Current Status and Development Trends of Research on Autonomous Decision-Making Methods for Unmanned Swarms

Shang Jiang, Weihe Xie, Lin Zhang*,Gang Zhang, Xinyu Liang, Yuxiang Zheng
Dalian Naval Academy, Dalian, China

ABSTRACT

Autonomous decision-making has the advantages of strong information processing ability, fast response, and high cost-effectiveness, which is a key technical support for achieving unmanned, clustered, and intelligent combat. Firstly, clarify and sort out the basic concepts of autonomous decision-making in unmanned clusters and the development history of major countries and regions. Subsequently, in line with the trend of modern combat style transformation, combined with the main technical methods, the basic working principles of autonomous decision-making were analyzed in depth, mainly involving multi-source information fusion, battlefield situation assessment, task allocation optimization, and cluster path planning. Finally, the future development trends of autonomous decision-making methods were analyzed from the perspectives of enhancing intelligence, improving adaptability, enhancing system stability and sound security.

Keywords. Autonomous decision-making; information fusion; situation assessment; task allocation; path planning

1. INTRODUCTION

In the military and civilian domains of the 21st century, unmanned intelligent swarm systems are progressively showcasing their pivotal role, particularly in intricate and hazardous environments, demonstrating substantial potential and value[1]. Autonomous decision-making, characterized by robust processing capabilities, rapid responses, and high efficiency, empowers unmanned swarm systems to function in complex and dynamic environments independently, without direct human intervention[2]. They can autonomously adapt, allocate, coordinate, plan, and control, which has emerged as a crucial factor in the effective execution of tasks by unmanned systems. This significantly enhances task performance and diminishes the risks of human casualties in increasingly intricate and volatile combat scenarios as well as everyday applications[3].

Despite these advancements, the development and enhancement of autonomous decision-making encounter several challenges, encompassing the assurance of decision-making accuracy and reliability[4], the maintenance of efficient collaboration among unmanned swarm systems under extreme conditions, and the reinforcement of system adaptability and flexibility when faced with unfamiliar situations[5]. These prevailing challenges epitomize the existing research dilemmas and obstacles.

2. BASIC CONCEPTS AND DEVELOPMENT HISTORY

2.1 Basic concepts

Unmanned group autonomous decision-making entails the collaborative completion of intricate tasks by unmanned systems. This process operates autonomously, responding in real-time to environmental shifts, devoid of direct human intervention[6]. It encompasses various technical disciplines, including machine learning, artificial intelligence, multi-agent systems, and adaptive control. Its aim is to enhance task execution efficiency, flexibility, and resilience, particularly in unpredictable and dynamic settings[7].

2.2 Development history

2.2.1. America. During the early research phase (1950-1970), the US government conducted research on unmanned systems, primarily for military applications such as unmanned aircraft and autonomous navigation systems[8]. The research primarily focused on fundamental technologies such as perception, control, and communication of unmanned systems. During the theoretical exploration and technology breakthrough stage (1980-2000), the research focus gradually shifted

* mailbox1015@126.com.

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towards unmanned groups, exploring cooperative control and autonomous decision-making methods between group individuals, and incorporating theoretical tools such as distributed algorithms, game theory, and machine learning [9]. During the application expansion and international cooperation stage (2010 to present), the US has continued to innovate and expand the application of autonomous decision-making methods in the field of unmanned group autonomous decision-making. The US has attempted to apply autonomous decision-making methods to practical scenarios, thereby increasing the intelligence and autonomy of the systems.

2.2.2. Europe. During the initial research phase (1980s to 1990s), institutions in countries such as France, Germany, and the United Kingdom embarked on related studies, focusing on theoretical exploration and algorithm development[10]. In the phase of technological practice (early 21st century to around 2010), institutions like Fraunhofer in Germany, the French National Defense Research Institute, and the UK Royal Air Force Scientific Laboratory played pivotal roles, emphasizing cluster collaboration, path planning, and decision optimization[11]. In the stage of application promotion (post-2010), various countries commenced applying these methods in practical scenarios. Institutes such as the Netherlands Organization for Applied Scientific Research, Leonardo in Italy, and ETH Zurich in Switzerland actively explored applications across diverse fields.

