Helicopter Formation Cooperative Command System Architecture with Fused Unmanned System

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Abstract. A helicopter formation cooperative command system architecture integrating unmanned systems is proposed in the context of multi-platform heterogeneous formation combat missions. With the four-layer module of "perception-fusion-decision-execution" as the core, the system constructs an intelligent cooperative command model based on graphical neural network (GCN), graphical attention network (GAT) and multi-intelligence reinforcement learning (MARL), and realizes the cooperative command of multiple sources and heterogeneous formations. We construct an intelligent collaborative command model based on graph neural network (GCN), graph attention network (GAT) and multi-intelligence reinforcement learning (MARL), which realizes the fusion processing of heterogeneous perceptual information from multiple sources and the joint scheduling control of task-path-avoidance. The model design incorporates a lightweight convolutional encoder and a Transformer timing alignment network to improve perceptual robustness, adopts a joint policy search and graph matching mechanism to achieve efficient task allocation, and introduces constrained optimized path generation and RVO dynamic obstacle avoidance strategy to construct a closed-loop control. The system is tested in ROS 2 and Gazebo simulation environments for three types of typical combat missions (patrol, reconnaissance, and proximity strike), and the results show that the system maintains the feature consistency FCI > 0.9, the mission average response time AAL < 50ms, and the trajectory deviation rate MTD < 3.0m in the scenarios of high mission density and communication delay, which verifies the adaptability of the proposed architecture in the complex combat environments. adaptability and stability of the proposed system architecture in the complex combat environment.

Keywords: helicopter formation; cooperative command; multi-intelligent body system; graph neural network.

1. Introduction

With the continuous evolution of air-ground integrated combat system, the coordinated combat integrating manned helicopters and unmanned systems has become a key trend in modern military operations. In the fast-changing battlefield environment, mission execution puts forward higher requirements for efficient command and control system, which not only needs real-time fusion and precise expression of sensory data, but also needs to realize dynamic synergy, intelligent decision-making and efficient scheduling between platforms. Especially in the complex situation of high interference, multi-target and strong mobility, the traditional static control and centralized scheduling methods are difficult to meet the core requirements of low latency of information transmission, sensitive response to mission commands and multi-platform mission reconfiguration. Therefore, the construction of a fusion command and control architecture with intelligent sensing, decision optimization and path avoidance capabilities has become an important technical path to enhance the effectiveness of formation combat.

In recent research, various intelligent technologies have been gradually introduced into the construction of collaborative command systems. Huang et al. proposed an unmanned equipment collaborative command model for amphibious operations, using multi-module integration and optimization to achieve initial collaboration [1], while Zeng et al. constructed a LVC simulation platform to explore the collaborative mechanism of manned-unmanned systems in the simulation environment [2]. Javaid et al. systematically analyzed the communication and control problems in collaborative UAVs and pointed out the key role of reinforcement learning and graph modeling in distributed decision making [3].Paul et al. focused on the selection of AI collaboration strategies in manned-unmanned formations, emphasizing the importance of strategy adaptation and multi-mode linkage [4]. In addition, Gans et al. generalized the autonomous collaboration capabilities in multi-robot military systems, pointing out the development potential of multi-intelligent body systems in tactical execution [5].

Current research has made progress in task allocation, autonomous path planning and intelligent sensing, e.g., Pan et al. proposed a sea-air cooperative mechanism based on swarm intelligence control [6], and Adoni et al. validated an autonomous control strategy for multi-UAV systems in a target detection mission [7]. However, most of the work still focuses on the ontological collaboration of purely unmanned systems, and lacks systematic modeling of the information sharing mechanism between heterogeneous platforms, and the closed loop of decision structure and path control. Especially in the dynamic high-dimensional mission environment, the timeliness and coupling mechanism between command-state-path have not yet formed a unified framework.

