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Collaborative Feature Analysis of UAV Swarm Task Based on Causal Emergence Theory

Ruyue Li

School of Reliability and Systems Engineering, Beihang University, China. E-mail: lry6688@buaa.edu.cn

Xiaohong Wang

School of Reliability and Systems Engineering, Beihang University, China. E-mail:wxhong@buaa.edu.cn

Jun Yao

School of Reliability and Systems Engineering, Beihang University, China. E-mail: 06967@buaa.edu.cn

Xiaohui Wang

School of Reliability and Systems Engineering, Beihang University, China. E-mail:xiaohuiw@buaa.edu.cn

Xiaogang Li

School of Reliability and Systems Engineering, Beihang University, China. E-mail:lxg@buaa.edu.cn

Sa Wu

School of Reliability and Systems Engineering, Beihang University, China. E-mail:wusa@buaa.edu.cn

Jiageng Li

School of Reliability and Systems Engineering, Beihang University, China. E-mail: zy2414126@buaa.edu.cn

Aiming at the problem that the cooperative behavior of UAV swarms in dynamic environments is hard to quantitatively evaluate, this paper proposes a quantitative method based on the causal emergence theory. Firstly, a microscopic model involving individual dynamics is constructed, and the mapping from microscopic states to macroscopic features is achieved by designing micro-macro indicators. On this basis, the effective information at both micro and macro levels is defined and calculated, and the occurrence of emergent behavior in the swarm is determined by causal gain. Finally, the causal emergence index is correlated with task success rate to verify its effectiveness as a new dimension for evaluating collaboration quality. Meanwhile, the influence of different task ratios on emergence values is explored. The research results show that the proposed method can effectively quantify the impact of emergent behavior on swarm tasks, providing theoretical support and technical references for the collaborative optimization of UAV swarm tasks.

Keywords: UAV swarm, Causal emergence, Coarse-graining,Task collaboration, Feature analysis, Effective information

1. Introduction

1.1. Research background and significance

With the rapid development of artificial intelligence and unmanned system technologies, UAV swarms have shown broad application prospects in fields such as smart agriculture, post-disaster rescue, and battlefield reconnaissance due to their advantages of low cost, high fault tolerance, and strong collaboration. During the execution of UAV swarm tasks, local interactions among multiple agents form globally ordered emergent behaviors, which may have a certain impact on the efficiency and success rate of swarm tasks. For example, in offensive and defensive confrontation scenarios, emergent behaviors such as cooperative encirclement and dynamic evasion of the swarm are crucial for breaking through enemy defenses and completing tasks; in disaster rescue scenarios, emergent behaviors such as distributed search and information fusion of the swarm directly affect the rescue scope and response speed.

However, the emergent behaviors of UAV swarms exhibit complex characteristics such as dynamics, nonlinearity, and coupling. Existing quantitative methods based on statistical features lack a micro-macro causal mapping mechanism, making it impossible to establish a direct connection between emergent behaviors and task objectives, and thus difficult to accurately reflect the impact of emergence on task results. The application of causal emergence theory in the field of UAV swarms is still in its infancy. The core challenges lie in how to design coarse-graining mapping rules combined with the dynamic interaction characteristics of the swarm and how to construct a quantitative correlation model between emergence indicators and task effectiveness. This leads to lag and ambiguity in the quantitative evaluation of emergent behaviors, making it difficult to meet the real-time optimization needs of UAV swarm task collaboration.

Emergence has always been an important feature in complex systems and a core concept in many discussions on system complexity and the relationship between micro and macro levels . Emergence can be simply understood as "the whole is greater than the sum of its parts", that is, the whole exhibits new characteristics that the individuals composing it do not possess. Although scholars have pointed out the existence of emergence in various fields, such as the collective behavior of birds, the formation of consciousness in the brain, and the emergent capabilities of large language models, there is currently no universally recognized unified understanding of this phenomenon. Previous studies on emergence mostly remained at a qualitative stage. For example, Bedau et al. classified emergence into nominal emergence, weak emergence, and strong emergence . As an emerging complex system analysis tool, causal emergence theory reveals the causal efficacy of macroscopic emergent behaviors by constructing micro-macro causal mapping relationships, providing a new idea for solving the quantitative problem of emergent behaviors in complex systems. This theory holds that the macro level may have stronger causal predictive power than the micro level. Applying causal emergence theory to the collaborative analysis of UAV swarm tasks, establish a quantitative connection between emergent behaviors and task objectives, and provide theoretical support for the optimization of swarm collaborative strategies and the improvement of reliability, which has important academic value and engineering application significance.

