Research Article

Memory Augmented Neural Network-Based Intelligent Adaptive Fault Tolerant Control for a Class of Launch Vehicles Using Second-Order Disturbance Observer

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This paper focuses on the MANN-based intelligent adaptive fault tolerant control for a class of launch vehicles. Firstly, the attitude dynamic model of the launch vehicles suffering from the actuator faults and disturbances has been formulated. Secondly, the second-order disturbance observer has been designed for the launch vehicle to achieve the exact estimation and compensation of the time-varying disturbances. Meanwhile, the MANN has been introduced as online approximator, suppressing the adverse influence of the unknown nonlinearities. Moreover, several adaptive laws have been proposed to achieve the quick response to the actuator faults and the update of the MANN weights. As a result, the MANN-based intelligent adaptive fault tolerant control structure has been constructed for the launch vehicles. It has been proven that all the signals in the closed-loop system are bounded. Simulation results demonstrate the desired performance and the advantages of the proposed control algorithm.

1. Introduction

As an important medium for the development of aerospace technology, launch vehicles require high reliability and low risk. It is inevitable that the control systems of launch vehicles are subjected to the system faults on account of its complex structure and enormous components [1]. Therefore, the capability of fault tolerant in the control system of launch vehicle plays an important role in improving the reliability of aerospace missions [2].

Generally, the fault tolerant control (FTC) method can be categorized into passive fault tolerant control (PFTC) and active fault tolerant control (AFTC) [3]. In PFTC, a controller with fixed structure and parameters is proposed to compensate the anticipated faults, which render the closed-loop system insensitive to the unexpected breakdowns [4]. In [5], a robust tracking controller based on mixed LQ and multiobjective optimization is constructed to solve the problem of actuator failure and control surface impairment. Paper [6] has established an LQ state feedback controller using the algebraic Riccati equation for discrete-time systems with actuator failures, which maintained the reliability of the control system. Paper [7] presents a linear quadratic state feedback control strategy for linear descriptor systems under component faults to guarantee the stability and the desired control performance. Aiming at the actuator faults in a class of nonlinear uncertain systems, an adaptive PFTC method is put forward in [8]. In [9], a Lyapunov-based feedback PFTC method for nonlinear affine systems is proposed considering both additive and loss-of-effectiveness faults. For a class of overactuated nonlinear systems, a PFTC which can automatically distribute control efforts to offset the effect of actuator fault is proposed in [10]. In [11], a PFTC scheme based on nonlinear PID backstepping is proposed for a quadrotor unmanned aerial vehicle to ensure robustness to actuator faults and parameter changes. However, the lack of online feedback for fault information in the controller enables the robustness extremely limited. In
terms of AFTC, the impacts of faults are usually compensated either by selecting a precomputed control law or by reconfiguring a controller online [4]. It can cope with not only predetermined faults but also sudden faults. Apparently, this mechanism requires the system to detect and identify unknown faults in real time. In [12], the multiple model adaptive estimation (MMAE) method has been introduced to detect and compensate for sensor and actuator failures in the design of the flight control system. Considering disturbances and partial actuator failures in flexible spacecraft, paper [13] presents a robust fault tolerant control scheme using LMI technique. To achieve attitude control objective, a robust reconfigured controller is designed for a satellite launch vehicle under disturbances in [14]. In [15], an adaptive fault tolerant controller is developed for some particular actuator faults in a class of reusable launch. In [16], a robust adaptive nonlinear fault tolerant control method with norm estimation to deal with actuator fault is proposed. Directing at actuator loss-of-effectiveness fault in hypersonic flight vehicle, an adaptive AFTC strategy based on fault observer and backstepping method is sketched in [17]. In [18], a sliding mode fault tolerant controller based on high-order observer and differentiator is designed to achieve attitude tracking control for reusable launch vehicle. Paper [19] proposes a novel sliding mode-based fault tolerant control scheme for reusable launch vehicle under actuator fault, unknown uncertainty, external disturbances, and input limitation simultaneously. In [20], a model predictive fault tolerant controller against actuator faults is proposed for networked control systems. In [21], a discrete-time fault tolerant control system actuated by a state feedback controller in noisy environment is successfully developed. To tolerate the limited faults for launch vehicles, a neural network fault tolerant control method with high accuracy is proposed in [22]. In [23], a stochastic nonlinear AFTC approach is introduced to realize the insensitiveness to system component failures. So far, AFTC has been widely used in the flight control system as it has stronger robustness to various faults compared with PFTC [4].