Aiming at the above problems, in this paper, for the helicopter formation combat scenario of fused unmanned systems, we construct a four-layer integrated command system architecture of "perception-fusion-decision-execution", which integrates graph neural network, multi-intelligence body, reinforcement learning, graph matching optimization, and path control closed loop. Reinforcement learning, graph matching optimization and dynamic avoidance control technologies are integrated to achieve intelligent, low-latency and robust collaborative command capabilities in heterogeneous and highly dynamic environments. The system model builds a structural closed loop through modular deployment, and verifies its stability and adaptability in multiple simulation tasks, providing theoretical support and engineering solutions for multi-platform intelligent command in complex combat environments.

2. Collaborative command and control architecture based on machine learning

2.1 System Functional Requirements Analysis

In the modern air-ground integrated combat environment, the cooperative command and control system integrating manned helicopters and unmanned systems needs to have core functions such as multi-dimensional perception, real-time situational assessment, intelligent task scheduling and safe path planning. The system must support low-latency data transmission and efficient collaborative decision-making between heterogeneous platforms, and ensure dynamic reconfiguration and task redistribution under multi-objective missions [8]. In order to cope with the complex electromagnetic environment and high mobility combat requirements, the system should integrate models with adaptive learning capabilities to realize intelligent identification and prediction of battlefield status. In addition, the command architecture needs to be scalable and support multi-platform parallel access and modularization upgrade to ensure the continuous and stable operation of the system in tactical execution, resource management and anomaly avoidance.

2.2 Overall System Architecture Design

In order to meet the intelligent command requirements of helicopter formation and unmanned systems in a highly dynamic environment, the overall architecture of the system adopts the layered system of "perception and decision-making as a whole, modularized deployment, and intelligent drive", which is divided into four subsystems: data acquisition layer, intelligent fusion layer, decision-making and control layer, and mission execution layer. Each layer builds a two-way information path through heterogeneous communication buses, and combines machine learning models to assess the state of heterogeneous information from multiple sources and make task decisions, so that the system has the ability of environmental adaptation, autonomous learning and cooperative control. The intelligent fusion layer is the core computing hub, deploying graph convolutional neural network (GCN) and multi-intelligence reinforcement learning (MARL) models for battlefield situational awareness, and running in a training-inference decoupling mode to improve inference real-time and model scalability [9]. Figure 1 shows the functional interaction relationship of the overall system architecture; among them, a low-latency linkage channel based on shared feature graph is constructed between the sensing nodes and the decision-making module to provide interface standards and data flow support for the module layer design.

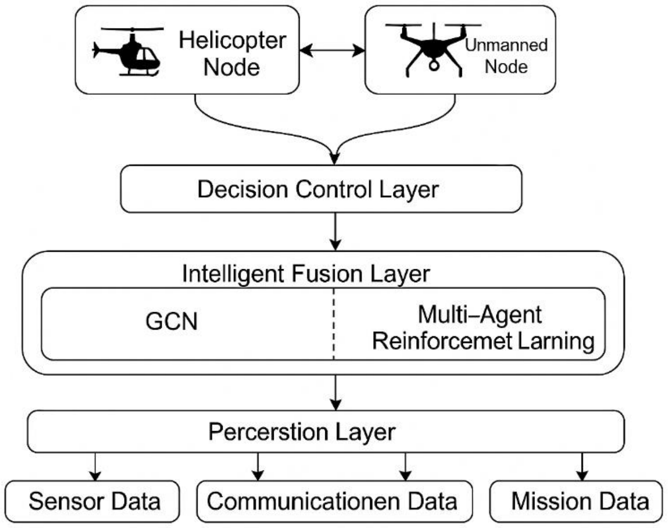

Figure 1 Overall system architecture

2.3 Key Module Division

2.3.1 Sensing and Communication Module

Sensing and communication module, as the underlying support unit in the system architecture, undertakes the tasks of real-time acquisition of heterogeneous environmental information from multiple sources and highly reliable data transmission. The module design adopts distributed sensing node deployment, integrates infrared imaging, millimeter-wave radar, inertial navigation, GPS and air-ground communication links, and combines the multi-channel synchronization mechanism to ensure the consistency of the data flow in highly dynamic scenarios. The communication submodule is based on bidirectional time division multiple access (TDMA) scheduling protocol and adaptive frequency hopping technology, which optimizes the allocation of spectrum resources and effectively avoids the link interruption problem in high interference areas.

