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Article

Finite-Time RBFNN-Based Observer for Cooperative Multi-Missile Tracking Control Under Dynamic Event-Triggered Mechanism

Jiong Li ¹, Yadong Tang ^{2,*}, Lei Shao ¹, Xiangwei Bu ¹ and Jikun Ye ¹

¹ Air Defence and Antimissile School, Air Force Engineering University, Xi'an 710038, China

² Graduate School, Air Force Engineering University, Xi'an 710038, China

* Correspondence: 17854287020@163.com

Abstract

This paper proposes a hierarchical cooperative tracking control method for multi-missile formations under dynamic event-triggered mechanisms, addressing parameter uncertainties and saturated overload constraints. The proposed hierarchical structure consists of a reference trajectory generator and a trajectory tracking controller. The reference trajectory generator considers communication and collaboration among multiple interceptors, imposes saturation constraints on virtual control inputs, and generates reference trajectories for each receptor, effectively suppressing aggressive motions caused by overload saturation. On this basis, a Radial Basis Function Neural Network (RBFNN) combined with a sliding mode disturbance observer is adopted to estimate unknown external disturbances and unmodeled dynamics, and the finite-time convergence of the disturbance observer is proved. A tracking controller is then designed to ensure precise tracking of the reference trajectory by missile. This approach not only reduces communication and computational burdens but also effectively avoids Zeno behavior, enhancing the practical feasibility and robustness of the proposed method in engineering applications. Simulation results verify the effectiveness and superiority of the proposed method.

Keywords: multi-missile formation; radial basis function neural network (RBFNN); sliding mode disturbance observer; finite-time convergence; event-triggered mechanism

1. Introduction

In the current complex aerospace security environment [1–3], targets characterized by long range, high speed, and strong maneuverability pose significant challenges to national aerospace security. These types of vehicles integrate multiple advanced technologies and, compared to conventional aerospace equipment, possess substantial advantages in terms of speed, operational radius, and penetration capability, thereby creating pronounced threat effects. However, the unpredictability of their trajectories due to high maneuverability, coupled with the limited detection range of interceptors at long distances, makes it difficult for interception systems to match both speed and agility. As a result, single interception methods often prove inadequate against such targets. Consequently, leveraging the cooperative capabilities of multiple interceptors to counter these targets has become a key research focus in the field of aerospace defense.

When countering such targets, due to the limitation of their detection range, the common approach is to predict their High Probability Region (HPR)[3]. Interceptors need to fly along reference trajectories to the vicinity of the target to maximize their detection effectiveness [4–7]. This requires designing appropriate trajectory tracking control schemes for multiple interceptors, which is further transformed into a multi-interceptor formation tracking control problem. Through information interaction and cooperative actions, multiple interceptors can enhance the system's situational awareness, mission resilience, and decision-making efficiency[8–12], demonstrating obvious

advantages over single-vehicle tracking in terms of coverage, anti-jamming capability, sensing precision, and task execution. In the related literature on cooperative tracking control of vehicles, Chen et al. [13] designed a neural network-based disturbance observer and a fixed-time sliding mode controller for a single missile model, achieving finite-time trajectory tracking and disturbance rejection. Yang et al. [14] proposed a hierarchical formation approach for multiple quadrotor UAVs to address aggressive maneuvering in cooperative tracking, where the upper-level controller utilizes saturation functions and virtual reference generation, combined with neural network-based disturbance observers and error-weighted adaptation to accelerate estimation error convergence. Wang et al. [15] unified the handling of model uncertainties and nonlinear dynamics for heterogeneous spacecraft by constructing a distributed observer based on neighbor information and a cooperative control protocol. Ding et al. [16] presented a fixed-time distributed observer and time-varying functions to guarantee error convergence within a prescribed time. Yang et al. [17] addressed distributed time-varying formation of linear systems with heterogeneous uncertainties and directed graph topology, designing a fully distributed protocol based on neighbor-relative state information and proposing a novel adaptive mechanism to simultaneously handle state- and input-dependent uncertainties without requiring knowledge of their bounds or leader input information. Huang et al. [18] integrated exponential zeroing control barrier functions and prescribed performance control to address both limited communication and collision avoidance, thereby unifying formation performance and safety. Fang et al. [19] reduced communication and computational complexity while enhancing formation flexibility via a complex Laplacian matrix approach. Li et al. [20] introduced a centroid-based distributed formation control method for three-dimensional formations relying solely on inter-agent distance and position. Zhi et al. [21] developed a prescribed-time formation control framework for T-S fuzzy multi-agent systems, addressing heterogeneous and non-autonomous leader state estimation and unknown input compensation. Dou et al. [22] proposed a fully distributed adaptive control protocol with local output-based observers and sliding mode control, suitable for systems with unknown disturbances and leaders, ensuring bounded tracking errors. He et al. [23] designed a dynamic event-triggered mechanism for multi-vehicle systems, effectively reducing inter-agent communication during cooperative tracking.