With the development of control theory, more and more control methods are applied to the design of the launch vehicle control system. In [24], an adaptive augmented controller based on the PID and augmented control is designed with the performance of antidisturbance and load-reliance. Paper [25] proposes a PID-based adaptive augmented fault tolerant controller to realize online controller reconstruction with the pseudo-inverse method for the heavy lift launch vehicle control system. In [26], a Lyapunov-based model reference adaptive PD and PID controllers to cope with time-varying characteristics in satellite launch vehicle (SLV) systems are proposed. To improve robustness and achieve stability in extreme failure situations, a classical adaptive augmentation controller is designed for launch vehicle in [27]. Paper [28] has developed an adaptive controller based on gain scheduling and model reference filter approach for flexible launch vehicles which is simpler and faster than other methods. In [29], a robust adaptive backstepping control method is proposed to realize the desired attitude tracking in the presence of unknown disturbances and uncertainties. In [30], a nonlinear robust adaptive controller augmented by barrier Lyapunov function is constructed to assure robust tracking of the guidance commands for launch vehicles. Paper [31] explores a neural network (NN)-based adaptive control method with stable online weight-tuning algorithms to conquer the disturbances and uncertainties in flight systems. To improve the robustness and accuracy of the flight control systems for launch vehicle, paper [32] proposes higher order sliding mode (HOSM) control scheme driven by sliding mode disturbance observer (SMDO). Paper [33] has developed a dynamic integral sliding mode control scheme aiming at various perturbations and uncertainties during the flight process. In [34], an integral sliding mode controller based on extended states observer (ESO) is structured to compensate uncertainties and disturbances in the flight process. For a vertical take-off and vertical landing (VTOL) reusable launch vehicle, a nonsingular fast terminal sliding mode control strategy is illustrated in [35]. In [36], a second-order sliding mode controller based on nonlinear disturbance observer is constructed which enhances the robustness of launch vehicles. Paper [37] develops an adaptive-gain multivariable super-twisting sliding mode controller with the unknown bounds of uncertainty and perturbation for reusable launch vehicle. The problem of attitude control is settled by combining sliding mode control and adaptive method in [38]. In [39], a novel active disturbance rejection controller of attitude is designed to attenuate effect of parameter variation and disturbances of launch vehicle. Paper [40] presents a robust active disturbance rejection control approach driven by linear extended state observer so that the launch vehicle system is well decoupled and quite robust. An active disturbance rejection-based trajectory linearization control approach is proposed in [41] to guarantee the ability of anti-interference and low-energy consumption. In [42], a new robust disturbance rejection controller scheme using dynamic inversion technique and extended state observer is designed for launch vehicle attitude control.

Most recently, fruitful results have been obtained in the area of intelligent algorithms and can be utilized to address the complex control problem or improve the control performance [43–45]. The MANN is a class of intelligent systems that possess the storage modular and the read/write mechanisms. The conventional neural networks usually neglect the logical flow control or the external memory and cannot obtain the memory ability by utilizing the trainable parameters [46]. The MANN can mimic the memory mechanisms of the human brain, increasing or decreasing the number of neurons to improve the approximation ability [47]. By properly introducing the MANN in the control design of the launch vehicles, the robustness with respect to the unmodeled dynamics or the system nonlinearities can be improved [48, 49]. However, to the best of our knowledge, the MANN-based control law of the launch vehicle control system has never been reported. Furthermore, the issue of applying the MANN to the adaptive fault tolerant control design of the launch vehicle has never been investigated yet [50].
Therefore, in this paper, we investigate the MANN-based intelligent adaptive fault tolerant control for a class of launch vehicles. Firstly, the attitude dynamic model of the launch vehicles subjected to the actuator faults has been formulated. Secondly, to handle the time-varying disturbances, the second-order disturbance observer has been designed for the launch vehicle. In order to suppress the influence of the unknown nonlinearities, the MANN has been introduced as an online approximator. Moreover, several adaptive laws have been proposed to achieve the quick response to the actuator faults and the update of the MANN weights. Finally, a novel MANN-based intelligent control structure has been established for the launch vehicles. Compared with the existing work, the proposed control algorithm possesses the following advantages:

(i) By using the SODO and the MANN, the established control method can solve the tracking control problem of the launch vehicles suffering from time-varying actuator faults and disturbances

