

Disturbance Observer and Adaptive Control for Disturbance Rejection of Quadrotor: A Survey

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Abstract: Quadrotors are widely applied in many fields, but they often face various external disturbances in actual operation. This makes it necessary to design a controller that can handle disturbances. Disturbance observer and adaptive control techniques are commonly used disturbance rejection techniques, the core idea of which is to estimate the disturbances in real time and incorporate the estimated values into the controller to suppress the disturbances. In this paper, various disturbance observers and adaptive control techniques, including nonlinear disturbance observers, extended state observers, neural networks, and fuzzy logic systems, are introduced, along with their variants or different structures. These techniques improve the adaptability and robustness of quadrotors to complex environments. Finally, future research directions for the disturbance rejection of quadrotors are also presented.

Keywords: disturbance observers; adaptive control techniques; quadrotor



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1. Introduction

In recent years, the rapid development of unmanned aerial vehicles (UAVs) technology has attracted widespread attention. UAVs are reusable aircrafts that do not carry an operator and rely on an onboard flight control system to adjust their flight states in real time according to predetermined procedures. They can fly autonomously along a predetermined route or be controlled by wireless control equipment and ground control stations. The value of UAVs lies in their ability to form aerial platforms that can be used to extend the range of applications by integrating a variety of equipment. UAVs can replace human labor in high-altitude operations in various areas such as logistics delivery [1,2], agricultural plant protection [3,4], forest management [5,6], power patrols [7,8], displacement monitoring [9,10], disaster monitoring [11,12], disaster rescue [13,14], traffic analysis [15,16], railway inspections [17,18], and so on.

Most UAVs can be classified into two categories: fixed-wing UAVs and rotorcraft UAVs. Fixed-wing UAVs rely on the pressure differences generated by their wings to stay in flight and need to maintain a certain speed to do so [19]. On the other hand, rotorcraft UAVs like quadrotors use the lift generated by their propellers to stay in the air, which allows them to operate in tight spaces and make quick changes in their flying position, giving them a significant advantage in agility and maneuverability [20]. Quadrotors are known for their small size, light weight, simple mechanical structure, quick assembly, and easy maintenance, which makes them cost-effective. They are also highly maneuverable, produce low flight noise, and can perform vertical take-off, landing, and hovering. They are adaptable to different environments, including harsh ones, making them ideal for special missions such as disaster rescue. Due to their potential applications, the motion control of quadrotors have gained unprecedented interest from academia and industry in recent years.

However, quadrotors face external disturbances while operating in complex environments, which can harm their control performance and even lead to control instability [21]. Disturbance observers and adaptive control techniques are commonly used disturbance

rejection techniques, the core idea of which is to estimate the disturbances in real time and incorporate the estimated values into the controller to suppress the disturbances. Disturbance observers include the nonlinear disturbance observer (NDO) [22], the extended state observer (ESO) [23], etc. They construct the observers through a mathematical model to estimate external disturbances in real time. The adaptive control techniques include adaptive estimation methods [24], neural networks (NN) [25], fuzzy logic systems (FLS) [26], etc., which use tracking errors to estimate and compensate for disturbances independently of the model.

Disturbance estimation methods are widely used in various motion control scenarios such as attitude control [27,28], trajectory tracking [29–31], obstacle avoidance [32–34], and formation flying [35–37]. In [38], three major challenges in quadrotor controller design, including underdrivability, model uncertainty, and actuator failure, were described, and existing control methods were summarized. In [39], the methods of adaptive nonlinear control techniques for quadrotors, including traditional nonlinear control methods and their adaptive/observer-enhanced variants, were summarized. In [40], the methods of controller design for quadrotors when subjected to external uncertainties such as wind were summarized, which focus on describing the wind field model, the dynamic model of the quadrotor under wind, and various control methods used for wind resistance. However, disturbance rejection techniques are not exhaustively described in [40]. In summary, most of the works focus on reviewing the control methods for quadrotors but lack a systematic review and analysis of disturbance estimation methods for quadrotors.

In light of the above discussion, we provide a survey of common disturbance rejection techniques for quadrotors. Section 2 describes the nonlinear dynamic model of quadrotors. Section 3 introduces two disturbance observer techniques and their variants. Section 4 discusses the application of adaptive control techniques in disturbance rejection. Section 5 proposes future work on disturbance rejection techniques. Section 6 is the conclusion of the survey. The structure of the survey is shown in Figure 1.

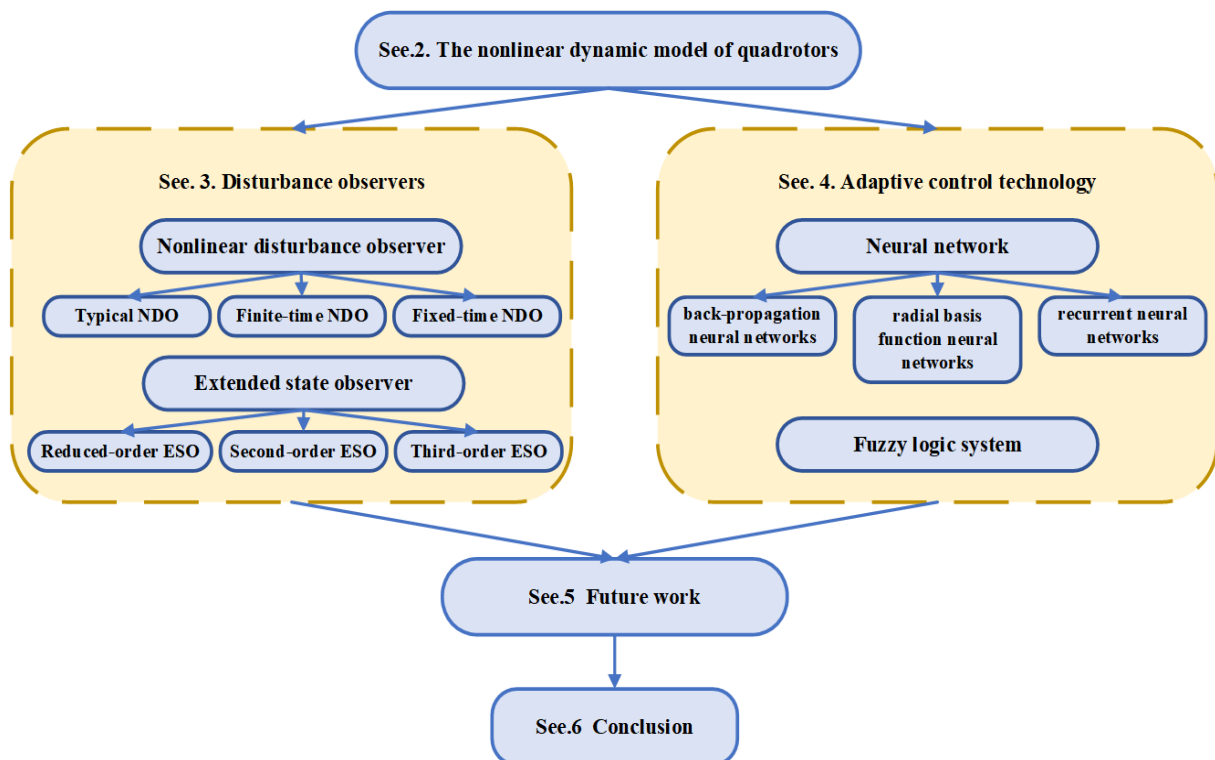


Figure 1. Structure of the survey.

2. The Nonlinear Dynamic Model of Quadrotors

The quadrotor is a system with four inputs and six outputs. It is a strongly coupled nonlinear system with coupling between its three attitude angles and position. To describe the dynamic model of the quadrotor, two coordinate systems need to be established, which are the inertial coordinate system $I = \{X_I, Y_I, Z_I\}$ and the body coordinate system $B = \{X_B, Y_B, Z_B\}$. The schematic diagram of the coordinate system is shown in Figure 2.

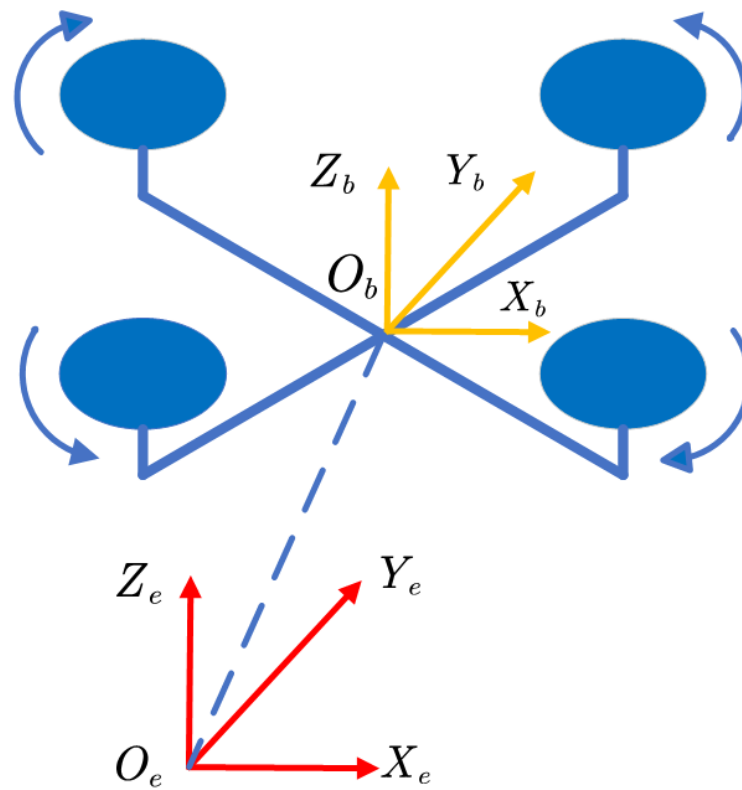


Figure 2. Schematic of the coordinate system.

