of $N(k)$ targets. First, the predicted covariance matrix of each target is calculated and used to compare with the preset expected covariance to determine whether the active sensor will participate in the collaboration at the next moment. Then, according to whether the active sensor participates in the next moment of coordination, it traverses the optional tracking units and constructs a feasible target tracking scheme based on the maximum total tracking benefit. Note that the scheme must meet the constraints of the model. Its main functions are described in Table 2.

4. Experimental Results

Consider the following scenario for simulation experiments: a single UAV to track four target UAVs, and the UAV is equipped with three types of space-based platform sensors, i.e., the first sensor S_1 , the second sensor S_2 , and the third sensor S_3 . Build a 1-to-4 oriented digital simulation platform to support simulation verification. Figure 6 shows the deployment diagram of the digital simulation platform, which supports the 1-to-4 confrontation scenario. One computing node on the red side simulates one aircraft, four computing nodes on the blue side simulate four aircraft, and the middle station is the white node (integrated with the red node) for comprehensive evaluation, where the computer adopts PC and is connected through Ethernet. The PCs used in the experiments are desktop computer with Win7 operation system, Intel (R) Core (TM) i7-7700T CPU, and 16 GB of RAM.

4.1. Simulation of Fuzzy Decision Tree Algorithm. Take the following scenario as an example to demonstrate the implementation process of sensor management plan generation technology. The scene is shown in Figure 7. First, the scene is defined, and the airborne photoelectric sensor is used. Its visual range is 20 km, the detection probability is set to 90%, the field of view (FOV) range is 15 degrees, and the scanning angle is 120 degrees to track the moving target. The target moves in a two-dimensional horizontal plane, and its starting position is located at (500m, 2000m) and moves at a speed of 20 m/s in the X direction and 1.35 m/s in the Y direction within [0, 20] time steps. Within [21, 50] time steps, it provides an acceleration of 5 m/s in the X direction, and the speed in the Y direction remains unchanged. Within [51, 65] time steps, it provides an acceleration of -5 m/s in the X direction, and the speed in the Y direction remains unchanged. Within [66, 73] time steps, it performs steering operation, in which the speed in the X direction is $(v_{x_{T_{step-1}}} - 5) * (T_{step} - 73)^2 / 15$, and the speed in the Y direction is $v_{x_{T_{step-1}}} * (T_{step} - 65)^2 / 80$, within [73, 90] time steps, the speed in X direction remains unchanged, and the deceleration in Y direction is -5 m/s.

Set up a control group, and compare the azimuth error of beam pointing under the two ways of not using sensor control feedback technology and using sensor control

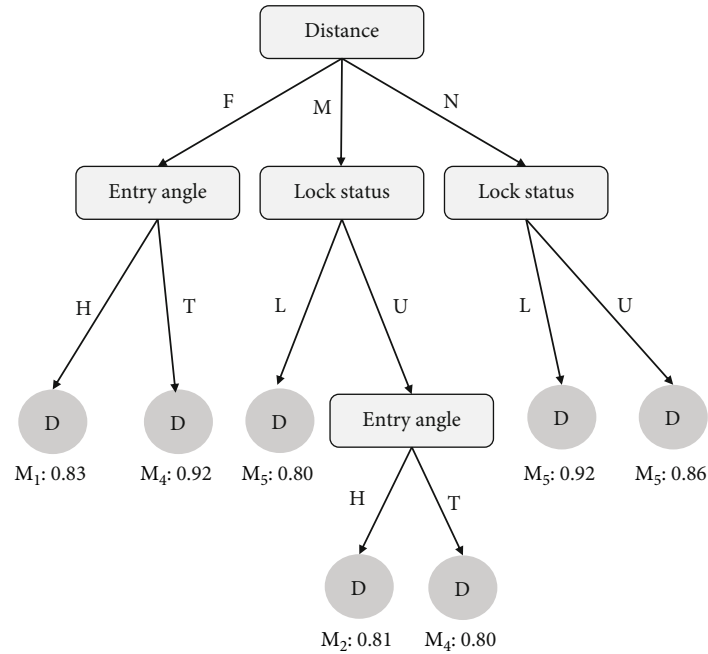


FIGURE 5: Fuzzy decision tree of RD to empty pattern management.