1.2. Research status at home and abroad

Scholars at home and abroad have carried out extensive research on the analysis of emergent behaviors and task collaboration of UAV swarms. In terms of the quantification of emergent behaviors, existing studies are mainly divided into two categories: one is quantitative methods based on statistical features, such as indirectly characterizing the degree of emergence by calculating statistical indicators such as speed consistency, spatial distribution entropy, and topological connectivity of the swarm. For example, Zhang *etal.* proposed a method for evaluating the emergence degree of UAV swarms based on the improved entropy method, which realized the quantification of the emergent behavior of swarm collaborative patrol by calculating indicators such as speed entropy and position entropy; Li et al. adopted a deep learning model to predict the macroscopic collaborative state of the swarm with the individual motion parameters of UAVs as input. However, these methods do not consider the causal correlation between emergent behaviors and task objectives, making it difficult to accurately reflect the impact of emergent behaviors on task results.

In terms of the application of causal emergence theory, this theory has been initially applied to the analysis of complex systems such as neural networks, ecosystems, and social networks. For example, Hoel et al.analyzed the information processing mechanism of neural networks through causal emergence theory and found that the macroscopic network structure has stronger causal predictive power; Wang et al. applied causal emergence theory to the analysis of ecosystem stability and revealed the causal relationship between macroscopic ecological structure and system anti-interference ability. However, the research on applying causal emergence theory to the collaborative analysis of UAV swarm tasks is still in its infancy. How to combine the dynamic characteristics and task requirements of UAV swarms to construct causal emergence quantitative indicators that conform to the swarm collaboration rules and establish an evaluation system between emergent behaviors and task objectives is a key challenge in current research.

2. Collaborative Characteristic Index System for UAV Swarm Task

2.1. Design of micro-macro feature system

The premise of causal emergence analysis is to construct an adaptive micro-macro feature system, which must satisfy the principle that microscopic features cover the core states of individual UAVs and macroscopic features reflect the essence of swarm collaboration.

2.1.1. *Design of microscopic features*

According to the task characteristics of UAV swarms, the following microscopic indicators are established:

(i) Spatial position feature: The coordinates (x_i, y_i) of individual UAVs are used to characterize the spatial position distribution, reflecting the relative positional relationship of individuals in the task space.

(ii) Individual motion feature: Including speed magnitude v_i (reflecting the motion capacity of the individual) and speed vector v_i (characterizing the individual motion state).

(iii) Task state feature: The load working mode M is designed and quantized by discrete coding: 1=reconnaissance (information collection); 2=strike(task output); 3=decision-making; 4=failure(unable to perform tasks), which is used to represent the task type and capability that a single UAV can undertake currently.

2.1.2. Design of macroscopic features

Based on causal emergence theory, the micro-macro mapping relationship of UAV swarms is constructed by the coarse-graining method to quantify the predictive power of macroscopic emergence on tasks. Macroscopic features focus on the overall state of UAV swarms and reflect the emergent behaviors at the swarm level. Based on microscopic features, combined with causal emergence theory and swarm task requirements, corresponding macroscopic indicators are established. The micro-macro mapping relationship is shown in Figure 1:

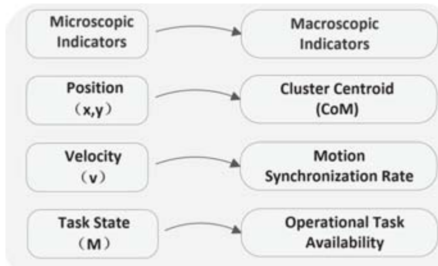

Fig. 1.Micro-Macro Mapping Relationship

(i) Cluster Centroid (CoM):Calculated by the average value of the three-dimensional positions of all UAVs ($CoM_x = \frac{1}{N}\sum_{i=1}^{N} X_i$ similarly for CoM_y),reflecting the overall spatial center of gravity and motion trend of the swarm;

