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Yi Qu
Mancang Gu
Yifeng Niu
Wenxing Fu *Editors*

# Proceedings of 3rd 2023 International Conference on Autonomous Unmanned Systems (3rd ICAUS 2023)

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# Lecture Notes in Electrical Engineering 1171

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Editors

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# Contents

# Robust Neural Control for Distributed Formation of UAVs Under Uncertain Disturbances

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**Abstract.** Multi-quadrotor formations have received wide attention in recent years because of their mobility, flexibility, ability to perform complex tasks instead of humans and higher performance than a single quadrotor. However, formation flight is inevitably affected by model uncertainties and external disturbances, which significantly challenge the design of quadrotor formation controllers. Traditional robust controllers tend to limit the performance of the intelligence, and deep reinforcement learning can achieve high performance in control tasks but needs more robustness. This paper uses a neural network-based robust control strategy to control a quadrotor formation to ensure robustness and performance under uncertainty disturbances. The formation is modeled using the leader-follower approach. We conducted simulation experiments to verify the feasibility of the method.

**Keywords:** quadrotor · robust control · distributed formation · neural networks

## 1 Introduction

Multi-quadrotor cooperative formation control is a critical application of multi-agent system cooperative control theory. By leveraging the performance advantages of individual quadrotors, flying in formation enhances their capabilities and finds widespread use in military and civilian fields. Existing methods of multi-UAV formation control include the leader-follower method, behavior control method, and virtual structure method. Among these, the leader-follower method is widely employed due to its excellent control performance.



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However, the dynamical system characteristics of quadrotors, such as high uncertainty, underdriving, and strong coupling, introduce parameter uncertainty and external perturbations that challenge the design of a quadrotor formation controller. The conventional approach of constructing a robust controller limits its performance in general scenarios, as it focuses on worst-case stability. In contrast, deep reinforcement learning offers the ability to capture complex, non-linear policies and has demonstrated state-of-the-art performance in various control tasks. Neural networks can handle uncertain systems while possessing strong information synthesis capabilities that enable good performance in quadrotor formation control. However, these techniques lack robustness guarantees and have limited application in safety-critical areas.

In this paper, we propose a neural network-based robust controller for application in the collaborative formation of quadrotor UAVs. We construct a class of neural network-based non-linear policies that project the output of a neural network onto a stable set with robustness guarantees to form a robust policy. The main contributions of this paper are as follows: (1) We combine neural networks with robust control to obtain a non-linear control strategy that both maintains the same stability as a general robust controller in the presence of disturbances and can be trained to maintain good performance using deep reinforcement learning. (2) We innovatively applied the constructed controller to quadrotor formation and used the leader-follower method to form multiple quadrotors, ensuring stability and high performance of quadrotor formation flight.

## 2 Relate Work

Scholars have done a lot of research on nonlinear system controllers, and the combination of robust control with deep reinforcement learning. Xinning Chen et al. designed a multi-intelligent error-tolerant reinforcement learning algorithm for training an agent in a noisy environment and established a mechanism for the agent to detect its errors [1]. Fan Bo et al. investigated the optimal control problem of nonlinear systems and designed a RADP-based controller to transform the system into an unconstrained control problem [2]. Jian Li et al. proposed a robust adaptive neural network control method. Through a radial basis function (RBF) neural network, the unknown dynamics and perturbations of the agent are converted to a linear parameter with only one unknown parameter [3]. Zhenwei Ma et al. designed an RBF neural network robust adaptive global control method applied to quadrotor flight control under model uncertainty and a strong perturbation environment [4]. Kaicheng Zhang et al. used switching functions to connect robust adaptive control with neural network control and proposed a robust adaptive neural network-based finite-time attitude stabilization control method with fast convergence speed and good control accuracy for better control performance [5]. Amir Razzaghian et al. propose a robust adaptive neural network sliding film controller to overcome the effects of uncertainty in control. The RBF neural network was used to design the model, and the Liapunov stability theory was used to design the controller [6]. Ding Wang et al. address the robustness of nonlinear control systems under dynamic uncertainty and propose a robust stabilization method for nonlinear systems with dynamic uncertainty through adaptive criticism techniques based on neural network learning components [7].

Research on UAV formation methods is relatively mature. Amador et al. proposed two UAVs formation strategies based on leader-follower techniques with fixed global differences and dual fixation [8]. Zonghang Gu et al. used the sliding mode control method on three UAVs formed by the leader-follower method to build a virtual navigator identical to the real drone model to avoid navigator malfunction [9]. Mingwei Zhen et al. divided the system into an estimation layer and a control layer, so that the distributed multi-robot cooperative control is separated from the single-robot control, effectively realizing the formation control of underdriven quadrotor UAV swarms [10]. Liu Y et al. proposed the concept of virtual linkage for robot formation, where a group of robots is designed and controlled as particles embedded in mechanical linkages. By changing the angle of the corresponding linkage, the robots are formed into various formations [11].

## 3 Quadrotor UAV Modeling

The leader-follower approach is a well-established method for determining the formation of UAVs by controlling the direction and position of the leader UAV. This approach has been extensively studied and is considered mature in the field.

We use the leader-follower method to form quadrotors, with one as the leader and the rest of the UAVs as followers. The controller is applied to the leader UAV, and then the quadrotor UAVs are formed into a formation for the purpose of controlling the formation stability and maintaining good performance.