The rotation matrix from B to I can be described by

$$R = \begin{bmatrix} C_\theta C_\psi & -C_\phi S_\psi + S_\phi S_\theta C_\psi & S_\theta S_\psi + C_\phi S_\theta C_\psi \\ C_\theta S_\psi & C_\phi C_\psi + S_\phi S_\theta S_\psi & -S_\theta C_\psi + C_\phi S_\theta S_\psi \\ -S_\theta & S_\phi C_\theta & C_\phi C_\theta \end{bmatrix},$$

where $C_{(\cdot)}$ and $S_{(\cdot)}$ represent $\cos(\cdot)$ and $\sin(\cdot)$, and ϕ, θ , and ψ denote the roll angle, pitch angle, and yaw angle of the quadrotor, respectively.

To simplify the nonlinear dynamic model of quadrotors, certain physical quantities that have a small effect on the quadrotor are often omitted or simplified. The following assumptions are commonly used:

- **Assumption 1:** The quadrotor structure is symmetric.
- **Assumption 2:** The quadrotor is not affected by the Earth's rotation and revolution.
- **Assumption 3:** The gravitational acceleration to which the quadrotor is subjected remains constant.
- **Assumption 4:** The quadrotor performs low-speed, small-angle flight.
- **Assumption 5:** The disturbances meet $|d_v| \leq \bar{D}_v$, $|d_\eta| \leq \bar{D}_\eta$, where $\bar{D}_v$ and $\bar{D}_\eta$ are constants.

According to the Newton–Euler principle, the dynamic model of the quadrotor is established as [41]:

$$\begin{cases} \dot{\xi} = v, \\ \dot{v} = \frac{U}{m} - ge_3 + d_v, \end{cases} \quad (1)$$

$$\begin{cases} \dot{\Omega} = \eta, \\ \dot{\eta} = I^{-1}\tau - I^{-1}(\dot{\eta} \times I\dot{\eta}) + d_\eta, \end{cases} \quad (2)$$

where m is the mass of the quadrotor; g is the acceleration due to gravity; $\xi = [x, y, z]^T$, where x , y , and z are the position of the quadrotor; $v = [v_x, v_y, v_z]^T$, where v_x , v_y , and v_z are the linear velocity of the quadrotor; $\Omega = [\varphi, \theta, \psi]^T$ is the attitude angle vector; $\eta = [p, q, r]^T$, where p , q , and r are the angular velocity; $d_v = [d_{vx}, d_{vy}, d_{vz}]^T$ and $d_\eta = [d_{\eta\varphi}, d_{\eta\theta}, d_{\eta\psi}]^T$ are external disturbances; $I = \text{diag}(I_x, I_y, I_z)$, where I_x , I_y , and I_z are the moment inertias of the quadrotor; $e_3 = [0, 0, 1]^T$; $\tau = [u_2, u_3, u_4]^T$; and

$$U = Re_3 u_1 = \begin{bmatrix} u_x \\ u_y \\ u_z \end{bmatrix} = \begin{bmatrix} S_\theta S_\psi + C_\varphi S_\theta C_\psi \\ -S_\theta C_\psi + C_\varphi S_\theta S_\psi \\ C_\varphi C_\theta \end{bmatrix} u_1, \quad (3)$$

where u_1 , u_2 , u_3 , and u_4 are the control inputs of the quadrotor.

Remark 1. This paper presents the nonlinear dynamic model of quadrotors based on the Newton–Euler principle. The dynamic model of quadrotors can also be expressed by the Lagrange–Euler formalism [42,43]. In addition, quaternions can be used instead of Euler angles to circumvent the singularity problem that may result from the use of Euler angles [44].

To address the underdrive and coupling issues of the quadrotor, the hierarchical control structure is commonly employed [45], as is the control block diagram in the case of disturbances, as shown in Figure 3. This paper will focus on the disturbance estimation part. The quadrotor is divided into two control loops, which are the position control loop and the attitude control loop. The position control loop is governed by a single control input u_1 , whereas the attitude loop is controlled by three control inputs u_2 , u_3 , and u_4 . The ground operator provides the desired position and yaw angle of the quadrotor, i.e., x_d , y_d , z_d , and ψ_d . According to Equation (3), the desired roll angle φ_d and pitch angle θ_d can be obtained through u_x and u_y , enabling the decoupling between the position and the attitude.

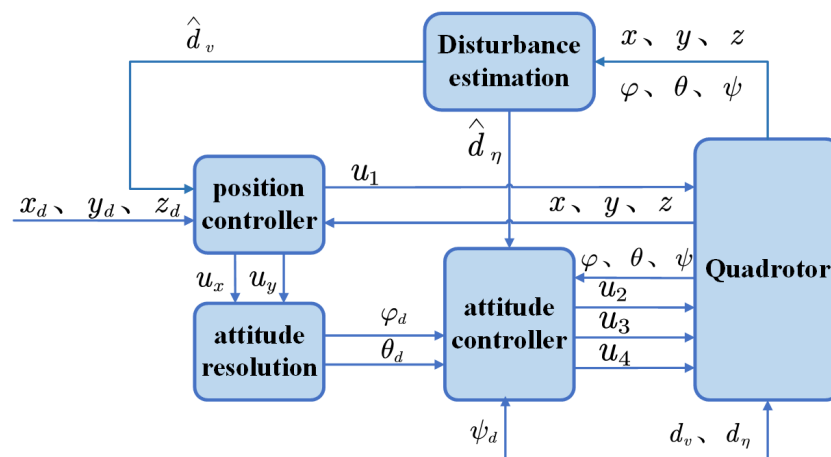


Figure 3. The structure of controller.

3. Disturbance Observers

3.1. Nonlinear Disturbance Observer

Research on the NDO has been going on for a long time. The NDO was summarized in [46] and the global uniform ultimate boundedness of the tracking errors was demonstrated by applying the Lyapunov stability theory. This approach was subsequently widely applied to deal with uncertainties and external disturbances in various nonlinear systems [47–49].

Combining the NDO with other control strategies has become an important way to solve various disturbances in quadrotor systems and improve their performance. In [21], the nonlinear dynamic model of quadrotors considering wind disturbances was developed, and a controller that can compensate for negative wind effects was designed by combining backstepping and an NDO. In [50], a robust backstepping sliding mode control method was proposed for the trajectory tracking of a quadrotor, while an NDO was employed to address the effects of external disturbances and parameter uncertainties. In [51], a quadrotor attitude control technique based on a composite disturbance observer was proposed, which achieves effective control of a quadrotor attitude subjected to an unknown bounded perturbation by introducing an NDO in combination with an adaptive backstepping sliding mode control and auxiliary gain. In [52], an adaptive sliding mode control strategy based on an NDO was presented. This strategy employs an adaptive sliding mode approach to cope with actuator faults, while incorporating an NDO to mitigate the effects of external disturbances. In [53], a control method based on feedback linearization and an NDO was proposed, which effectively addresses model uncertainty, and suppresses high nonlinearities in the model. In [54], an adaptive fuzzy controller was proposed that integrates a modified NDO to estimate uncertainties and disturbances. The experimental results showed that the controller has stronger elastic stability and tracking performance compared to the conventional method. In [55], an adaptive fuzzy tracking control scheme for quadrotors was proposed, which uses an FLS and NDO to approximate the unknown dynamics of the quadrotor system. By combining NDO with various control methods, various disturbance problems in quadrotor control systems can be effectively solved, improving their performance and enabling them to operate stably and reliably in complex environments.

The application of NDO has also been extended to wider areas such as collision avoidance, target tracking, and multi-UAV formation control. In [56], a method combining the fast finite-time convergence guidance law and an NDO was proposed for the collision avoidance problem to ensure the safety of UAVs. In [57], a standoff tracking and guidance method for UAVs under windy conditions was proposed. The method uses an NDO to estimate wind disturbance, and combines it with the Lyapunov guided vector field technique to compensate for wind effects and achieve ground target tracking successfully. In [58], a disturbance rejection formation control method was proposed, which uses an NDO to estimate external disturbances. These works further demonstrate the wide applicability and effectiveness of NDO in modern control systems.

The mathematical expression for NDO is presented next. As described by [46], the NDO derived from models (1) and (2) can be expressed in the following manner:

$$\begin{cases} \dot{z}_1 = -l(v)z_1 - l(v)(p(v) + \frac{U}{m} - ge_3), \\ \hat{d}_v = z_1 + p(v), \end{cases} \quad (4)$$

$$\begin{cases} \dot{z}_2 = -l(\eta)z_2 - l(\eta)(p(\eta) + I^{-1}\tau - I^{-1}(\dot{\eta} \times I\dot{\eta})), \\ \hat{d}_\eta = z_2 + p(\eta), \end{cases} \quad (5)$$

where z_1 and z_2 are auxiliary variables, $l(v)$ and $l(\eta)$ are gain matrices, $p(v) = l(v)\dot{v}$, $p(\eta) = l(\eta)\dot{\eta}$, and $\hat{d}_v$ and $\hat{d}_\eta$ are the estimation of d_v and d_η , respectively.