However, most existing multi-agent cooperative tracking techniques are based on simple integrator models. In real missile flight, issues such as overload saturation must be considered, which may prevent the system from following the planned trajectory and can cause large attitude changes leading to aggressive maneuvers. To reduce inter-missile communication, traditional static event-triggered mechanisms suffer from insufficient flexibility and adaptability, and are less effective in complex scenarios. Based on the above analysis, the main contributions of this paper are as follows:

1. Building upon the work in [14] a hierarchical control structure based on a dynamic event-triggered mechanism is proposed. The reference trajectory generator incorporates communication and cooperation among multiple interceptors and imposes saturation constraints on the virtual control inputs to generate reference trajectories for the trajectory tracking controller. This effectively suppresses aggressive maneuvers caused by overload saturation.
2. On the basis of robust control for generating feasible reference trajectories, and inspired by [24], a radial basis function neural network (RBFNN) combined with a sliding mode finite-time disturbance observer is employed to estimate unknown disturbances and unmodeled dynamics. The observer exhibits strong robustness and is proven to converge in finite time.
3. For the tracking controller, a dynamic event-triggered mechanism is developed, integrating disturbance estimation into the event-triggering process. This approach not only avoids Zeno behavior but also reduces communication and computational burdens, thereby improving engineering feasibility and robustness.

2. Preliminaries

2.1. Dynamic Model of the Interceptor Missile

Consider a distributed heterogeneous multi-interceptor formation consisting of N ($N > 1$) interceptors, where the dynamics of the i -th missile can be expressed as:

$$\begin{cases} \dot{V}_i = (T_i \cos \alpha_i - D_i) / m_i - g \sin \gamma_i \\ \dot{\gamma}_i = ((L_i + T_i \sin \alpha_i) \cos \phi_i - m_i g \cos \gamma_i) / (m_i V_i) \\ \dot{\psi}_i = (L_i + T_i \sin \alpha_i) \sin \phi_i / (m_i V_i \cos \gamma_i) \\ \dot{x}_i = V_i \cos \gamma_i \cos \psi_i + d_{ix} \\ \dot{y}_i = V_i \cos \gamma_i \sin \psi_i + d_{iy} \\ \dot{z}_i = V_i \sin \gamma_i + d_{iz} \end{cases} \quad (1)$$

In Equation (1), T_i is the thrust of the missile, m_i is the mass of the missile, D_i is the drag of the missile, $p_i = [x_i, y_i, z_i]^T$ is the position of the missile, $v_i = \dot{p}_i = [v_{ix}, v_{iy}, v_{iz}]^T$ is the velocity of the missile, γ_i is the flight path angle, ψ_i is the heading angle, α_i is the angle of attack, ϕ_i is the bank angle, g is the gravitational constant, and $d_i = [d_{ix}, d_{iy}, d_{iz}]^T$ represents external disturbances.