(ii) Velocity Synchronization Rate: Characterizes the maneuver consistency of UAVs in the same task group:

$$S_r = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{v_i}{\|v_i\|}\bullet\frac{\overline{v_i}}{\|\overline{v_i}\|}\right| \tag{1}$$

(iii) Operational Task Availability:

$$A = \frac{\sum_{i=1}^{n}(I(M_i \in \{1,2,3\}) \times E_i)}{n} \tag{2}$$

Where, I is the indicator function, taking one when $M_i \in 1,2,3$,and A is the operational task availability. A higher availability indicates that the swarm has a stronger ability to perform reconnaissance and strike tasks simultaneously, directly related to the completion efficiency of objectives.

2.2. *Task effectiveness indicator*

$$\textit{Task success rate} = \frac{\textit{Number of completed task objectives}}{\textit{Total number of objectives}} \times 100\% \tag{3}$$

3. Causal Emergence

3.1. Calculating Continuous Effective Information Based on Differential Entropy

3.1.1. Definition of differential entropy

Given the highly continuous and dynamically evolving motion characteristics of drone swarms in physical space, this paper introduces a differential entropy-based continuous effective information computation nX framework to more accurately capture causal features in swarm dynamics.For a continuous n-dimensional random variable X, its differential entropy is defined as:

$$h(X) = -\int_S f(x) \ln f(x) dx \tag{4}$$

In this context, $f(x)$ denotes the probability density function of the system state on the phase space $\mathbb{S}$.

Since the system state is a multi-dimensional continuous vector, the Gaussian distribution is adopted in this paper, which can satisfy the statistical characteristics of the disturbance superposition under the central limit theorem, and can describe the coupling relationship between the state components through the covariance matrix, and can guarantee the closed-form analytical solution of the differential entropy and the effective information, so as to realize the reliable and efficient calculation of the high-dimensional system.

Specifically, let state X follow an n-dimensional multivariate Gaussian distribution $X \sim \mathcal{N}(\mu, \Sigma)$, where $\mu \in \mathbb{R}^n$ is the mean vector and $\Sigma \in \mathbb{R}^{n\times n}$ is the positive definite covariance matrix. The probability density function is then given by:

$$f(x) = \frac{1}{(2\pi)^{n/2} |\Sigma|^{1/2}} \cdot \exp\left(-\frac{1}{2}(x-\mu)^\top \Sigma^{-1} (x-\mu)\right) \tag{5}$$

Here, the $\{x^{(i)}\}_{i=1}^N$ determinant of the covariance matrix is defined. Using maximum likelihood estimation (MLE), the parameters are estimated from the observed data.

Here, $|\Sigma|$ denotes the determinant of the covariance matrix. Using maximum likelihood estimation (MLE), the parameters are estimated from the observed data $\{x^{(i)}\}_{i=1}^N$.

$$\hat{\mu} = \frac{1}{N}\sum_{i=1}^{N} x^{(i)} \tag{6}$$

$$\hat{\Sigma} = \frac{1}{N-1}\sum_{i=1}^{N}(x^{(i)} - \hat{\mu})(x^{(i)} - \hat{\mu})^\top \tag{7}$$

In high-dimensional scenarios, to prevent the singularity of the covariance matrix and overfitting, this study introduces L2 regularization: $\hat{\Sigma} \leftarrow \hat{\Sigma} + \lambda I$ where $\lambda > 0$ is the regularization coefficient and I is the identity matrix. The regularization coefficient λ is determined via 5-fold cross-validation over the range $[10^{-3}, 10^{-1}]$, selecting the value that minimizes the prediction error of the state transition model.