### 3.1 Quadrotor Dynamics Model

Our goal is to control the force of the quadrotor UAV thrusters to keep the system stable at $x = \overrightarrow{0}$. Define the state for the leader UAV as

$$x = \left[\, s_x \; s_y \; \psi \; \dot{s}_x \; \dot{s}_y \; \dot{\psi} \,\right]^T , \tag{1}$$

where $(s_x, s_y)$ is the position of the quadrotor UAV in the plane coordinate system, $\psi$ is its roll angle, $(\dot{s}_x, \dot{s}_y)$ is its speed, and $\dot{\psi}$ is its angular velocity. We assume that the force $F$ balances out the additional forces other than gravity. We assume that the mass of the quadrotor is $m_q$, the force arm of the thruster is $l_q$, and the moment of inertia is $J_q$. Therefore, the dynamics of the quadrotor can be written as

$$\dot{x} = \begin{bmatrix} \dot{s}_x \cos\psi - \dot{s}_y \sin\psi \\ \dot{s}_x \sin\psi + \dot{s}_y \cos\psi \\ \dot{\psi} \\ \dot{s}_y \psi - g \sin\psi \\ -\dot{s}_x \psi - g \cos\psi \\ 0 \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 1/m_q & 1/m_q \\ l_q/J_q & l_q/J_q \end{bmatrix} F , \tag{2}$$

where $g = 9.81\,\mathrm{m/s^2}$.

### 3.2 Quadrotor Formation Model

For the leader, its kinematic model is determined only based on its position attitude information, while the follower describes its information indirectly through the relative position and angle information with the leader. First, the mathematical model of the leader is established. Then the corresponding mathematical model of the position pose of a virtual UAV and the position pose error of the follower is determined based on the position pose of the leader. The virtual UAV is the position that the follower needs to reach for the next action. Figure 1 shows a formation model of a leader, a follower, and a virtual UAV.

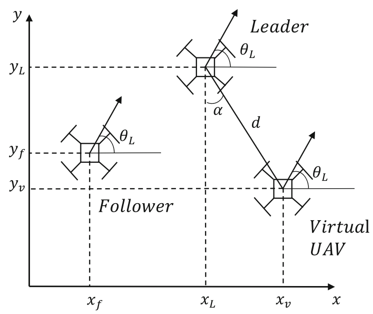


**Fig. 1.** Leader-follower formation structure model

The straight line distance between the leader quadrotor and the virtual UAV is $d$, the motion direction angle is $\theta_L$, the position of the leader UAV is $(x_L, y_L)$, and the linear and angular velocities of the leader's motion are $v$, $\omega$. The kinematic model of the leader is (follow [12])

$$\begin{cases} \dot{x}_L = \cos\theta_L \cdot v, \\ \dot{y}_L = \sin\theta_L \cdot v, \\ \theta_L = \omega. \end{cases} \tag{3}$$

The state information of the virtual UAV can be described as

$$\begin{cases} x_v = x - d \cdot \cos(\alpha + \theta_L), \\ y_v = y - d \cdot \sin(\alpha + \theta_L), \\ \theta_v = \theta_L. \end{cases} \tag{4}$$

where $(x_v, y_v)$ and $\theta_v$ indicate the position and motion direction angle of the virtual UAV respectively. The expression between the virtual UAV and the follower can be described as follow, where $(x_f, y_f)$ and $\theta_f$ indicate the position and motion direction angle of the follower respectively.

$$\begin{cases} x_d = x_v - x_f, \\ y_d = y_v - y_f, \\ \theta_d = \theta_v - \theta_f. \end{cases} \tag{5}$$

## 4 Robust Neural Network-Based Controllers

### 4.1 Controller Design

Given a continuous-time nonlinear dynamical system,

$$\dot{x}(t) \in A(t)x(t) + B(t)u(t) + G(t)\omega(t), \tag{6}$$

where $x(t)$ means the state at the moment $x$, $u(t)$ is a control input, $\omega(t)$ is interference and error, $\dot{x}(t)$ means the time derivative of the state $x$, and $A(t)$, $B(t)$, $G(t)$ is the system matrix. This type of model is known as linear differential inclusions, but it describes nonlinear systems.

Given a Lyapunov function $V(x) = x^T Px$ and a linear control system $u(x) = Kx(t)$, let

$$\dot{V}(x(t)) \leq -\alpha V(x(t)),\ \alpha > 0, \tag{7}$$

be the exponential stability condition for creating a control strategy, which means, a function that decreases along the trajectory when the equation is satisfied. Consider a norm-bounded dynamical system (NBDS)

$$\dot{x}(t) = A(t)x(t) + B(t)u(t) + G(t)\omega(t), \parallel \omega(t) \parallel_2 \leq \parallel Cx(t) + D\omega(t) \parallel_2, \tag{8}$$

where $\omega(t)$ is unknown. For this system, the stabilization policy can be specified by the following inequality,

$$\begin{bmatrix} AM + MA^T + GG^T + BN + N^T B^T + \alpha M & MC^T + N^T D^T \\ CM + DN & -I \end{bmatrix} \preceq 0, \tag{9}$$

where $M > 0, \lambda > 0,\ M \in \mathbb{R}^{s \times s}, N \in \mathbb{R}^{s \times a}, K = NM^{-1}, P = M^{-1}, I$ is the unit matrix. This inequality is a linear matrix inequalities (LMI) specific to the above NBDS system.

