Research Article

Further Results on Stability Analysis for Uncertain Delayed Neural Networks with Reliable Memory Feedback Control

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This study proposes further results for the stability analysis issue of uncertain delayed neural networks (UDNNs) via the reliable memory feedback control scheme. First, an improved quadratic function method is introduced for constructing a novel term $V_1(x(t))$, which can fully excavate some intrinsic relationships between the delay derivative information and time-delay information. Based on the time-delay-product function (TDPF) and linear convex combination method (LCCM), the information storage is further improved for obtaining new theoretical results. Second, by using resultful integral inequalities and correlation analysis approaches, several relaxed criteria are established with respect to the asymptotical stability of the considered UDNNs. Third, the desired reliable memory feedback controller (RMFC) is achieved, which can ensure the system stability of UDNNs. Lastly, two numerical experiments are given to illustrate the significance of the theoretical results.

1. Introduction

As we all know, because the structure of the NN model is similar to the synapse structure of the human brain, it can be described by a variety of differential equations [1–7]. The wide application of NNs in various fields has received widespread attention, such as signal processing [8], fault diagnosis [9], optimization problem solving [10], pattern recognition [11], image processing [12], and other fields [13–16]. However, artificial NNs always need to be maintained in practical engineering applications, so the stability of NNs has also been extensively studied by scholars at home and abroad [15, 17–19]. In the engineering application of NNs, the signal transmission between synapses has a time delay, and this delay may lead to instability of the NNs, increased oscillation, or performance degradation [20–22]. Therefore, the stability research of time-varying neural networks (DNNs) has also received extensive attention [23–26]. Compared with NNs, the latter requires more

technical means and engineering requirements to maintain stability in technical analysis [27–29]. Therefore, the research on DNNs is obviously more important.

Thus, in order to effectively solve this problem, Lyapunov–Krasovskii functional (LKF) method is proposed [18, 30–33]. So far, many researchers have made a lot of contributions of how to establish a suitable LKF in order to better study the delayed systems [13, 34–37]. In [30], the authors proposed a novel LKF, which contains a common double-integral term, an augmented double-integral term, and two delay-product-type terms, was constructed to analyze the exponential stability. In [31, 32], the reciprocally convex matrix inequality was an important technique to develop stability criteria for the systems with a time-varying delay which was studied. In [18, 33, 35], based on some effective integral inequalities, the integral term in LKF was reasonably scaled. In [34], the authors first proposed robust H_∞ control for T-S fuzzy systems with state and input time-varying delays via DTPF. In [13], the authors proposed novel

weighting-delay-based stability criteria for system research. In [36, 37], the authors mainly studied the sampled-data control and gave the analysis and proof of related stability.

However, there are many methods to construct a reasonable LKF, but only increasing the cross-sectional area will hardly improve, and it will cause a heavy calculation burden [23, 38, 39]. Therefore, the method of constructing LKF from a new perspective has become a hot issue in current research [34, 40]. Through in-depth study of existing work, this paper proposes an improved DTPF strategy to construct a new LKF, which fully considers information concerning time delays and the derivative information of both states and time delays, and the conservativeness of the guidelines can be further reduced. The issues discussed above have inspired the purpose of this study.

Based on the above discussions, we establish some new stability criteria for UDNNs, and a reliable memory feedback controller is designed to ensure that the considered system is asymptotically stable. Compared with the existing results [22–25], the main contributions of this paper are as follows:

- (1) A novel quadratic function $V_1(x(t))$ is constructed via developing an improved TDPF approach, which can fully excavate some intrinsic relationships between the delay derivative information and the time delay
- (2) Based on this construction method of LKF, the information storage performance of the function is strengthened, an appropriate integral inequality and linear convex combination method are adopted, and a more conservative stability criterion is obtained
- (3) Different from the earlier work, this paper designs a new RMFC, which fully considers the effective transmission of the three state signals of the controller while enhancing the performance of the controller

2. Preliminaries

Consider the following UDNN system:

$$\begin{aligned} \dot{z}(t) = & -\mathcal{A}z(t) + \mathcal{W}_0 g(z(t)) \\ & + \mathcal{W}_1 g(z(t-h(t))) + u(t) + a, \end{aligned} \quad (1)$$

where $z(t) = [z_1(t), z_2(t), \dots, z_n(t)]^T \in \mathbb{R}^n$ denotes the neuron state vector and $u(t)$ is the control input signal. $g(\cdot) = [g_1(\cdot), g_2(\cdot), \dots, g_n(\cdot)]^T \in \mathbb{R}^n$ represents the neuron activation function; $\mathcal{A}(t) = \mathcal{A} + \Delta\mathcal{A}(t)$, and $\Delta\mathcal{A}(t)$ is the revalued unknown matrix representing time-varying parameter uncertainties of (1) and satisfies $\Delta\mathcal{A}(t) = \mathcal{H}\mathcal{F}(t)\mathcal{E}$. Here, $\mathcal{A} > 0$ is a symmetric matrix; $\mathcal{H}, \mathcal{E}$ are known real constant matrices of appropriate dimensions. $\mathcal{F}(t) \in \mathbb{R}^{l_1 \times l_2}$ is an unknown time-varying matrix function satisfying $\mathcal{F}^T(t)\mathcal{F}(t) \leq \mathcal{I}$. $\mathcal{W}_0$ indicates the connection weight matrix, and $\mathcal{W}_1$ expresses the delayed connection weight matrix; $a = [a_1, \dots, a_n]^T \in \mathbb{R}^n$ is a vector. $h(t)$ is time varying and satisfies

$$\begin{aligned} 0 & \leq h(t) \leq h, \\ 0 & \leq \dot{h}(t) \leq \mu. \end{aligned} \quad (2)$$

Based on Assumption 1 in [25], suppose that z^* is the balance point of UDNN (1), which can be transferred to the origin by conversion, $x(\cdot) = z(\cdot) - z^*$. Then, system (1) can be expressed as

$$\dot{x}(t) = -\mathcal{A}x(t) + \mathcal{W}_0 f(x(t)) + \mathcal{W}_1 f(x(t-h(t))) + u(t), \quad (3)$$

where $x(\cdot) = [x_1(\cdot), x_2(\cdot), \dots, x_n(\cdot)]^T \in \mathbb{R}^n$ is the state vector of the transformed system and $f(\cdot) = [f_1(\cdot), \dots, f_n(\cdot)]^T \in \mathbb{R}^n$ with $f_j(x_j(\cdot)) = g_j(x_j(\cdot) + z_j^*) - g_j(z_j^*)$ being the activation function of the converted system. Based on (3), it holds that

$$\begin{aligned} l_i^- & \leq \frac{g_i(u_i + y_i^*) - g_i(y_i^*)}{u_i + y_i^* - y_i^*} = \frac{f_i(u_i)}{u_i} \\ & \leq l_i^+, \quad f_i(0) = 0, \quad \forall u \neq 0, i = 1, \dots, n. \end{aligned} \quad (4)$$

In order to express a reliable control problem, the following actuator failure models are used in this technical description: for $m = 1, \dots, \vartheta$, $n = 1, \dots, n$:

$$u_{mn}^F(t) = (1 - \pi_m^n)u(m)(t), \quad 0 \leq \underline{\pi}_m^n \leq \pi_m^n \leq \bar{\pi}_m^n, \quad (5)$$

where π_m^n is an unknown constant. Here, n is the n th case of failure, and j is the total number of failure cases. $u_{mn}^F(t)$ indicates the control signal from the signal of the m th actuator in the n th fault situation. $\underline{\pi}_m^n$ and $\bar{\pi}_m^n$ represent the lower and upper bounds of π_m^n . First, when $\underline{\pi}_m^n = \bar{\pi}_m^n = 0$, in the n th failure mode, the m th actuator has no failure. When $\underline{\pi}_m^n = \bar{\pi}_m^n = 1$, the m th actuator u_m stops working in the n th fault situation. When $0 \leq \underline{\pi}_m^n \leq \bar{\pi}_m^n < 1$, in the n th fault condition, the type of actuator failure is a gradual descent condition.