TABLE 2: The list of main functions.

Number	Software name	Function description
1	Sensor usage plan	Provide automatic start and stop control for sensor usage and status maintenance; provide control management based on stealth level.
2	Sensor scheduling	Provide the ability to control all sensor functional models; provide sensor active state maintenance function.
3	Display control	Provides control and monitoring of sensors; provide the display function of two-dimensional situation map (red/blue platform running track display)
4	Simulation model	Provide sensors' function model; provide communication function model.
5	Simulation operation configuration management	Configuration management of environment parameters required for system operation; graphical configuration management of simulation model interaction.
6	Evaluation software	Provide real-time analysis and evaluation of measurement error.

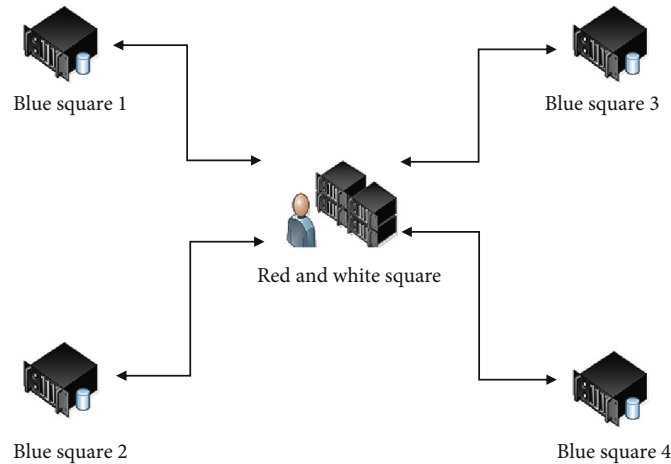


FIGURE 6: Digital simulation deployment diagram.

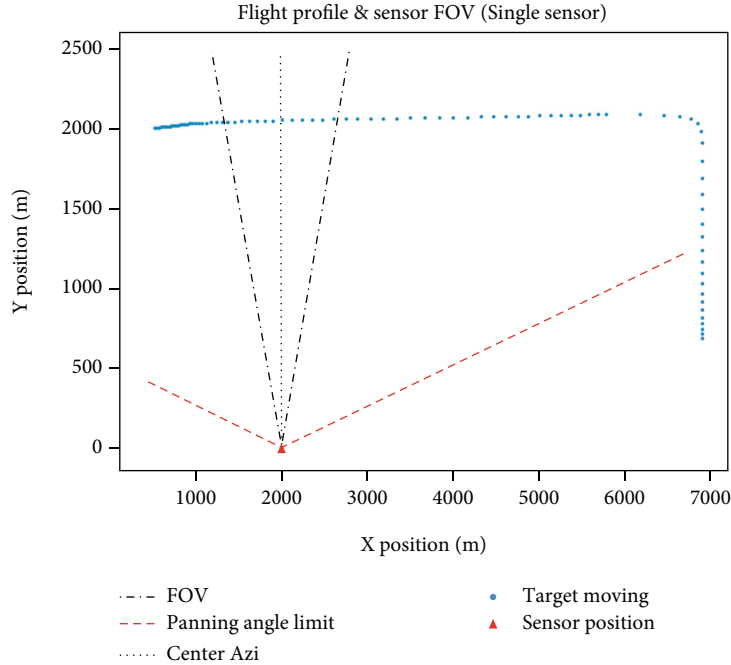


FIGURE 7: Basic setting diagram of scene.

