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Adaptive robust control of the UAV-USV heterogeneous system with unknown fractional-order dynamics under multiple disturbances

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Abstract:
This paper addresses the robust formation tracking problem for a heterogeneous multi-robot system consisting of unmanned aerial vehicles (UAVs) and unmanned surface vehicles (USVs). When performing complex marine missions involved with the oil spills, such as oil spill cleanup tasks or marine search and rescue tasks, the USV in the marine multi-robot system will become a fractional-order system with uncertain dynamics and the UAV will be affected by multiple dynamic disturbances. This work proposed a distributed formation control scheme for the UAVs to track the fractional-order USV while maintaining a desired heterogeneous formation. Radial Basis Function Neural Network (RBFNN) is used in the design of the controller for the UAVs to approximate the uncertain dynamics of the USV. The estimation and compensation of the multiple disturbances of each UAV are handled by the Uncertainty Disturbance Estimator (UDE) method. Then, the stability of the distributed control law for the heterogeneous multi-robot system was mathematically proved based on a Lyapunov function term. A simulation case study with four UAVs and a USV was conducted to validate the effectiveness of the proposed control scheme and the results have successfully demonstrated the robustness of the formation tracking control strategy.

Key Words: Fractional-order, tracking control, RBFNN, UDE, heterogeneous multi-robot system

1 Introduction

Nowadays, increasing attention has been paid to heterogeneous system, such as land-air cooperation system composed of UAVs and unmanned ground vehicles (UGVs) [1], sea-air cooperation system composed of UAVs and USVs [2], and others composed of robots of different dynamic models [3]. The distributed adaptive fixed-time output time-varying formation tracking problem of heterogeneous multiagent systems (MASs) with actuator faults is explored, where the leader has unknown constrained input and the followers have loss-of-effectiveness actuator faults [4]. The time-varying formation tracking problem of heterogeneous multiagent systems with dynamic event-triggered control is discussed by Song [5]. The problem of bipartite time-varying output formation containment tracking control is investigated by Li [6] for general linear heterogeneous multiagent systems with multiple non-autonomous leaders and incomplete knowledge of the agents' states.

As the exploration of heterogeneous systems continues in practical applications and research, it is found that these agents tend to perform fractional-order dynamics when moving in complex environments, such as vehicles moving on the surface of macromolecular fluids and porous media , high-speed aircraft traveling in sandstorms, rainy, or snowy environments. Some researchers are turning to the study of the fractional-order heterogeneous system. Yin devoted to the consensus protocols design for a set of fractional-order heterogeneous agents, composed of two kinds of agents that differ by their dynamics where the fractional-order α satisfies $0 < \alpha < 2$ [7]. More specifically, multiple fractional-order systems with heterogeneous unknown nonlinearities and external disturbances are considered, including the second-order multiagent systems as their special cases [8].

In the case of disturbing situations or the existence of uncertainty, the attainment of robust control in heterogeneous systems is often regarded as a challenging task. To design model-independent estimation algorithms, neural networks are often used to estimate the uncertainty part. Sharafian [9] proposes a novel methodology to cover the problem of consensus of multiagent systems with sliding mode control based on the Radial Basis Function (RBF) neural network. The adaptive neural network consensus control problem is addressed for a class of non-affine multiagent systems (MASs) with actuator faults and stochastic disturbances [10]. Another common solution is to use the existing input and output information of the system to estimate the error and feed it back to the input for compensation, thus reducing the impact of uncertainty and disturbance on the system. The observers accordingly developed are, for example, unknown input observer (UIO) [11], disturbance observer (DO) [12], uncertainty disturbance estimator (UDE) [13], etc. In particular, the UDE has effectively dealt with wing sway motion control problems [14] and nonlinear systems with uncertainty disturbances [15].

However, to the best of our knowledge, there are few studies on robust tracking control for heterogeneous system consisting of fractional-order USVs and UAVs, and how to com-

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bine proper strategies to enhance the robustness and overall performance is still an open topic. In this paper, the dynamic model of the target USV is unknown to all UAVs, but it can communicate with one UAV so that the multi-UAV can track the USV by continuously building a fractional-order dynamic model through RBFNN-learning (see Fig. 1). Besides, the UAV team is disturbed in all directions. The contribution of this paper is mainly threefold. (i) This paper extends the robust consensus tracking problem to the UAV-USV heterogeneous system robust tracking control, in particular, the USV has a fractional-order dynamic model. (ii) Unlike the existing control method, by applying RBFNN to estimate the unknown-model USV, a y-direction consense tracking control and an all-direction robust tracking control method are proposed to address the heterogeneous system robust tracking problem. (iii) UDE is used in all three directions to estimate and compensate for the disturbances in the UAV team.