(ii) As far as the authors know, it is also the first attempt to apply the MANN to the control design of the nonlinear systems, providing a canonical form for the MANN-based intelligent control

(iii) By using the proposed method, the boundaries of the disturbances and actuator faults are not required to be known in advance

2. Problem Formulation

2.1. The Attitude Dynamic Model of the Launch Vehicle with Actuator Faults. According to [1], by ignoring the elastic vibration, the long period centroid motion, and the shaking of liquid propellant, the small perturbation equation of the attitude dynamic model of the launch vehicle can be formulated by

\[
\begin{align*}
\dot{\phi} + b_1^\phi \dot{\phi} + \Delta \Delta \dot{\phi} + b_3^\phi \phi + b_4^\phi \phi + b_5^\phi \delta = \mathbf{M}_{B_2} - b_2^\phi \alpha_\omega, \\
\dot{\psi} + b_1^\psi \psi + \Delta \dot{\psi} + b_3^\psi \psi + b_4^\psi \psi + b_5^\psi \delta = \mathbf{M}_{B_3} - b_2^\psi \beta_\omega, \\
\dot{\gamma} + d_1^\gamma \dot{\gamma} + \Delta d_1^\gamma \dot{\gamma} + d_2^\gamma \delta = \mathbf{M}_{B_4},
\end{align*}
\]

(1)

where \(\phi, \psi, \gamma\) are the pitch, yaw, and roll angle, respectively; \(\alpha_\omega\) and \(\beta_\omega\) are the angle of attack and angle of sideslip caused by the unknown winds; \(b_1^\phi, b_2^\phi, b_3^\phi, b_4^\phi, b_5^\phi\), and \(d_1^\phi\) are the dynamic derivatives, whose physical meanings can be found in [2]; \(\Delta \Delta \dot{\phi}, \Delta \dot{\psi}, \Delta \dot{\psi}, \Delta \dot{\psi}, \) and \(\Delta d_1^\gamma\) represent the uncertainties existing in \(b_1^\phi, b_2^\phi, b_3^\phi, b_4^\phi, b_5^\phi,\) and \(d_1^\phi\), respectively; \(\mathbf{M}_{B_2}, \mathbf{M}_{B_3},\) and \(\mathbf{M}_{B_4}\) represent the structural disturbance torques; and \(\delta, \delta_\phi, \delta_\psi,\) and \(\delta_\gamma\) denote the three-channel equivalent swing angle of the core engine, respectively.

In this paper, the “+” type configuration of the rocket engines is considered, as shown Figure 1. Obviously, the cone engines complete the cross swing, and the swing angles are defined by \(\delta_{C_{1}}, \delta_{C_{2}}, \delta_{C_{3}},\) and \(\delta_{C_{4}}\). Moreover, four booster engines complete tangential swing, and the swing angles are defined as \(\delta_{Z_{1}}, \delta_{Z_{2}}, \delta_{Z_{3}},\) and \(\delta_{Z_{4}}\). The relationship between the channel swing angles and the actual swing angles can be formulated by \(\delta_{C_{i}}(t) = N(t)\delta_{i}(t)\) where \(\delta_{C_{i}}(t) = [\delta_{C_{1}, i}^{\phi}, \delta_{C_{2}, i}^{\psi}, \delta_{C_{3}, i}^{\psi}, \delta_{C_{4}, i}^{\psi}]^{T}\) denotes the three-channel equivalent swing angle of the core engine, \(\delta_{i}(t) = [\delta_{Z_{1}, i}, \delta_{Z_{2}, i}, \delta_{Z_{3}, i}, \delta_{Z_{4}, i}]^{T}\) denotes the actual swing angle of the servo mechanism, and \(N(t) \in \mathbb{R}^{3 \times 8}\) is the time varying control distribution matrix. Define \(B(t) = \text{Diag}[-b_3^{\phi}(t), -b_3^{\psi}(t), -d_1^{\gamma}(t)]\). In practical, the thrusters of the launch vehicle may encounter the undesired faults and loss their effectiveness. In this situation, it can be known that

\[
N(t) = N_{0}(t)[\Lambda + \Delta \Lambda],
\]

(2)

where \(N_{0}(t) \in \mathbb{R}^{3 \times 8}\), \(\Lambda\) is the desired effectiveness matrix, and \(\Delta \Lambda\) is the uncertainties existing in \(\Lambda\).