In order to enhance the pre-processing intelligence of sensing data, the system introduces a lightweight convolutional encoder fenc(x) for low-dimensional embedding representation of the original sensing data [10]:

$$z = f_{enc}(x) = \mathrm{Re}\,LU(W_1 x + b_1)$$

Where x denotes the original data vector, W1 is the weight matrix, b1 is the bias term, and z is the embedded feature vector. The encoding result is directly used as the GCN input feature node in the intelligent fusion layer to ensure the structural integrity and spatial consistency of the data semantics in the upload stage.

2.3.2 Collaborative Command Module

As the core hub of the system, the collaborative command module undertakes the unified scheduling and command generation of multi-platform resources, and its design is based on the Multi-Agent Reinforcement Learning (MARL) framework in order to solve the problem of decision-making and coordination among multi-tasks and multi-nodes in dynamic environments. The system constructs a state space S, an action space A and a joint reward function R. Through the centralized training and distributed execution architecture, each commanding intelligence can reason autonomously based on the shared battlefield information. The state representation vector is encoded and output by the front-end GCN, while the action output is the scheduling command assignment matrix Aij ∈ {0,1}, which indicates whether the ith execution unit receives the jth type of task; its optimization objective is to maximize the following policy expectation function:

$$\max_{\pi} E_{\pi}\left[\sum_{t=0}^{T} \gamma^{t} R(s_t, a_t)\right]$$

where π denotes the joint policy, γ is the discount factor, and st and at are the state and action at moment t, respectively. The module maintains a low-latency bi-directional data interface with the perception layer, while the command output is directed to the execution nodes and the task management subsystem.

2.3.3 Decision Optimization Module

In order to realize real-time updating of task allocation and path control strategies in highly dynamic environments, the decision optimization module is designed based on the policy gradient algorithm fused with the dynamic modeling mechanism of graph structure, which improves the decision convergence speed and local optimum avoidance ability of multi-intelligence system. A local neighborhood modeling subsystem based on graph attention network (GAT) is integrated inside the module for sensing the interference relationship between intelligences under complex spatial topology [11]. Considering that the state space S possesses a non-Euclidean structure, its node interaction characteristics are modeled by the adjacency matrix A ∈ {0,1}^{n×n} and the allocation of weights is guided by the attention coefficients αij for policy updating. The optimization function is constructed in the form of a gradient of the expected cumulative returns:

$$\nabla_{\theta} J(\theta) = E_{s,a \sim \pi_{\theta}}\left[\nabla_{\theta} \log \pi_{\theta}(a|s) \cdot Q^{\pi}(s,a)\right]$$

where θ is a strategy parameter, $Q^{(\pi)}$(s,a) is the value function of the current state-action pair, and πθ is a parameterized strategy function. In order to improve the training efficiency and generalization ability, the module introduces an asynchronous parallel update mechanism, so that multiple decision threads compute in parallel and periodically share the global policy weights based on the local graph structure. The internal structure of the module is shown in Fig. 2, demonstrating the complete data flow path from input embedding, local neighborhood construction, attention scheduling to gradient back propagation.