The actuator fault matrix Π is designed as the following:

$$0 \leq \underline{\Pi} = \text{diag}\{\underline{\pi}_1^n, \dots, \underline{\pi}_m^n\} \leq \Pi \leq \bar{\Pi} = \text{diag}\{\bar{\pi}_1^n, \dots, \bar{\pi}_m^n\} \leq I_i. \quad (6)$$

Next, we denote the following notation:

$$\bar{\pi}_{am}^n = \frac{\bar{\pi}_m^n + \underline{\pi}_m^n}{2}, \quad \Pi_a = \text{diag}\{\bar{\pi}_{a1}^n, \dots, \bar{\pi}_{am}^n\}, \quad (7)$$

$$\bar{\pi}_{bm}^n = \frac{\bar{\pi}_m^n - \underline{\pi}_m^n}{2}, \quad \Pi_b = \text{diag}\{\bar{\pi}_{b1}^n, \dots, \bar{\pi}_{bm}^n\}. \quad (8)$$

From (7) and (8), Π can be expressed as follows:

$$\Pi = \Pi_a + \Pi_b \Delta \Pi_0, \quad (9)$$

where $\|\Delta \Pi_0\| \leq I_m$.

Thus, we get the reliable controller design as follows:

$$u^F(t) = (\mathcal{J} - \Pi)u(t). \quad (10)$$

Remark 1. Compared with the current design methods of the reliability controller [26–29], this paper introduces the RMFC design with effective lowering of the brake. The reliability control design considered in (10) is more comprehensive than the general reliability control design, which has a wider range of applications. Then, the RMFC is as follows:

$$u(t) = \mathcal{K}_1 x(t) + \mathcal{K}_2 x(t - h(t)) + \mathcal{K}_3 x(t - h). \quad (11)$$

From the above discussion, consider combining (10) and (11) to get the reliability controller design as follows:

$$u^F(t) = (\mathcal{F} - \Pi)\mathcal{K}_1 x(t) + (\mathcal{F} - \Pi)\mathcal{K}_2 x(t - h(t)) + (\mathcal{F} - \Pi)\mathcal{K}_3 x(t - h). \quad (12)$$

(3) with controller (12) can be represented as

$$\begin{aligned} \dot{x}(t) = & (-\mathcal{A}(t) + (\mathcal{F} - \Pi)\mathcal{K}_1)x(t) + \mathcal{W}_0 f(x(t)) \\ & + \mathcal{W}_1 f(x(t - h(t))) \\ & + (\mathcal{F} - \Pi)\mathcal{K}_2 x(t - h(t)) + (\mathcal{F} - \Pi)\mathcal{K}_3 x(t - h). \end{aligned} \quad (13)$$

Lemma 1 (see [38]). *Given a symmetric positive definite matrix $\mathcal{R}$, scalar α , scalar β , and $\alpha < \beta$, and e in $[\alpha, \beta] \rightarrow \mathbb{R}^n$. The following are the inequalities under the given conditions:*

$$\begin{cases} (\beta - \alpha) \int_{\alpha}^{\beta} e^T(s) \mathcal{R} \dot{e}(s) ds, & \geq \chi_1^T \mathcal{R} \chi_1, \\ (\beta - \alpha) \int_{\alpha}^{\beta} e^T(s) \mathcal{R} e(s) ds, & \geq \hat{\chi}_1^T \mathcal{R} \hat{\chi}_1, \\ (\beta - \alpha) \int_{\alpha}^{\beta} e^T(s) \mathcal{R} \dot{e}(s) ds, & \geq \chi_1^T \mathcal{R} \chi_1 + 3\chi_2^T \mathcal{R} \chi_2, \\ (\beta - \alpha) \int_{\alpha}^{\beta} e^T(s) \mathcal{R} e(s) ds, & \geq \hat{\chi}_1^T \mathcal{R} \hat{\chi}_2 + 3\hat{\chi}_2^T \mathcal{R} \hat{\chi}_2, \end{cases}$$

$$(\beta - \alpha) \int_{\alpha}^{\beta} e^T(s) \mathcal{R} \dot{e}(s) ds \geq \chi_1^T \mathcal{R} \chi_1 + 3\chi_2^T \mathcal{R} \chi_2 + 5\chi_3^T \mathcal{R} \chi_3, \quad (14)$$

where $\chi_1 = e(\beta) - e(\alpha)$, $\chi_2 = e(\beta) + e(\alpha) - (2/(\beta - \alpha)) \int_{\alpha}^{\beta} e(s) ds$, $\hat{\chi}_1 = \int_{\alpha}^{\beta} e(s) ds$, $\hat{\chi}_2 = \int_{\alpha}^{\beta} e(s) ds - (2/(\beta - \alpha)) \int_{\alpha}^{\beta} \int_{\theta}^{\beta} e(s) ds d\theta$, and $\chi_3 = e(\beta) - x(\alpha) + (6/(\beta - \alpha)) \int_{\alpha}^{\beta} e(s) ds - (12/(\beta - \alpha)^2) \int_{\alpha}^{\beta} \int_{\theta}^{\beta} e(s) ds d\theta$.

3. Main Results

In this section, we will provide a novel RMFC design scheme for (12). In the following theorem, the asymptotic condition for system (13) is provided under the designed gain matrices $\mathcal{K}_i$ ($i = 1, 2, 3$). For simplicity, some relevant notations are defined as in Appendix A.

Theorem 1. *Given positive scalars h , μ , and ε . System (13) is asymptotically stable if there exist symmetric positive definite matrices $\mathcal{P}_1$, $\mathcal{M}_2$, $\mathcal{M}_3$, $\mathcal{G}_1$, $\mathcal{G}_2$, $\mathcal{D}_1$, and $\mathcal{D}_2$, any symmetric matrices $\mathcal{P}_2$, $\mathcal{M}_1$, $\mathcal{M}_4$, and $\mathcal{Q}_i$ ($i = 1, 2, \dots, 5$), any matrices $\mathcal{U}_1$, $\mathcal{U}_2$, $\mathcal{N}_1$ and $\mathcal{N}_2$ with appropriate dimensions such that the following LMIs hold:*

$$\begin{aligned} \mathcal{P}_{h(t)=0} &> 0, \\ \mathcal{M}_{1,h(t)=h} &> 0, \\ \mathcal{M}_{2,h(t)=0} &> 0, \end{aligned} \quad (15)$$

$$\begin{bmatrix} \Sigma_1 & \frac{\sqrt{h}}{h} \mathcal{G}_1^T \mathcal{U}_2 & \Gamma & \Theta \\ * & -\Pi_{2,h(t)} & 0 & 0 \\ * & * & -\varepsilon^{-1} \mathcal{F} & 0 \\ * & * & * & -\varepsilon \mathcal{F} \end{bmatrix} < 0, \quad (16)$$

$$\begin{bmatrix} \Sigma_2 & \frac{\sqrt{h}}{h} \mathcal{G}_1^T \mathcal{U}_2 & \Gamma & \Theta \\ * & -\Pi_{2,h(t)} & 0 & 0 \\ * & * & -\varepsilon^{-1} \mathcal{F} & 0 \\ * & * & * & -\varepsilon \mathcal{F} \end{bmatrix} < 0, \quad (17)$$

$$\begin{bmatrix} \Sigma_3 & \frac{\sqrt{h}}{h} \mathcal{G}_2^T \mathcal{U}_1 & \Gamma & \Theta \\ * & -\Pi_{1,h(t)} & 0 & 0 \\ * & * & -\varepsilon^{-1} \mathcal{F} & 0 \\ * & * & * & -\varepsilon \mathcal{F} \end{bmatrix} < 0, \quad (18)$$

$$\begin{bmatrix} \Sigma_4 & \frac{\sqrt{h}}{h} \mathcal{G}_2^T \mathcal{U}_1 & \Gamma & \Theta \\ * & -\Pi_{1,h(t)} & 0 & 0 \\ * & * & -\varepsilon^{-1} \mathcal{F} & 0 \\ * & * & * & -\varepsilon \mathcal{F} \end{bmatrix} < 0, \quad (19)$$

where other symbols and related equations are listed in Appendix B.