By defining \(\xi_{1}(t) = [\phi(t), \psi(t), \gamma(t)]^{T}\) and \(\xi_{2}(t) = [\phi(t), \psi(t), \gamma(t)]^{T}\), then from (1) we can get that

\[
\begin{align*}
\dot{\xi}_{1}(t) &= \xi_{2}(t), \\
\dot{\xi}_{2}(t) &= f(\xi_{1}(t), \xi_{2}(t)) + \Delta f(\xi_{1}(t), \xi_{2}(t)) + B(t)N_{0}(t)[\Lambda + \Delta \Lambda]\delta(t) + d_{1} + d_{2}(t),
\end{align*}
\]

(3)

where

\[
\begin{align*}
f(\xi_{1}(t), \xi_{2}(t)) &= \left[-b_3^{\phi}(t) - b_3^{\psi}(t) - d_1^{\gamma}(t)\right]^{T}, \\
\Delta f(\xi_{1}(t), \xi_{2}(t)) &= \left[-\Delta b_3^{\phi}, -\Delta b_3^{\psi}, -\Delta d_1^{\gamma}\right]^{T}, \\
d_{1} &= \left[b_2^{\phi}, b_2^{\psi}, b_2^{\psi}, 0\right]^{T}, \\
d_{2}(t) &= \left[b_2^{\phi}(t), b_2^{\psi}(t), 0, 0\right]^{T}.
\end{align*}
\]

(4)

Note that \(\alpha_\omega\) and \(\beta_\omega\) often possess high-dynamic behavior, and the corresponding disturbances are regarded as time-varying disturbances.
The control objective is to develop a dynamic controller such that desired signal $\xi(t) = [\varphi(x(t)), \psi(x(t)), \gamma(x(t))]^T$ can be tracked by the output of system (1) in the presence of the thrust loss of the launch vehicle and the time-varying and unvarying uncertainties.

In this paper, we make the following assumptions.

**Assumption 1.** The disturbance torques induced by the structural uncertainties are bounded, i.e., there exists a constant $\overline{d}_1$ such that $\|d_1\| \leq \overline{d}_1$. The disturbance torques caused by $\alpha_w$ and $\beta_w$ are first-order time varying, which means that $d_2(t) = 0$.

**Assumption 2.** In the vicinity of the equilibrium, the uncertain part of $\Lambda$ remains unchanged and cannot change the positive or negative characteristics of $\Lambda$, respectively. In other words, it is assumed that $M = M^T, \lambda_{\min}(M) > 0$, where $M = [\Lambda + \Delta \Lambda]/\Lambda$.

### 2.2. Memory Augmented Neural Networks (MANNs).

Memory augmented neural network (MANN) is a kind of width learning neural network with memory augmented cell, possessing the advantages of high efficiency, adjustable, and strong practicality, as shown in Figure 2. Generally speaking, MANN can be divided into two parts: the neural network computing part and the memory augmented (MA) cell. Firstly, the input signal enters the embedding layer, and the embedding layer calculates and outputs the prediction results. Secondly, the error feedback signal is obtained and sent to the MA cell to perform multiple judgments, including choosing which neural network to extend the neurons and the final prediction result can be obtained. The structure diagram of the MANN is provided in Figure 2. In this paper, the MANN is utilized to achieve the approximation for the unknown nonlinearities.

The output of the MANN can be described by

$$O(x_1, x_2, \ldots, x_n) = W^T \Phi_i(x_i),$$

where $x \in \mathbb{R}^n$ and $O \in \mathbb{R}^n$ are the MANN’s input and output. $W^T \in \mathbb{R}^{n\times n}$ is the weight matrix, and $\Phi(x) \in \mathbb{R}^{n\times n}$ is the basis function which is chosen as the Gaussian function.

$$\Phi_i(x_i) = \exp \left( -\frac{(x_i - \mu_i)^T(x_i - \mu_i)}{\sigma_i} \right),$$

where $\sigma_i$ is the width of the Gaussian function and $\mu_i \in \mathbb{R}^n$ are the center shops. It is known that for an arbitrary real continuous function $f(x)$ on a compact set $\Omega \subseteq \mathbb{R}^n$, there exist the following MANN and optimal parameter vectors $W_i$ such that

$$f(x_1, x_2, \ldots, x_n) = W^T \Phi(x) + \epsilon_f,$$

where $\epsilon_f$ is the reconstruction error, satisfying that $\|\epsilon_f\| \leq \|\epsilon_f\|, \|\epsilon_f\| > 0$ is the supremum of reconstruction error.