Let $S(x) = \{u \in \mathbb{R}^a | \dot{V}(x(t)) \leq -\alpha V(x(t))\}$ represents a stable set, and this set is guaranteed to satisfy the exponential stability condition Eq. (7). It can be found that $Kx$ holds for all states $x$ when the set is nonempty.

Next, we use $S(x)$ to construct a nonlinear robust strategy class that projects the output of a neural network onto the above set. Give a neural network-based nonlinear policy $\hat{\tau}_\vartheta(x) = Kx + \tilde{\tau}_\vartheta(x)$, where $K$ will be obtained in the next section by robust LQR optimization, $\tilde{\tau}_\vartheta(x)$ is a neural network, which consists of $\vartheta$ parameterized, and let $\pi$ indicates the projection of some output onto some set. Next, the class of robust strategies $\tau_\vartheta(x) = \pi_{\hat{\tau}_\vartheta(x) \to S(x)}$ is defined. Since this strategy class can satisfy the stability condition Eq. (7), it can be proved to be robust. This policy class can be trained with deep reinforcement learning or model-based planning algorithms.

In addition to maintaining stability, the performance of the controller needs to be optimized, and we utilize the linear quadratic regulator (LQR) cost as the performance target $a$, the formula is

$$\int_0^\infty x(t)^T Qx(t) + u(t)^T Ru(t)dt. \tag{10}$$

We need to enter our performance objective in the above controller. Given the policy class and the performance objective, we need to obtain the parameter $\vartheta$ and calculate

$$\min_{\vartheta} \int_0^{\infty} a(x, \tau_{\vartheta}(x))dt \quad s.t.\ \dot{x}(t) \in A(t)x(t) + B(t)\tau_{\vartheta}(x) + G(t)\omega(t), \tag{11}$$

to optimize the performance objective. Also, minimizing this objective can then be used as semi-definite programming to construct a proof that ensures the system is stable. We obtain the optimal linear time-varying controller for the above NBDS system by solving

$$\min_{M,N}\ tr(QM) + TR(R^{1/2}NM^{-1}N^T R^{1/2}) \quad \text{s.t. Eq.(9) holds} \tag{12}$$

while being able to then find $P$, $K$ that satisfy the LMI constraint. The pseudo-code for the complete robust neural network-based controller is shown below.

## 4.2 Model an NBDS

We need to write a quadrotor as an NBDS system for control. We do this by writing the quadrotor model as an NBDS and constructing the stable set $S(x)$ and the differentiable projection $\pi_{\hat{\tau}_{\vartheta}(x)\rightarrow S(x)}$ applicable to the quadrotor NBDS system.

We write the quadrotor as NBDS by defining $\dot{x} = h(x, F)$, the NBDS equation for the quadrotor is then written out by linearizing.

$$\dot{x} = J_{h(0,0)}[x\ F]^T + I\omega,\ \parallel \omega \parallel \leq \parallel Cx + D\omega \parallel . \tag{13}$$

For the quadrotor NBDS system, the perturbation error is considered only the linearized error of about $x$. According to the dynamics model, it can be found that the quadrotor dynamics are linear concerning $F$. Therefore, the matrix $D = 0$.

Based on the quadrotor dynamics model developed in Sect. 3, calculate the Jacobi matrix of $\dot{x} = h(x, F)$

$$J_{h(x,F)} = \begin{bmatrix} 0 & 0 & -\dot{s}_x \sin\psi - \dot{s}_y \cos\psi & \cos\psi & -\sin\psi & 0 & 0 \\ 0 & 0 & \dot{s}_x \cos\psi - \dot{s}_y \sin\psi & \sin\psi & \cos\psi & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & -g\cos\psi & 0 & \dot{\psi} & \dot{s}_y & 0 \\ 0 & 0 & g\sin\psi & -\dot{\psi} & 0 & \dot{s}_x & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}, \tag{14}$$

from this equation we get

$$J_{h(0,0)} = \begin{bmatrix} 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & -g & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}. \tag{15}$$

Next, the matrix $C$ is calculated to limit the error $\omega$. Give the following equation

$$\omega_i^2 = (\bigtriangledown h_i[x\ F]^T - \dot{x}_i)^2 \leq [x\ F]T_i[x\ F]^T. \tag{16}$$

We try to find for each $i = 1 \cdots s$, satisfying $T_i$ for all $x$ and $F$ in the range, to obtain a matrix of $T$, $C = [T_1\ T_2\ T_3\ T_4\ T_5\ T_6]_{1:s}$.