Next, the stability of the NDO is proved. This part of the proof focus on the NDO of the position system, and the process of proving the NDO of the attitude system is the same as that of the position system. We take the Lyapunov function as

$$V_{11} = \frac{1}{2} \tilde{d}_v^2, \quad (6)$$

where $\tilde{d}_v = d_v - \hat{d}_v$.

According to (1) and (4), it can be obtained that

$$\begin{aligned} \dot{\tilde{d}}_v &= \dot{d}_v - \dot{\hat{d}}_v \\ &= \dot{d}_v - \dot{z}_1 - p(v) \\ &= \dot{d}_v + l(v)z_1 + l(v)(p(v) + \frac{U}{m} - ge_3) - p(v) \\ &= \dot{d}_v + l(v)(\hat{d}_v - p(v)) + l(v)(p(v) + \dot{v} - d_v) - p(v) \\ &= \dot{d}_v - l(v)\tilde{d}_v + l(v)\dot{v} - p(v). \end{aligned} \quad (7)$$

Due to $p(v) = l(v)\dot{v}$, it can be obtained that

$$\dot{V}_{11} = \tilde{d}_v \dot{\tilde{d}}_v = \tilde{d}_v \dot{d}_v - l(v)\tilde{d}_v^2 \leq -(l(v) - \frac{1}{2})\tilde{d}_v^2 + \frac{1}{2}\dot{D}_v^2. \quad (8)$$

From (8), we can obtain

$$V_{11} \leq \frac{\bar{D}_v^2}{2(l(v) - \frac{1}{2})} + (V_{11}(0) - \frac{\bar{D}_v^2}{2(l(v) - \frac{1}{2})})e^{-(l(v) - \frac{1}{2})t}, \quad (9)$$

From the above equation, it can be seen that, as long as $l(v) > \frac{1}{2}$, then the disturbance estimate $\hat{d}_v$ of the NDO will converge to its true value d_v .

In [59], it is described how to choose the appropriate gain matrix such that the NDO (4) and (5) are exponentially stable. In addition, to apply this approach to assess the effect of uncertainty, the error dynamics of the observer must be faster than the dynamics of the closed-loop system, as can be seen in [48].

With the theoretical development, the finite-time NDO has been proposed in recent years. In [60], the finite-time control problem of a quadrotor under input saturation and external disturbances was investigated, using a finite-time NDO to estimate the external disturbances and a combination of an auxiliary system and a fast-terminal sliding mode controller for stabilization control and trajectory tracking of the quadrotor. In [61], a control scheme based on a perturbation observer and an integral sliding mode technique was proposed for spacecrafts affected by external perturbation moments and actuator failures. The scheme uses a finite-time NDO to reconstruct the composite uncertainties caused by actuator failures and external disturbances. In [62], a composite control scheme combining a finite-time NDO and adaptive non-singular fast terminal sliding mode control was proposed to cope with the problems of parameter uncertainty, external disturbances, and actuator failures. The finite-time NDO ensures that the estimation of the disturbance is completed within a finite time. This can reduce the response time of the system and enhance its dynamic performance and robustness. One of the finite-time NDO are as follows [62]:

$$\begin{cases} \dot{z}_1 = -l_1(\frac{U}{m} - ge_3 + \hat{d}_v), \\ \dot{\hat{d}}_v = z_1 + l_1 v - l_2 \int_0^t \text{sgn}^e(\tilde{d}_v) d\tau, \end{cases} \quad (10)$$

$$\begin{cases} \dot{z}_2 = -l_3(I^{-1}\tau - I^{-1}(\dot{\eta} \times I\dot{\eta}) + \hat{d}_\eta) \\ \dot{\hat{d}}_\eta = z_2 + l_3 \eta - l_4 \int_0^t \text{sgn}^e(\tilde{d}_\eta) d\tau, \end{cases} \quad (11)$$

where $\hat{d}_v$ and $\hat{d}_\eta$ are the estimations of d_v and d_η , $\tilde{d}_v = d_v - \hat{d}_v$, $0 < \varrho < 1$, z_1 and z_2 are auxiliary variables, and l_1, l_2, l_3 , and l_4 are gain matrices.

We take the Lyapunov function as

$$V_{12} = \frac{1}{2} \tilde{d}_v^2, \quad (12)$$

According to (1) and (10), it can be obtained that

$$\begin{aligned} \dot{\tilde{d}}_v &= \dot{d}_v - \dot{\hat{d}}_v \\ &= \dot{d}_v - \dot{z}_1 - l_1 \dot{v} - l_2 \operatorname{sgn}^\varrho(\tilde{d}_v) \\ &= \dot{d}_v + l_1 \left(\frac{U}{m} - g e_3 + \hat{d}_v \right) - l_1 \dot{v} - l_2 \operatorname{sgn}^\varrho(\tilde{d}_v) \\ &= \dot{d}_v - l_1 \tilde{d}_v - l_2 \operatorname{sgn}^\varrho(\tilde{d}_v). \end{aligned} \quad (13)$$

It can be obtained that

$$\begin{aligned} \dot{V}_{12} &= \tilde{d}_v \dot{\tilde{d}}_v = \tilde{d}_v \dot{d}_v - l_1 \tilde{d}_v^2 - l_2 \tilde{d}_v \operatorname{sgn}^\varrho(\tilde{d}_v) \\ &\leq - \left(l_1 - \frac{1}{2} \right) \tilde{d}_v^2 - l_2 \tilde{d}_v^{1+\varrho} + \frac{1}{2} \tilde{D}_v^2, \\ &\leq - 2 \left(l_1 - \frac{1}{2} \right) V_{12} - 2 l_2 V_{12}^{\frac{1+\varrho}{2}} + \frac{1}{2} \tilde{D}_v^2, \end{aligned} \quad (14)$$

Based on the Lemma 1 in [62], it can be concluded that the disturbance estimate $\hat{d}_v$ will converge to its true value d_v in finite time.

The fixed-time NDO was proposed as a further development of the finite-time NDO. In [63], a robust fault-tolerant tracking control scheme for uncertain quadrotors was proposed, which uses a fixed-time NDO to cope with model uncertainty, external disturbances, actuator failures, and input delays to ensure that the quadrotor can track the predefined trajectory. In [64], a fixed-time dynamic surface control method based on a fixed-time NDO was proposed to achieve trajectory tracking control tasks under disturbances. In [65], a fixed-time perturbation observer was constructed to accurately estimate the wind perturbation, and a robust fixed-time controller was designed for the position attitude system by combining the sliding mode control theory with the fixed-time technique. Compared with the finite-time NDO, the fixed-time NDO can not only complete the disturbance estimation within a fixed time, but, also, the upper time limit is not affected by initial conditions, which makes it more flexible and predictable in practical applications. One of the fixed-time NDO are as follows:

$$\begin{cases} \dot{z}_1 = \frac{U}{m} - g e_3 + K_{11} \sigma_v, \\ \dot{\hat{\sigma}}_v = \dot{\sigma}_v + K_{12} \operatorname{sign}(\tilde{\sigma}_v)^{\alpha_{11}} + K_{13} \operatorname{sign}(\tilde{\sigma}_v)^{\alpha_{12}} + K_{14} \tilde{\sigma}_v, \\ \dot{\hat{d}}_v = K_{11} \hat{\sigma}_v + \dot{\sigma}_v, \end{cases} \quad (15)$$

$$\begin{cases} \dot{z}_2 = I^{-1} \tau - I^{-1} (\dot{\eta} \times I \dot{\eta}) + K_{21} \sigma_\eta, \\ \dot{\hat{\sigma}}_\eta = \dot{\sigma}_\eta + K_{22} \operatorname{sign}(\tilde{\sigma}_\eta)^{\alpha_{21}} + K_{23} \operatorname{sign}(\tilde{\sigma}_\eta)^{\alpha_{22}} + K_{24} \tilde{\sigma}_\eta, \\ \dot{\hat{d}}_\eta = K_{21} \hat{\sigma}_\eta + \dot{\sigma}_\eta, \end{cases} \quad (16)$$

where z_1 and z_2 are auxiliary variables; $\sigma_v = v - z_1$ and $\sigma_\eta = \eta - z_1$, where $\hat{\sigma}_v$ and $\hat{\sigma}_\eta$ are the estimations of σ_v and σ_η , respectively; $\tilde{\sigma}_v = \sigma_v - \hat{\sigma}_v$ and $\tilde{\sigma}_\eta = \sigma_\eta - \hat{\sigma}_\eta$; $K_{11}, K_{12}, K_{13}, K_{14}, K_{21}, K_{22}, K_{23}$, and K_{24} are gain matrices; and $0 < \alpha_{11} < 1$, $\alpha_{21} > 1$, and $\alpha_{12} > 1$, $0 < \alpha_{22} < 1$.