### 3. Main Results

#### 3.1. MANN-Based Adaptive Fault Tolerant Control Law Design.

The structure of the proposed MANN-based adaptive fault tolerant control law is given in Figure 3. In the inner loop, a virtual control law has to be designed to force the attitude angular tracking error to converge to zero. To force the angular velocity error to track the virtual control input of the inner loop, the outer loop control law is designed. Because of the disturbances and the actuator failure of the launch vehicle, the second-order disturbance observer is designed in the outer loop. The MANN is utilized to approximate and suppress the adverse effects of the unknown nonlinear part.

In view of the dynamic equation,

$$\dot{\xi}_1(t) = \xi_2(t),$$

$$\dot{\xi}_2(t) = f(\xi_1(t), \xi_2(t)) + \Delta f(\xi_1(t), \xi_2(t)) + B(t)N_\theta(t)[\Lambda + \Delta \Lambda \delta(t)] + d_1 + d_2(t).$$

The tracking error is defined as

$$z_1(t) = \xi_1(t) - \xi_d(t),$$

$$z_2(t) = \xi_2(t) - \xi_{2c}(t),$$

where $\xi_d(t)$ is the desired signal and $\xi_{2c}(t)$ is the virtual controller.

To achieve the control of the inner loop, the virtual controller $\xi_{2c}$ can be designed as follows:

$$\xi_{2c}(t) = -K_1z_1(t) + \dot{\xi}_d(t),$$

where $K_1 > 0$ is a design matrix.

Because of the unavailability of $\Delta f(\xi_1(t), \xi_2(t))$, we have to eliminate its influence by using MANN. Hence, we can get that

$$\Delta f(\xi_1(t), \xi_2(t)) = W^T \Phi(\xi) + \epsilon_{\Delta f},$$

For the updating law of the weight matrix of MANN, the adaptive law is designed as

$$\dot{W} = \eta_w \left[ \Phi(\xi)z_1^T(t) - \sigma_w \dot{W} \right],$$

where $\eta_w$ is the gain of MANN and $\sigma_w$ is the designed constant.

For unknown constant disturbance $d_1$, define $\tilde{d}_1$ as the estimated value. The following adaptive law is designed to suppress the adverse effect caused by $d_1$:

$$\dot{\tilde{d}}_1(t) = \eta_d \left[ z_2(t) - \sigma_d \tilde{d}_1(t) \right],$$

where $\eta_d$ is the adaptive gain and $\sigma_d$ is a designed constant which represents the damping factor $\|	ilde{M}(t)\|$.
To obtain the estimated value of time-varying disturbance $d_2(t)$, the following second-order disturbance observer is utilized:

$$\hat{d}_2(t) = p_1(t) + L_1 \xi_2,$$

$$\dot{p}_1(t) = -L_1 \left[ f + \tilde{W}^T \Phi(\xi) + BN_0 \delta(t) + \hat{d}_1 + \hat{d}_2(t) \right] + \hat{d}_2(t),$$

$$\hat{d}_2(t) = p_2(t) + L_2 \xi_2,$$

$$\dot{p}_2(t) = -L_2 \left[ f + \tilde{W}^T \Phi(\xi) + BN_0 \delta(t) + \hat{d}_1 + \hat{d}_2(t) \right],$$

(14)

where $\hat{d}_1(t)$ and $\hat{d}_2(t)$ are the estimated values of $\bar{d}_1(t)$ and $\bar{d}_2(t)$, $p_1(t)$ and $p_2(t)$ are the auxiliary variables, and $L_1$ and $L_2$ are the gain of the SODO.

With regard to input uncertainty $\Delta \Lambda$, the input is divided into two parts as follows:

$$\delta(t) = \delta_C(t) + \delta_A(t),$$

(15)

where $\delta_C(t)$ is the indirect input of the system and $\delta_A(t)$ is the compensation input to deal with the input uncertainty.

To ensure system stability, the indirect controller $\delta_C(t)$ can be designed as
where $K_2 > 0$ is a design matrix.

To overcome input uncertainty, the compensation input is designed as
\[
\delta_A(t) = -\hat{M}\delta_c(t),
\]
where $\hat{M}$ the estimated value of $M$, $M = \Delta\Lambda/[A + \Delta\Lambda]$, and we use adaptive method to approximate
\[
\hat{M} = \eta_M [N_2^TB^Tz_2(t)\delta_c(t) - \sigma_M\hat{M}],
\]
where $\eta_M$ is the gain of the adaptive law and $\sigma_M$ is a designed constant.