To address the high-dimensional challenges in drone swarm state space, this study employs an optimal linear coarsening strategy to mitigate dimensionality issues. This strategy defines a linear projection matrix $W \in \mathbb{R}^{k\times n}$ (where $k < n$) to transform n-dimensional states x_t into k-dimensional coarse-grained states y_t :

$$y_t = Wx_t \tag{8}$$

The projection matrix W is constructed using Principal Component Analysis (PCA), where the dimension k is chosen such that the cumulative explained variance ratio of the top k principal components exceeds 95%. This ensures that the coarse-grained representation retains the essential information for causal analysis while reducing computational complexity.

Furthermore, to validate the Gaussian distribution assumption for the drone swarm states, we perform the Kolmogorov-Smirnov (KS) test on the marginal distributions of each state variable. The test results confirm that the state variables follow a Gaussian distribution at a significance level of $\alpha = 0.05$, justifying the use of Gaussian-based differential entropy calculations.

3.1.2. Analysis and Calculation of Continuous Valid Information

The continuous effective information (EI) quantifies the causal constraint from the current system state to the next state, defined as the mutual information between X_t and X_{t+1} under the intervention $do(X_t)$:

$$\begin{aligned} \mathrm{EI} &= I(X_t; X_{t+1} \mid \mathrm{do}(X_t)) \\ &= h(X_{t+1}) - h(X_{t+1} \mid \mathrm{do}(X_t)) \end{aligned} \tag{9}$$

Assuming X_{t+1} follows an n-dimensional Gaussian distribution with covariance matrix Σ_{t+1} , the unconditional differential entropy is:

$$h(X_{t+1}) = \frac{1}{2}\ln((2\pi e)^n \mid \Sigma_{t+1} \mid) \tag{10}$$

Where $|\Sigma_{t+1}|$ denotes the determinant of Σ_{t+1} , representing the total uncertainty of X_{t+1}. The conditional differential entropy, given the intervention $do(X_t)$, is:

$$h(X_{t+1} \mid X_t) = \frac{1}{2}\ln((2\pi e)^n \mid \Sigma_{t+1|t} \mid) \tag{11}$$

with $\Sigma_{t+1|t}$ being the conditional covariance matrix of X_{t+1} given X_t . The difference between these two entropies yields the effective information, which measures the degree of causal predictability in the system's state transition.

3.2. Quantitative calculation of causal emergence

The causal gain ΔEI is defined as a quantitative determination indicator of causal emergence. The causal advantage of the macro scale relative to the micro scale is measured by the difference between the effective information of the macro and micro levels. The formula is as follows:

$$\Delta EI = EI_{macro} - EI_{micro} \tag{13}$$

The determination criterion is: if $\Delta E > 0$,it indicates that the system has significant causal emergence, the causal explanatory power of the macro state is better than that of the micro state, and the collaborative behavior of the swarm presents obvious macroscopic emergent characteristics; if $\Delta EI \leq 0$,it indicates that there is no obvious causal emergence, and the swarm behavior relies more on the independent actions of individuals with weak collaborative effects.

4. Simulation Experiments and Result Analysis

4.1. Design of simulation scenarios

4.1.2. Simulation platform and parameter setting

Netlogo 6.1.0 is adopted as the simulation platform, which has strong multi-agent modeling and simulation capabilities and can accurately simulate the dynamic interaction and emergent behaviors of UAV swarms.

Basic scenario parameters: The scenario size is 300 patches×140 patches (1 patch corresponds to 1km×1km in actual space), the red swarm size is 198 UAVs, the total number of blue targets is 80 (30 dynamic targets and 50 static targets), and the single simulation cycle is 1000 ticks.

During the task, the main changes of the UAV swarm are as follows:

The UAV swarm will be attacked by targets, resulting in the destruction of UAVs, the failure of corresponding nodes, and the disconnection of structure, communication, and task hierarchy connections.

After the communication network is damaged, the UAV swarm reconnects the communication links through self-organization to maintain information interaction.

Finally, the termination condition is the clearing of the target quantity. The detailed Netlogo simulation scenario is shown in Figure 2 below.