We take the Lyapunov function as

$$V_{13} = \frac{1}{2} \tilde{\sigma}_v^2, \quad (17)$$

From (15), we can obtain

$$\dot{\tilde{\sigma}}_v = \dot{\sigma}_v - \dot{\hat{\sigma}}_v = -K_{12}\text{sign}(\tilde{\sigma}_v)^{\alpha_{11}} - K_{13}\text{sign}(\tilde{\sigma}_v)^{\alpha_{12}} - K_{14}\tilde{\sigma}_v, \quad (18)$$

It can be obtained that

$$\begin{aligned} \dot{V}_{13} &= \tilde{\sigma}_v \dot{\tilde{\sigma}}_v = -K_{12}\tilde{\sigma}_v \text{sign}(\tilde{\sigma}_v)^{\alpha_{11}} - K_{13}\tilde{\sigma}_v \text{sign}(\tilde{\sigma}_v)^{\alpha_{12}} - K_{14}\tilde{\sigma}_v^2 \\ &\leq -K_{12}\tilde{\sigma}_v^{\alpha_{11}+1} - K_{13}\tilde{\sigma}_v^{\alpha_{12}+1} \\ &\leq -K_{12}V_{13}^{\frac{\alpha_{11}+1}{2}} - K_{13}V_{13}^{\frac{\alpha_{12}+1}{2}}, \end{aligned} \quad (19)$$

Based on the Lemma 1 in [63], it can be concluded that the estimate $\hat{\sigma}_v$ will converge to zero in fixed time.

By recalling (1) and (15), the error $\tilde{d}_v$ can be calculated as follows:

$$\begin{aligned} \dot{\tilde{d}}_v &= \dot{d}_v - \dot{\hat{d}}_v = \dot{d}_v - K_{11}\dot{\hat{\sigma}}_v - \dot{\sigma}_v \\ &= \dot{d}_v - K_{11}\dot{\hat{\sigma}}_v - \dot{v} + \dot{z}_1 \\ &= \dot{d}_v - K_{11}\dot{\hat{\sigma}}_v - \dot{v} + \dot{v} - \dot{d}_v + K_{11}\sigma_v \\ &= K_{11}\tilde{\sigma}_v \end{aligned} \quad (20)$$

Because the estimate $\hat{\sigma}_v$ will converge to zero in fixed time, the disturbance estimate $\hat{d}_v$ will converge to its true value d_v in fixed time.

Next, the estimation performance of the NDO, finite-time NDO, and fixed-time NDO are simulated and compared, as shown in Figure 4, analyzed only for the roll angle channel. The external disturbance is modeled as a sinusoidal signal. The simulation results show that the fixed-time NDO outperforms the finite-time NDO, which, in turn, outperforms the NDO, and all three observers have smaller errors and are able to estimate the disturbance more accurately. Their advantages and disadvantages are summarized in Table 1.

Table 1. NDO: advantages and disadvantages.

Estimation Methods	Advantage	Disadvantage
NDO	Capable of handling complex perturbations in nonlinear systems. Simple structural design, easy-to-adjust parameters.	Unknown convergence time.
Finite-time NDO	Converges within a finite time. Quick response to disturbance changes. Ideal for systems requiring rapid response.	The convergence time depends on the initial conditions and system parameters. Sensitive to parameter selection.
Fixed-time NDO	Converges within a fixed time regardless of initial conditions. Ideal for applications with strict time requirements.	Complex design. Requires high computational resources.

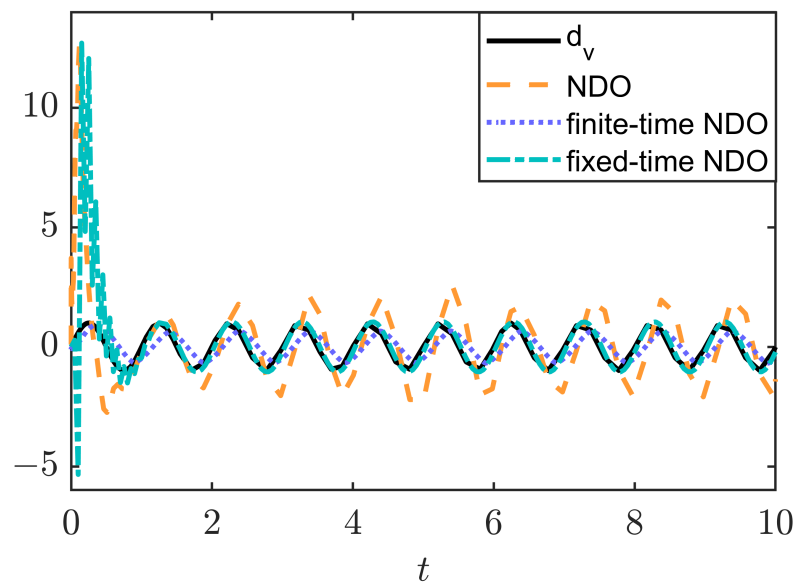


Figure 4. Estimation performance of NDOs.

This subsection details the classical form of the NDO and its finite-time and fixed-time variants. In addition to the specific forms mentioned, many other variants of the NDO exist that can be adapted for different control methods and application scenarios. However, NDO usually require an accurate system model to estimate disturbances.

3.2. Extended State Observer

In this section, we will introduce the ESO, which is an observation technique that can observe the external disturbances of the system and estimate its internal state simultaneously. This property makes the ESO widely applicable in the disturbance rejection of quadrotors.

The ESO is an important part of active disturbance rejection control (ADRC), but the application of ESO in quadrotor control is not limited to a single control strategy; it can be combined with other control methods. In [66], a fast non-singular terminal sliding mode tracking controller was proposed, and an ESO was integrated into the controller, which can guarantee accurate trajectory tracking in the presence of disturbances. In [67], ADRC and a predictive control strategy were employed for solving the trajectory tracking problem of the quadrotors with gust. The approach also combined an ESO for estimating and compensating gust disturbances to achieve accurate trajectory tracking. In [68], an ESO-based disturbance compensator and a novel sliding mode controller were proposed for quadrotor attitude control under unknown disturbances. The method can effectively estimate the low-frequency and high-frequency components of the superimposed disturbances and reduces the effect of the virtual disturbance estimation error, which improves the performance and robustness of the attitude control. In [69], a cascaded ADRC strategy with a two-stage Kalman filter was proposed and an ESO was designed in the ADRC controller to further compensate the effect of the Kalman filter estimation error. In [70], a novel U-model-enhanced double sliding mode controller based on a multiple-input and multiple-output ESO was presented, where the ESO was designed to estimate unmeasurable velocities and uncertain aerodynamics. In [71], a tracking differentiator was introduced to obtain a smooth tracking signal, and an ESO was proposed to estimate the modeling uncertainty and unknown disturbances of the system. Based on the tracking differentiator and ESO, a novel finite-time convergent smooth tracking controller was developed, which enabled the system to achieve the desired tracking performance in finite time. In [72], a variable gain ESO was developed to accurately estimate unknown external disturbances. It effectively mitigated the peak problem that conventional methods face.

In more complex application scenarios, such as fault diagnosis and localization of UAVs, and target tracking and path tracing, the ESO demonstrates its applicability and flexibility. In [73], ESO successfully completed the fault diagnosis and localization tasks of UAVs by combining residual feature analysis and deep forest techniques. In [74], an ESO-based controller was proposed to ensure precise tracking performance of UAVs in 2D space, demonstrating the great potential of ESO in group intelligence and cooperative control. In [75], a guidance law based on a novel ESO was proposed for the broken path tracking problem of UAVs, which was combined with a folded path switching method, and the ESO parameter tuning method was further proposed for engineering applications.

The mathematical expression for the ESO is presented next. Its basic idea is to expand the disturbance into a new state variable in the original system, and design a state observer for the expanded state system. For systems (1) and (2), the model of the system after adding the expanded state becomes

$$\begin{cases} \dot{\xi} = v, \\ \dot{v} = \frac{U}{m} - ge_3 + \varrho_v, \\ \dot{\varrho}_v = \dot{d}_v, \end{cases} \quad (21)$$

$$\begin{cases} \dot{\Omega} = \eta, \\ \dot{\eta} = I^{-1}\tau - I^{-1}(\dot{\eta} \times I\dot{\eta}) + \varrho_\eta, \\ \dot{\varrho}_\eta = \dot{d}_\eta, \end{cases} \quad (22)$$

where ϱ_v and ϱ_η are extended states.

Firstly, the reduced-order ESO is introduced; for systems (21) and (22), the reduced-order ESO can be represented as follows [76]:

$$\begin{cases} \dot{z}_v = -K_1\hat{d}_v - K_1(\frac{U}{m} - ge_3), \\ \hat{d}_v = z_v + K_1v, \end{cases} \quad (23)$$

$$\begin{cases} \dot{z}_\eta = -K_2\hat{d}_\eta - K_2(I^{-1}\tau - I^{-1}(\dot{\eta} \times I\dot{\eta})), \\ \hat{d}_\eta = z_\eta + K_2\eta, \end{cases} \quad (24)$$

where z_v and z_η are auxiliary variables, and K_1 and K_2 are gain matrices. In [76], it is demonstrated that by appropriately choosing the gain matrices of the ESO, it can make the estimations asymptotically track the state of the system, and that it can efficiently compensate for unknown disturbances suffered in the control system.