The lift and drag of the i -th missile can be described by Equation (2)

$$D_i = 0.5 c_{Di} \rho s_i V_i^2, L_i = 0.5 c_{Li} \rho s_i V_i^2 \quad (2)$$

where ρ is the air density, s_i is the reference area of the missile, and c_{Di} and c_{Li} are the drag coefficient and lift coefficient, respectively. The missile thrust T_i generates the maneuvering acceleration of the missile, which is a crucial factor in the missile control process. In this paper, thrust T_i , angle of attack α_i , and bank angle ϕ_i are selected as the control variables:

$$u_i = [T_i \cos \alpha_i - D_i, (L_i + T_i \sin \alpha_i) \cos \phi_i, (L_i + T_i \sin \alpha_i) \sin \phi_i]^T = [F_{xi}, F_{yi}, F_{zi}]^T \quad (3)$$

The velocity state of the i -th missile is thus chosen as $v_i = \dot{p}_i = [v_{ix}, v_{iy}, v_{iz}]^T$, and the above model can then be represented by Equation (4):

$$\begin{aligned} \dot{p}_i &= v_i \\ \dot{v}_i &= B_i u_i - E_i + d_i \end{aligned} \quad (4)$$

In this regard, we have the following equations:

$$B_i = \frac{1}{m_i} \begin{bmatrix} \cos \gamma_i \cos \psi_i & -\sin \gamma_i \cos \psi_i & -\sin \psi_i \\ \cos \gamma_i \sin \psi_i & -\sin \gamma_i \sin \psi_i & \cos \psi_i \\ \sin \gamma_i & \cos \gamma_i & 0 \end{bmatrix} \quad (5)$$

$$E_i = \frac{1}{m_i} \begin{bmatrix} D_i \cos \gamma_i \cos \psi_i \\ D_i \cos \gamma_i \sin \psi_i \\ D_i \sin \gamma_i + m_i g \end{bmatrix} \quad (6)$$

$$d_i = \begin{bmatrix} -d_{iy} V_i \sin \gamma_i \cos \psi_i + d_{ix} \\ -d_{iy} V_i \sin \gamma_i \sin \psi_i + d_{iy} \\ d_{iy} V_i \sin \gamma_i + d_{iz} \end{bmatrix} \quad (7)$$

Remark 1: Generally, the external disturbances d_i encompass various sources such as aerodynamic perturbations, uncertainties in the system model, and other unpredictable environmental factors. It

is assumed that these disturbances, which influence the controller's performance, are uniformly bounded within known limits. This boundedness ensures that the control system can maintain robust performance in the presence of such uncertainties.

2.2. Graph Theory

In this paper, the missiles in the formation are indexed from 1 to N , and their cooperative flight relies solely on local communication between neighboring nodes. The communication network of the missile swarm is modeled using a directed graph. Let the directed graph $\mathcal{G} = (\mathcal{V}, \mathcal{E}, A)$ represent the communication links among the i -th missile,

1. The node set $\mathcal{V} = \{v_1, v_2, \dots, v_N\}$ denotes the set of individual missiles.
2. The edge set $\mathcal{E} \subseteq \{(v_i, v_j) | v_i, v_j \in \mathcal{V}\}$ characterizes the communication connections between the missiles, there exists an edge (i, j) , if missile i can send information to missile j .
3. The weighted adjacency matrix $A = [a_{ij}] \in \mathbb{R}^{N \times N}$ defines the weights of the communication links, where a_{ij} if and only if there is a communication edge from node i to node j .
4. The neighbor set of node v_i is defined as $\mathcal{N}_i = \{j | (v_j, v_i) \in \mathcal{E}\}$, and its in-degree is given by $d_i = \sum_{j \in \mathcal{N}_i} w_{ij}$, which represents the total weight of incoming information.

The communication topology can further be characterized by its Laplacian matrix $L = D - A$, where $D = \text{diag}\{d_1, d_2, \dots, d_N\}$ is the in degree diagonal matrix. If there exists at least one node in $\mathcal{G}$ that has a directed path to every other node, then the graph $\mathcal{G}$ is said to contain a spanning tree, and such a node is referred to as the root node.

Lemma 1 ([25]). *consider a strongly connected graph G and a non-negative diagonal matrix B with at least one positive element. Under these conditions, $(L + B)$ forms an irreducible, nonsingular M-matrix. Let $q = [q_1, q_2, \dots, q_N]^T = (L + B)^{-1}$. Then, defining $P = \text{diag}\{p_1, p_2, \dots, p_N\} = \text{diag}\{1/q_1, 1/q_2, \dots, 1/q_N\}$ yields a positive definite matrix. Accordingly, $Q = P(L + B) + (L + B)^T P$ is both symmetric and positive definite.*