### 4.3 Construction of Stable Sets and Projections

The optimal linear time-varying controller for NBDS is first obtained by solving the optimization problem of the system using LQR cost as a semidefinite programming and calculating the quadratic Lyapunov function. Next, the stable set $S(x)$ specific to the quadrotor NBDS system is calculated. Define

$$S(x) = \{u \in \mathbb{R}^a \mid 2x^T PBu \leq -x^T(2PA + \alpha P)x - 2 \parallel G^T Px \parallel_2 \parallel Cx \parallel_2\}, \tag{17}$$

where $P$ satisfies Eq. (4). The equation is derived from Eq. (7) and Eq. (8). Then create a differentiable solver for projection. In the case of D = 0, define

$$\pi_{\hat{\tau}_\vartheta(x)\to S(x)} = \begin{cases} \hat{\tau}(x) & \mu^T\hat{\tau}(x) \leq \delta, \\ \hat{\tau}(x) - \frac{\mu^T\hat{\tau}(x)-\delta}{\mu^T\mu} & \text{otherwise}, \end{cases} \tag{18}$$

where $\mu^T = 2x^T PB, \delta = -x^T(2PA + \alpha P)x - 2 \parallel G^T Px \parallel_2 \parallel Cx \parallel_2$.

## 5 Experiments

In this section, the controller control effect and the quadrotors formation flight effect will be experimentally verified.

Firstly, we form the UAVs into formations. We randomly set the initial position of the quadrotor. Also set the formation angle as 45°, the formation distance as 200 m, and the line speed of the leader as 6 m/s.

The UAVs start to move from the initial position, form a formation, and keep the formation angle and formation distance forward. We use three quadrotors and nine quadrotors respectively to verify the feasibility of the formation model. Figures 2 and 3 show the results of our simulations.

**Table 1.** Stability of different methods in two dynamic settings.

| Application Scenarios | Dynamic settings | MBP | PPO | Robust MBP | Robust PPO |
|---|---|---|---|---|---|
| NDBS (D = 0) | Original | 16.8 | 66.5 | 69.2 | 59.0 |
| NDBS (D = 0) | Adversarial | – | – | 3289.7 | 2188.3 |
| Quadrotor | Original | 12.6 | 15.7 | 11.1 | 8.7 |
| Quadrotor | Adversarial | 2639.2 | 1758.7 | 27.8 | 26.4 |

Next, we use the controller to control the quadrotor formation. We experimented with the controller frame on a general NBDS (D = 0) system and a

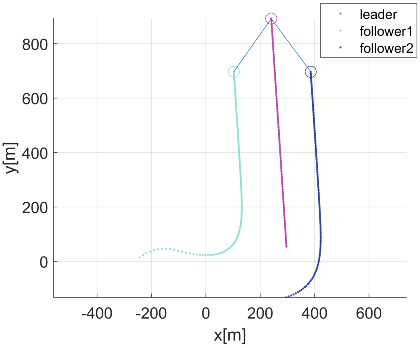


**Fig. 2.** Formation of three quadcopters

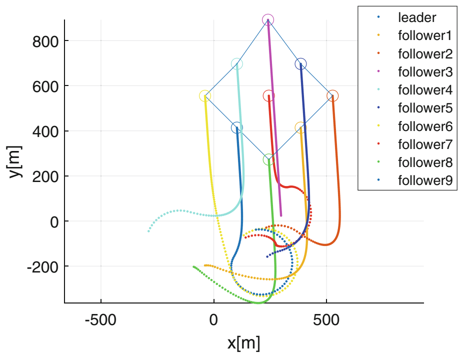


**Fig. 3.** Formation of nine quadcopters

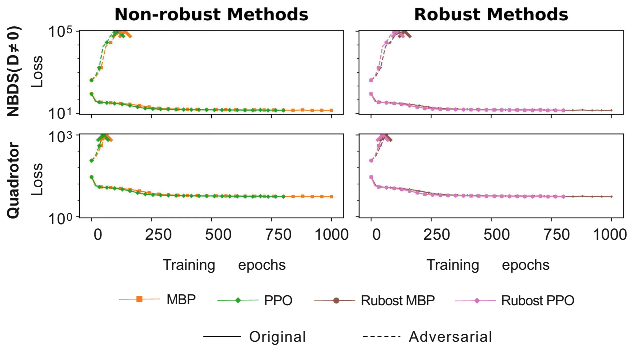


**Fig. 4.** Controller training results

quadrotor NBDS system. And we use two different robust methods to optimize our strategy classes $\pi_\vartheta(x)$. Robust PPO, a neural network-based reinforcement learning PPO algorithm, and robust MBP, a model-based planner. Non-robust MBP and non-robust PPO were also utilized as a control group.

We conduct experiments in each of the following two scenarios. Original dynamics: average case. Adversarial dynamics: worst case, using a modified adversarial interference $\omega(t)$ to maximize the loss. The initialization states for all experiments are randomly generated. We use randomly generated LQR targets with independent identical distributions for matrices $Q^{1/2}$ and $R^{1/2}$. We add a small perturbation to the quadrotor NBDS system. Episodes are run for 200 steps at a discretization of 0.02 s.

Figure 4 and Table 1 show the experimental results. In Fig. 4, the vertical coordinate is the loss value, and we want the loss value to be as small as possible, specifically, the absence of a number indicates instability. The horizontal coordinate is the training epochs. The figure on the left is the non-robust approaches i.e., non-robust MBP and non-robust PPO. the figure on the right is robust MBP and robust PPO methods. As can be obtained from Table 1, the non-robust MBP and non-robust PPO methods generally perform better under the primal dynamics in both the normal NDBS and quadrotor application scenarios, but have poor stability when adversarial perturbations are added. In contrast, we show that the robust MBP and robust PPO methods improve performance in the primal case compared to the other methods, while being able to maintain better stability under adversarial dynamics. In the normal NDBS scenario, the non-robust MBP performed best in the pristine case, the non-robust PPO was similar to the robust MBP and robust PPO methods, while the two non-robust methods were unstable and the two robust methods were able to be stable after adding adversarial disturbances. In the quadrotor scenario, the robust MBP and robust PPO methods outperformed the non-robust methods in terms of stability, both in the original case and after the addition of adversarial interference, and the two robust methods showed good stability after the addition of adversarial interference. The above simulation results demonstrate that the controller can improve the performance of the conventional robust controller under average conditions while maintaining stability in the worst case.