The rest of this paper is organized as follows. Section 2 describes the dynamic model of fractional-order USV and UAVs. The tracking control method of multi-UAV to track the target USV is presented in Section 3. The experimental results are discussed in Section 4 followed by the conclusion in Section 5.

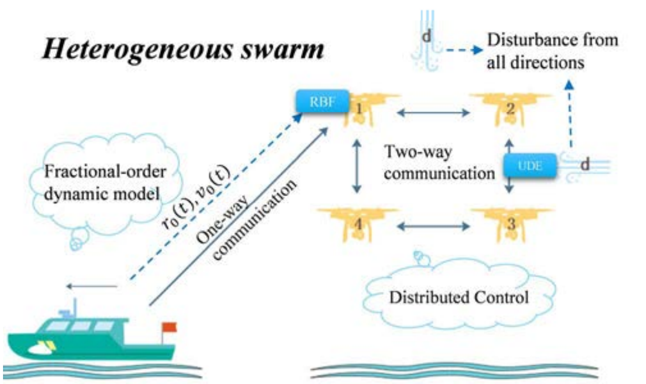

Fig. 1: UAV-USV heterogeneous system schematic

2 Dynamic model

2.1 Fractional-order target USV modeling by RBFNN

The size of the USV model can be simplified because the USV's physical size is much smaller than that of the formation, and its impact on the overall system dynamics is minimal. The state information of the USV consists of position (x, y) and heading θ, and let $r = [x, y, \theta]^T$ be the position vector of the USV. The dynamic model of the fractional-order USV is given in fractional-order differential form as $\mathbf{D}_t^q r(t) = f_0(r, t)$, where the fractional order satisfies $0 < q \leq 2$, and the smoothing function $f_0(r, t)$ is unknown to all other agents. The time origin of $\mathbf{D}_t^q$ is 0.

Assumption 1: Let $\gamma(r, t) \triangleq \mathbf{D}_t^{1-q} f_0(r, t)$, it can be expressed as a linear parametric neural network over a prescribed tight set $\Omega_{\gamma i} \subset \Re^2$ as:

$$\gamma(r, t) = \phi_\gamma^T(r, t)\,\theta_\gamma + e_\gamma,$$

where $\phi_\gamma^T = [\phi_{\gamma i1}, \phi_{\gamma i2}, \cdots, \phi_{\gamma il}]^T \in \Re^{l_{\gamma i}}$ represents the radial basis function, the parameter $\theta_\gamma^T = [\theta_{\gamma i1}, \theta_{\gamma i2}, \cdots, \theta_{\gamma il}]^T \in \Re^{l_{\gamma i}}$ is the unknown constant vector, e_γ is the neural network estimation error.

From the expression $\gamma(r_0, t)$ in Assumption 2, it can be obtained:

$$D_t^{1-q}(D_t^q r(t)) = D_t^{1-q} f_0(r, t) = \dot{r}(t) = \gamma(r, t).$$

Assumption 2: Estimation error of the neural network defined in Assumption 1 is 0, i.e., $e_\gamma = 0$.

So the estimation of $\gamma(r, t)$ can be written as:

$$\hat{\gamma}(r, t) \triangleq \phi_\gamma^T(r, t)\,\hat{\theta}_\gamma.$$

The corresponding estimation error is $\tilde{\gamma}(r, t)$. Assume that all approximation errors are equal to zero, i.e. $e_\gamma = 0$. In this case, $\tilde{\gamma}_i(r, t) = \phi_\gamma^T(r, t)\,\hat{\theta}_{\gamma_i} - \phi_\gamma^T(r, t)\,\theta_{\gamma_i} = \phi_{\gamma_i}^T(r, t)\,\tilde{\theta}_{\gamma_i}$, where $\tilde{\theta}_{\gamma_i} = \hat{\theta}_{\gamma_i} - \theta_\gamma$.

2.2 Quadrotor UAV modeling

Firstly, the six-DOF nonlinear model of the UAV is established (see Fig. 2). According to Newton's second theorem, we can get the following expression:

$$\begin{cases} \ddot{x} = \frac{u_1(\cos\psi\sin\theta\cos\phi + \sin\phi\sin\psi)}{m}, \\ \ddot{y} = \frac{u_1(\sin\psi\sin\theta\cos\phi - \sin\phi\cos\psi)}{m}, \\ \ddot{z} = \frac{u_1(\cos\theta\cos\phi)}{m} - g, \\ \ddot{\phi} = \frac{(I_y - I_z)\dot{\theta}\dot{\psi} + u_2}{I_x}, \\ \ddot{\theta} = \frac{(I_z - I_x)\dot{\phi}\dot{\psi} + u_3}{I_y}, \\ \ddot{\psi} = \frac{(I_x - I_y)\dot{\phi}\dot{\theta} + u_4}{I_z}, \end{cases} \tag{1}$$

where the mass of the quadrotor body is denoted by m; x, y, z denote the displacement in three directions under the ground coordinate system; The moment of inertia is I_x, I_y, I_z respectively; u_1 is the control input to the position of the body; u_2, u_3, u_4 are the control input of the roll, pitch, and yaw respectively; The Euler angles ϕ, θ, ψ indicate the roll, pitch, and yaw respectively.