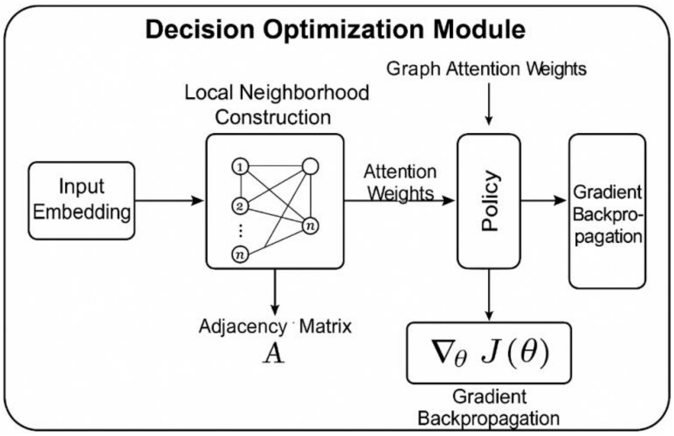

Fig. 2 Schematic diagram of the internal structure of the decision optimization module

In addition, in order to support the adaptive migration of the module to different combat scenarios, the design presets a strategy cache pool and a prioritized experience replay mechanism to ensure that the strategy stability and robustness are maintained during multi-task switching. The module ultimately outputs the optimized action strategy distribution to feedback to the cooperative command module, forming a complete perception-command-optimization closed loop, which provides a dynamic strategy basis for the subsequent path avoidance and task scheduling modules.

2.4 Information flow and command flow modeling

In the system architecture, the modeling of information flow and command flow directly determines the timeliness and robustness of perception-decision-execution. The information flow starts from the distributed perception nodes, and is fused with the GCN graph structure via a lightweight convolutional encoder to construct a unified state space $St \in R^{n \times d}$ at the intelligence fusion layer, where n is the number of intelligences and d is the feature dimension. The synchronized instruction flow then starts from the decision optimization module and outputs the instruction matrix $Aij \in \{0,1\}$ through the policy network, whose semantics is whether the ith platform responds to the jth task request. To ensure that the instruction mapping has interpretability and hierarchical control, the design adopts the dynamic mapping function $f_{(cmd)}$ (st,at)=Ct, where Ct denotes the instruction encoding vector, which, combined with the internal link delay parameter $\Delta\tau$ of the system, allows for the construction of a complete timing synchronization mapping function [12]:

$$I_t = f_{trans}(S_t, C_t, \Delta\tau)$$

where It is the effective instruction set at the scheduling moment. Figure 3 illustrates the transmission path and coupling logic of the information flow and instruction flow in the system hierarchy. To support cross-module modeling consistency, the system adopts a unified timestamp and buffer synchronization mechanism, maintains asynchronous perception queues and decision priority queues within the intelligent fusion layer, and improves the transmission stability of high-frequency information through a sliding window strategy.