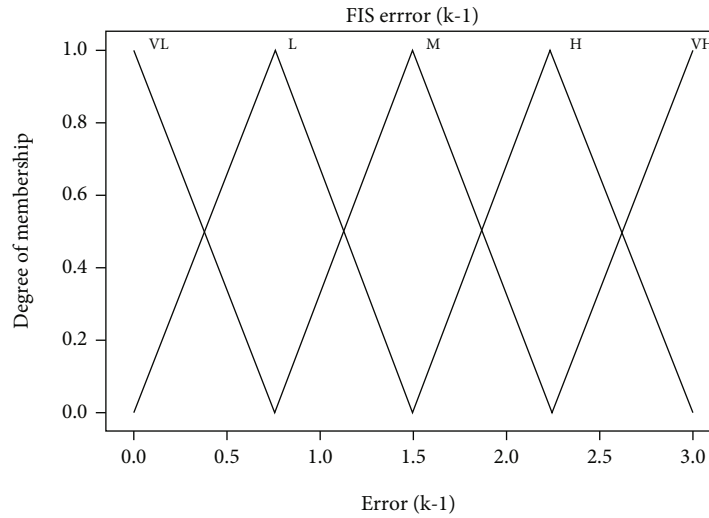


FIGURE 8: Input fuzzy controller.

feedback technology. For multisensor fusion, this index is reflected by track quality evaluation. The data fusion in the process of target tracking is carried out through the IMM Kalman filter. According to the fused data information, the beam pointing azimuth errors (i.e., error k and error $k - 1$ between the current time and the previous time) are calculated and sent to the sensor using the plan generation module. The sensor uses the plan generation module to request the azimuth error from the data fusion system as the input.

By constructing the prior knowledge, the prior knowledge is modeled into a fuzzy system to generate a fuzzy controller. As shown in Figures 8 and 9, the fuzzy controller

takes error (k) and error ($k - 1$) as inputs for discrete fuzzification and constructs five levels of language values, VL (very low error), L (low error), M (medium error), H (high error), and VH (very high error). Each language value corresponds to a specific triangular membership function. The output of the fuzzy system is constructed. The decision outputs the scanning frequency and fuzzy nodes, which are divided into 13 levels of language values, VL (very low), MVL (very low), L (low), ML (medium low), M (medium), MH (medium high), H (high), MVH (very high), VH (particularly high), MVVH (extremely high), VVH (very, very high), MVVVH (sky-high), and VVVH (most high).

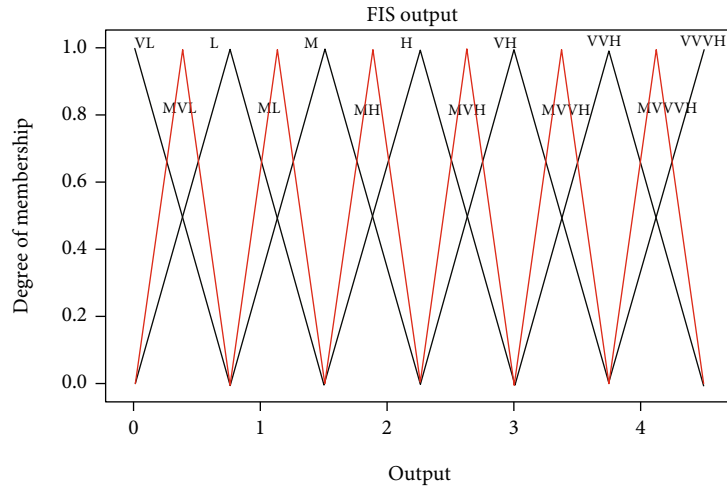


FIGURE 9: Output fuzzy controller.