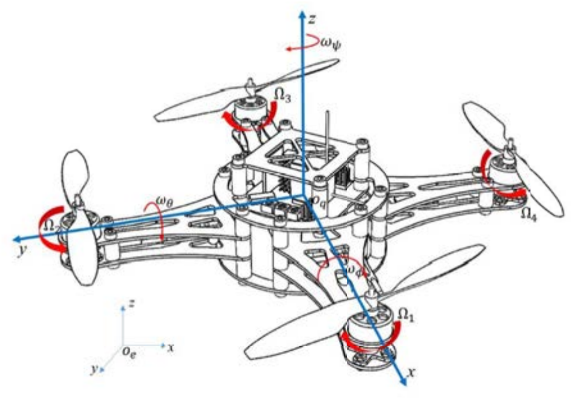

Fig. 2: UAV coordinates schematic

From equation (1), it can be seen that the control input u_1 has an effect on all three directions x, y, and z, which is a typical characteristic of quadrotor underdrivability. Since the z-direction coupling is relatively small, let z-direction be directly represented by u_1, while the virtual control inputs u_x and u_y are introduced in the x, y directions, respectively:

$$\begin{cases} u_x = (\cos\psi\sin\theta\cos\phi + \sin\phi\sin\psi), \\ u_y = (\sin\psi\sin\theta\cos\phi - \sin\phi\cos\psi). \end{cases}$$

By giving the desired trajectory (x_0, y_0, z_0, ψ_0), the expression for the expected value of Euler angles ϕ_0, θ_0 can be obtained:

$$\begin{cases} \phi_0 = \arcsin\left(u_x \sin\psi_0 - u_y \cos\psi_0\right), \\ \theta_0 = \arcsin\left(\frac{u_x \cos\psi_0 + u_y \sin\psi_0}{\cos\phi_0}\right). \end{cases}$$

Ensuring the validity of the inverse trigonometric function arcsin, the domain of expressions in parentheses is restricted to $[-1, 1]$.

3 Control method

Now considering a swarm with n UAVs. For the ith quadrotor $i \in \{1, 2, \ldots, n\} \triangleq \mathcal{I}$, when all directions are subject to external disturbances such as gusts, the following dynamic model can be established:

$$\begin{cases} \dot{z}_i = v_{zi} \\ \dot{v}_{zi} = U_{zi} + d_{zi}(t) \end{cases}, i \in \mathcal{I}, \tag{2}$$

$$\begin{cases} \dot{x}_i = v_{xi} \\ \dot{v}_{xi} = U_{xi} + d_{xi}(t) \end{cases}, i \in \mathcal{I}, \tag{3}$$

$$\begin{cases} \dot{y}_i = v_{yi} \\ \dot{v}_{yi} = U_{yi} + d_{yi}(t) \end{cases}, i \in \mathcal{I}, \tag{4}$$

where $U_{zi} = u_{1i}\cos\theta\cos\phi/m - g$, $U_{xi} = u_{1i}u_{xi}/m$, $U_{yi} = u_{1i}u_{yi}/m$. $d_{zi}(t)$, $d_{yi}(t)$, $d_{xi}(t)$ denotes the unknown disturbances in three directions.

Here, the y direction is chosen to accomplish the UAV tracking task of the target USV in the horizontal plane. Let $U_{yi} = U_{0yi} - \hat{d}_{yi}$, then we need to design the nominal controller U_{0yi}. Let

$$\begin{cases} y_{i1} = y_i - r_0, \\ y_{i2} = v_i - \hat{\gamma}(r_i, t) = v_i - \phi_\gamma(r_i, t)\hat{\theta}_\gamma. \end{cases} \tag{5}$$