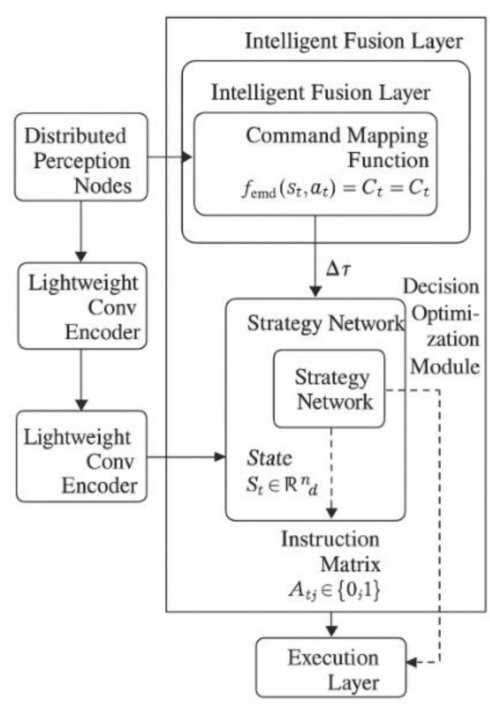

Figure 3 Information flow and command flow modeling structure diagram

3. Core technology and algorithm design

3.1 Multi-source heterogeneous information fusion

In order to realize the unified expression and structural alignment of environmental situational information among different platforms (manned helicopter, fixed-wing UAV, multi-rotor, and ground unit), the design of multi-source heterogeneous information fusion module adopts graph embedding augmented feature alignment mechanism. The raw data generated by each sensing node is first encoded into an initial representation vector $x_i^m \in R^{dm}$, where m denotes the modal type (e.g., infrared, radar, image, and bit-attitude), respectively, through specific subchannels, and then enters into the modal normalization and temporal alignment layer, where the alignment tensor $X_t \in R^{M\times T\times d}$ within a unified time window is generated by a Transformer-based temporal alignment network. To further construct the heterogeneous graph structure between spatial semantics, the system designs the following fusion function [13]:

$$Z = \sigma\left(\sum_{m=1}^{M} \alpha_m \cdot f_m(X_t^m)\right)$$

Where α m is the modal attention coefficient, fm(-) is the nonlinear mapping function of the corresponding modality, and σ (-) is the fusion activation function, and the final output of the fused feature map $Z \in R^{(n\times d')}$ is available for spatial mapping and task encoding in the subsequent GCN.

3.2 Task Allocation and Scheduling Optimization

Facing the highly dynamic battlefield environment and multi-objective task requirements, the design of the task allocation and scheduling optimization module is based on Joint Policy Search and graph matching optimization mechanism, aiming to construct a distributed scheduling strategy with scalability and real-time performance. Consider a heterogeneous set of executables A={a1,a2,... ,aN} and the set of tasks T={t1,t2,... ,tM}, the design introduces a two-part graph task mapping structure G=(A,T,E), where each edge weight wij in the edge set E is determined by the state of the executor si, the task demand characteristics τ j and the context cost cij, i.e:

$$w_{ij} = \phi(s_i, \tau_j c_{ij}) = \psi(x_i, y_j) + \lambda \cdot c_{ij}$$

where ψ is the similarity function of the embedding space and λ is the cost regulation factor. To achieve optimal task coverage and scheduling efficiency, the system adopts a reinforcement learning-driven dynamic graph matching strategy to complete scheduling policy learning by minimizing the following scheduling loss function [14]:

$$L_{assign} = -\sum_{i=1}^{N}\sum_{j=1}^{M} \pi_\theta (a_{ij} | s_j, \tau_j) \cdot r_{ij}$$

Where π θ is the policy network and rij is the task-executor matching reward function. Figure 3 demonstrates the multi-intelligent body graph modeling process and matching structure of the task allocation scheduling mechanism in real scheduling, ensuring that the system has the ability to dynamically adapt to task complexity, platform heterogeneity, and resource constraints, and providing input boundary conditions for subsequent path generation and conflict avoidance.

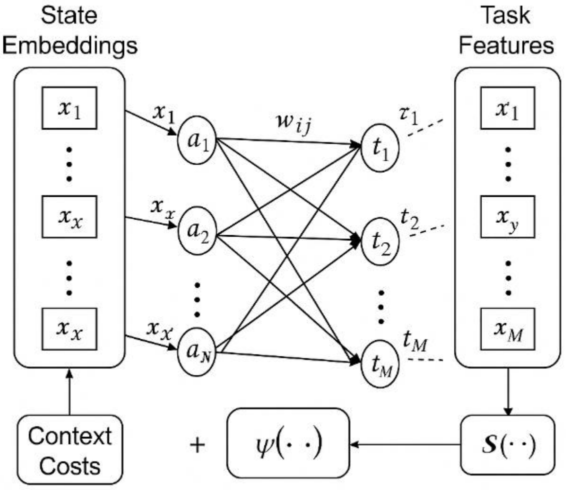

Fig. 3 Graph matching modeling structure for task allocation and scheduling optimization