2.2.3. Asia. In the early 21st century, research in the field of autonomous decision-making in Asia commenced comparatively later, characterized by a modest level of sophistication. Primarily, emphasis was placed on traditional control theory and algorithms, overlooking a thorough investigation into collaborative decision-making among multi-agent systems within intricate environments[12]. Over time, research endeavors gradually pivoted towards unmanned swarm autonomous decision-making methods. Successively, several nations established dedicated research institutions to delve into theoretical underpinnings and technological advancements in this domain, with a specific focus on fostering more intelligent and self-reliant unmanned swarm systems, as shown in Figure 1. In recent years, significant strides have been made by various countries in applying continuous theoretical innovation and technological breakthroughs across multiple sectors, thus emerging as a pivotal force in global research concerning unmanned swarm autonomous decision-making methods[13].

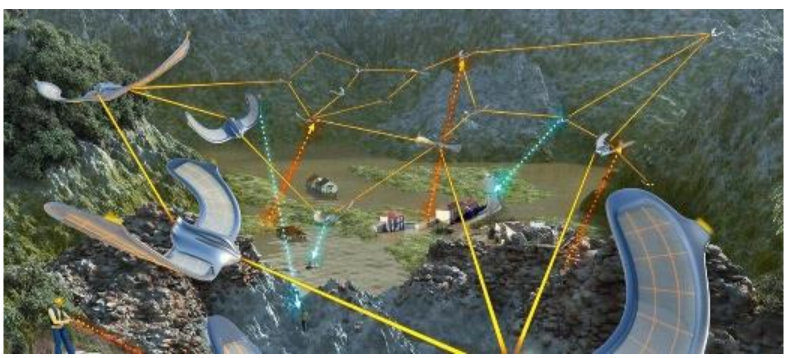

Figure 1. Schematic diagram of unmanned cluster application.

2.2.4 Middle East. In the early stages of technology adoption (from the 1980s to the 1990s), advanced technology from the United States and Europe was introduced, focusing on initial applications that established the basis for subsequent independent research and development. During the phase of independent research and development (from the early twenty-first century to the 2010s), autonomous research projects gradually evolved[14]. This period witnessed the establishment of numerous research institutions with a heightened focus on unmanned swarm autonomous decision-making methods, leading to the emergence of numerous significant research findings and technical solutions[15]. Subsequently, in the phase of application promotion (from the 2010s to the present), unmanned swarm autonomous decision-making methods started to find practical applications in various scenarios, with countries actively endorsing their use in national defense security, disaster relief, and energy exploration.

3. BASIC PRINCIPLES

3.1 Multi-source information fusion

3.1.1 Improving the Kalman filter. The application of enhanced Kalman filtering in multi-source information fusion is a complex technical field aimed at optimizing autonomous decision-making through the effective integration of multiple sensors and information sources[16]. It addresses challenges arising from the inherently nonlinear nature of models or non-Gaussian noise distributions, leading to more accurate system state estimates and improved observability and reliability of the entire system[17]. Alan S. Willsky of the Massachusetts Institute of Technology has conducted pioneering research in multi-source information fusion and dynamic system estimation, particularly in the application of enhanced Kalman filter methods at multiple resolutions, with the goal of improving estimation accuracy and reducing required computational resources.

3.1.2 Deep learning. The integration of deep learning within multisource information fusion aims to harness the complementarity among various sensors and data sources to enhance the decision accuracy and robustness of autonomous systems[18]. Typically, data from multiple sensors undergo a sequence of processes including standardization, denoising, and feature extraction to establish a comprehensive perceptual environment for autonomous system analysis and decision-making, as shown in Figure 2. Features extracted from diverse information sources are subsequently merged, with these features being automatically learned and extracted through hierarchical structures in multilayer neural networks[19]. Yiannis Demiris, of Imperial College London, has devised deep learning algorithms for multisource information and sensor fusion, accentuating their application in adaptive and interactive learning. Nonetheless, mitigating the reliance on extensive datasets in complex robotic applications persists as a challenge.

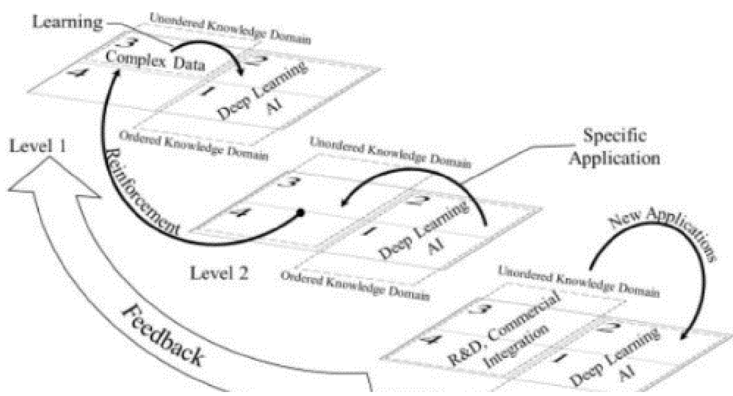

Figure 2. Schematic diagram of deep learning principles.