The derivative of y_{i2} yields:

$$\begin{aligned} \dot{y}_{i2} &= \dot{v}_i - \phi_\gamma(r_i, t)\dot{\hat{\theta}}_\gamma - \frac{\partial}{\partial r_i}\phi_\gamma(r_i, t)\hat{\theta}_\gamma(y_{i2} \\ &\quad + \phi_\gamma(r_i, t)\hat{\theta}_\gamma) - \frac{\partial}{\partial t}\phi_\gamma(r_i, t)\hat{\theta}_\gamma \\ &= u_i + d_i - \phi_\gamma(r_i, t)\dot{\hat{\theta}}_\gamma - \frac{\partial}{\partial r_i}\phi_\gamma(r_i, t)\hat{\theta}_\gamma(y_{i2} \\ &\quad + \phi_\gamma(r_i, t)\hat{\theta}_\gamma) - \frac{\partial}{\partial t}\phi_\gamma(r_i, t)\hat{\theta}_\gamma, \end{aligned} \tag{6}$$

where $\tilde{\theta}_\gamma = \hat{\theta}_\gamma - \theta_\gamma$, r_0 is the position vector of the target USV. Next, the UDE will be used to estimate the unknown disturbance $d_i(t)$, which is obtained according to the dynamic model (4) $\dot{v}_{yi} = U_{yi} + d_{yi}(t)$. Then we have $d_{yi}(t) = \dot{v}_{yi} - U_{yi}$.

According to the UDE theory, d_{yi} can be estimated as $\hat{d}_{yi}(t) = G_d(s)(\dot{v}_{yi}(t) - U_{yi}(t))$, where $G_{yd}(s) = 1/(1 + T_y s)$, T_y is the time scale parameter. Substituting $G_{yd}(s)$ into $\hat{d}_{yi}(t)$, we get:

$$\begin{aligned} \hat{d}_{yi} &= \frac{1}{1 + Ts}\left(\dot{v}_{yi} - U_{0\mathrm{y}i} + \hat{d}_{yi}\right) \\ &= \frac{1}{T}\left(v_{yi}(t) - v_{yi}(0) - \int_0^t U_{0\mathrm{y}i}(\tau)\,d\tau\right), \end{aligned} \tag{7}$$

where $v_{yi}(0)$ is the initial value of the velocity of agent i in the y direction. Define e_{iy} as the consensus tracking error in the y direction: $e_{yi} = \sum_{i=1}^{n} a_{ij}(y_i - y_j) + b_i(y_i - r_0)$. The designed control input is as follows:

$$\begin{aligned} U_{yi} &= -ce_{yi} - \hat{d}_{yi} + \phi_\gamma(r_i, t)\dot{\hat{\theta}}_\gamma + \frac{\partial}{\partial t}\phi_\gamma(r_i, t)\hat{\theta}_\gamma \\ &\quad + \frac{\partial}{\partial r_i}\phi_\gamma(r_i, t)\hat{\theta}_\gamma(y_{i2} + \phi_\gamma(r_i, t)\hat{\theta}_\gamma). \end{aligned} \tag{8}$$

Substituting the designed control input back into (5), we get:

$$\begin{cases} \dot{y}_{i1} = y_{i2} + \phi_\gamma(r_i, t)\tilde{\theta}_\gamma, \\ \dot{y}_{i2} = -\tilde{d}_{yi} - ce_{yi}. \end{cases} \tag{9}$$

Let

$$\begin{aligned} \mathrm{Y}_1 &= [y_{11}, \cdots y_{i1}, \cdots y_{n1}]^\top, \\ \mathrm{Y}_2 &= [y_{12}, \cdots y_{i2}, \cdots y_{n2}]^\top, \\ \tilde{D} &= \left[\tilde{d}_{y1}, \cdots \tilde{d}_{yi}, \cdots \tilde{d}_{yn}\right]^\top, \\ \Phi_\gamma &= [\phi_1, \cdots \phi_i, \cdots \phi_n]^\top, \\ \tilde{\theta}_\gamma &= [\tilde{\theta}_1, \cdots \tilde{\theta}_i, \cdots \tilde{\theta}_n]^\top. \end{aligned} \tag{10}$$

Then the following matrix form can be obtained:

$$\begin{cases} \dot{\mathrm{Y}}_1 = \dot{\mathrm{Y}}_2 + \Phi_\gamma(r_i, t)\tilde{\theta}_\gamma, \\ \dot{\mathrm{Y}}_2 = -\tilde{D} - c(L + B)Z_1. \end{cases} \tag{11}$$

The parameter update rate of the RBFNN is:

$$\dot{\hat{\theta}}_{\gamma_i} = -c\phi_\gamma(r_i, t)e_i \tag{12}$$

Theorem 1: For the multi-agent system (4), when the control input $U_{\mathrm{y}i}$ has the form of (8), the update rate of the relevant parameters satisfies (12), and the control gain satisfies $c > 0$, then consensus tracking control for the target USV in the y- direction can be achieved.