Proof. Construct an augmented LKF as follows:

$$V(x(t)) = \sum_{i=1}^5 V_i(x(t)), \quad (20)$$

where

$$\begin{aligned}
V_1(x(t)) &= \alpha^T(t) \mathcal{P}_{h(t)} \alpha(t), \\
V_2(x(t)) &= \eta^T(t) \mathcal{Q} \eta(t), \\
V_3(x(t)) &= \int_{t-h(t)}^t \dot{x}^T(s) \mathcal{M}_{1,h(t)} \dot{x}(s) ds + \int_{t-h}^{t-h(t)} \dot{x}^T(s) \mathcal{M}_{2,h(t)} \dot{x}(s) ds, \\
V_4(x(t)) &= \int_{-h(t)}^0 \int_{t+\theta}^t \dot{x}^T(s) \mathcal{G}_1 \dot{x}(s) ds d\theta + \int_{-h}^{-h(t)} \int_{t+\theta}^t \dot{x}^T(s) \mathcal{G}_2 \dot{x}(s) ds d\theta, \\
V_5(x(t)) &= 2 \sum_{i=1}^n d_{1i} \int_0^{x(t-h(t))} (f_i(s) - l_i^- s) ds + 2 \sum_{i=1}^n d_{2i} \int_0^{x(t-h(t))} (l_i^+ s - f_i(s)) ds,
\end{aligned} \tag{21}$$

$\alpha(t)$, $\eta(t)$, $\mathcal{P}_{h(t)}$, $\mathcal{Q}$, $\mathcal{M}_{1,h(t)}$, $\mathcal{M}_{2,h(t)}$, and $\xi(t)$ are given in Appendix A.

The time derivative of $V(x(t))$ along the trajectory of system (12) is given. Then, the derivative of $V_i(x(t))$ is derived:

$$\begin{aligned}
\dot{V}_1(x(t)) &= 2\alpha^T(t) \mathcal{P}_{h(t)} \dot{\alpha}(t) + \dot{h}(t) \alpha^T(t) \mathcal{P}_2 \alpha(t) \\
&= \dot{h}(t) \alpha^T(t) \mathcal{P}_2 \alpha(t) + 2\alpha^T(t) \mathcal{P}_{h(t)} \\
&\quad \times \begin{bmatrix} \dot{x}(t) \\ \dot{x}(t-h) \\ x(t) - (1 - \dot{h}(t))x(t-h(t)) \\ (1 - \dot{h}(t))x(t-h(t)) - x(t-h) \end{bmatrix} \\
&= \xi^T(t) \{ \dot{h}(t) \Phi_1^T(h(t)) \mathcal{P}_2 \Phi_1(h(t)) + \text{Sym} \{ \Phi_1^T(h(t)) \mathcal{P}_{h(t)} \Phi_2(\dot{h}(t)) \} \} \xi(t),
\end{aligned} \tag{22}$$

$$\begin{aligned}
\dot{V}_2(x(t)) &= 2\eta^T(t) \begin{bmatrix} \frac{\mathcal{Q}_1^T + \mathcal{Q}_1 - \mathcal{Q}_2^T - \mathcal{Q}_2}{2} & \mathcal{Q}_2 & \mathcal{Q}_3 \\ * & \frac{-\mathcal{Q}_1^T - \mathcal{Q}_1 - \mathcal{Q}_2^T - \mathcal{Q}_2}{2} & \mathcal{Q}_4 \\ * & * & \mathcal{Q}_5^T + \mathcal{Q}_5 \end{bmatrix} \dot{\eta}(t) \\
&= 2\eta^T(t) \begin{bmatrix} \frac{\mathcal{Q}_1^T + \mathcal{Q}_1 - \mathcal{Q}_2^T - \mathcal{Q}_2}{2} & \mathcal{Q}_2 & \mathcal{Q}_3 \\ * & \frac{-\mathcal{Q}_1^T - \mathcal{Q}_1 - \mathcal{Q}_2^T - \mathcal{Q}_2}{2} & \mathcal{Q}_4 \\ * & * & \mathcal{Q}_5^T + \mathcal{Q}_5 \end{bmatrix} \begin{bmatrix} \dot{x}(t) \\ (1 - \dot{h}(t))\dot{x}(t-h(t)) \\ \dot{x}(t-h) \end{bmatrix} \\
&= \xi^T(t) \text{Sym} \{ \Phi_3^T \mathcal{Q} \Phi_4(\dot{h}(t)) \} \xi(t),
\end{aligned} \tag{23}$$

$$\begin{aligned}
\dot{V}_3(x(t)) &= \dot{x}^T(t) \mathcal{M}_{1,h(t)} \dot{x}(t) - (1 - \dot{h}(t)) \dot{x}^T(t-h(t)) \mathcal{M}_{1,h(t)} \dot{x}(t-h(t)) + (1 - \dot{h}(t)) \\
&\quad \times \dot{x}^T(t-h(t)) \mathcal{M}_{2,h(t)} \dot{x}(t-h(t)) - \dot{x}^T(t-h) \mathcal{M}_{2,h(t)} \dot{x}(t-h) \\
&\quad + \dot{h}(t) \int_t^{t-h(t)} \dot{x}^T(s) \mathcal{M}_1 \dot{x}(s) ds - \dot{h}(t) \int_{t-h(t)}^{t-h} \dot{x}^T(s) \mathcal{M}_1 \dot{x}(s) ds,
\end{aligned} \tag{24}$$

$$\begin{aligned}\dot{V}_4(x(t)) &= h(t)\dot{x}^T(t)\mathcal{G}_1\dot{x}(t) + (h-h(t))\dot{x}^T(t)\mathcal{G}_2\dot{x}(t) - (1-\dot{h}(t))\int_{t-h(t)}^t \dot{x}^T(s)\mathcal{G}_1\dot{x}(s)ds \\ &\quad - \dot{h}(t)\int_{t-h(t)}^t \dot{x}^T(s)\mathcal{G}_2\dot{x}(s)ds - \int_{t-h}^{t-h(t)} \dot{x}^T(s)\mathcal{G}_2\dot{x}(s)ds.\end{aligned}\quad (25)$$

Combining (24) and (25), we can get the derivative of $\dot{V}_T(x(t))$ as follows:

$$\begin{aligned}V_T(x(t)) &= \dot{x}^T(t)\left[\mathcal{G}_{h(t)} + \mathcal{M}_{1,h(t)}\right]\dot{x}(t) + (1-\dot{h}(t))\dot{x}^T(t-h(t))\left[\mathcal{M}_{2,h(t)} - \mathcal{M}_{1,h(t)}\right]\dot{x}(t-h(t)) \\ &\quad - \dot{x}^T(t-h)\mathcal{M}_{2,h(t)}\dot{x}(t-h) - \int_{t-h(t)}^t \dot{x}^T(s)\bar{\Pi}_{1,\dot{h}(t)}\dot{x}(s)ds - \int_{t-h}^{t-h(t)} \dot{x}^T(s)\bar{\Pi}_{2,\dot{h}(t)}\dot{x}(s)ds.\end{aligned}\quad (26)$$