We take the Lyapunov function as

$$V_{21} = \frac{1}{2}\tilde{d}_v^2, \quad (25)$$

According to (1) and (23), it can be obtained that

$$\begin{aligned} \dot{\tilde{d}}_v &= \dot{d}_v - \dot{\hat{d}}_v \\ &= \dot{d}_v - \dot{z}_v - K_1\dot{v} \\ &= \dot{d}_v + K_1\hat{d}_v + K_1(\frac{U}{m} - ge_3) - K_1\dot{v} \\ &= \dot{d}_v - K_1\tilde{d}_v, \end{aligned} \quad (26)$$

It can be obtained that

$$\dot{V}_{21} = \tilde{d}_v \dot{\tilde{d}} = \tilde{d}_v \dot{d}_v - K_1 \tilde{d}_v^2 \leq -(K_1 - \frac{1}{2}) \tilde{d}_v^2 + \frac{1}{2} \bar{D}_v^2. \quad (27)$$

From (27), we can obtain

$$V_{21} \leq \frac{\bar{D}_v^2}{2(K_1 - \frac{1}{2})} + (V_{21}(0) - \frac{\bar{D}_v^2}{2(K_1 - \frac{1}{2})}) e^{-(K_1 - \frac{1}{2})t}, \quad (28)$$

From the above equation, it can be seen that, as long as $K_1 > \frac{1}{2}$, then the disturbance estimate $\hat{d}_v$ of the reduced-order ESO will converge to its true value d_v .

The reduced-order ESO, described above, can only estimate the disturbances. In [66], a second-order ESO was used that is capable of estimating the velocity and disturbance of the system:

$$\begin{cases} \dot{z}_{v1} = \frac{U}{m} - ge_3 + z_{v2} - K_{11}(z_{v1} - v), \\ \dot{z}_{v2} = -K_{12}(z_{v1} - v), \end{cases} \quad (29)$$

$$\begin{cases} \dot{z}_{\eta1} = I^{-1}\tau - I^{-1}(\dot{\eta} \times I\eta) + z_{\eta2} - K_{21}(z_{\eta1} - \eta), \\ \dot{z}_{\eta2} = -K_{22}(z_{\eta1} - \eta), \end{cases} \quad (30)$$

where z_{v1} , z_{v2} , $z_{\eta1}$, and $z_{\eta2}$ are the estimations of v , d_v , η , and d_η , respectively, and K_{11} , K_{12} , K_{21} , and K_{22} are gain matrices.

According to (1) and (29), it can be obtained that

$$\begin{aligned} \dot{\tilde{z}}_{v1} &= \dot{v} - \dot{z}_{v1} \\ &= \dot{v} - \frac{U}{m} + ge_3 - z_{v2} + K_{11}(z_{v1} - v) \\ &= \tilde{z}_{v2} - K_{11}\tilde{z}_{v1}, \\ \dot{\tilde{z}}_{v2} &= \dot{d}_v - \dot{z}_{v2} = \dot{d}_v - K_{12}\tilde{z}_{v1}, \end{aligned} \quad (31)$$

It can be obtained that

$$\begin{bmatrix} \dot{\tilde{z}}_{v1} \\ \dot{\tilde{z}}_{v2} \end{bmatrix} = \begin{bmatrix} -K_{11} & 1 \\ -K_{12} & 0 \end{bmatrix} \begin{bmatrix} \tilde{z}_{v1} \\ \tilde{z}_{v2} \end{bmatrix} + \begin{bmatrix} 0 \\ \dot{d}_v \end{bmatrix}. \quad (32)$$

Based on the Lemma 1 in [77], it can be proved that z_{v1} will converge to its true value v and the disturbance estimate z_{v2} will converge to its true value d_v .

In addition to the above two ESO, a third-order ESO has been proposed in [71] to estimate the full state of the system, which is the most commonly used method, with the following expression:

$$\begin{cases} \dot{z}_{v1} = z_{v2} - K_{11}(z_{v1} - \xi), \\ \dot{z}_{v2} = \frac{U}{m} - ge_3 + z_{v3} - K_{12}(z_{v1} - \xi), \\ \dot{z}_{v3} = -K_{13}(z_{v1} - \xi), \end{cases} \quad (33)$$

$$\begin{cases} \dot{z}_{\eta1} = z_{\eta2} - K_{21}(z_{\eta1} - \Omega), \\ \dot{z}_{\eta2} = I^{-1}\tau - I^{-1}(\dot{\eta} \times I\eta) + z_{\eta3} - K_{22}(z_{\eta1} - \Omega), \\ \dot{z}_{\eta3} = -K_{23}(z_{\eta1} - \Omega), \end{cases} \quad (34)$$

where z_{v1} , z_{v2} , z_{v3} , $z_{\eta1}$, $z_{\eta2}$, and $z_{\eta3}$ are the estimations of ξ , v , d_v , Ω , η , and d_η , respectively, and K_{11} , K_{12} , K_{13} , K_{21} , K_{22} , and K_{23} are gain matrices.

According to (1) and (33), it can be obtained that

$$\begin{aligned}\dot{z}_{v1} &= \dot{\xi} - \dot{z}_{v1} \\ &= v - z_{v2} + K_{11}(z_{v1} - \xi) \\ &= \tilde{z}_{v2} - K_{11}\tilde{z}_{v1}, \\ \dot{z}_{v2} &= \dot{v} - \dot{z}_{v2} \\ &= \dot{v} - \frac{U}{m} + ge_3 - z_{v3} + K_{12}(z_{v1} - \xi) \\ &= \tilde{z}_{v3} - K_{12}\tilde{z}_{v1}, \\ \dot{z}_{v3} &= \dot{d}_v - \dot{z}_{v3} = \dot{d}_v - K_{13}\tilde{z}_{v1},\end{aligned}\quad (35)$$

It can be obtained that

$$\begin{bmatrix} \dot{\tilde{z}}_{v1} \\ \dot{\tilde{z}}_{v2} \\ \dot{\tilde{z}}_{v3} \end{bmatrix} = \begin{bmatrix} -K_{11} & 1 & 0 \\ -K_{12} & 0 & 1 \\ -K_{13} & 0 & 0 \end{bmatrix} \begin{bmatrix} \tilde{z}_{v1} \\ \tilde{z}_{v2} \\ \tilde{z}_{v3} \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ \dot{d}_v \end{bmatrix}. \quad (36)$$

Based on the Lemma 1 in [77], it can be proved that z_{v1} will converge to its true value ξ , z_{v2} will converge to its true value v , and the disturbance estimate z_{v3} will converge to its true value d_v .

Next, the estimation performance of the reduced-order ESO, second-order ESO, and third-order ESO are simulated and compared, as shown in Figure 5, analyzed only for the roll angle channel. The external disturbance is modeled as a sinusoidal signal. The simulation results show that all three observers have smaller errors and are able to estimate the disturbance more accurately. Their advantages and disadvantages are summarized in Table 2.

Table 2. ESO: advantages and disadvantages.

Estimation Methods	Advantage	Disadvantage
Reduced-order ESO	Simpler to design and implement. Less computationally burdensome, suitable for resource-constrained systems. Used only for disturbance estimation.	Only disturbances can be estimated, not other states of the system.
Second-order ESO	Ability to estimate the speed and disturbances of the system for a wide range of applications. Relatively simple design and moderate computational burden.	Cannot estimate the position of the system and may not be comprehensive enough for some application scenarios. More sensitive to the choice of observer parameters.
Third-order ESO	Ability to simultaneously estimate the position, velocity, and disturbance of the system, providing comprehensive state information.	More complex to design and implement. Heavier computational burden. Parameter adjustment is difficult.

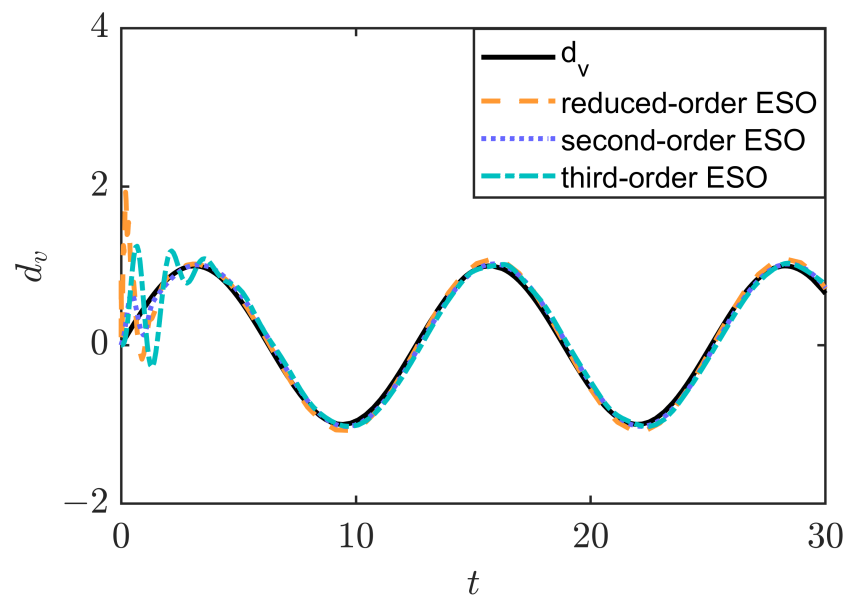


Figure 5. Estimation performance of ESOs.

Similarly to NDO, the derivatives of disturbances in ESO need to be bounded and ESO require accurate mathematical modeling. It should be noted that the forms of ESO may change depending on different control methods and are not necessarily limited to the forms given above. These ESO can be adapted and improved to suit different control scenarios and applications based on specific control requirements and system characteristics.