Proof:

The Lyapunov function is chosen as follows:

$$V = \frac{c}{2}\mathrm{Y}_1^\top(L + B)\mathrm{Y}_1 + \frac{1}{2}\mathrm{Y}_2^\top\mathrm{Y}_2 + \frac{1}{2}\sum_{i=1}^{n}\tilde{\theta}_{\gamma i}^\top\tilde{\theta}_{\gamma i}. \tag{13}$$

Clearly, the positivity of V can be observed, and the derivative of V can be obtained. Moreover, based on the equations (10) and (12), the following relation can be established:

$$\begin{aligned} (L + B)\mathrm{Y}_1 &= [e_{y1}, \cdots e_{yi}, \cdots e_{yn}]^\top, \\ \sum_{i=1}^{n}\tilde{\theta}_{\gamma i}^\top\dot{\tilde{\theta}}_{\gamma i} &= -c\sum_{i=1}^{n}\phi_\gamma(r_i, t)\tilde{\theta}_{\gamma i}^\top e_i \\ &= -c(L + B)\mathrm{Y}_1^\top\Phi_\gamma(r_i, t)\tilde{\theta}_\gamma. \end{aligned}$$

So We get from (13):

$$\begin{aligned} \dot{V} &= -c(L + B)\mathrm{Y}_1^\top\Phi_\gamma(r_i, t)\tilde{\theta}_\gamma - \mathrm{Y}_2(\tilde{D} + c(L + B)\mathrm{Y}_1^\top) \\ &\quad + c(L + B)\mathrm{Y}_1^\top(\mathrm{Y}_2 + \Phi_\gamma(r_i, t)\tilde{\theta}_\gamma \\ &= -\tilde{D}\mathrm{Y}_2 - c(L + B)\mathrm{Y}_1^\top\Phi_\gamma(r_i, t)\tilde{\theta}_\gamma \\ &\quad + c(L + B)\mathrm{Y}_1^\top\Phi_\gamma(r_i, t)\tilde{\theta}_\gamma \\ &= -\tilde{D}\mathrm{Y}_2. \end{aligned} \tag{14}$$

Except for the case when $e_{yi} \equiv 0$, the above equation yields: $\left\|\dot{V}\right\| \le \left\|\tilde{D}\right\| \|\Upsilon_2\| \le \left\|\tilde{D}\right\| \|V\| \le \sqrt{2}\sqrt{V}\tilde{D}$, when $V \neq 0$, we can get: $dV/\sqrt{V} \le \sqrt{2}\tilde{D}dt$. By reducing the value of T sufficiently, the error of the UDE $\tilde{d}_{yi}(t)$ can be reduced to 0 (or to a negligible value), which in turn leads to $\left|\tilde{d}_{yi}(t)\right| \le \bar{d}$, and $\bar{d}$ is a small positive value that guarantees the boundedness of $\tilde{d}_{yi}(t)$. Based on the relationship of $\tilde{D}$ and $\tilde{d}_{yi}(t)$, $\left\|\tilde{D}\right\| \le n\bar{d}$, we can obtain: $dV/\sqrt{V} \le \sqrt{2}n\bar{d}dt$, so there are:

$$\sqrt{V(t)} - \sqrt{V(0)} \le \frac{\sqrt{2}}{2} n\bar{d}(t - t_0). \qquad (15)$$

Since (15) is obtained by integrating over a finite interval, it will not overflow in finite time. Then obviously, we can obtain that for all $i \in \mathcal{I}$, we eventually have $\lim_{t\to\infty} \Upsilon_1 = 0$, which means that for all agents $i \in \mathcal{I}$, we have $\lim_{t\to\infty} |y_i - r_0| = 0$, i.e., consensus tracking in the y-direction is achieved. The proof of Theorem 1 is complete. So we can get the actual control input as shown below,

$$\begin{aligned} u_{1i} = &\frac{1}{(\sin\psi_i \sin\theta_i \cos\phi_i - \sin\phi_i \cos\psi_i)}(m - ce_{yi} - \hat{d}_{yi} \\ &+ \phi_\gamma(r_i, t)\dot{\hat{\theta}}_\gamma + \frac{\partial}{\partial r_i}\phi_\gamma(r_i, t)\hat{\theta}_\gamma(y_{i2} + \phi_\gamma(r_i, t)\hat{\theta}_\gamma) \\ &+ \frac{\partial}{\partial t}\phi_\gamma(r_i, t)\hat{\theta}_\gamma). \end{aligned} \qquad (16)$$

Since both the x and z directions receive disturbances, the same UDE estimation is applied to compensate for the disturbances. So the principle and process of the UDE are not repeated here, and the conclusion is given directly. The virtual control input for the x direction is obtained:

$$u_{xi} = \frac{m(-c_{pxi}e_{xi} - c_{dxi}\dot{e}_{xi} - \hat{d}_{xi})}{u_{1i}}. \qquad (17)$$

Because $c_{pz} > 0, c_{dz} > 0$, according to the Rouse stability criterion that $\det(\begin{bmatrix} 0 & 1 - c_{px} & -c_{dx} \end{bmatrix}) = c_{px} > 0$, the stability of the PD-based controller can thus be demonstrated.