3.3 Collaborative Path and Avoidance Control

After the multi-intelligent body task scheduling is completed, in order to ensure that each platform avoids physical conflicts and meets the time window constraints during the dynamic task execution process, the system design integrates the joint mechanism of distributed path generation and dynamic conflict avoidance. The path generation part adopts the constraint optimization model based on the time window, which maps the start and end time of task execution $\left(t_i^{start}, t_i^{end}\right)$ with the platform state space S={s1,.... ,sn} is mapped to a weighted graph structure Gp=(V,E, ω), where nodes denote platform states and edge weights ω ij denote joint time-consuming and risk-cost metrics. The path planning objective is to minimize the cost function within the feasibility set Pij [15]:

$$C_{path} = \min_{p_{ij} \in P_{ij}} \sum_{k=1}^{K} \omega(p_k) + \eta \cdot \xi(p_k)$$

Where ω (pk) is the path segment elapsed time, ξ (pk) is the conflict probability function, and η is the penalty weight. During the path execution phase, the system runs the avoidance control algorithm based on the Reciprocal Velocity Obstacle (RVO) mechanism synchronously to construct the feasible velocity set and predict the conflict time domain in real time. This design ensures spatial decoupling and dynamic adaptability between platforms during mission execution, providing control support for system safety and continuity.

4. Simulation verification and effect evaluation

4.1 Simulation environment construction

In order to verify the adaptability and stability of cooperative command and control system in multi-platform formation mission, this paper builds a distributed heterogeneous platform simulation environment based on ROS 2 and Gazebo integration. The system adopts the master-slave structure, the master control node runs on the GPU server, responsible for multi-intelligence body strategy reasoning and command generation, and the slave nodes simulate all kinds of platform entities (manned helicopters, rotary and fixed-wing UAVs, ground communication stations, etc.), and realize low-latency communication through the DDS protocol. The sensing data sources are generated by Gazebo's embedded sensor plug-in, covering 3D laser point clouds, image sequences, infrared thermograms, and inertial guidance information, with the data frequency controlled in the range of 10Hz-50Hz and aligned to the multi-source modality through a custom time synchronization mechanism.

The communication environment integrates frequency drift modeling module and controlled interference injection mechanism to support TDMA and frequency hopping protocol scheduling test; meanwhile, it embeds an event-driven task controller to realize task-level asynchronous triggering and multi-cycle update logic. The task scenarios are designed to include area patrol, multi-point reconnaissance and coordinated strike to cover different time constraints and platform heterogeneity under the command response verification path.

4.2 Experimental Results and Analysis

In the multi-batch mission simulation, the system performance is evaluated around the three core dimensions of information fusion accuracy, mission response efficiency and path coordination stability. Fusion accuracy is measured by modal feature consistency index FCI (Feature Consistency Index), which compares the average cosine similarity of GCN input features under different fusion strategies in the multimodal alignment phase; task response efficiency is evaluated by AAL (Average Assignment Latency), which is the average time from task release to scheduling decision generation; path cooperative stability is evaluated by AAL (Average Assignment Latency), which is the average time from task release to scheduling decision generation; and path cooperative stability is evaluated by path cooperative stability. Generation; Path Collaboration Stability is measured by Mean Trajectory Divergence (MTD), which measures the average degree of deviation between each platform and the theoretical shortest path during execution. Figure 4 illustrates the feature mapping results of the multimodal fusion inputs compared to the GCN response surface, reflecting the feature stability of the lightweight encoder and attention fusion structure in a high interference context.

Table 1 summarizes the metrics comparison results of the system in three types of task scenarios, where the architecture of this paper is compared with a static scheduling system and a centralized path planning system, respectively. From the data results, under the conditions of high target density (>12) and high communication delay (>80ms), the system in this paper still maintains the stability performance of FCI > 0.9, AAL < 50ms, and MTD < 3.0m, which verifies the collaborative sense-command-control mechanism's The overall linkage and robustness of the cooperative sensing-command-control mechanism is verified.

In addition, in the sensitivity test under dynamic contingencies (e.g., communication interruption, target disappearance), the system scheduling strategy can complete the strategy reconfiguration within 3 rounds of cycles to ensure uninterrupted task succession. Figure 5 further demonstrates the temporal linkage process of task scheduling-path planning-avoidance control, which verifies the response closure and structural synergy between the system functional modules, and provides quantitative support for the conclusion part.