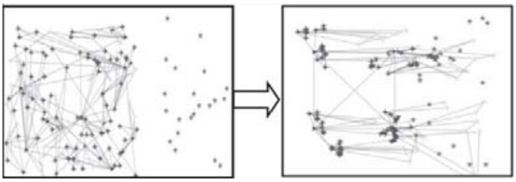

Fig. 2.UAV Swarm Confrontation Simulation Scenario Based on Netlogo

4.1.1. *Task description*

The red UAV swarm formation conducts coverage reconnaissance of threat targets, locates the detected targets, and cleans up and strikes the located targets; the red swarm includes three types of UAVs (reconnaissance type, decision-making type, and attack type), and the swarm has certain communication link networking reconstruction capabilities and swarm node reinforcement capabilities within a certain threshold. Reconnaissance type: UAV entities that reconnaissance, detect, and acquire information from the environment. Decision-making type: UAV entities that make judgments, issue instructions, and perform control. Attack type: UAV entities that receive commands and directly execute specific tasks. The three types of UAVs form a task chain in sequence to output task capabilities to the target. At the same time, there are collaborative connections and task interactions among nodes of the same type, such as information sharing among sensing nodes and task redistribution among decision-making nodes. As shown in Figure 3 below.

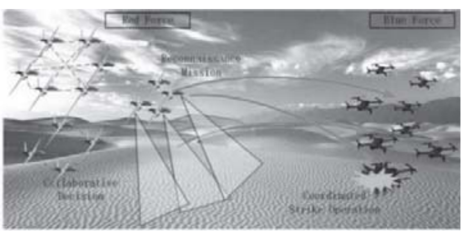

Fig. 3. UAV Swarm Confrontation Scenario

4.2. *Experimental scheme*

The control variable method is adopted to focus on the impact of UAV swarm task ratios on emergent behaviors. Three groups of experimental variables (reconnaissance: decision-making: attack ratio) are set, as shown in Table 1:

Table 1 Red Swarm Ratios

Experimental Group	Task Ratio	Total Swarm Size	Number of Repetitions	Simulation Cycle (1tick=1s)
Ratio1	2:1:4	198 UAVs	10 times	1000 ticks
Ratio2	3:1:5	198 UAVs	10 times	1000 ticks
Ratio3	4:1:6	198 UAVs	10 times	1000 ticks

During the experiment, other factors such as the total swarm size, target quantity, and scenario parameters are kept unchanged. Data such as task progress, node status, emergence value, and task success rate are recorded in real time. The average value of 10 repeated results of each group of experiments is taken to eliminate random errors.

4.3. *Experimental results and analysis*

4.3.1. *Calculation results of emergence values and the impact of different ratios on emergence values*

From the overall trend, during the entire task cycle, the UAV swarm always exhibits emergent behaviors, confirming the self-organizational characteristics of the swarm system in dynamic task scenarios. It can be specifically divided into three stages, as shown in Figure 4 below:

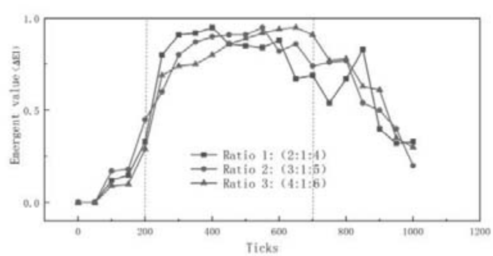

Fig. 4. Quantitative Diagram of Emergence Values with Different Ratios

Initialization Stage (0~200 ticks): The emergence values under the three ratios all start to rise gradually from 0, indicating that the swarm begins to form initial collaboration from scattered individuals. Among them, the emergence value of Ratio2 (3:1:5) is always in the leading position, because the high coupling between the proportion of sensing units and execution units in this ratio can quickly respond to the environmental sensing and collaborative triggering needs in the initial stage of the task.

Collaborative Peak Stage (400~700 ticks): The emergence value reaches the peak range, corresponding to the core stage of swarm collaborative attack. At this time, the UAV swarm forms highly synchronized collaborative behaviors through efficient interaction between "reconnaissance-decision-making-attack" units. The jump of the emergence value reflects the phase transition process of the system from "scattered individuals" to "collaborative whole". Among them, the emergence value of Ratio3 (4:1:6) surpasses and maintains the highest level, benefiting from the higher proportion of sensing units that ensures the comprehensiveness of situational awareness, and the stronger proportion of execution units that improves the behavior synchronization ability, making the swarm have better collaborative stability in complex dynamic scenarios.