4. Adaptive Control Technology

In Section 3, it was established that NDO and ESO can observe disturbances, but need to know the nonlinear dynamics of the quadrotor. Adaptive control methods usually only need the tracking error information without having a detailed model of the system. In this section, some adaptive control methods are described. The simplest adaptive estimation method is as follows [78]:

$$\dot{\hat{d}}_v = K_1 e_v, \quad (37)$$

$$\dot{\hat{d}}_\eta = K_2 e_\eta, \quad (38)$$

where $\hat{d}_v$ and $\hat{d}_\eta$ are estimations of d_v and d_η ; $e_v = v - v_d$, $e_\eta = \eta - \eta_d$, $v_d = [v_{dx}, v_{dy}, v_{dz}]^T$, and $\eta_d = [\eta_{d\phi}, \eta_{d\theta}, \eta_{d\psi}]^T$ are desired values; and K_1 and K_2 are the controller parameters.

Some work has added the convergence term to the above adaptive law as follows:

$$\dot{\hat{d}}_v = K_{11}(e_v - K_{12}\hat{d}_v), \quad (39)$$

$$\dot{\hat{d}}_\eta = K_{21}(e_\eta - K_{22}\hat{d}_\eta), \quad (40)$$

where K_{11} , K_{12} , K_{21} , and K_{22} are the controller parameters. The error terms e_v and e_η can vary depending on the control method; for example, in sliding mode control they can be sliding mode variables, but the basic form is shown above. The equations for estimating disturbances using NN and FLS all have similar forms.

As the proof of convergence of the adaptive estimation method needs to be combined with a controller, it will not be described in detail here, nor will the subsequent NN and FLS.

4.1. Neural Network

The powerful learning ability and excellent nonlinear function approximation capability of NN make them widely applied in the controller of the quadrotor. Travis et al. [79] used an NN combined with output feedback to construct a nonlinear controller. The controller uses an NN to approximate the uncertain nonlinear terms in the dynamics model and estimates the translational and angular velocities of quadrotors via an NN observer. In [80], an NN-based adaptive compensatory control scheme was proposed. The scheme ensures bounded trajectory tracking for the position subsystem and asymptotic trajectory tracking for the attitude subsystem under external disturbances. Yang et al. [81] used a non-singular fast terminal sliding mode control strategy incorporating an NN to ensure fast convergence and high robustness of the quadrotor. In [82], a robust neural adaptive backstepping control method was proposed. The method utilizes the global estimation property of NN to estimate external disturbances. In [83], an adaptive predetermined time sliding mode controller based on an NN was used to enable the quadrotor formation to track the planned trajectory within a specified time. In [84], a geometrically adaptive controller for quadrotors incorporating three layers of NN was presented. This controller adapts the NN weights to the variations of unstructured forces and moments online by means of an adaptive law. In [85], an adaptive integral sliding mode control strategy was proposed and the equivalent control law of the system was estimated using an NN. Through online learning and real-time updating, the controller achieves adaptive tuning, ensures the finite-time stability of the system, and verifies the effectiveness of the method in experiments.

There are three types of NN discussed below. The first and most commonly used one is the radial basis function neural network (RBFNN). RBFNN has three layers, including an input layer, a hidden layer, and an output layer, as shown in Figure 6. The input layer is responsible for transferring input data to the nodes in the hidden layer. The hidden layer nodes are connected to the output layer through transfer functions, which are usually Gaussian. The output layer produces a linear combination of the input signals, and the final output data is a linear weighted sum of the hidden layer neuron outputs.

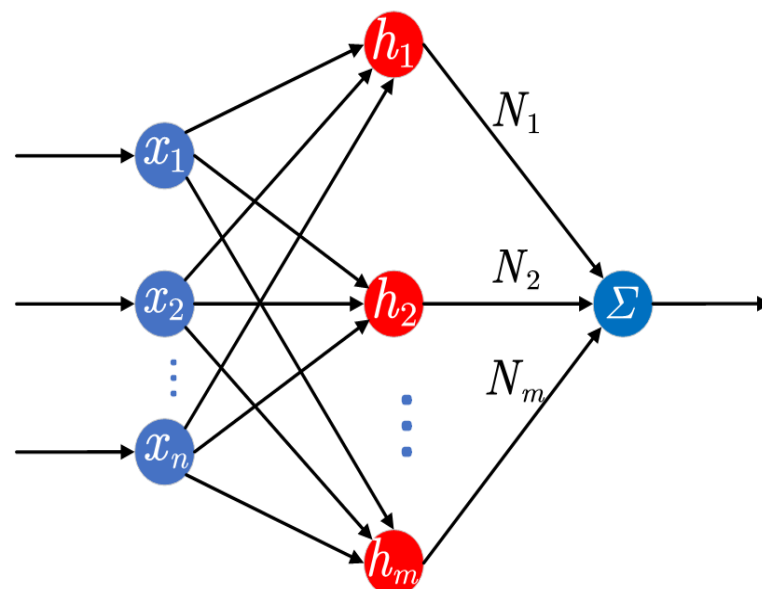


Figure 6. The structure of RBFNN.

Disturbance estimation can be achieved using back-propagation neural networks (BPNN) in addition to RBFNN. Unlike the single hidden layer structure of RBFNN, BPNN can have multiple hidden layers, as shown in Figure 7. This allows for the construction of deeper models that can capture more complex nonlinear relationships in the data.

Each layer nonlinearly transforms the input using an activation function, then passes the information to the next layer through weights and biases. The algorithm core of BPNN lies in the error back-propagation mechanism, which optimizes the model's performance by calculating the output error and back-propagating it through the network, updating the weights and biases layer by layer.

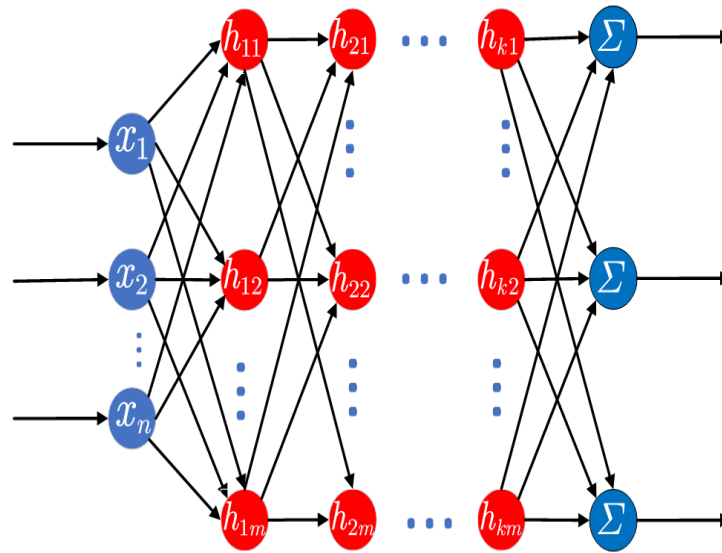


Figure 7. The structure of BPNN.

The recurrent neural network (RNN) is a popular tool for disturbance estimation. The RNN is particularly useful when working with sequential data, due to their ability to pass states through their layers in a cyclic fashion. This allows them to retain information over time and take into account the effects of historical data, which leads to more accurate predictions and adjustments for interference due to time-dependent changes. In RNN, there is an input layer, one or more hidden layers that are cyclically connected, and an output layer, which is depicted in Figure 8. These cyclic connections enable the network to generate outputs, not just based on current inputs, but on previous activities as well. This provides continuous data flow analysis and prediction capabilities for dynamic systems. The RNN is well-suited for handling disturbances in dynamic and nonlinear systems, due to their ability to remember past information.

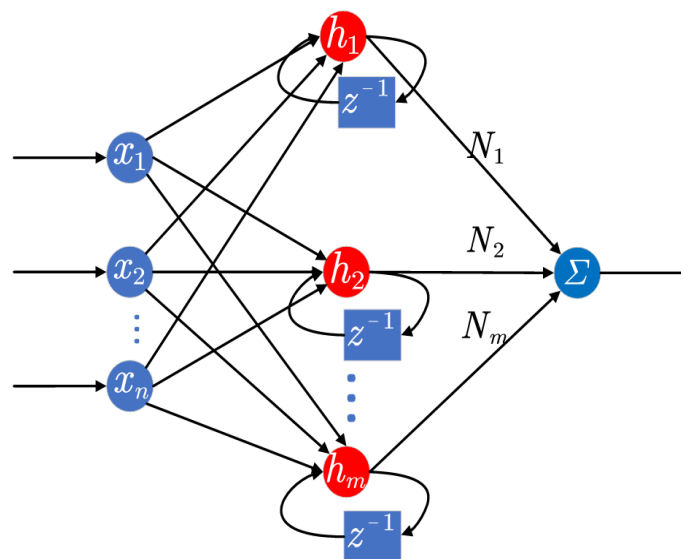


Figure 8. The structure of RNN.

Although the various NN have different structures, their expressions are usually similar when used to estimate disturbances, and the RBFNN is used here as an example. According to [86], the disturbances can be expressed by the RBFNN as

$$d_{vi} = N_{vi}^T P(x) + \varepsilon_{vi}, \quad (41)$$

$$d_{\eta j} = N_{\eta j}^T P(x) + \varepsilon_{\eta j}, \quad (42)$$

where x is the input of the RBFNN, N_{vi} and $N_{\eta j}$ are the optimal output weight matrices, and ε_{vi} and $\varepsilon_{\eta j}$ are the approximation errors of the RBFNN, which are generally small. $P(e_{vi})$ and $P(e_{\eta j})$ are radial basis functions, and most work is usually done with Gaussian functions of the following form:

$$P(e_{vi}) = \exp\left(-\frac{(e_{vi} - \chi)^2}{2\varsigma}\right), \quad (43)$$

$$P(e_{\eta j}) = \exp\left(-\frac{(e_{\eta j} - \chi)^2}{2\varsigma}\right), \quad (44)$$

where χ represents the value of the center point of the basis function, and ς represents the width parameter of the basis function.