Based on Lemma 1, we can get

$$\begin{aligned}& - \int_{t-h(t)}^t \dot{x}^T(s)\bar{\Pi}_{1,\dot{h}(t)}\dot{x}(s)ds - \int_{t-h}^{t-h(t)} \dot{x}^T(s)\bar{\Pi}_{2,\dot{h}(t)}\dot{x}(s)ds \\ & \leq \xi^T(t)\left(\frac{h-h(t)}{h^2}\mathcal{E}_1^T\mathcal{U}_2^T\Pi_{2,\dot{h}(t)}^{-1}\mathcal{U}_2\mathcal{E}_1 + \frac{h(t)}{h^2}\mathcal{E}_2^T\mathcal{U}_1^T\Pi_{1,\dot{h}(t)}^{-1}\right. \\ & \quad \times \mathcal{S}_3\mathcal{W}_2 - \frac{1}{h}\begin{bmatrix} \mathcal{E}_1 \\ \mathcal{E}_2 \end{bmatrix}^T \begin{bmatrix} \frac{2h-h(t)}{h}\bar{\Pi}_{1,\dot{h}(t)} & \frac{h-h(t)}{h}\mathcal{U}_1 + \frac{h(t)}{h}\mathcal{U}_2 \\ * & \frac{1}{h-h(t)}\bar{\Pi}_{2,\dot{h}(t)} \end{bmatrix} \begin{bmatrix} \mathcal{E}_1 \\ \mathcal{E}_2 \end{bmatrix} \Bigg)\xi(t) \\ & = \xi^T(t)\left\{\Psi_{h(t)} - \frac{1}{h}\left(\frac{2h-h(t)}{h}\mathcal{E}_1^T\Pi_{1,\dot{h}(t)}\mathcal{E}_1 + \frac{h-h(t)}{h}\mathcal{E}_2^T\mathcal{U}_1^T\mathcal{E}_1 + \frac{h-h(t)}{h}\mathcal{E}_2^T\right.\right. \\ & \quad \times \mathcal{U}_2^T\mathcal{E}_1 + \frac{h-h(t)}{h}\mathcal{E}_1^T\mathcal{U}_1\mathcal{E}_2 + \frac{h-h(t)}{h}\mathcal{E}_1^T\mathcal{U}_2\mathcal{E}_2 + \left.\frac{h-h(t)}{h}\mathcal{E}_2^T\Pi_{2,\dot{h}(t)}\mathcal{E}_2\right)\Bigg\}\xi(t) \\ & = \xi^T(t)(\Psi(h(t)) + \Omega(h(t)))\xi(t).\end{aligned}\quad (27)$$

Then, $\dot{V}_T(x(t))$ can be expressed as follows:

$$\begin{aligned}\dot{V}_T(x(t)) &\leq \xi^T(t)\left(e_4^T\left[\mathcal{G}_{h(t)} + \mathcal{M}_{1,h(t)}\right]e_4 + (1-\dot{h}(t))e_5^T\left[\mathcal{M}_{2,h(t)} - \mathcal{M}_{1,h(t)}\right]e_5\right. \\ &\quad \left.- e_6^T\mathcal{M}_{2,h(t)}e_6 + \Psi(h(t)) + \Omega(h(t))\right)\xi(t),\end{aligned}\quad (28)$$

where $\mathcal{G}_{h(t)}$, $\Pi_{1,\dot{h}(t)}$, $\Pi_{2,\dot{h}(t)}$, $\Psi(h(t))$, and $\Omega(h(t))$ are given in Appendix B.

$$\begin{aligned}\dot{V}_5(x(t)) &= 2(1-\dot{h}(t))f^T(x(t-h(t)))(\mathcal{D}_1 - \mathcal{D}_2)\dot{x}(t-h(t)) \\ &\quad + 2(1-\dot{h}(t))x^T(t-h(t))(\mathcal{D}_2\mathcal{L}_2 - \mathcal{D}_1\mathcal{L}_1)\dot{x}(t-h(t)) \\ &= \xi^T(t)\Xi_4\xi(t).\end{aligned}\quad (29)$$

Based on system (13), the following zero formula holds:

$$0 = 2 \left[x^T(t) \mathcal{N}_1 + \dot{x}(t) \mathcal{N}_2 \right] \begin{bmatrix} (-\mathcal{A} + \Delta \mathcal{A}(t) + (\mathcal{F} - \Pi) \mathcal{K}_1) x(t) + \mathcal{W}_0 f(x(t)) \\ + \mathcal{W}_1 f(x(t-h(t))) + (\mathcal{F} - \Pi) \mathcal{K}_2 x(t-h(t)) + (\mathcal{F} - \Pi) \mathcal{K}_3 x(t-h) - \dot{x}(t) \end{bmatrix} \quad (30)$$

$$= \xi^T(t) (\text{Sym}\{\mathcal{L}\varphi\} + 2\mathcal{L}\Delta \mathcal{A}(t)e_1)\xi(t).$$

Then, based on Lemma 3 in [34], we can get

$$2\mathcal{L}\Delta \mathcal{A}(t)e_1 \leq \varepsilon(\mathcal{L}\mathcal{H})(\mathcal{L}\mathcal{H})^T + \varepsilon^{-1}(\mathcal{E}e_1)(\mathcal{E}e_1)^T \quad (31)$$

$$= \varepsilon\Gamma^T + \varepsilon^{-1}\Theta\Theta^T.$$

Based on the convex combination technique, $\sum_{i=1}^5 \dot{V}(x(t)) < 0$ holds for all, if only if. By utilizing Schur complement, we can derive that $\sum_{i=1}^5 \dot{V}(x(t)) < 0$ is equal to

$$\begin{bmatrix} \Sigma_{h(t),\dot{h}(t)} & \frac{\sqrt{h-h(t)}}{h} \mathcal{E}_1^T \mathcal{U}_2 & \frac{\sqrt{h(t)}}{h} \mathcal{E}_2^T \mathcal{U}_1 & \Gamma & \Theta \\ * & -\Pi_{2,\dot{h}(t)} & 0 & 0 & 0 \\ * & * & -\Pi_{1,\dot{h}(t)} & 0 & 0 \\ * & * & * & -\varepsilon^{-1} \mathcal{F} & 0 \\ * & * & * & * & -\varepsilon \mathcal{F} \end{bmatrix} < 0. \quad (32)$$

Based on (15)–(19), it is easy to come to the conclusion that system (13) is asymptotically stable. This concludes the proof. $\square$

Remark 2. In this paper, we consider $\mathcal{P}_{h(t)} = \mathcal{P}_1 - (h - h(t))\mathcal{P}_2$. (I) When $h - h(t) = 0$, $\mathcal{P}_{h(t)}$ will be degenerated to the constant matrix $\mathcal{P}$. (II) Compared with the existing methods [25], this paper only needs to consider that $\mathcal{P}_2$ and $\mathcal{P}_2$ are arbitrary symmetric matrices. Furthermore, as long as (25) and (26) are guaranteed, this constraint helps reduce the strength of positive definite conditions. (III) In addition, this construction method makes full use of the delay information and the delay derivative information, thereby increasing the amount of LKF information storage, which helps to construct a more general LKF to further reduce the conservativeness of the criteria. At present, the method used in this paper is more general in constructing the LKF and includes a wider range of usage background and research significance.

Remark 3. Compared with existing research [24], this paper fully considers the relaxation of the requirements for matrix positive definiteness. In $V_3(x(t))$, by using $\mathcal{M}_{1,h(t)}$ and $\mathcal{M}_{2,h(t)}$ to replace the constant matrices, the LCCM is used to make constraints. Therefore, this method can obtain less conservative criteria through more relaxed positive definite

conditions and increase the time-delay information contained in the LKF.

Remark 4. In order to better solve integral terms (24) and (25), $-\int_{t-h(t)}^t \dot{x}^T(s) \bar{\Pi}_{1,\dot{h}(t)} \dot{x}(s) ds - \int_{t-h}^{t-h(t)} \dot{x}^T(s) \bar{\Pi}_{2,\dot{h}(t)} \dot{x}(s) ds$, in this paper, considers Lemma 1. Compared with the Wirtinger-based integral inequality, Jensen's inequality, and other existing inequalities, Lemma 1 has a tighter bound in order to obtain a less conservative criterion.