Obviously, we can obtain the virtual control input of the z direction: $U_{zi} = u_{1i}\cos\theta_i \cos\phi_i / m - g$.

To realize the tracking of the target USV by the UAV team in fixed formation, the position point information generated by the virtual structure method is directly set as (x_{0i}, z_{0i}). Meanwhile, according to the desired attitude angle ψ_{0i}, the desired values of the roll and pitch angles ϕ_{0i}, θ_{0i} can be obtained.

The PD control is used for the inner loop control. The actual control inputs u_{2i}, u_{3i}, u_{4i} for the three Euler angles are given here without proof:

$$\begin{cases} u_{2i} = (c_{p\phi i}\Delta\phi_i + c_{d\phi i}\Delta\dot{\phi}_i)I_x - (I_y - I_z)\dot{\theta}_i\dot{\psi}_i, \\ u_{3i} = (c_{p\theta i}\Delta\theta_i + c_{d\theta i}\Delta\dot{\theta}_i)I_y - I_z - I_x)\dot{\phi}_i\dot{\psi}_i, \\ u_{4i} = (c_{p\psi i}\Delta\psi_i + c_{d\psi i}\Delta\dot{\psi}_i)I_z - (I_x - I_y)\dot{\phi}_i\dot{\theta}_i, \end{cases}$$

where $\Delta\phi_i = (\phi_{0i} - \phi_i)$, $\Delta\theta_i = \theta_{0i} - \theta_i)$, $\Delta\psi_i = (\psi_{0i} - \psi_i)$, and $c_{p\phi i}$, $c_{d\phi i}$, $c_{p\theta i}$, $c_{d\theta i}$, $c_{p\psi i}$, $c_{d\psi i}$ are all positive real constants.

4 Simulation results

In this section, the numerical simulation will be given to illustrate the proposed tracking control scheme for the heterogeneous system. The UAV parameters used in this paper are shown in Table 1.

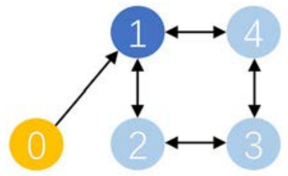

Fig. 3: The communication topology

Table 1: UAV model parameters

Mass m	1.5 kg
Gravity acceleration g	9.81 m/s^2
Moment of inertia I_x	1.745×10^{-2} $kg*m^2$
Moment of inertia I_y	1.745×10^{-2} $kg*m^2$
Moment of inertia I_z	3.175×10^{-2} $kg*m^2$
length of arm l	0.225 m
air resistance (x, y, z)	0.056,0.056,0.078
air resistance $(roll, pitch, yaw)$	0.0059,0.0059,0.0228

Considering a group of four UAVs and a USV, the communication topology of the heterogeneous system is shown in Fig. 3, where node 0, marked in yellow, is the target USV and the remaining four nodes are UAVs. Moreover, node 1, marked in dark blue, is the UAV that can obtain the target USV's position. The multi-UAV communicate with each other, and the target USV only transmits signals to the UAV of node one but does not receive information from it. Based on the communication topology, the Laplace matrix and the weighted information exchange matrix are obtained as

$$L = \begin{bmatrix} 0 & 0.5 & 0 & 0.5 \\ 0.5 & 0 & 0.5 & 0 \\ 0 & 0.5 & 0 & 0.5 \\ 0.5 & 0 & 0.5 & 0 \end{bmatrix}, B = \begin{bmatrix} 0.5 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}.$$