To estimate the unknown disturbance, the RBFNN is used as follows:

$$\hat{d}_{vi} = \hat{N}_{vi}^T P(e_{vi}), \quad (45)$$

$$\hat{d}_{\eta j} = \hat{N}_{\eta j}^T P(e_{\eta j}), \quad (46)$$

where $\hat{d}_{vi}$ and $\hat{d}_{\eta j}$ are the estimations of d_{vi} and $d_{\eta j}$, and $\hat{N}_{vi}$ and $\hat{N}_{\eta j}$ are the estimations of N_{vi} and $N_{\eta j}$. The adaptive law of the output weight matrices are designed as follows:

$$\dot{\hat{N}}_{vi} = k_{i1}(e_{vi}P(e_{vi}) - k_{i2}\hat{N}_{vi}), \quad (47)$$

$$\dot{\hat{N}}_{\eta j} = k_{j1}(e_{\eta j}P(e_{\eta j}) - k_{j2}\hat{N}_{\eta j}), \quad (48)$$

where k_{i1} , k_{i2} , k_{j1} and k_{j2} are the controller parameters.

It can be observed from the equation mentioned above that NN do not require a system model for disturbance estimation. Only the tracking error is sufficient. However, a suitable basis function and some parameters, such as the width of the basis function, must be chosen and adjusted appropriately to achieve good estimation performance. Furthermore, NN can usually demonstrate their stability without strictly constraining the disturbances, which expands their range of applications. Moreover, different control methods might have different requirements for NN, and, thus, the design of NN must be changed based on specific control schemes and system characteristics.

4.2. Fuzzy Logic System

Fuzzy control is a method of dealing with complex systems based on fuzzy mathematics. In classical control theory, the performance of the control system is assumed to be better when the system model is more accurate. However, real systems often have complex nonlinearities and unknown parameters, making accurate modeling difficult. To overcome these challenges, researchers have turned to intelligent control methods, such as fuzzy control.

FLS are an important part of fuzzy control, which use fuzzy linguistic information to deal with system uncertainty and complexity. In adaptive FLS control methods, controllers can be adjusted in real time by adaptive laws to cope with system changes. Compared to traditional adaptive control methods, FLS are more flexible, using fuzzy instructions to enhance the adaptability and robustness of the control system. A number of quadrotor control works have used this control approach and superior results have been reported. Liu et al. [26] proposed an adaptive FLS based on a nonsingular fast terminal sliding mode controller for compensating block disturbances and adjusting the control gain in

real time. In [87], an adaptive fuzzy output feedback control method was proposed for a quadrotor with random perturbations. The method uses an FLS to approximate unknown nonlinear functions in the model. In addition, an observer with an FLS was designed for estimating the unmeasurable states through an adaptive backstepping technique. In [88], a novel fuzzy adaptive nonlinear fault-tolerant control design scheme was proposed for the attitude dynamics of a quadrotor with four sensor failures, in which an FLS was used to approximate the mismatched uncertainty and unknown nonlinear function vectors. In [89], an FLS was combined with adaptive backstepping control, which was used to observe mass variations and external disturbances. In [90], a combination of an FLS and adaptive integral terminal sliding mode controller was used to solve the trajectory tracking problem of quadrotors with actuator failure, external disturbances, and input saturation. In [91], an adaptive fuzzy output feedback control method was proposed for quadrotors with stochastic disturbance, which used an FLS to approximate unknown nonlinear functions and introduce a dynamic surface control technique and an adaptive backstepping observer that ensures that the system error converges in a small neighborhood of the origin.

The FLS consists of four basic parts: the fuzzification operator, fuzzy rule base, fuzzy inference, and defuzzification operator. The basic structure of the FLS is shown in Figure 9. Fuzzy rule bases are formed by "if-then" of the following form:

$$\begin{aligned} \text{Rules : If } x_1 \text{ is } \Psi_1^l, \text{ and } \dots \text{ and } x_n \text{ is } \Psi_n^l, \\ \text{then } y_1 \text{ is } \Phi^l, l = 1, \dots, N, \end{aligned}$$

where N is the number of rules, $x_i (i = 1, \dots, n)$ and y are inputs and outputs, respectively, and Ψ_i^l and Φ^l are the fuzzy set. From single point fuzzification, product inference and center average weighted defuzzification, the following FLS can be obtained:

$$y(x) = \frac{\sum_{l=1}^N \bar{y}_l \prod_{i=1}^n \mu_{\Psi_i^l}(x_i)}{\sum_{l=1}^N \left[\prod_{i=1}^n \mu_{\Psi_i^l}(x_i) \right]}, \quad (49)$$

where $\bar{y}_l = \max_{y \in R} \mu_{\Phi^l}(y)$, and $\mu_{\Psi_i^l}(x_i)$ and $\mu_{\Phi^l}(y)$ are the membership functions.

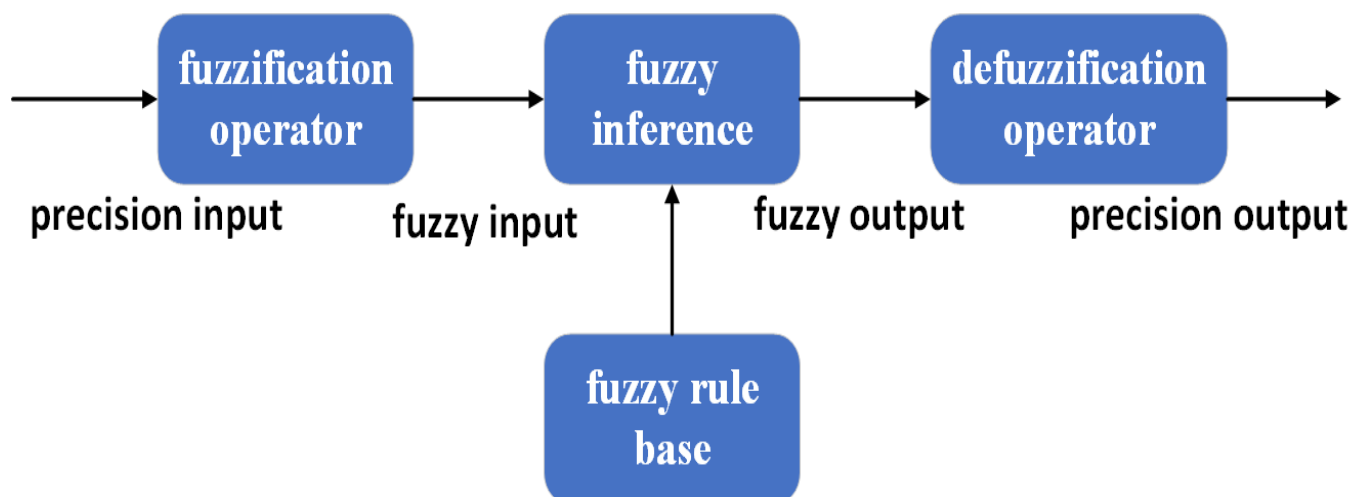


Figure 9. The basic structure of FLS.

We define the fuzzy basis function as

$$h_l(x) = \frac{\prod_{i=1}^n \mu_{\Psi_i^l}(x_i)}{\sum_{l=1}^N \left[\prod_{i=1}^n \mu_{\Psi_i^l}(x_i) \right]}, \quad (50)$$

We define $\vartheta = [\bar{y}_1, \dots, \bar{y}_N]^T = [\bar{\vartheta}_1, \dots, \bar{\vartheta}_N]^T$, and $h(x) = [h_1(x), \dots, h_N(x)]^T$, $x = [x_1, \dots, x_N]^T$; it can be obtained that

$$y(x) = \vartheta^T h(x). \quad (51)$$

According to [26], the disturbances can be expressed by FLS as

$$d_{vi} = \vartheta_{vi}^T h(e_{vi}) + \varepsilon_{vi}, \quad (52)$$

$$d_{\eta j} = \vartheta_{\eta j}^T h(e_{\eta j}) + \varepsilon_{\eta j}, \quad (53)$$

where $e_{vi} = v_i - v_{di}$ ($i = x, y, z$) and $e_{\eta j} = \eta_j - v_{dj}$ ($j = \varphi, \theta, \psi$) are the inputs of the FLS, ϑ_{vi} and $\vartheta_{\eta j}$ are the optimal output weight matrices, and ε_{vi} and $\varepsilon_{\eta j}$ are the approximation errors of the FLS, which are generally small. The unknown disturbance is estimated using the FLS as follows:

$$\hat{d}_{vi} = \hat{\vartheta}_{vi}^T h(e_{vi}), \quad (54)$$

$$\hat{d}_{\eta j} = \hat{\vartheta}_{\eta j}^T h(e_{\eta j}), \quad (55)$$

where $\hat{d}_{vi}$ and $\hat{d}_{\eta j}$ are the estimations of d_{vi} and $d_{\eta j}$, and $\hat{\vartheta}_{vi}$ and $\hat{\vartheta}_{\eta j}$ are the estimations of ϑ_{vi} and $\vartheta_{\eta j}$. The adaptive law of the output weight matrices is designed as follows:

$$\dot{\hat{\vartheta}}_{vi} = k_{i1}(e_{vi}h(e_{vi}) - k_{i2}\hat{\vartheta}_{vi}), \quad (56)$$

$$\dot{\hat{\vartheta}}_{\eta j} = k_{j1}(e_{\eta j}h(e_{\eta j}) - k_{j2}\hat{\vartheta}_{\eta j}), \quad (57)$$

where k_{i1} , k_{i2} , k_{j1} , and k_{j2} are the controller parameters.