Table 2 Comparison of performance metrics of each system under different task scenarios

Scenario type	System Type	FCI ↑	AAL(ms) ↓	MTD(m) ↓
Patrol Mission	System in this article	0.94	42.8	2.6
	Static dispatch system	0.80	86.3	5.9
	Centralized control system	0.85	63.5	4.1
Multi-Target Reconnaissance	System	0.91	44.1	2.4
Proximity Strike	This system	0.92	46.5	2.7

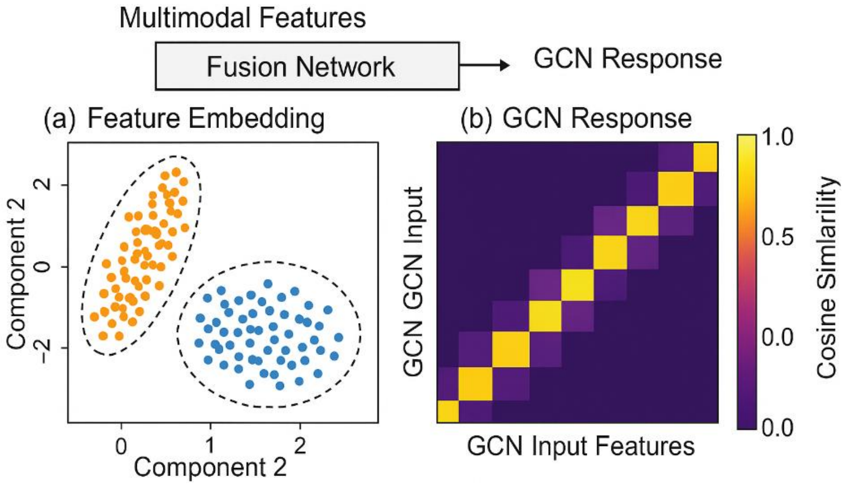

Fig. 4 Comparison of multimodal feature fusion with GCN inputs

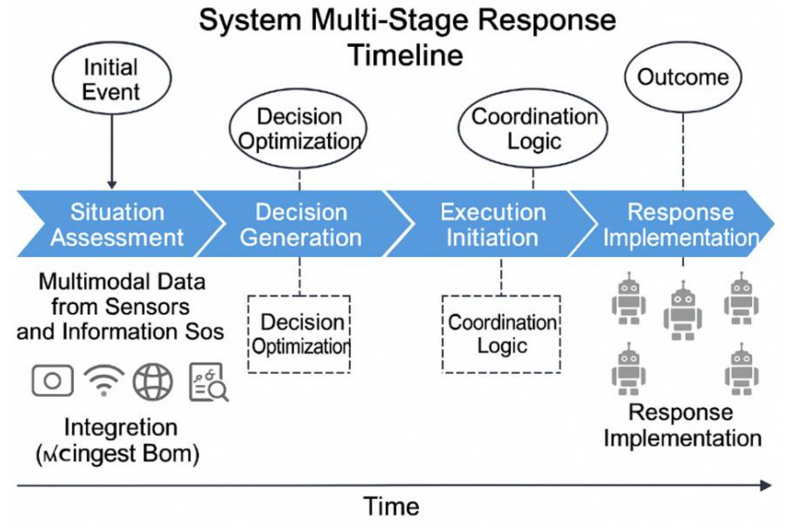

Fig. 5 Schematic of the system multi-stage response linkage time line

5. Conclusion

The research centers on the requirements of multi-platform heterogeneous formation combat, and builds an integrated collaborative command system architecture that integrates perception, command, decision-making and control. Through the introduction of graph neural network and multi-intelligence body reinforcement learning mechanism, it realizes the intelligent identification and task allocation of complex battlefield situation under high dynamic environment; combined with graph matching optimization and path avoidance control strategy, it improves the real-time performance of multi-task execution and system stability. The system simulation verification shows that the designed functional modules have strong robustness and environmental adaptability. However, the current model still suffers from response lag in the face of extreme communication disruption or platform physical constraints, and the strategy generalization ability needs to be further enhanced. Future work will focus on the flexibility improvement of cross-domain platform access, the introduction of mission priority dynamic regulation mechanism, and the integration verification with the field flight control system, to further expand the system's practicability and scalability in complex operational environments.