## 6 Conclusion

In this paper, a neural network-based robust controller is applied to a quadrotor UAV cooperative formation to achieve a balance between robustness and performance of formation flight. The leader-follower method is used to form a formation of UAVs, and the distance and angle between the follower and the leader are controlled to represent the position that the follower should reach through a virtual UAV. Meanwhile, a robust control strategy is created, which projects the output of a nonlinear neural network-based strategy onto a stable set to form a controller combining robust control and deep reinforcement learning, which is applied in the formation. According to the experimental simulation results, the controller can effectively control the formation created in this paper to maintain a stable flight while maintaining good performance.

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# Conception of Foreign Heterogeneous Electronic Warfare UAV Cross Domain Cooperative Operations

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**Abstract.** Heterogeneous unmanned aerial vehicles (UAVs), as an important means of implementing Decision Centeric Warfare, will become an important factor influencing the trend of future warfare. Starting from the concept of UAV swarm operations, the operational requirements and characteristics of heterogeneous electronic warfare UAVs are analyzed. New combat styles such as heterogeneous UAV swarm battlefield electromagnetic situation ubiquitous reconnaissance, systematic collaborative battlefield network fragmentation, and distributed collaborative strike are studied. Based on the new trend of UAV swarm cross domain cooperation, three typical operational concepts for UAV swarm to perform air to air cooperative maritime reconnaissance, air to ground cooperative ground penetration, and air to sea cooperative joint strike are proposed, providing reference for the technical development and operational application of heterogeneous UAV swarms.

**Keywords:** UAV swarm · cross domain collaboration · operational concept

## 1 Introduction

The US military regards drone warfare as an important form of future air control and information control. In 2020, the US Navy and Air Force proposed new operational concepts such as "mosaic warfare" and "global joint command and control" in order to balance the Anti-Access/Area Denial capabilities of major powers in the Asia Pacific region, with the intention of achieving its operational intent of Decision Centeric Warfare through joint land, sea, air, and space operations, and eliminating the adversary's local electromagnetic denial advantage in the Indo-Pacific region [1–3]. Heterogeneous unmanned aerial vehicles (UAVs) are a new application mode proposed in recent years, which is a typical intelligent cluster application behavior. They can complete complex combat tasks at a lower cost with a large number of electronic reconnaissance, high-resolution imaging, radar countermeasures, and anti radiation UAVs. Heterogeneous drone cluster is a distributed system that is integrated under an open architecture, based on collaborative control between platforms, with the goal of improving the ability of collaborative tasks such as reconnaissance, detection, communication, interference, and


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destruction. Therefore, in-depth analysis of the operational characteristics of heterogeneous UAV swarms, research on new combat styles of heterogeneous UAVs [4], and propose typical combat scenarios for cross domain collaboration of heterogeneous UAV systems have important significance and application value for improving the operational capability of heterogeneous UAV swarms in the future [5–7].

## 2 Operational Characteristics of Heterogeneous UAV Swarm

The first is to acquire joint electromagnetic sensing and strike capabilities. The UAV swarm is based on ubiquitous networking technology, integrating the operational fields of land, sea, air, sky, network, and electricity as well as the formation operations of UAVs among operational systems, so as to decentralize operational forces such as radar countermeasures, communication countermeasures, and electronic reconnaissance, while highly centralizing anti radiation attack firepower, thereby improving the operational capabilities of the full-time, full spectrum, and multi domain UAV system.

The second is to improve the combat intensity and operational effectiveness of UAV systems. Heterogeneous drone swarms can decentralize various drone combat elements and expand the kill chain into a kill network through dynamic combination and collaborative cooperation. According to the real-time situation of the battlefield, build or change the UAV combat force formation system, increase the battlefield fog, improve the difficulty of Orientation in the “OODA” ring, make the opponent have decision-making difficulties, and achieve “degradation” of the opponent’s combat ability.

The third is to win the decision-making advantage of unmanned combat. Unlike pre-defined kill chains, heterogeneous drone swarm operations focus on the operational requirements of large country confrontation, breaking down mission forces into more dispersed “kill nets” or “effect nets.”. In the initial stage of operations, various active/passive sensors, countermeasures, manned/unmanned weapons, and decision-making elements are combined according to different configurations to accelerate the construction of operational systems, accelerate the “OODA” cycle, and achieve the transformation from “information superiority” to “decision-making superiority” using artificial intelligence technology.