3.2 Battlefield situation assessment

3.2.1 Fusion bayesian networks. Bayesian networks, which describe the probabilistic dependencies between variables, are probabilistic graphical models suitable for representing and processing uncertain information. They have significant potential applications in situation awareness for autonomous decision-making by unmanned clusters on the battlefield [20]. Various types of sensors gather a large amount of real-time battlefield information, serving as nodes in the Bayesian network and forming the network structure. Yossi Keshet's research at the Israel Institute of Technology focuses on the application of Bayesian networks in dynamic battlefield environments, characterized by strong adaptability to dynamic conditions and rapid response to changes in the battlefield environment, albeit performing poorly in cases of inadequate data quality or quantity.

3.2.2 Knowledge graphs. A knowledge graph effectively organizes information via a graph structure, portraying entities as nodes and their interconnections as edges, as shown in Figure 3. Within the domain of unmanned swarm situational assessment, knowledge graph methodologies amalgamate diverse information reservoirs to establish a comprehensive knowledge framework that mirrors the drone swarm and its operational milieu[21]. The Chinese Academy of Sciences' Institute of Automation integrates environmental characteristics, task requirements, object relationships, and other pertinent information into knowledge graphs, allowing unmanned swarms to gain a more precise understanding of their operational environment.

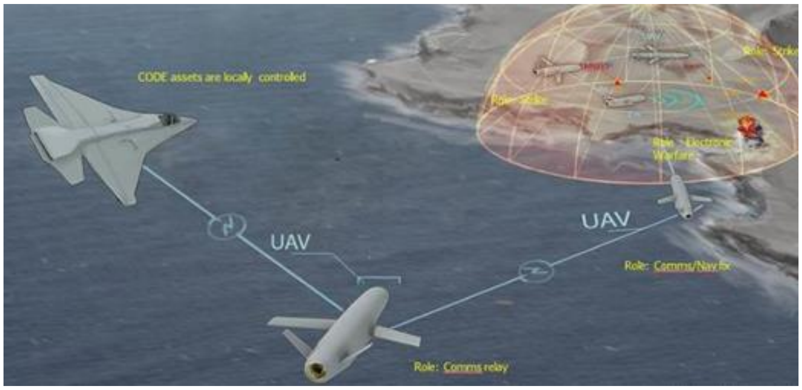

Figure 3. Schematic diagram of nodes and edges.

3.3 Task allocation optimization

3.3.1. Market auction methods. The central concept is to approach the task allocation problem as a market system, where tasks are regarded as commodities and unmanned agents as buyers. Each drone provides a bid for each task based on factors such as task difficulty, the drone's current state, and capabilities[22]. Katia Sycara from Carnegie Mellon University has made significant contributions to the design of task allocation mechanisms using market principles, emphasizing the importance of decentralized decision-making, which effectively mitigates the risk of single-point failures and enhances system robustness, though it may increase computational costs for each node.

3.3.2 Game theory. It is a mathematical theory that studies the interaction and decision-making of rational decision-makers under certain rules. This theory is utilized to simulate and resolve decision conflicts in the task allocation of drone swarms. Each drone functions as a decision player, needing to make choices among limited resources and multiple task demands[23]. By constructing mathematical models to describe the strategic interactions between these drones, the goal of each drone is to maximize its utility function. The distributed decision framework developed by John S. Tsitsiklis of the Massachusetts Institute of Technology effectively coordinates task allocation among drones, reducing the need for central control and improving the scalability and robustness of the system. In some highly dynamic environments, distributed decision-making may result in insufficient real-time performance.

3.4. Cluster path planning

3.4.1 Image search methods. Nodes symbolize potential locations, and edges indicate viable paths from one location to another. The objective of the graph search is to find a path from the initial node to the target node. The commonly utilized algorithms are Dijkstra and A*, known for optimizing the search process by amalgamating the actual path length traveled and the estimated distance to the destination, swiftly determining the shortest path[24]. Nicholas Roy from the Massachusetts Institute of Technology integrated dynamic programming and machine learning techniques to enhance graph search methods, enabling drones to adapt to intricate and highly uncertain environments, showcasing notable advantages. Nonetheless, when dealing with large-scale drone swarms, there are limitations in computational load and real-time response capabilities.