Collaborative Attenuation Stage (800~1000 ticks): The emergence value shows a continuous downward trend. The reason is that with the gradual elimination of enemy targets, the collaborative demand of the swarm decreases, and the intensity of system self-organization weakens, reflecting the dynamic adaptability of swarm behavior to task requirements. Among them, the attenuation rate of the emergence value of Ratio1 (2:1:4) is relatively gentle. Due to the streamlined proportion of decision-making units in this ratio, the cost of the system maintaining basic collaboration is lower in the scenario of low collaborative demand in the later stage of the task.

4.3.2. *Correlation analysis between emergence value and task success rate*

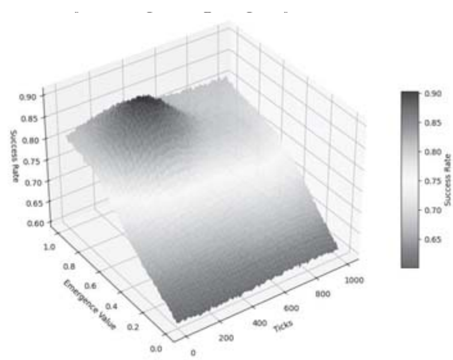

Fig. 5. 3D Surface Diagram of Emergence Value, Success Rate, and Time Step

From the quantitative data, there are correlations between emergence value and task success rate, between success rate and time step, and between emergence value and time step. This correlation can be intuitively verified through the three-dimensional surface diagram in Figure 5. The diagram systematically depicts the dynamic correlation between emergence value, time step, and task success rate: from the gradient change of the surface, it can be observed that the emergence value is significantly positively correlated with the task success rate, that is, the higher the emergence value, the more obvious the improvement of the task success rate. When $\Delta EI > 0.3$,the task success rate all exceeds 80%. This result indicates that efficient collaborative emergence is a core factor for improving the effectiveness of multi-agent collaborative tasks.

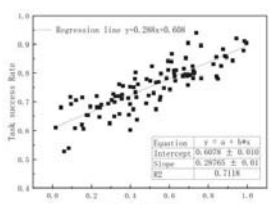

Fig. 6. Scatter Plot and Regression Fitting of Emergence Values and Task Success Rate

To quantitatively evaluate the association between causal emergence and task effectiveness, this study conducted statistical testing on 100 simulation datasets. As illustrated in Figure 6 above, the coefficient of determination (R^2) is 0.7118, indicating a positive linear correlation between the two. Univariate linear regression yielded the equation $y=0.288x+0.608$ (where y represents task success rate and x denotes emergence values). t-tests of the regression coefficients revealed a significance level of $p<0.01$, statistically rejecting the null hypothesis and confirming that the causal emergence index exhibits substantial explanatory power for task success rate.

5. Conclusions and Prospects

Aiming at the difficulty of quantitatively evaluating the cooperative behavior of UAV swarms in dynamic environments, this study proposes a quantitative analysis framework based on causal emergence theory. The main conclusions are as follows:

(i). The proposed method realizes the effective mapping between the microscopic individual states and macroscopic emergent behaviors of realizes the quantitative characterization of UAV swarm emergence through the causal gain ΔEI .

(ii). The quantitative results of emergence show a significant positive correlation with task effectiveness, and the ratio of perception-decision-execution units has a notable impact on the emergence level.

(iii). This method provides theoretical support and technical reference for phased resource allocation and collaborative optimization of swarm tasks, with potential applications in typical scenarios such as reconnaissance-strike integration and area surveillance.

This study has limitations: it does not consider the impact of extreme environments (e.g., strong electromagnetic interference, complex terrain) on emergent behaviors, and the computational efficiency for ultra-large swarms (more than 200 UAVs) needs further improvement. In future work, we will:

(i). Combine digital twin technology to optimize the coarse-grained mapping in complex terrain scenarios;

(ii). Explore distributed computing strategies to improve the efficiency of large-scale swarm analysis.

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