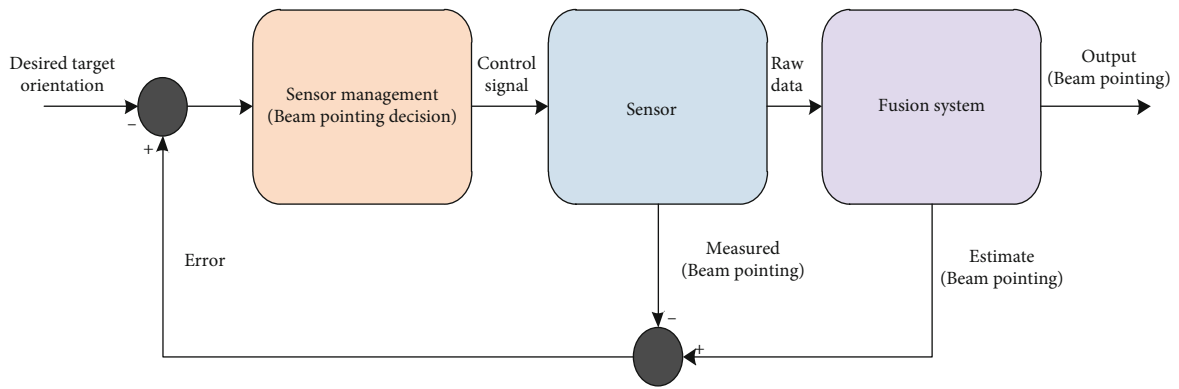


FIGURE 10: Sensor feedback closed loop control block diagram.

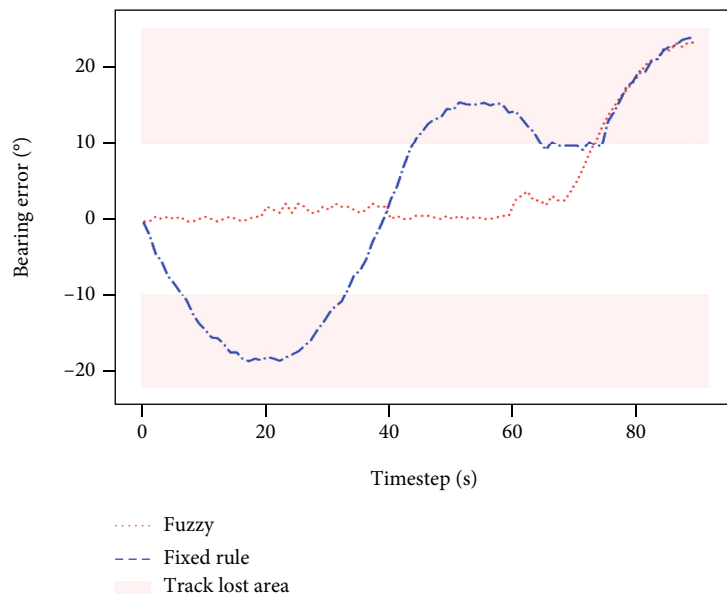


FIGURE 11: Comparison between single sensor based on fuzzy control and fixed rules.