Theorem 2. Given positive scalars h, μ, ε , and κ . System (13) is asymptotically stable if there exist symmetric positive definite matrices $\tilde{\mathcal{P}}_1, \tilde{\mathcal{M}}_2, \tilde{\mathcal{M}}_3, \tilde{\mathcal{E}}_1, \tilde{\mathcal{E}}_2, \tilde{\mathcal{D}}_1$, and $\tilde{\mathcal{D}}_2$. Any symmetric matrices $\tilde{\mathcal{P}}_2, \tilde{\mathcal{M}}_1, \tilde{\mathcal{M}}_4$, and $\tilde{\mathcal{Q}}_i$ ($i = 1, 2, \dots, 5$), any matrices $\tilde{\mathcal{U}}_1, \tilde{\mathcal{U}}_2, \tilde{\mathcal{Y}}_1, \tilde{\mathcal{Y}}_2, \tilde{\mathcal{Y}}_3$ and $\tilde{\mathcal{V}}$ with appropriate dimensions such that the following LMIs hold:

$$\begin{aligned} \tilde{\mathcal{P}}_{h(t)=0} &> 0, \\ \tilde{\mathcal{M}}_{1,h(t)=h} &> 0, \\ \tilde{\mathcal{M}}_{2,h(t)=0} &> 0, \end{aligned} \quad (33)$$

$$\begin{bmatrix} \tilde{\Sigma}_1 & \frac{\sqrt{h}}{h} \mathcal{E}_1^T \tilde{\mathcal{U}}_2 & \tilde{\Gamma} & \tilde{\Theta} \\ * & -\tilde{\Pi}_{2,\dot{h}(t)} & 0 & 0 \\ * & * & -\varepsilon^{-1} \mathcal{F} & 0 \\ * & * & * & -\varepsilon \mathcal{F} \end{bmatrix} < 0, \quad (34)$$

$$\begin{bmatrix} \tilde{\Sigma}_2 & \frac{\sqrt{h}}{h} \mathcal{E}_1^T \tilde{\mathcal{U}}_2 & \tilde{\Gamma} & \tilde{\Theta} \\ * & -\tilde{\Pi}_{2,\dot{h}(t)} & 0 & 0 \\ * & * & -\varepsilon^{-1} \mathcal{F} & 0 \\ * & * & * & -\varepsilon \mathcal{F} \end{bmatrix} < 0, \quad (35)$$

$$\begin{bmatrix} \tilde{\Sigma}_3 & \frac{\sqrt{h}}{h} \mathcal{E}_2^T \tilde{\mathcal{U}}_1 & \tilde{\Gamma} & \tilde{\Theta} \\ * & -\tilde{\Pi}_{1,\dot{h}(t)} & 0 & 0 \\ * & * & -\varepsilon^{-1} \mathcal{F} & 0 \\ * & * & * & -\varepsilon \mathcal{F} \end{bmatrix} < 0, \quad (36)$$

$$\begin{bmatrix} \tilde{\Sigma}_4 & \frac{\sqrt{h}}{h} \mathcal{E}_2^T \tilde{\mathcal{U}}_1 & \tilde{\Gamma} & \tilde{\Theta} \\ * & -\tilde{\Pi}_{1,h(t)} & 0 & 0 \\ * & * & -\varepsilon^{-1} \mathcal{J} & 0 \\ * & * & * & -\varepsilon \mathcal{J} \end{bmatrix} < 0, \quad (37)$$

where other symbols and related equations are listed in Appendix C.

We define $\mathcal{K}_1 = \mathcal{Y}_1 \mathcal{V}^{-1}$, $\mathcal{K}_2 = \mathcal{Y}_2 \mathcal{V}^{-1}$, and $\mathcal{K}_3 = \mathcal{Y}_3 \mathcal{V}^{-1}$ to solve the corresponding controller gain.

Proof. Define

$$\begin{aligned} \mathcal{N}_1 &= \mathcal{V}^{-1}, \\ \mathcal{N}_2 &= \kappa \mathcal{V}^{-1}, \\ \tilde{\mathcal{P}}_{h(t)} &= \text{diag}\{\mathcal{V}^T, \mathcal{V}^T, \mathcal{V}^T, \mathcal{V}^T\} \mathcal{P}_{h(t)} \text{diag}\{\mathcal{V}, \mathcal{V}, \mathcal{V}, \mathcal{V}\}, \\ \tilde{\mathcal{G}}_1 &= \mathcal{V}^T \mathcal{G}_1 \mathcal{V}, \\ \tilde{\mathcal{G}}_2 &= \mathcal{V}^T \mathcal{G}_2 \mathcal{V}, \\ \tilde{\mathcal{Q}}_i &= \mathcal{V}^T \mathcal{P}_{h(t)} \mathcal{V}, \\ \tilde{\mathcal{M}}_1 &= \mathcal{V}^T \mathcal{M}_1 \mathcal{V}, \\ \tilde{\mathcal{M}}_2 &= \mathcal{V}^T \mathcal{M}_2 \mathcal{V}, \\ \tilde{\mathcal{M}}_3 &= \mathcal{V}^T \mathcal{M}_3 \mathcal{V}, \\ \tilde{\mathcal{M}}_4 &= \mathcal{V}^T \mathcal{M}_4 \mathcal{V}, \\ \tilde{\mathcal{U}}_1 &= \text{diag}\{\mathcal{V}^T, \mathcal{V}^T, \mathcal{V}^T\} \mathcal{U}_1 \text{diag}\{\mathcal{V}, \mathcal{V}, \mathcal{V}\}, \\ \tilde{\mathcal{D}}_1 &= \mathcal{V}^T \mathcal{M}_1 \mathcal{V}, \\ \tilde{\mathcal{U}}_2 &= \text{diag}\{\mathcal{V}^T, \mathcal{V}^T, \mathcal{V}^T\} \mathcal{U}_2 \text{diag}\{\mathcal{V}, \mathcal{V}, \mathcal{V}\}, \\ \tilde{\mathcal{D}}_2 &= \mathcal{V}^T \mathcal{M}_2 \mathcal{V}. \end{aligned} \quad (38)$$

Premultiplying and postmultiplying (15)–(19) by $\text{diag}\{\mathcal{V}^T, \mathcal{V}^T, \mathcal{V}^T, \mathcal{V}^T\}$ and $\text{diag}\{\mathcal{V}, \mathcal{V}, \mathcal{V}, \mathcal{V}\}$, in view of the Schur complement, we can obtain LMIs (33)–(37). Thus, the proof is completed. $\square$

4. Illustrative Example

In this section, two simulation examples are exhibited to express the effectiveness of the established results.

Example 1. Consider DNN (13) with the following matrix parameters, and these matrices are based on [13–18]:

$$\begin{aligned} \mathcal{A} &= \begin{bmatrix} 2 & 0 \\ 0 & 2 \end{bmatrix}, \\ \mathcal{W}_0 &= \begin{bmatrix} 1 & 1 \\ -1 & -1 \end{bmatrix}, \\ \mathcal{W}_1 &= \begin{bmatrix} 0.88 & 1 \\ 1 & 1 \end{bmatrix}, \\ \mathcal{L}_1 &= \text{diag}\{0.4, 0.8\}, \\ \mathcal{L}_2 &= 0, \\ \Pi &= \text{diag}\{0.5, 0.5, 0.5, 0.5\}. \end{aligned} \quad (39)$$

The MAUBs are obtained by Theorem 1, and the other results are listed in Table 1. When $\mu_2 = 0.8$, from Table 2, we can clearly see that our result is markedly better than [13–18, 25]. In addition, it is worth noting that the result obtained in this paper is improved by 21.8325% compared to [25]. For the reason that the TDPF method is employed, the conservativeness of the obtained criterion is reduced and the performance is improved in this paper.