3.2. The Adjustment Strategy of the MANN. In this paper, we propose the adjustment strategy of the MANN. The adjustment strategy includes two parts: the first part is used to determine the sub-NN which should change the nodes and the second part is utilized to determine that the sub-NN should increase or decrease its nodes.

Part 1. The following index is defined to judge the contribution of the sub-NN for the fitting effect:
\[
E_{1i} = \frac{\|W_i\|_2/N_i}{\sum_{i=1}^N\|W_i\|_2/N_i},
\]
where $N_i$ represents the number of nodes of the $i$th sub-NN. A larger $E_{1i}$ indicates that this sub-NN has a larger contribution and will be given priority when increasing the number of nodes, while a smaller $E_{1i}$ indicates that this sub-NN has a small contribution and will be reduced first when the number of nodes is reduced.

Part 2. The following index is introduced which is obtained by integrating the error within a time span:
\[
E_{II} = \int_{t_i}^{t_i + \Delta t} |z_i(t)|\,dt, \quad i = 1, 2, \ldots,
\]
where $t_i$ represents the start time of the $i$th sampling and $\Delta t$ represents the time length of the sampling. By comparing the size of $E_1$ and the set constants $E_{in}$ and $E_{d}$, we can judge the increase or decrease in the number of nodes. In detail, if $E_1 > E_{in}$, the error is too large and does not reach the predetermined value, and the nodes should be added to ensure the fitting effect; if $E_1 < E_{d}$, the error satisfies the requirement and the nodes can be reduced to save the calculation resource. Moreover, it should be pointed out that when adding nodes, the number of nodes is increased by reducing the distance between nodes and then increasing node density. To reduce nodes, first reduce and remove nodes on both sides.

3.3. Stability Analysis

Theorem 1. Considering system (8), suppose that Assumptions 1 and 2 are satisfied. If the control law is designed as (10), (16), and (17), the adaptive laws are designed as (18), (13), and (12), then the closed-loop control system in the existence of disturbances $d_1$ and $d_2(t)$ is stable, and all the signals are bounded.

Proof. The disturbance estimation error of the SODO is defined as follows:
\[
\hat{d}_1(t) = \tilde{d}_1(t) - d_1(t),
\]
\[
\hat{d}_2(t) = \tilde{d}_2(t) - d_2(t).
\]

Hence, we can calculate that
\[
\dot{\hat{d}}_1(t) = -Ld_1\tilde{d}_1(t) - Ld_1\tilde{d}_1(t) + d_1(t) = -Ld_1\tilde{d}_1(t) + d_1(t),
\]
\[
\dot{\hat{d}}_2(t) = -Ld_2\tilde{d}_2(t) - Ld_2\tilde{d}_2(t) + d_2(t) = -Ld_2\tilde{d}_2(t) + d_2(t),
\]
where $\tilde{w} = \hat{w} - \hat{w}$. Define $M = \hat{M} - M$ and $\Delta = \tilde{d}_1 - \hat{d}_1$. From the definition of the tracking error, we can get the following equations:
\[
\dot{\hat{z}}_1(t) = -K_1z_1(t) + z_2(t),
\]
\[
\dot{\hat{z}}_2(t) = -K_2z_2(t) + z_1(t) - \hat{w}^T\Phi(\xi) - \hat{d}_1 - \tilde{d}_2(t) - BN_0(\Delta\Lambda + \Lambda)\hat{M}\delta_c(t).
\]

Consider the Lyapunov function as
\[
V = \frac{1}{2}\eta_\hat{M}^T\hat{M} + \frac{1}{2}\eta_\hat{d}_1^T\hat{d}_1(t) + \frac{1}{2}\eta_\hat{w}^T\hat{w}^T
\]
\[
= \frac{1}{2}\eta_\hat{M}^T\hat{M} + \frac{1}{2}\eta_\hat{d}_1^T\hat{d}_1(t) + \frac{1}{2}\eta_\hat{w}^T\hat{w}^T.
\]