3.42 Bionic algorithms. Bio-inspired algorithms belong to a class of algorithms inspired by behaviors in nature, commonly used for solving path planning challenges for drone clusters. They derive insights from social behaviors and evolutionary mechanisms in the natural world to determine one or multiple optimal paths from the starting point to the destination. Particle swarm optimization mirrors the collective behaviors of birds and fish, as shown in Figure 4. Drone particles update their positions by emulating optimal peers and drawing from their own successful experiences, guiding the swarm toward an optimal state[25]. Yoshua Matsuo from the University of Tokyo advanced drone formation flight and complex maneuver coordination through bio-inspired algorithms, employing particle swarm optimization algorithms to enhance path planning efficiency and minimize conflicts and collisions.

Figure 4. Schematic diagram of unmanned cluster imitating biological particle swarm.

4. FUTURE DEVELOPMENT TRENDS

4.1 Enhance intelligence level

The advancement of AI technologies, particularly in deep learning and reinforcement learning, holds significant implications for the autonomous decision-making capabilities of unmanned swarms. These technological advancements empower unmanned swarms to autonomously make more sophisticated decisions, thereby diminishing their reliance on human operators. By leveraging deep learning algorithms for sound and image recognition, unmanned swarms can accurately perceive and comprehend their surrounding environments, thus enhancing their navigation and task execution capabilities, especially in complex scenarios.

4.2 Improve adaptability

To tackle increasingly intricate tasks and environmental challenges, future unmanned swarms will prioritize bolstering adaptability and flexibility amid complex and uncertain conditions. Empowered by AI technologies, these swarms will swiftly learn and adjust within real-time environments, leveraging past experiences and current environmental cues to make informed decisions. Utilizing advanced adaptive algorithms, they will dynamically alter their behavior to address environmental fluctuations, thereby sustaining efficient and effective decision-making in the face of unfamiliar or evolving conditions.

4.3 Enhance stability

In high-intensity interference environments, ensuring the stability and reliability of unmanned swarm systems poses a significant challenge. The ability to resist interference is paramount for maintaining effective operation amidst hostile or natural disruptions. Techniques like frequency hopping and spread spectrum communication enhance resistance to signal interference, while deploying multiple communication methods, such as optical or acoustic communication, serves as alternative means. Real-time deployment of sensors and monitoring systems enables the detection of interference intensity and type, as shown in Figure 5, while predictive models forecast interference trends and impacts, facilitating timely adjustment of anti-interference strategies.

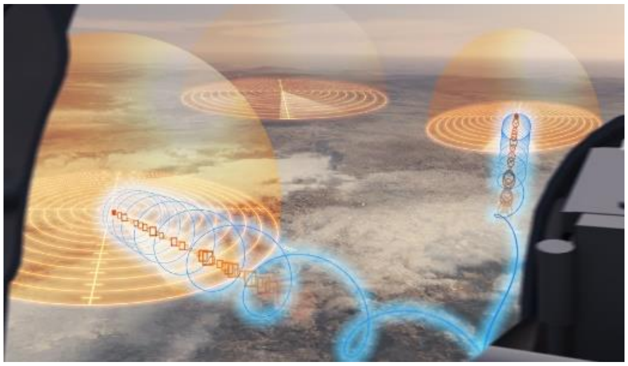

Figure 5. Schematic diagram of adaptive anti radar interference.

4.4 Establish sound security mechanisms

With the continuous evolution and escalation of network threats, the security measures of unmanned swarm systems require constant updates, particularly in thwarting network attacks and tampering. Advanced encryption technology is employed to safeguard data transmission and storage, thereby preventing the interception or manipulation of sensitive information. Encryption protocols ensure the integrity of command and control signals. Rigorous identity authentication and authorization mechanisms are implemented, enabling authorized users to access systems and data, coupled with periodic updates of authentication protocols and keys.

4.5 Future development trends

Unmanned swarm autonomous decision-making technology plays a critical role in the development of unmanned, clustered, and intelligent systems. It synthesizes cutting-edge research in artificial intelligence, information fusion, autonomous control, and related disciplines, offering substantial economic and military benefits. This paper reviews current research to highlight the distinctive features and emerging trends in this area globally. It delves into the core principles of prevalent techniques in multi-source information fusion, battlefield situation analysis, task allocation optimization, and swarm trajectory planning. The goal is to furnish insights and stimulate further investigation into more intelligent, adaptable, and robust decision-making strategies that enhance security.

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