Setting $\mu = 1$, $h(t) \leq 6.0917$, $h(t) = (60917/20000)\sin((20000/60917)t) + (60917/20000)$, and $f(x(t)) = \text{diag}(0.4, 0.8)\tanh(x(t))$. In order to verify the stability of the system, we randomly select different initial values to simulate the dynamic response of the system as shown in Figure 1. From Figure 1, we can clearly see that when different initial values are selected, the system tends to a stable state as time increases.

Based on Theorem 2, setting $\kappa = 1$, we can get the controller gains as follows:

$$\begin{aligned} \mathcal{K}_1 &= \begin{bmatrix} -0.1488 & -0.4091 \\ 0.2762 & -0.2079 \end{bmatrix}, \\ \mathcal{K}_2 &= \begin{bmatrix} -0.2986 & 0.1950 \\ -0.7407 & -0.1002 \end{bmatrix}, \\ \mathcal{K}_3 &= \begin{bmatrix} -0.5131 & -0.3584 \\ 0.2236 & -0.1432 \end{bmatrix}. \end{aligned} \quad (40)$$

Here, the control input trajectory of DNNs is presented in Figure 2.

TABLE 1: Notations and descriptions.

Notation	$\mathbb{R}^m$	$\mathbb{R}^{l \times k}$	$\mathcal{I}$
Description	m -dimensional Euclidean space	$l \times k$ matrices	Identity matrix
Notation	$\mathcal{P} > 0$	$\mathcal{A}^{-1}$	$\mathcal{A}^T$
Description	Positive definite matrix	Inverse of matrix $\mathcal{A}$	Inverse of matrix $\mathcal{A}$
Notation	$\ \cdot\ $	$\text{sym}\{X\}$	$\text{diag}\{\dots\}$
Description	Inverse of matrix $\mathcal{A}$	$X^T + X$	Stands for a block diagonal matrix

TABLE 2: The achieved MAUBs for different values of μ .

Methods	$\mu = 0.1$	$\mu = 0.5$	$\mu = 0.9$
[19]	3.3068	2.5802	2.2736
[22]	3.8025	2.7427	2.3811
[23]	3.8026	2.7440	2.3811
[25]	4.6754	3.0587	2.7368
Theorem 1	5.5721	4.0916	3.9594
Improvement	16.0927%	25.2444%	30.8784%

FIGURE 1: State trajectories for $\mu = 1$ and $h = 6.0917$.

FIGURE 2: Control input of the system.

TABLE 3: The achieved MAUBs for different values of μ .

Methods	$\mu = 0.8$	$\mu = 0.9$
[13]	2.5406	1.7273
[14]	2.2495	1.5966
[15]	2.1105	1.4268
[16]	2.8794	1.9562
[17]	2.8980	1.9562
[15]	3.1409	1.6375
[18]	4.8167	3.4245
[25]	5.2756	4.6281
Theorem 1	6.7491	5.9291
Improvement	21.8325%	21.9426%

FIGURE 3: State trajectories $x_1(t)$ and $x_2(t)$ for $\mu = 0.1$ and $h = 4.2290$.

Example 2. Consider DNN (13) with the following matrix parameters, and these matrices are based on [19–25]:

$$\begin{aligned}
 \mathcal{A} &= \text{diag}\{1.2769, 0.6231, 0.9230, 0.4480\}, \\
 \mathcal{L}_1 &= \text{diag}\{0.1137, 0.1297, 0.7994, 0.2368\}, \\
 \mathcal{W}_0 &= \begin{bmatrix} -0.0373 & 0.4852 & -0.3351 & 0.2336 \\ -1.6033 & 0.5988 & 0.3224 & 1.2352 \\ 0.3394 & -0.0860 & -0.3824 & -0.5785 \\ -0.1311 & 0.3253 & -0.9534 & -0.5015 \end{bmatrix}, \\
 \mathcal{W}_1 &= \begin{bmatrix} 0.8674 & -1.2405 & -0.5325 & 0.0220 \\ 0.0474 & -0.9164 & 0.0360 & 0.9816 \\ 1.8495 & 2.6117 & -0.3788 & 0.8428 \\ -2.0413 & 0.5179 & 1.1734 & -0.2775 \end{bmatrix}, \\
 \mathcal{L}_2 &= 0, \\
 \Pi &= \text{diag}\{0.5, 0.5, 0.5, 0.5\}.
 \end{aligned} \tag{41}$$

By employing Theorem 1, for different μ , Table 3 lists the MAUBs based on Theorem 1. From Table 3, we can see that when μ takes different values, the MAUBs obtained in this paper are always the largest. For example, when $\mu = 0.5$, the existing result shows $h = 3.0587$, but the result obtained by applying Theorem 1 in this paper is $h = 4.0916$. Compared with results in [25], the criterion proposed in this paper improves MAUBs by up to 25.2444%.

When $\kappa = 1$, by solving LMIs in Theorem 2, the controller gains are obtained as follows:

$$\begin{aligned}
 \mathcal{K}_1 &= \begin{bmatrix} -2.8807 & -1.3407 & -0.4210 & -0.1567 \\ -0.1579 & -0.1483 & -0.1396 & 1.5440 \\ -1.9637 & -1.0886 & -0.1666 & -0.1519 \\ -0.1573 & -0.1539 & 0.9762 & 1.9872 \end{bmatrix}, \\
 \mathcal{K}_2 &= \begin{bmatrix} -1.6769 & -0.1564 & -0.1578 & -0.1525 \\ -0.1651 & 0.3745 & 1.3234 & 3.1923 \\ -0.1484 & -0.1550 & -0.1652 & -0.1642 \\ -0.1488 & -0.4091 & 0.2762 & -0.2079 \end{bmatrix}, \\
 \mathcal{K}_3 &= \begin{bmatrix} -0.1979 & -0.1569 & -0.1676 & -0.2986 \\ 0.1950 & -0.7407 & -0.1002 & -0.2256 \\ -0.1683 & -0.1543 & -0.5131 & -0.3584 \\ -0.1432 & 0.3253 & -0.1054 & -0.2237 \end{bmatrix}.
 \end{aligned} \tag{42}$$

Letting $\mu = 0.1$, $h(t) \leq 4.2290$, $f(x(t)) = \text{diag}(0.1137, 0.1297, 0.7994, 0.2368)\tanh(x(t))$, and $h(t) = (42290/10000)\sin((1000/42290)t) + (42290/10000)$. We verify the stability of the system by choosing different initial values. As shown in Figures 3–8, we give a dynamic response graph through node combination. Through the figures, we can directly see that the system eventually tends to a stable state under the controller involved. In addition, the control input trajectory of DNNs is presented in Figure 9.

FIGURE 4: State trajectories $x_3(t)$ and $x_4(t)$ for $\mu = 0.1$ and $h = 4.2290$.

FIGURE 5: State trajectories $x_1(t)$ and $x_3(t)$ for $\mu = 0.1$ and $h = 4.2290$.

FIGURE 6: State trajectories $x_2(t)$ and $x_4(t)$ for $\mu = 0.1$ and $h = 4.2290$.

FIGURE 7: State trajectories $x_1(t)$ and $x_4(t)$ for $\mu = 0.1$ and $h = 4.2290$. FIGURE 8: State trajectories $x_2(t)$ and $x_3(t)$ for $\mu = 0.1$ and $h = 4.2290$.

FIGURE 9: Control input of the considered system.