The derivative of $V$ can be given by
\[
\dot{V} = -K_1\hat{z}_1^T(t)z_1(t) - K_2\hat{z}_2^T(t)z_2(t) - \hat{z}_2^T(t)\hat{w}^T\Phi(\xi) - \hat{w}^T(\Delta\Lambda + \Lambda)\hat{M}\delta_c(t)
\]
\[
- \hat{z}_2^T(t)\tilde{d}_1 - \hat{z}_2^T(t)\tilde{d}_2(t) + \hat{z}_2^T(t)BN_0(\Delta\Lambda + \Lambda)\hat{M}\delta_c(t)
\]
\[
+ \hat{z}_2^T(t)\tilde{d}_2(t) + \hat{z}_2^T(t)\tilde{d}_2(t) + \hat{z}_2^T(t)\tilde{d}_2(t) + \hat{z}_2^T(t)\tilde{d}_2(t)
\]
\[
+ \frac{1}{2}\eta_\hat{M}^T\hat{M} + \frac{1}{2}\eta_\hat{d}_1^T\hat{d}_1(t) + \frac{1}{2}\eta_\hat{w}^T\hat{w}^T.
\]

Further, computation shows that
\[
\dot{V} = -K_1\hat{z}_1^T(t)z_1(t) - K_2\hat{z}_2^T(t)z_2(t) - \hat{z}_2^T(t)\hat{w}^T\Phi(\xi) - \hat{w}^T(\Delta\Lambda + \Lambda)\hat{M}\delta_c(t)
\]
where

\[ \mathcal{L} = \sup_{\delta \in \mathbb{R}} \| \Phi(\xi) \|, \quad \bar{\epsilon}_{\delta} = \sup_{\delta \in \mathbb{R}} \| \Delta \Lambda \delta(t) \|, \quad \text{and} \quad \mathcal{L}_1 = L_1 B(t) N_0(t) N_0^T(t) B^T(t) L_1^T. \]
By using Young’s inequalities again, it can be obtained that
\[ -z_2^T(t)\dot{\bar{d}}_2(t) \leq \rho_2 z_2^T(t)z_2(t) + \frac{1}{4\rho_2} \bar{d}_2^T(t)\bar{d}_2(t). \]  
(30)

Combining (25), (29), and (30) generates that
\[ \dot{V} \leq -K_1 z_1^T(t)z_1(t) - [K_2 - \rho_2] z_2^T(t)z_2(t) \]
\[ - \left[ L_1 - \sum_{i=0}^{\infty} \rho_i - \rho_3\lambda_{\text{max}}(\mathbb{T}_i) - \frac{1}{4\rho_2} \right] \bar{d}_2^T(t)\bar{d}_2(t) \]
\[ - \frac{\eta_0}{2} z_2^T(t)BN_0(\Delta\Lambda + \Lambda)\bar{M}_C(t) \]
\[ + \frac{1}{\eta_d} z_1^T(t)\bar{d}_1(t) + \frac{\lambda_{\text{max}}[L_1^T L_1]}{4\rho_2} \bar{d}_1^T(t)\bar{d}_1(t) \]
\[ + \frac{1}{\eta_v} \bar{W}^T\bar{W} + \left[ \frac{\lambda_{\text{max}}[L_1^T L_1]}{4\rho_2} + \frac{\lambda_{\text{max}}[L_2^T L_2]}{4\rho_4} \right] \Delta_l \bar{W}^T \bar{W} \]
\[ + \left[ \frac{1}{4\rho_3} + \frac{1}{4\rho_5} \right] \bar{\varepsilon}_f. \]
\[ \text{we can rewrite (31) as} \]
\[ \dot{V} \leq -K_1 z_1^T(t)z_1(t) - [K_2 - \rho_2] z_2^T(t)z_2(t) \]
\[ - \left[ L_1 - \sum_{i=0}^{\infty} \rho_i - \rho_3\lambda_{\text{max}}(\mathbb{T}_i) - \frac{1}{4\rho_2} \right] \bar{d}_2^T(t)\bar{d}_2(t) \]
\[ - \frac{\sigma_M}{2} \bar{M}^T(\Delta\Lambda + \Lambda)\bar{M} \]
\[ + \frac{\sigma_d}{2} \bar{d}_1^T(t)\bar{d}_1(t) + \frac{\sigma_d}{2} \bar{d}_1^T(t) \]
\[ + \frac{\sigma_v}{2} \bar{W}^T\bar{W} + \left[ \frac{1}{4\rho_3} + \frac{1}{4\rho_5} \right] \bar{\varepsilon}_f. \]
\[ \text{By defining} \]
\[ \dot{\hat{M}} = \eta_M [N_0^TB \hat{z}_2(t) - \sigma_0 M \bar{M}], \]
\[ \dot{\hat{d}}_1(t) = \eta_d [z_2(t) - \sigma_0 \hat{d}_1(t)], \]
\[ \dot{\bar{W}} = \eta_v [\Phi(\xi)z_2^T(t) - \sigma_0 \bar{W}], \]
\[ \text{we know that for any time,} \]
\[ \dot{V} \leq -2IV + \bar{\varepsilon}_f. \]
\[ \text{Further, derivations yield that} \forall t \geq 0, \]
\[ \dot{V} \leq -2IV + \bar{\varepsilon}_f. \]