## 3 Operational Styles of Heterogeneous UAV Swarms

### 3.1 UAV Multi-domain Joint Ubiquitous Reconnaissance

Through precise tactical coordination and configuration, heterogeneous UAVs and weapon systems such as space-based satellites, manned aerial vehicles, and cruise missiles can rapidly generate distributed collaborative reconnaissance capabilities in groups, networks, and formations. Through a collaborative configuration with or without a center, the rapid capability combination of UAV swarms can be skillfully realized, and joint reconnaissance operations such as lurking, detecting, and positioning can be carried out on key attacking targets. In cross domain joint reconnaissance, unmanned early warning aircraft, reconnaissance aircraft, manned early warning aircraft, space-based low orbit satellites, etc. jointly generate battlefield electromagnetic situation, which involves technologies such as airspace, airspace sensor collaboration, space-time consistent collaboration, and multi-source data structures.

### 3.2 Collaborative Segmentation of Early Warning Netted Radars

Heterogeneous drones rely on high-performance equipment and intelligent electromagnetic countermeasures technology to implement accurate electromagnetic segmentation of the early warning detection network. Although ground air defense systems and surface warship formations have relatively complete protection capabilities and strong attack capabilities, due to their high reliance on electronic information systems, integrated radio frequency electronic masts and interception system capacity are still weak links in their protection. With the core demand of attacking the enemy's IBCS (Integrated Air Defense and Anti Missile Command System) and aircraft carrier battle group, heterogeneous UAVs swarm over weak confrontation areas to conduct reconnaissance and interception of enemy long-range early warning radar, surface to air missile radar, and communication system. Various types of dedicated unmanned aerial vehicles (UAVs) such as radar countermeasures, communication countermeasures, and data link jamming, as well as bee swarm attack aircraft, participate in the combat network as the main combat force, build a dynamic, reconfigurable, and adaptive UAV combat system, and continuously transform the mission roles as the battle progresses. They use "collaborative array layout, multi-dimensional suppression, and formation shaping" to implement air-ground and air-sea network electrical information segmentation for sensors and communication nodes of the ground air defense early warning detection network, Highlight the operational advantages of asymmetric attack of heterogeneous drone swarms.

### 3.3 Distributed Kill Chain Integrated Attack

In recent years, the US military has vigorously developed an information sensing and fusion system based on the Global Information Grid (GIG), and has deployed the "Sade" system, the "Paving Claw" long-range early warning radar, the shore based air surveillance radar, and the ocean based integrated reconnaissance ship deployed in South Korea, Japan, and Taiwan as network information nodes to provide key information support for its strategic early warning and long-range precision strike. To this end, a heterogeneous UAV integrated strike style can be adopted. Although the new advanced air defense system has relatively complete defense capabilities, due to its high reliance on electronic information systems, the capacity of key sensor nodes and interception systems remains a weak link. Heterogeneous UAV swarms can collaborate with detection, reconnaissance, navigation, and jamming units of different flight platforms, maneuvering speeds, operational rhythms, and force formations to implement persistent suppression jamming, damage strikes, and compensate for the shortcomings of a single combat link and a single adversary force. As shown in Fig. 1, the Harlop anti radiation UAV in Azerbaijan successfully destroyed the Armenian S-300 air defense system according to intelligence instructions.


**Fig. 1.** Harlop anti-radiation UAV destroy ground S-300 air defense systems.

# 4 Typical Conception of Heterogeneous UAV Swarm Combat Application

## 4.1 Optimized Deployment of Air-Air Cooperative Maritime Detection Forces

The optimized layout of maritime reconnaissance and detection forces is based on drones as the main application means, giving full play to the advantages of ISR drones in low altitude flight, covert reconnaissance, and collaborative positioning, and closely cooperating with air early warning forces and electronic reconnaissance forces to implement ubiquitous reconnaissance and detection in key maritime directions. Due to the limitations of the sea clutter environment on radar, conventional radar may encounter blind spots when detecting near the sea surface. The Cross-Domain Maritime Surveillance and Targeting (CDMAST) project launched by DARPA transforms the current naval force formation system of the United States Navy through the integration of maritime cross domain collaborative systems, decomposes multiple maritime combat functions into a large number of scalable low-cost unmanned systems, and deploys them dispersed in highly adversarial wide area waters, achieving a combat system capable of performing surveillance and targeting tasks across domains. Firstly, large electronic reconnaissance aircraft can be attached to unmanned reconnaissance aircraft, and with the support of space-based reconnaissance satellites, various sensor mission loads can be comprehensively utilized to complete operations such as search and interception, collaborative positioning, and stable tracking of targets in a given area. In the future, heterogeneous drone swarms can also combine other sensors such as aerostats and maritime buoys to conduct networked detection and continuous precision tracking of warship formation targets in the region through the communication and data sharing network architecture of early warning aircraft, providing an effective way to solve the problem of battlefield situation awareness in the maritime direction.