References

[1] Huang H, Zeng Y P. Research on intelligent cooperative command and control system of unmanned equipment in amphibious operations[C]//International Conference on Autonomous Unmanned Systems. Singapore: Springer Nature Singapore, 2022: 305-319.

[2] Zeng W, Wang Y, Pan T, et al. LVC Simulation Technology for Manned Helicopter UAV Cooperative Combat System[C]//China Aeronautical Science and Technology Conference. Technology Conference. Singapore: Springer Nature Singapore, 2023: 464-476.

[3] Javaid S, Saeed N, Qadir Z, et al. Communication and control in collaborative UAVs: Recent advances and future trends[J]. IEEE Transactions on Intelligent Transportation Systems, 2023, 24(6): 5719-5739.

[4] Paul T S, Lafond D, Benzakine P Y. AI-Driven Collaboration Mode Selection for Manned-Unmanned Teaming in Future Combat Air Systems[C]//2025 International Conference on Military Communication and Information Systems (ICMCIS). IEEE, 2025: 1-10.

[5] Gans N R, Rogers III J G. Cooperative multirobot systems for military applications[J]. Current Robotics Reports, 2021, 2(1): 105-111.

[6] Pan Z, Niu J, Kang M, et al. Research on Sea-Air Unmanned Systems Collaboration for Amphibious Assault[C]//Chinese Conference on Swarm Intelligence and Cooperative Control. Singapore: Springer Nature Singapore, 2023: 175-187.

[7] Adoni W Y H, Lorenz S, Fareedh J S, et al. Investigation of autonomous multi-UAV systems for target detection in distributed environment: current developments and open challenges[J]. Drones, 2023, 7(4): 263.

[8] Zhou X, Huang L, Xu Y, et al. Research on the Development of Unmanned Systems for Joint Operations[C]//China Conference on Command and Control. Singapore. Singapore Conference on Command and Control. Singapore: Springer Nature Singapore, 2023: 581-592.

[9] Wang X, Cao Y, Ding M, et al. Research Progress in Modeling and Evaluation of Cooperative Operation System-of-Systems for Manned-Unmanned Aerial Vehicles[J]. IEEE Aerospace and Electronic Systems Magazine, 2023, 39(4): 6-31.

[10] Wang X, Cao Y. An Optimization Method for Manned/Unmanned Aerial Vehicle Collaborative Operation System Architecture Based on PGQNSGA-II[J]. Aerospace, 2024, 11(12): 1003.

[11] Ciolponea C A. The Integration of Unmanned Aircraft System (UAS) in Current Combat Operations[J]. Land Forces Academy Review, 2022, 27(4): 108.

[12] Hamissi A, Dhraief A. A survey on the unmanned aircraft system traffic management[J]. ACM Computing Surveys, 2023, 56(3): 1-37.

[13] Kim S, Kim Y. Development of an MUM-T integrated simulation platform[J]. IEEE Access, 2023, 11: 21519-21533.

[14] Zhao L, Liu Z, Zhou J, et al. Analysis of Heterogeneous Cooperative Unmanned System with System Engineering[C]//China Aeronautical Science and Technology Conference. Technology Conference. Singapore: Springer Nature Singapore, 2023: 217-230.

[15] White J T. Autonomous Multi-layer Integrated Macro-/Micro-Swarming Networked System-of-Systems for UAM[C]//AIAA SCITECH 2024 Forum. 2024: 1288.