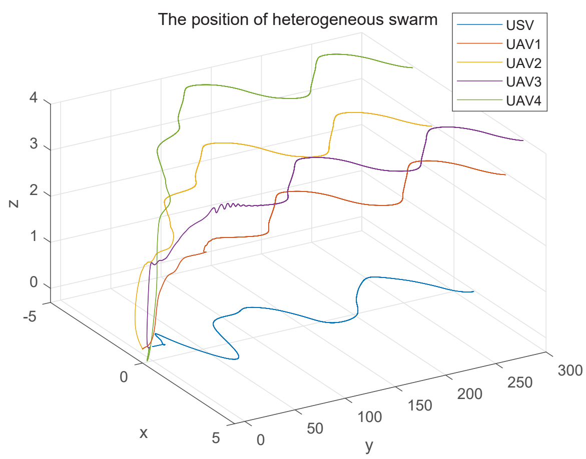

Fig. 4: The trajectories of heterogeneous system

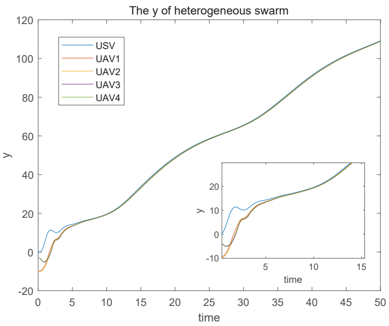

Fig. 5: The y-direction trajectories

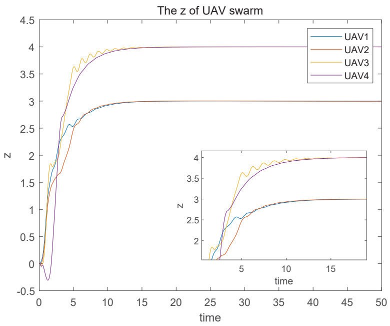

Fig. 6: The z-direction trajectories

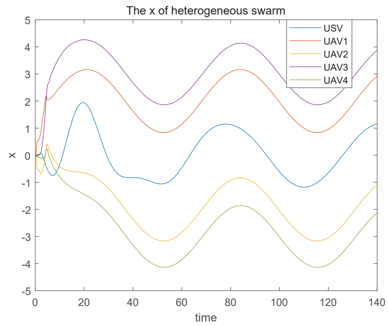

Fig. 7: The x-direction trajectories

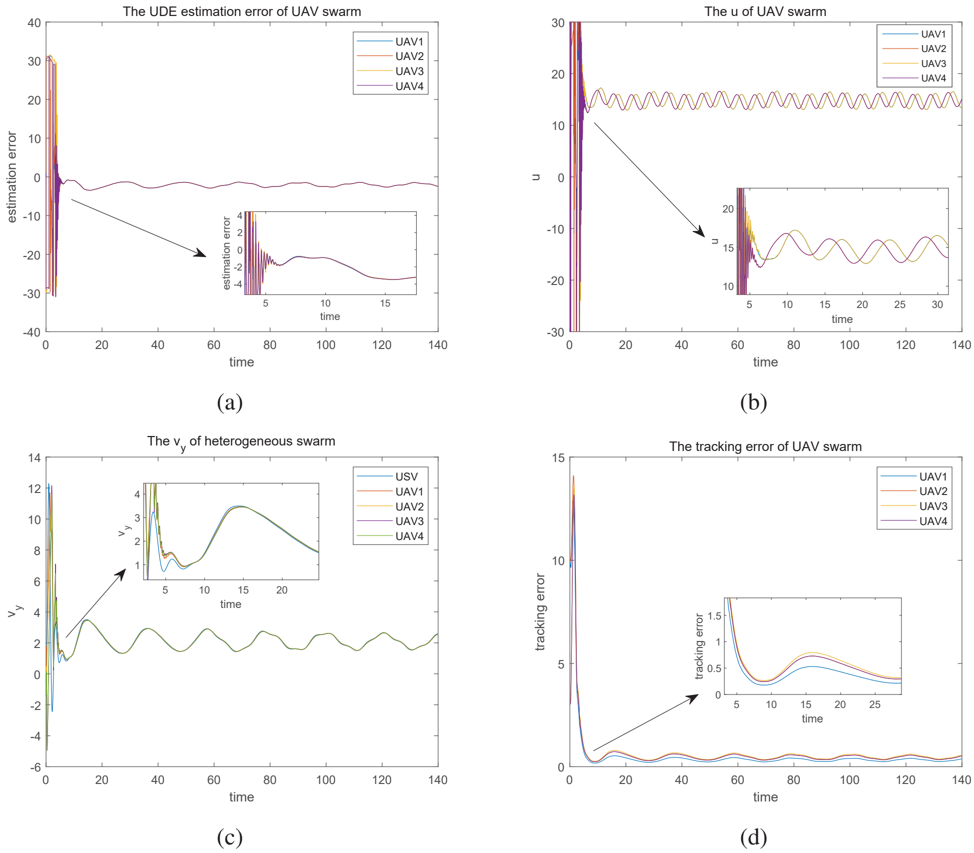

Fig. 8: (a) is the trajectories of UDE estimation error; (b) is the trajectories of u_i; (c) is the trajectories of v_i in y-direction; (d) is the trajectories of tracking error

The dynamics model of a USV of fractional order is chosen as $\mathbf{D}_t^{0.6} r_0 = -0.03{r_0}^2 + 2\cos(0.03t) + 0.01t + 1$. The RBF basis function chosen for the estimation of $\gamma(x,t)$ is $\phi_\gamma^\top(r,t) = exp\left\{-[(r-\mu_{\gamma ir,k})^2 + (t-\mu_{\gamma it,k})^2]/\sigma_{\gamma i,k}^2\right\}$, $k \in \{1,2,\ldots,h_{\gamma i}\}$. The neural network center $(\mu_{\gamma ix,k}, \mu_{\gamma it,k})$ is uniformly distributed in the interval $[-25,25]\times[0,50]$. The initial values of the states of the USV and the four UAVs are:

$$[x_i(0), y_i(0), z_i(0)]^\top = \begin{bmatrix} 0 & -3 & 0 \\ 0 & -3 & 0 \\ 0 & -10 & 0 \\ 0 & -10 & 0 \end{bmatrix}, i = 1,2,3,4$$

$$r_0(0) = 3, \hat{\theta}_{\gamma i}(0) = 0, \hat{\delta}_\gamma(0) = 0.$$

The initial speed of the UAV is zero, and it is in a hovering state, and the initial pitch, yaw, roll angles, and angular velocity are also zero. Each control parameter is set as follows, where $i = 0,1,...,4$, $c = 10; c_{pzi} = 2, c_{dzi} = 10; c_{pxi} = 2, c_{dxi} = 10; c_{p\phi i} = 2, c_{d\phi i} = 20; c_{p\theta i} = 2, c_{d\theta i} = 20; c_{p\psi i} = 2, c_{d\psi i} = 20$. The time scale function for all UDE estimators is set as 0.01. The disturbance to the y-direction of the multi-UAV is set as follows:

$$\begin{cases} d_1(t) = \sin(t)e^{-t} + \sin(t), \\ d_2(t) = \sin(t)e^{-t} + \cos(t), \\ d_3(t) = 2\sin(t)e^{-t} + \sin(t), \\ d_4(t) = 2\cos(t)e^{-t} + \cos(t). \end{cases}$$

The disturbances to the UAV team in the x and z directions are set as $d_x(t) = \sin(0.1t), d_z(t) = 0.5\sin(0.1t)$.

The simulation results are shown in Fig 4, 5, 6, 7. Looking at Fig. 4, all four UAVs can track the target USV's trajectory r_o eventually. Furthermore, there is no divergence afterward, which confirms that the integrated control scheme proposed in this paper for heterogeneous system in all directions can effectively achieve tracking. Next, each direction will be analyzed in terms of convergence time, tracking error, etc.

Fig. 5 illustrates that in the y direction, the heterogeneous system can finally achieve consensus, and the convergence time is about $6s$. Then there is no more dispersion, indicating that the consensus tracking control scheme in y direction is effective.

Fig. 6 shows the trajectories of the UAVs team, except the one of USV because it does not have motions in the z-direction. Moreover, the trajectories in Fig. 6 converge to two altitudes respectively because we set the desired altitudes of the UAVs team according to the fixed formation. The convergence time of UAVs is different from the detail enlargement; UVA1,2,4 converge in about $7s$, while UAV3 converges in about $10s$, which can be explained from the communication topology because UAV3 is the most extended node on the USV communication link, while the UAV1,2,4 communication link is about the same.

In the x direction, five desired positions are set in the x-direction respectively, so the final trajectories in the x-direction converge to five positions respectively in Fig. 7. Still, the trend of the UAVs trajectories is finally consistent with the USV. The convergence time is about $50s$, which is much longer than the convergence speed in the y and z directions because the desired position set in the x direction is time-varying and therefore converges more slowly.

The disturbances estimation errors of UDE are shown in Fig. 8a, which illustrate the sum of the errors in the x and z directions. From the enlarged plot, it can be seen that they converge to the bounded set in about $6s$. This demonstrates that the UDE is effective in estimating and compensating for disturbances, which is essential to be able to achieve robust tracking control.

To match the actual controller, we have limited the control input u to be within 30, so in Fig. 8b, it can be seen that the control input is restricted and eventually stabilizes around 15, which suggests that the proposed control input is stable and feasible.

In addition, a velocity simulation in the y-direction was done in Fig. 8c to prove that not only was the position kept up (Fig. 5), but also the velocity was steadily kept up, and the convergence time was about $7s$.

Fig. 8d shows the tracking errors for each of the four UAVs, which converge to a bounded set in about $6s$. As can be seen from the detailed plot, the tracking error for UVA1 is always the smallest, while the tracking error for UAV3 is always the largest, which is consistent with the results for the length of the communication link to the USV in the communication topology.

5 Conclusion

In this paper, an adaptive robust control scheme was presented for multiple UAVs to track a fractional-order USV so that the heterogeneous multi-robot system would maintain a desired working formation in the specific marine missions related to oil spill. In the robust tracking control strategy, RBFNN is added for the distributed control of the UAVs to estimate the uncertainties of a moving USV. As for the UAV control, UDE approach is utilized to estimate and compensate uncertain disturbances caused by wind and other environmental factors. A simulation case study with four UAVs and a USV was performed and the results show that the multi-UAV team successfully forms a desired rectangular formation by tracking a target USV in a reasonable convergent time, which demonstrates that the adaptive control scheme is effective and robust and will provide potential solutions for the cooperative control of the marine heterogeneous system.

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