**Fig. 2.** Global Hawk Coordinates Manned Aerial Vehicles to Implement Maritime Surveillance.

### 4.2 Air Ground Cooperative Ground Combat Support

Air-ground collaborative ground air defense combat support is based on medium and short range unmanned aerial vehicles, relay aircraft, and manned aerial vehicles as the main means to leverage the asymmetric electromagnetic attack advantages of heterogeneous unmanned aerial vehicles. With the core requirement of breaking down the ground defense system, it is necessary to decoy, locate, deceive, and strike the key supporting targets of the enemy's ground air defense system, and cooperate with manned aerial vehicles to weaken or paralyze the enemy's air defense combat system. The heterogeneous cluster composed of the Probot UAV and the Raytheon UAV developed by Israel Elbit Systems is shown in Fig. 2. All unmanned systems are equipped with the "Torch X" autonomous kit, which has functions such as unmanned cluster construction, autonomous planning and navigation, intelligence monitoring and reconnaissance (ISR), etc. Heterogeneous cluster composed of human-machine Raytheon Company's "Coyote" UAV is a 13 lb tubular unmanned aircraft with a five foot pop-up wing, which has preliminarily possessed the cluster function. The "hyena" drone can carry various payload types, mainly including electronic warfare devices or explosive warheads. The US military's LOCUST program (abbreviation for low-cost unmanned aerial vehicle cluster technology) has previously demonstrated up to 50 "hyenas" clusters to carry out cluster attacks on typical targets.

Currently, foreign military unmanned swarms are taking shape, capable of undertaking multiple tasks such as electronic jamming, situational awareness, intelligence surveillance, and communication relay. They will play an important role in land battlefield support, maritime combat support, and air maneuver support. During the "EDGE-22" exercise, the United States Army launched a four wave airborne effect (ALE) drone swarm, and conducted capability testing and evaluation of the ALE drone's "air reconnaissance ground suppression cooperative strike damage evaluation" operational closed-loop. The basic operational process can be described as follows: First, the reconnaissance

**Fig. 3.** Heterogeneous cluster composed of Probot unmanned vehicles and "Thor" unmanned aerial vehicles.

drone decoys the enemy's radar to start up, thereby positioning it, and mastering its air defense early warning and fire strike force deployment. Then, the jamming UAV conducted cooperative suppression on the enemy's ground air defense system, resulting in a significant decrease in the detection power of the early warning radar, and was unable to provide intelligence support for the Integrated Air Defense System (IADS). Based on the reconnaissance target data of aerial drones, ground unmanned vehicles launch cruise missiles to conduct long-range strikes, search for and destroy enemy positions. The results of the exercise show that the combat capability of UAV formation can be significantly improved through air-ground coordination, which can create favorable conditions for subsequent joint operations of air assault forces and ground conventional forces (Fig. 3).

### 4.3 Sea Air Cooperative Sea Ship Cross Domain Attack

Since 2019, the US missile destroyers Dewey, Preble, and Carl Vinson have repeatedly cruised in circles in the relevant islands and reefs in the South China Sea. The twin aircraft carrier battle groups Nimitz and Reagan have conducted exercises in the South China Sea "to support the free and open Indo Pacific region," openly challenging national sovereignty and territorial sea security, and the threat from surrounding seas has significantly increased. In this regard, if anti-ship missiles are used to saturate ship targets, due to the significant characteristics of anti-ship missile targets that are easily detected and intercepted by shipborne defense systems, the actual cost is relatively low. Therefore, it is possible to adopt a cooperative attack mode of unmanned aerial vehicles (UAVs)/unmanned aerial vehicles (UAVs) against naval vessels. Firstly, space-based early warning satellites and aircraft are used to roughly reconnaissance and capture electromagnetic signals for maritime targets. The command and control center system interprets the number of ships based on intelligence data, and the mission planning subsystem allocates the composition and launch timing of unmanned aerial vehicles and unmanned spacecraft swarms. The drone and unmanned boat swarm approach the target under the unified command of the airborne early warning aircraft, and the reconnaissance drone opens the radar to track the target, sending the target information to the formation members through the data link; Jamming drones continue to release interference in the rear to shield low-profile drone groups from covert attacks on enemy ships; Attacking drones attract the firepower of enemy ship formation air defense systems, and can also launch small air-to-surface missiles before being destroyed. At the same time, in order to increase the effectiveness of the attack, missile destroyers deployed in the offshore launch medium and long range anti ship missiles, and cooperate with unmanned swarms to carry out coordinated attacks on the inner defense area of the ship formation. In October 2022, the Ukrainian military used an unmanned swarm consisting of at least 7 unmanned boats and 9 unmanned aerial vehicles to attack the Russian Navy's Black Sea Fleet located in the port of Sevastopol in Crimea, successfully hitting the flagship Admiral Makarov patrol ship and other ships (Fig. 4).