Therefore, from (36), it can be concluded that the system states \( z_1(t) \) and \( z_2(t) \), the disturbance estimation errors of the SODO \( \bar{d}_2(t) \) and \( \hat{d}_1(t) \), and the adaptive estimation errors \( \bar{M}(t), \bar{W}(t), \) and \( \hat{d}_1(t) \) are all stable and bounded.
Furthermore, it can be easily known that \(\xi_1(t), \xi_2(t), \ddot{\alpha}_2(t), \ddot{\beta}_2(t), \ddot{\gamma}(t), \ddot{W}(t), \) and \(\ddot{\delta}_1(t)\) are also bounded. Therefore, the stability of the closed-loop system and the boundness of all the signals can be verified. The proof is complete.

\[\square\]

4. Simulation Study

In order to evaluate the effectiveness and performance of the neural network-based adaptive fault tolerant control (NN-AFTC) law, a simulation experiment was conducted based on the mathematical model described by (8). It is assumed that the launch vehicle rises at a fixed attitude angle in the air. Moreover, the disturbance observer-based NN (DOBNN) control law and the neural network-based adaptive controller are introduced into the simulation to show the distinctions of the control performance.

In the simulation, the constant and changing disturbances are set as

\[
d_1 = [0.4, 0.75, 0.6]^T,
\]

\[
d_2(t) = \begin{cases} 
[3, 2, 5]^T, & 0 \leq t \leq 5, \\
[-3, -2, -5]^T, & 5 < t \leq 10.
\end{cases}
\]

The unknown nonlinearities are \(\Delta f = [-b_1\omega_x - b_2\omega_y, -b_3\omega_x - b_4\omega_y, -b_5\omega_z, b_6, b_7, b_8, b_9]\), where \(b_1, b_2, b_3, b_4, b_5\) are unknown parameters. For the proposed method, the control gain matrices are selected as \(K_1 = [1.6, 1.4, 1.5]\) and \(K_2 = [5, 3.8, 4.5]\) and the adaptive parameters are selected as \(\eta_d = 20, \eta_M = 3, \) and \(\sigma_d = 3, \sigma_M = 10, \) and \(\sigma_W = 3.\) The node number of the neural network is 9, and the approximating area is \([-4, 4]\).

The simulation results are shown in Figures 4–9. Obviously, under the actuator faults and constant or changing external disturbances, the proposed control method can achieve satisfactory results. The tracking errors can converge into a desired value, and all of the signals of the closed-loop control system are bounded during the whole tracking process. However, the DOBNN controller may induce undesired fluctuation, and the NNAC method may generate unacceptable tracking errors. Therefore, it can be concluded that the proposed method can guarantee control performance under the disturbances and actuator faults and can possess advantages with respect to the other two control laws.
Figure 7: The estimation performance of the changing disturbances by using the proposed controller.

Figure 8: The adaptive estimation performance of the constant disturbance by using the proposed controller.

Figure 9: The weight of the neural networks and the adaptive parameter matrices $\tilde{M}(t)$. 
5. Conclusions

This paper proposed a novel MANN-based intelligent adaptive fault tolerant control for a class of launch vehicles. The second-order disturbance observer has been introduced to exactly estimate and compensate the time-varying disturbances, the MANN has been introduced to suppress the adverse influence of the unknown nonlinearities, and several adaptive laws have been proposed to quickly handle the actuator faults. The closed-loop stability analysis has been completed, and all the signals are ensured to be bounded. Simulation results show that by using the proposed control algorithm, the tracking errors can converge into a desired value, while the DOBNN controller may induce undesired fluctuation and the NNAC method may generate unacceptable tracking errors. In the future, the MANN-based stochastic adaptive control for the launch vehicles will be considered.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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