5. Conclusion

This study has proposed further results for the stability analysis issue of UDNNs based on the RMFC scheme. First, an improved quadratic function method has been introduced for constructing a novel $V_1(x(t))$, which can fully excavate some intrinsic relationships between the delay derivative information and the time delay. Based on the TDPF and LCCM, the information storage has been further

improved for obtaining new theoretical results. Second, by using resultful integral inequalities and correlation analysis approaches, several relaxed criteria have been established with respect to the asymptotical stability of the considered UDNNs. Third, a new RMFC has been designed, which can ensure the system stability of UDNNs. Lastly, two numerical experiments have been given to illustrate the significance of the theoretical results. In the future research, we need to further study the UDNNs based on quantized measurements

in order to improve the entire system [41]. In addition, the results obtained in this paper will be extended to the chaotic Lurie system [42, 43], quaternion-valued or memristor-based neural networks [44–46], T-S fuzzy NNs [47, 48], Markov jump systems [49, 50], and complex dynamical networks [51–53]. These will occur in the near future.

Appendix

A. Some Relevant Notations

$$\begin{aligned} \nu_1(t) &= \int_{t-h(t)}^t \frac{x^T(s)}{h(t)} ds, \\ \nu_2(t) &= \int_{t-h}^{t-h(t)} \frac{x^T(s)}{h-h(t)} ds, \\ \nu_3(t) &= \int_{t-h(t)}^t \int_{\theta}^t \frac{x^T(s)}{h^2(t)} ds d\theta, \end{aligned} \tag{A.1}$$

$$\begin{aligned} \nu_4(t) &= \int_{t-h}^t \int_{\theta}^{t-h(t)} \frac{x^T(s)}{(h-h(t))^2} ds d\theta, \\ \alpha(t) &= \text{col}\{x(t), x(t-h), h\nu_1(t), (h-h(t))\nu_2(t)\}, \\ \eta(t) &= \text{col}\{x(t), x(t-h(t)), x(t-h)\}, \\ \xi(t) &= \text{col}\left\{ \begin{array}{l} x(t), x(t-h(t)), x(t-h), \dot{x}(t), \dot{x}(t-h(t)), \dot{x}(t-h), \\ f(x(t)), f(x(t-h(t))), \nu_1(t), \nu_2(t), \nu_3(t), \nu_4(t) \end{array} \right\}, \end{aligned} \tag{A.2}$$

$$\begin{aligned} \mathcal{P}_{h(t)} &= \mathcal{P}_1 - (h-h(t))\mathcal{P}_2, \\ \mathcal{Q} &= \begin{bmatrix} \frac{\mathcal{Q}_1^T + \mathcal{Q}_1 - \mathcal{Q}_2^T - \mathcal{Q}_2}{2} & \mathcal{Q}_2 & \mathcal{Q}_3 \\ * & \frac{-\mathcal{Q}_1^T - \mathcal{Q}_1 - \mathcal{Q}_2^T - \mathcal{Q}_2}{2} & \mathcal{Q}_4 \\ * & * & \mathcal{Q}_5^T + \mathcal{Q}_5 \end{bmatrix}, \\ \mathcal{M}_{1,h(t)} &= h(t)\mathcal{M}_1 + \mathcal{M}_2, \\ \mathcal{M}_{2,h(t)} &= (h-h(t))\mathcal{M}_3 + \mathcal{M}_4. \end{aligned} \tag{A.3}$$

B. Related Equations of Theorem 1

The appendix lists some notations and equations given in Theorem 1:

$$\begin{aligned}
\Sigma_{h(t),\dot{h}(t)} &= \sum_{i=1}^4 \Xi_i + \text{Sym}\{\mathcal{L}\varphi\}, \\
\Sigma_1 &= \Sigma_{h(t)=0, \dot{h}(t)=0}, \\
\Sigma_2 &= \Sigma_{h(t)=h, \dot{h}(t)=0}, \\
\Sigma_3 &= \Sigma_{h(t)=h, \dot{h}(t)=\mu}, \\
\Sigma_4 &= \Sigma_{h(t)=0, \dot{h}(t)=\mu}, \\
\Xi_1 &= \dot{h}(t)\Phi_1^T(h(t))\mathcal{P}_2\Phi_1(h(t)) + \text{Sym}\{\Phi_1^T(h(t))\mathcal{P}_{h(t)}\Phi_2(\dot{h}(t))\}, \\
\Xi_2 &= \Phi_3^T\mathcal{Q}\Phi_4(\dot{h}(t)), \\
\Xi_3 &= e_4^T[\mathcal{G}_{h(t)} + \mathcal{M}_{1,h(t)}]e_4 + (1 - \dot{h}(t))e_5^T[\mathcal{M}_{2,h(t)} - \mathcal{M}_{1,h(t)}]e_5 - e_6^T\mathcal{M}_{2,h(t)}e_6 + \Omega(h(t)), \\
\Xi_4 &= 2(1 - \dot{h}(t))e_8^T(\mathcal{D}_1 - \mathcal{D}_2)e_5 + 2(1 - \dot{h}(t))e_2(\mathcal{D}_2\mathcal{L}_2 - \mathcal{D}_1\mathcal{L}_1)e_5,
\end{aligned} \tag{B.1}$$

$$\begin{aligned}
\Gamma(h(t)) &= \frac{h-h(t)}{h^2}\mathcal{E}_1^T\mathcal{U}_2^T\Pi_{2,\dot{h}(t)}^{-1}\mathcal{U}_2\mathcal{E}_1 + \frac{h(t)}{h^2}\mathcal{E}_2^T\mathcal{U}_1^T\Pi_1^{-1,\dot{h}(t)}\mathcal{U}_1\mathcal{E}_2, \\
\Omega(h(t)) &= \frac{1}{h}\left(\frac{2h-h(t)}{h}\mathcal{E}_1^T\Pi_{1,\dot{h}(t)}\mathcal{E}_1 + \frac{h-h(t)}{h}\mathcal{E}_2^T\mathcal{U}_1^T\mathcal{E}_1 + \frac{h-h(t)}{h}\mathcal{E}_2^T\mathcal{U}_2^T\mathcal{E}_1 \right. \\
&\quad \left. + \frac{h-h(t)}{h}\mathcal{E}_1^T\mathcal{U}_1\mathcal{E}_2 + \frac{h-h(t)}{h}\mathcal{E}_1^T\mathcal{U}_2\mathcal{E}_2 + \frac{h-h(t)}{h}\mathcal{E}_2^T\Pi_{2,\dot{h}(t)}\mathcal{E}_2\right),
\end{aligned} \tag{B.2}$$

$$\begin{aligned}
\mathcal{G}_{h(t)} &= h(t)\mathcal{G}_1 + (h-h(t))\mathcal{G}_2, \\
\mathcal{L} &= e_1^T\mathcal{N}_1 + e_4^T\mathcal{N}_2, \\
\varphi &= (-\mathcal{A} + (\mathcal{F} - \Pi)\mathcal{K}_1)e_1 + \mathcal{W}_0e_7 + \mathcal{W}_1e_8 + (\mathcal{F} - \Pi)\mathcal{K}_2e_2 + (\mathcal{F} - \Pi)\mathcal{K}_3e_3 - e_4, \\
\Gamma &= \mathcal{L}\mathcal{H}, \\
\Theta &= \mathcal{E}e_1, \\
\Phi_1(h(t)) &= \text{col}\{e_1, e_3, h(t)e_9, (h-h(t))e_{10}\}, \\
\Phi_2(\dot{h}(t)) &= \text{col}\{e_4, e_6, e_1 - (1 - \dot{h}(t))e_2, (1 - \dot{h}(t))e_2 - e_3\}, \\
\Phi_3 &= \text{col}\{e_1, e_2, e_3\}, \\
\Phi_4(\dot{h}(t)) &= \text{col}\{e_4, (1 - \dot{h}(t))e_5 - e_6\}, \\
\mathcal{E}_1 &= \text{col}\{e_1 - e_2, e_1 + e_2 - 2e_9, e_1 - e_2 + 6e_9 - 12e_{11}\}, \\
\mathcal{E}_2 &= \text{col}\{e_2 - e_3, e_2 + e_3 - 2e_{10}, e_2 - e_3 + 6e_{10} - 12e_{12}\}, \\
\bar{\Pi}_{1,\dot{h}(t)} &= (1 - \dot{h}(t))\mathcal{G}_1 + \dot{h}(t)\mathcal{G}_2 - \dot{h}(t)\mathcal{M}_1, \\
\bar{\Pi}_{2,\dot{h}(t)} &= \mathcal{G}_2 + \dot{h}(t)\mathcal{M}_3, \\
e_i &= \begin{bmatrix} 0_{n \times (i-1)n} & I_{n \times n} & 0_{n \times (9-i)} \end{bmatrix}, \quad i = 1, 2, \dots, 12, \\
\Pi_{1,\dot{h}(t)} &= \begin{bmatrix} \bar{\Pi}_{1,\dot{h}(t)} & 0 & 0 \\ 0 & 3\bar{\Pi}_{1,\dot{h}(t)} & 0 \\ 0 & 0 & 12\bar{\Pi}_{1,\dot{h}(t)} \end{bmatrix}, \\
\Pi_{2,\dot{h}(t)} &= \begin{bmatrix} \bar{\Pi}_{2,\dot{h}(t)} & 0 & 0 \\ 0 & 3\bar{\Pi}_{2,\dot{h}(t)} & 0 \\ 0 & 0 & 12\bar{\Pi}_{2,\dot{h}(t)} \end{bmatrix}.
\end{aligned} \tag{B.3}$$