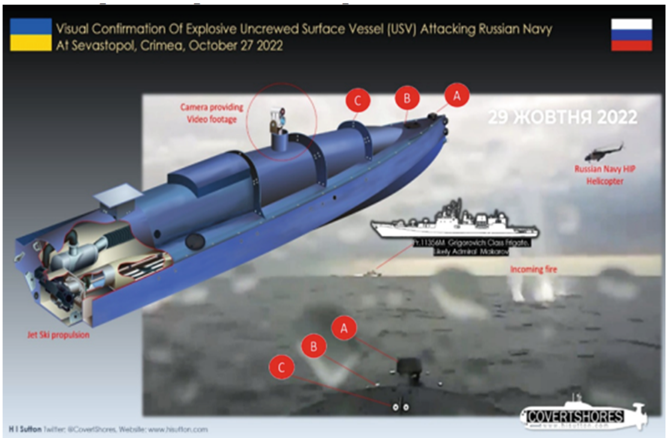


**Fig. 4.** Ukraine Coordinates Unmanned Sea and Air Attack on Russia's Black Sea Fleet.

## 5 Conclusion

Unmanned aerial vehicle systems have played an important role in the battlefield, providing warfighters with a large amount of information support capabilities. With the mature development of UAV and information technology, heterogeneous UAV clusters will integrate more functions, such as the ability to configure electronic warfare (EW), or launch air to ground guided munitions with Invisibility, which will greatly change the style of air operations in the future battlefield. Starting from the operational requirements of future unmanned battlefield operations, this article analyzes the operational characteristics of heterogeneous drone clusters and proposes three typical cross domain combat concepts for heterogeneous drone clusters. The cross domain collaborative application of UAV cluster in joint operations will certainly create a new operational mode. It is necessary to continue to strengthen the research on key issues of cross domain integration such as data acquisition and fusion of manned/unmanned platforms and space facilities in the air of heterogeneous UAV cluster, air and ground moving target indication, multi domain combat management and Command and control, and to guide the development direction of key technologies of heterogeneous UAV cluster with the concept of operations.

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# A Denoising Algorithm of Star Map Based on Wavelet Transform and Double-Window Combined Filtering

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**Abstract.** In view of the diversity of star map noise and the low signal-to-noise ratio of the star map, a denoising algorithm of star map based on the wavelet transform and double-window combined filtering is proposed. In this paper, the algorithm is combined with wavelet transform to deal with low frequency coefficients and high frequency coefficients respectively. For the similarity of the grey distribution of star map noise and star points, a double-window noise detection method is used to determine the type of pixel point, and a flexible filtering method is chosen to remove low-frequency noise. At the same time, a threshold denoising method is used to reduce high-frequency noise. The experimental results show that the filtering method in this paper is superior to other algorithms in peak signal-to-noise ratio and structural similarity analysis.

**Keywords:** Star map denoising · Double-window noise detection method · Combined filtering · Wavelet transform

## 1 Introduction

With the technological evolution of materials, manufacturing techniques, and other aspects as well as the development needs of air and space integration, starlight navigation technology has gradually developed to a broader field of space. A star sensor is used in starlight navigation as a highly accurate attitude measurement component [1]. The star map pre-processing part of the star sensor generally consists of denoising, background segmentation, centroid positioning, etc., in order to perform accurate star point extraction. Star point extraction is the basis for high accuracy attitude measurement of the star sensor [2], and its positioning accuracy directly affects the accuracy of subsequent star map recognition and attitude calculation. Star point extraction is the process by which the star sensor processes the captured star map image, separates the star point target from the complex background, and determines the position coordinates of each star point in the image coordinate system according to the grey scale distribution of the pixel points.

Due to the complexity of the working environment of the star sensor and the limitations of the image sensor itself, the original observed star map often contains a large


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amount of noise [3], mainly from stray light in the sky, various noises in the imaging system, generally expressed as Gaussian noise and salt and pepper noise, all these noises have a certain degree of influence on the star point positioning and star map feature extraction. Therefore, in order to ensure the accuracy of star point extraction, the image needs to be processed for noise reduction first. Common image denoising methods include median filtering, mean filtering, Gaussian filtering, etc. However, due to the small target of the star point, the signal-to-noise ratio of the star map is lower compared to the general image. Although the traditional filtering method can remove noise, it is usually at the cost of destroying star point morphology [4].

In recent years, wavelet transform-based image processing techniques have been widely used [5–9]. According to the characteristics of the image to be processed, the wavelet transform can subdivide the frequency signal of the image by selecting different wavelet bases, thus reducing the correlation between the image and noise and realizing targeted denoising [10]. After the processing, the inverse wavelet transform is used to reconstruct the wavelet coefficient, and the denoised image can be obtained.

In this paper, based on the wavelet transform, a double-window noise determination method is designed for the low-frequency components of the star map according to the grey-scale distribution characteristics of the star point image and the noise. The combined filtering algorithm of median filtering and bilateral filtering can be targeted to the noise of different properties. At the same time, the high-frequency components are denoised using a hard thresholding method. Finally, the inverse wavelet transform is used to reconstruct the wavelet coefficients, and the denoised images are obtained. In this paper, this method is compared with conventional filtering so as to verify the effectiveness of the method.

## 2 Analysis of Star Map Noise

Noise in star maps can be classified according to its source as ambient noise consisting of external disturbances such as stray light, and internal noise such as scattered grain noise and readout noise in CMOS image sensors [11].

Scattered noise mainly includes photon scattered noise and dark current noise. The size of photon particle noise is proportional to the intensity of incident light captured by the star sensor, which is difficult to be suppressed by hardware optimization. Dark current noise is generated by the thermal movement of electrons. The longer the exposure time and the higher the temperature of the image sensor, the greater the dark current noise. In this paper, Gaussian white noise is used to simulate these two kinds of loose particle noise. In addition, the transient effect of energetic charged particles injected into the sensitive layer of the CMOS sensor in a near-space atmospheric radiation environment will produce a large number of signal spikes, and timing errors in the sensor circuit will also produce similar peak noise [12]. In this paper, salt and pepper noise is used to simulate this interference.

The model of the star map can be simplified as:

$$I(x, y) = I_{PSF}(x, y) + B(x, y) + N_g(x, y) + N_s(x, y) \tag{1}$$