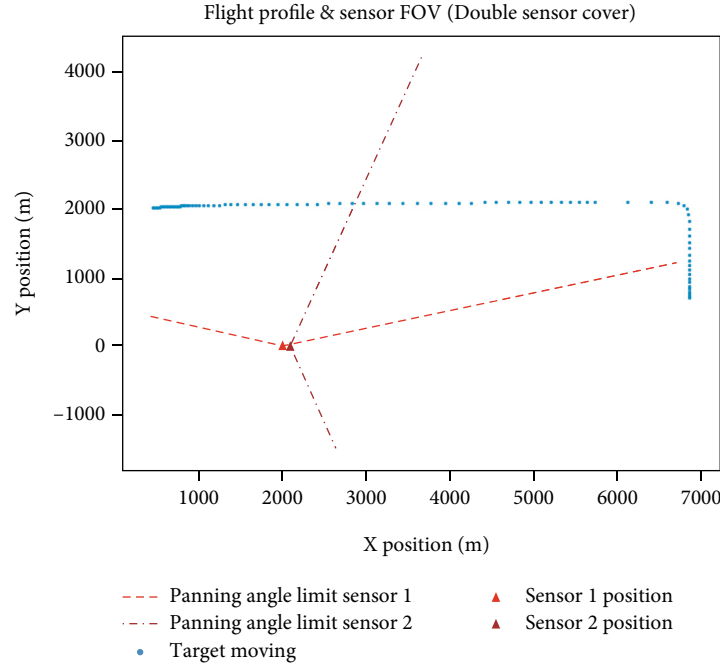


FIGURE 12: Dual sensor configuration scenario.

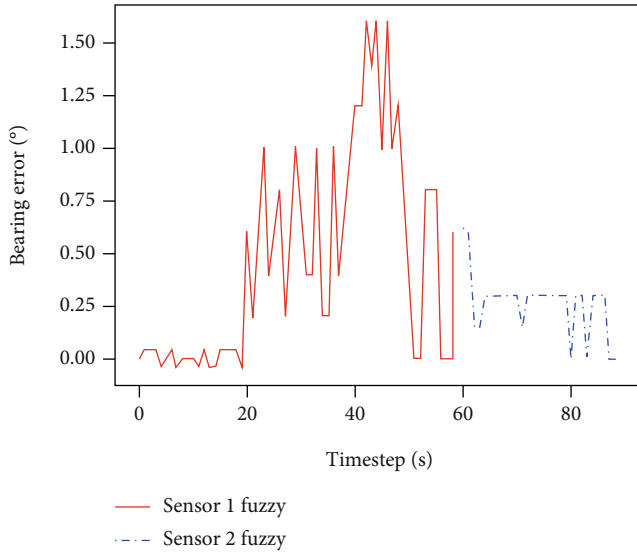


FIGURE 13: Error under dual sensor configuration.

Trigonometric membership functions are also used to define specific values.

The closed-loop flow chart of the whole simulation example is as shown in Figure 10. Case 1: Figure 11 plots the comparison diagram of sensor tracking error based on the above scenario using sensor control feedback technology (fuzzy system) and not using sensor control feedback technology (fixed rules). Without using the sensor control feedback technology, the method of changing 1° per time step is adopted. It can be seen that based on the fixed rule, the azimuth error is out of tolerance at about 10s and 50s, resulting in the loss of tracking, while based on the feedback

TABLE 3: Initial parameter setting of tracking units.

Tracking units	Coefficient	(Distance (m), angle)
S_1	1	(100, 0.2292° , 0.2292°)
S_2	1	(0.4° , 0.7°)
S_3	1	(100, 0.2292° , 0.2292°)
$\{S_1, S_2\}$	1.526	—
$\{S_1, S_3\}$	1.607	—
$\{S_2, S_3\}$	1.219	—
$\{S_1, S_2, S_3\}$	2.713	—

control, the tracking is lost only at about 70s, because the target at this time has exceeded the scanning range of the sensor (set the scanning area of the sensor unchanged). Case 2: based on the above simulation scenario, it is added a sensor, located at (2100,0), pointing at 85 to form a complete coverage of the target (as shown in Figure 12). For the sensor configuration at this time, the simulation results are shown in Figure 13. At about 60s, the sensor is switched and tracked by sensor 2. The error is small and relatively stable.

To sum up, take the above scenario as an example to build the basic closed-loop process of sensor control feedback technology. For future practical application scenarios, it is necessary to reasonably complicate the scenario and cover the fusion decision of multiple sensors. Accordingly, for the fuzzy control system and fuzzy rules used in simple simulation, and for the complexity of specific scenes, the knowledge base and corresponding reasoning algorithm described above are used to build a comprehensive model.

TABLE 4: One-step information gain/pair tracking benefit of the active sensor S_1 involved in the tracking unit to the target.