C. Related Equations of Theorem 2

The appendix lists some notations and equations given in Theorem 2:

$$\begin{aligned}\tilde{\Sigma}_{h(t),\dot{h}(t)} &= \sum_{i=1}^4 \tilde{\Xi}_i + \text{Sym}\{\tilde{\mathcal{L}}\varphi\}, \\ \tilde{\Sigma}_1 &= \tilde{\Sigma}_{h(t)=0,\dot{h}(t)=0}, \\ \tilde{\Sigma}_2 &= \tilde{\Sigma}_{h(t)=h,\dot{h}(t)=0}, \\ \tilde{\Sigma}_3 &= \tilde{\Sigma}_{h(t)=h,\dot{h}(t)=\mu}, \\ \tilde{\Sigma}_4 &= \tilde{\Sigma}_{h(t)=0,\dot{h}(t)=\mu},\end{aligned}\tag{C.1}$$

$$\begin{aligned}\tilde{\Xi}_1 &= \dot{h}(t)\Phi_1^T(h(t))\tilde{\mathcal{P}}_2\Phi_1(h(t)) + \text{Sym}\{\Phi_1^T(h(t))\tilde{\mathcal{P}}_{h(t)}\Phi_2(\dot{h}(t))\}, \\ \tilde{\Xi}_2 &= \Phi_3^T\tilde{\mathcal{Q}}\Phi_4(\dot{h}(t)), \\ \tilde{\Xi}_3 &= e_4^T[\tilde{\mathcal{G}}_{h(t)} + \tilde{\mathcal{M}}_{1,h(t)}]e_4 + (1 - \dot{h}(t))e_5^T[\tilde{\mathcal{M}}_{2,h(t)} - \tilde{\mathcal{M}}_{1,h(t)}]e_5 - e_6^T\tilde{\mathcal{M}}_{2,h(t)}e_6 + \tilde{\Omega}(h(t)), \\ \tilde{\Xi}_4 &= 2(1 - \dot{h}(t))e_8^T(\tilde{\mathcal{D}}_1 - \tilde{\mathcal{D}}_2)e_5 + 2(1 - \dot{h}(t))e_2(\tilde{\mathcal{D}}_2\mathcal{L}_2 - \tilde{\mathcal{D}}_1\mathcal{L}_1)e_5, \\ \tilde{\Gamma}(h(t)) &= \frac{h-h(t)}{h^2}\mathcal{E}_1^T\tilde{\mathcal{U}}_2^T\tilde{\Pi}_{2,\dot{h}(t)}^{-1}\tilde{\mathcal{U}}_2\mathcal{E}_1 + \frac{h(t)}{h^2}\mathcal{E}_2^T\tilde{\mathcal{U}}_1^T\tilde{\Pi}_1^{-1,\dot{h}(t)}\tilde{\mathcal{U}}_1\mathcal{E}_2, \\ \tilde{\Omega}(h(t)) &= -\frac{1}{h}\left(\frac{2h-h(t)}{h}\mathcal{E}_1^T\tilde{\Pi}_{1,\dot{h}(t)}\mathcal{E}_1 + \frac{h-h(t)}{h}\mathcal{E}_2^T\tilde{\mathcal{U}}_1^T\mathcal{E}_1 + \frac{h-h(t)}{h}\mathcal{E}_2^T\tilde{\mathcal{U}}_2^T\mathcal{E}_1\right. \\ &\quad \left.+ \frac{h-h(t)}{h}\mathcal{E}_1^T\tilde{\mathcal{U}}_1\mathcal{E}_2 + \frac{h-h(t)}{h}\mathcal{E}_1^T\tilde{\mathcal{U}}_2\mathcal{E}_2 + \frac{h-h(t)}{h}\mathcal{E}_2^T\tilde{\Pi}_{2,\dot{h}(t)}\mathcal{E}_2\right),\end{aligned}\tag{C.2}$$

$$\begin{aligned}\tilde{\mathcal{G}}_{h(t)} &= h(t)\tilde{\mathcal{G}}_1 + (h-h(t))\tilde{\mathcal{G}}_2, \\ \tilde{\mathcal{L}} &= e_1^T + \kappa e_4^T, \\ \tilde{\varphi} &= (-\mathcal{L}\mathcal{H} + (\mathcal{J} - \Pi)\mathcal{Y}_1)e_1 + \mathcal{W}_0\mathcal{V}e_7 + \mathcal{W}_1\mathcal{V}e_8 + (\mathcal{J} - \Pi)\mathcal{Y}_2e_2 + (\mathcal{J} - \Pi)\mathcal{Y}_3e_3 - e_4\mathcal{V},\end{aligned}$$

$$\begin{aligned}\tilde{\Gamma} &= \tilde{\mathcal{L}}\mathcal{H}, \\ \tilde{\Theta} &= \mathbf{E}e_1, \\ \tilde{\tilde{\Pi}}_{1,\dot{h}(t)} &= (1 - \dot{h}(t))\tilde{\mathcal{G}}_1 + \dot{h}(t)\tilde{\mathcal{G}}_2 - \dot{h}(t)\tilde{\mathcal{M}}_1, \\ \tilde{\tilde{\Pi}}_{2,\dot{h}(t)} &= \tilde{\mathcal{G}}_2 + \dot{h}(t)\tilde{\mathcal{M}}_3, \\ \tilde{\tilde{\Pi}}_{1,\dot{h}(t)} &= \begin{bmatrix} \tilde{\tilde{\Pi}}_{1,\dot{h}(t)} & 0 & 0 \\ 0 & 3\tilde{\tilde{\Pi}}_{1,\dot{h}(t)} & 0 \\ 0 & 0 & 12\tilde{\tilde{\Pi}}_{1,\dot{h}(t)} \end{bmatrix}, \\ \tilde{\tilde{\Pi}}_{2,\dot{h}(t)} &= \begin{bmatrix} \tilde{\tilde{\Pi}}_{2,\dot{h}(t)} & 0 & 0 \\ 0 & 3\tilde{\tilde{\Pi}}_{2,\dot{h}(t)} & 0 \\ 0 & 0 & 12\tilde{\tilde{\Pi}}_{2,\dot{h}(t)} \end{bmatrix}.\end{aligned}\tag{C.3}$$

Data Availability

The raw/processed data required to reproduce these findings cannot be shared at this time as the data also form part of an ongoing study.

Disclosure

The authors declare that the work described is original research that has not been published previously and not under consideration for publication elsewhere, in whole or in part.

Conflicts of Interest

The authors declare no conflicts of interest.

Authors' Contributions

All the authors listed approved the manuscript that is enclosed.

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