Next, the estimation performance of the adaptive estimation, NN and FLS are simulated and compared, as shown in Figure 10, analyzed only for the roll angle channel. The external disturbance is modeled as a sinusoidal signal. The simulation results show that all three observers have smaller errors and are able to estimate the disturbance more accurately. Their advantages and disadvantages are summarized in Table 3.

Table 3. Adaptive control technology: advantages and disadvantages.

Estimation Methods	Advantage	Disadvantage
Adaptive estimation	Direct estimation of disturbances with a simple design and implementation process.	Performance degrades in complex or noisy environments, requiring further filtering or enhancements.
NN	Fast learning speed, no need for complex training process, usually by adjusting the weights online to adapt to changes. Good approximation ability and generalization ability, can effectively approximate nonlinear functions and perturbations.	Requires selection of appropriate radial basis functions and network structure, poor selection may affect performance. More sensitive to the choice of scale and center of the input data. Higher computational volume.
FLS	Can handle ambiguity and uncertainty in the system and is suitable for non-precise or fuzzy information processing. The rule base can be interpreted and adjusted with high interpretability and flexibility.	Designing the rule base and the affiliation function is more complex and requires a lot of experiments and adjustments. The amount of computation is large. Expert knowledge is needed to design effective fuzzy rules and affiliation functions.

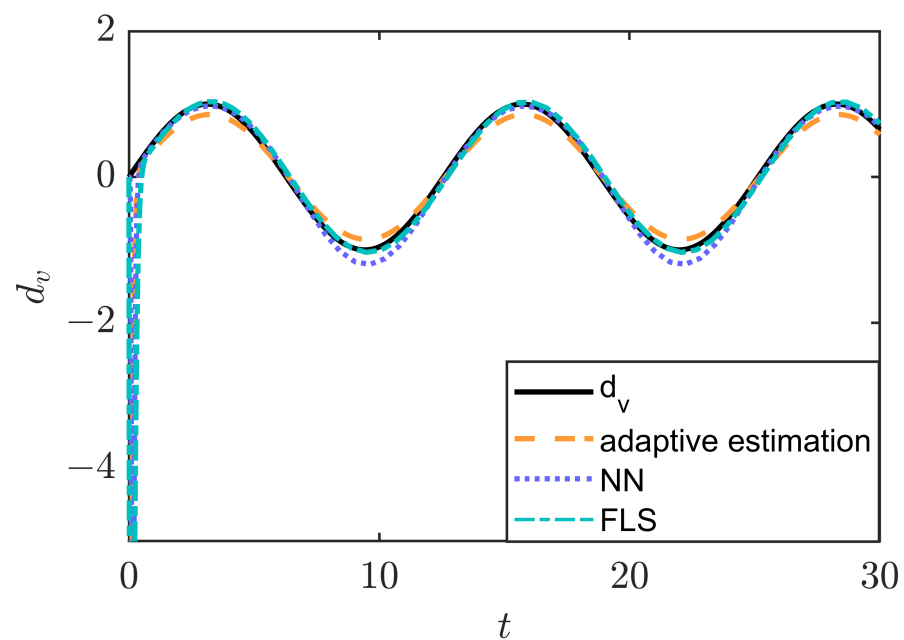


Figure 10. Estimation performance of adaptive control technology.

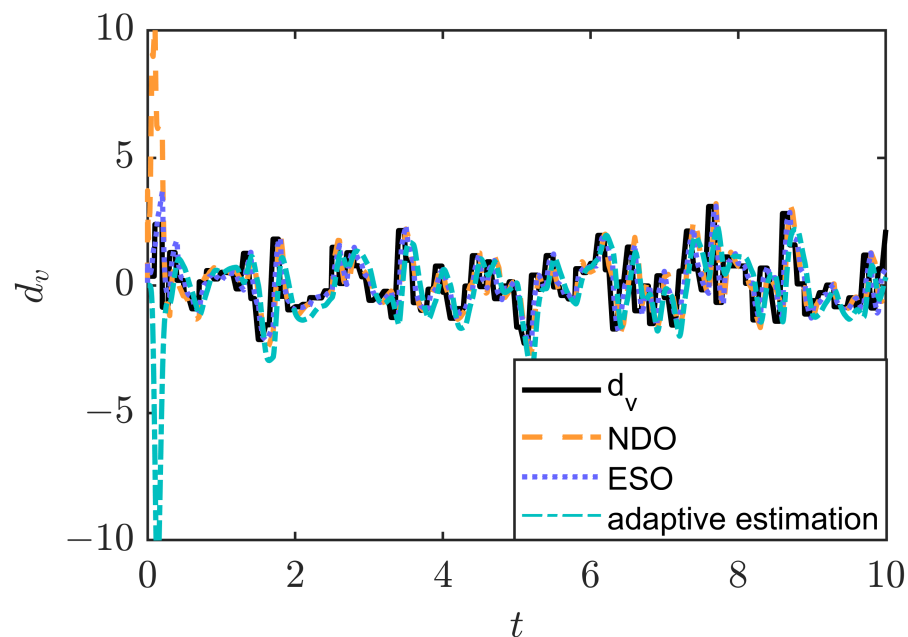
Both FLS and NN can estimate disturbances without relying on an accurate mathematical model of the system, instead using tracking errors directly. However, while FLS depend heavily on fuzzy sets and subordinate functions for describing and processing data, this approach may not be precise enough to handle highly precise or subtle variations. Moreover, the relatively high computational complexity of FLS may pose a challenge in resource-constrained application environments. Similarly, NN present similar challenges, especially when large amounts of data and complex network structures need to be processed. Therefore, the computational complexity and accuracy of these methods need to be considered in practical applications, as well as their applicability and efficiency in specific environments.

4.3. Simulation Comparison

In this subsection, the NDO, reduced-ESO, and adaptive estimation are selected as representatives of the three types of observers, and their estimation performances are compared through a simulation, as shown in Figure 11. To further validate the effectiveness of these observers, the external disturbances were modeled as irregular disturbances such as white noise. The simulation results show that the NDO and adaptive methods have more obvious overshooting phenomena during the estimation process, but the estimation performance of the NDO is better than that of adaptive methods, while the overall performance of the ESO is optimal. The NDO shows a strong ability in dealing with irregular disturbances, and its fast response characteristic makes the estimation error small despite the presence of certain overshoot. On the other hand, adaptive methods do not rely on mathematical models and are prone to large overshoots, leading to an unstable estimation in a short period of time. However, the ESO is able to better balance the response speed and stability due to its intrinsic structural design. Their respective advantages and disadvantages are shown in Table 4.

Table 4. Disturbance estimation methods: advantages and disadvantages.

Estimation Methods	Advantage	Disadvantage
NDO	Can effectively estimate various disturbances. Simple structure and easy to implement.	Requires accurate system model. The accuracy of model parameters is required to be high, and parameter errors may lead to degradation of estimation performance.
ESO	Can estimate external perturbations as well as the internal state of the system. Applicable to all types of systems and types of perturbations.	For higher-order systems, design and tuning of parameters may be more complex. Accurate system modeling is required.
Adaptive estimation	Adaptable to environmental changes and parameter variations, suitable for dynamically changing system environments. Does not require an accurate model of the system.	Algorithms are complex and require more computational resources. Disturbance estimation is imprecise and dependent on control parameters.

**Figure 11.** Estimation performance of the three types of observers.

5. Future Work

Disturbance observers such as NDO and ESO, and adaptive control techniques such as NN and FLS have shown great potential in observing disturbances and dealing with control problems. Although these techniques are very advanced in many aspects, there are still some aspects that need further improvement and development.

In high-speed dynamic systems, NDO and ESO may face the problem of insufficient response speed. To address this problem, it is possible to develop more efficient algorithms or advanced hardware implementations that can improve the observer response speed. In addition, it is crucial to enhance real-time performance, especially in systems with high safety requirements such as aerospace and self-driving cars.

Although NN and FLS can adapt to changing environmental conditions, they may not perform well when faced with complex and high-frequency disturbances. To improve their adaptability, better learning algorithms or online updating mechanisms are needed. At the same time, both NN and FLS are usually accompanied by high computational complexity, which can be a limiting factor, especially in resource-limited systems. Therefore, optimizing the structure of the algorithms or reducing the computational burden by using techniques such as edge computing and hardware acceleration are important ways to improve their practicality.

To improve the performance of the system, optimization algorithms can be studied and used to estimate and provide initial parameters. Additionally, new composite disturbance

estimation methods can be developed. This will make the control system more accurate and able to meet more requirements. Combining different technologies with complementary characteristics can significantly enhance the overall performance of the system.

6. Conclusions

This paper has focused on the application of disturbance observers and adaptive control techniques for disturbance rejection of quadrotors. This paper has provided a survey of the similarities and differences between these techniques, and their application to quadrotor control. Four main control methods were described: NDO, ESO, NN, and FLS, and their associated variants, which are classic NDO, finite-time NDO, and fixed-time NDO, reduced-order ESO, second-order ESO, and third-order ESO, and several forms of neural networks, including BPNN, RBFNN, and RNN. Finally, some guiding recommendations for future research were proposed to promote further development in related fields.

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