Tracking units	tar_1	tar_2	tar_3	tar_4
S_1	1.4946/0.7473	1.5011/0.7505	1.5087/1.5087	1.5163/0.5054
$\{S_1, S_2\}$	2.5668/1.9585	2.4477/1.8676	2.2843/3.4858	2.1051/1.0708
$\{S_1, S_3\}$	2.5802/2.0732	2.4564/1.9737	2.2919/3.6832	2.1153/1.1331
$\{S_1, S_2, S_3\}$	2.6371/2.6073	2.5055/2.5271	2.3318/3.8425	2.1453/1.8717

TABLE 5: One-step information gain/pair tracking benefit of the passive sensor S_2 and S_3 involved in the tracking unit to the target.

Tracking units	tar_1	tar_2	tar_3	tar_4
S_2	0.1411/0.0470	0.9328/0.9328	0.1538/0.0769	0.1307/0.0653
S_3	1.6350/0.5450	1.4780/1.4780	1.7198/0.8599	1.4046/0.7023
$\{S_2, S_3\}$	1.6371/1.4805	2.4389/2.9037	1.7280/2.3441	1.4123/1.9158

TABLE 6: One-step information gain/pair tracking benefit of the active sensor S_1 involved in the tracking unit to the target.

Tracking units	tar_1	tar_2	tar_3	tar_4	Tracking capacity
S_1	1	0	0	0	3
S_2	0	0	0	0	2
S_3	0	0	0	0	2
$\{S_1, S_2\}$	0	0	0	0	≤ 2
$\{S_1, S_3\}$	0	0	0	0	≤ 2
$\{S_2, S_3\}$	0	1	0	1	≤ 2
$\{S_1, S_2, S_3\}$	0	0	1	0	≤ 2

4.2. *Simulation of Multitarget and Multisensor Allocation Algorithm.* To verify the effectiveness of the multitarget and multisensor allocation method in this paper, the simulation experiments are carried out according to the following scenarios. A single UAV platform with multiple sensors is used to track four target UAVs. The sensor target allocation of four target tracking processes in the air is simulated. The airborne radar ranging function completes the angle measurement functions of ESM and infrared search and tracking, respectively, forming a high synergy coefficient. The parameter settings of the tracking unit are shown in Tables 3–5. A total of 7 tracking units (including four combinations) and 4 UAV platforms are set. Assuming that the current moment is in the h^{th} management period, the data sampling rate of each sensor is the same. Tables 4 and 5 show the one-step information gain of the tracking unit to the target and the total tracking benefit after pairing. Table 6 is based on the data in Tables 4 and 5 combined with the final distribution results of the model algorithm. When considering the target threat and the detection capacity of each sensor, the result of the optimal allocation is following: the first radar sensor S_1 tracks the target tar_1 . Sensors' combination $\{S_2, S_3\}$ tracks the target tar_2 and tar_4 . Sensors' combination $\{S_1, S_2, S_3\}$ tracks the target tar_3 . The total tracking benefit is 9.4093.

5. Conclusion

To make full use of the sensors in the formation and improve the overall tracking performance, it is necessary to allocate the targets for coordinated tracking units of multisensors while active sensor radiation is controlled. This paper proposes an allocation decision model and a matching algorithm based on multisensor and multitarget cooperative tracking under low radiation intensity. The first situation with the active sensors turned on, the radiation of the active sensors is controlled according to the tracking accuracy requirements of task performance, and the active sensors are used to participate in the radiation interval of the active sensor. Another situation with the active sensors turned off, the passive combined sensors are used to perform angle tracking or coordinated positioning of targets. These two situations are combined separately and alternately performed. Through intermittent passive sensor data and interval active sensor data for sequential coordinated tracking, a continuous target tracking trajectory is formed, which completes multisensors rationality for multitargets. The coordinated formation of UAV swarms based on 6G communication guarantees the realization of the method proposed in this paper. Finally, the optimization model and the matching algorithm are proved to be reasonable and effectiveness.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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