2.3. RBFNN Approximation

This paper adopts a method that combines Radial Basis Function Neural Networks (RBFNN) with a sliding mode disturbance observer. As a type of nonlinear parameterized network, RBFNNs are widely used for approximating unknown functions due to their excellent approximation capabilities. Specifically, the unknown continuous nonlinear function can be effectively approximated by an RBFNN.

$$w_i(x_i, v_i) = W_i^T r_i(\sigma_i) + \mu_i(\sigma_i), \forall x_i \in \Omega_x, v_i \in \Omega_v, i = 1, 2, \dots, n \quad (8)$$

where $\sigma_i = [x_i, v_i]^T \in \mathbb{R}$, and $\mu_i(\sigma_i)$ denotes the approximation error; meanwhile, Ω_v and Ω_x are compact sets composed of v_i and x_i , $W_i = [W_{i1}, W_{i2}, \dots, W_{in}]^T \in \mathbb{R}$ represents the optimal weight vector, which is defined as follows:

$$W_i = \arg \min_{W_i \in \mathbb{R}} \left\{ \sup_{\sigma_i \in \mathcal{C}} \|w_i(x_i, v_i) - W_i^T r_i(\sigma_i)\| \right\} \quad (9)$$

where $r_i(\sigma_i) = [r_{i1}(\sigma_i), r_{i2}(\sigma_i), \dots, r_{in}(\sigma_i)]^T \in \mathbb{R}$, represents the basis functions, where a is the number of nodes in the RBFNN. The Gaussian function will be chosen as the basis function:

$$r_i(\sigma_i) = \exp\left(-\frac{(\sigma_i - \sigma_{il})^2}{\xi_{il}^2}\right) \quad (10)$$

In Equation (10), $r_i(\sigma_i) = [r_{i1}(\sigma_i), r_{i2}(\sigma_i), \dots, r_{in}(\sigma_i)]^T \in R$ is the center of the Gaussian function, ξ_{il}^2 is the width of the Gaussian function.

Theorem 1. *The optimal weight matrix is bounded, i.e., $W_i < W_{Max}$ where W_{Max} is a positive constant. For the RBFNN sliding mode observer, the upper bound of the disturbance estimation error is solely determined by the approximation error of the radial basis function neural network (RBFNN). Theoretically, this upper bound can be made arbitrarily small as long as the accuracy of the RBFNN is sufficiently high. Similarly, the disturbance estimation error satisfies $\mu_i(\sigma_i) \leq \mu_{Max}$, where μ_M is a positive constant.*

3. Main Results

This paper investigates the problem of robust formation tracking control for multiple missiles under a dynamic event-triggered mechanism, with particular attention to trajectory tracking in the presence of model uncertainties for each missile and overload saturation. To reduce the complexity of controller design, a hierarchical control approach is proposed to address different considerations at each layer.

In the reference trajectory generator, the nominal second-order dynamics model (4) of the missile is introduced into virtual agents. These virtual agents serve as reference generators, providing feasible reference trajectories for the design of trajectory tracking controllers, thereby transforming the desired trajectory into an executable reference trajectory. Overload saturation is also taken into account. Moreover, a dynamic event-triggered mechanism is incorporated into the reference trajectory generator to alleviate the communication burden among multiple missiles. The trajectory tracking controller is responsible for generating control commands based on the executable reference trajectory, thus governing the actual motion of the missiles.

Additionally, a finite-time convergent disturbance observer based on a radial basis function neural network (RBFNN) is proposed to estimate and compensate for the uncertainties in the nonlinear model.

3.1. Design of Reference Trajectory Generator Based on Dynamic Event-Triggered Mechanism

For the dynamics equation of the missile (4), where p_i and v_i represent the position and velocity vectors of the i -th interceptor missile, the desired trajectory and desired velocity vector of the i -th missile are defined as p_{di} and v_{di} , respectively. Then, the position error vector and velocity error vector can be expressed as:

$$\begin{cases} e_{pi} = p_i - p_{di} \\ e_{vi} = v_i - v_{di} \end{cases} \quad (11)$$

To reduce communication resource consumption, a dynamic event-triggered mechanism is incorporated into the reference trajectory generation process. As per the description of distributed event-triggered control in (12), a triggering time sequence $\{t_1^i, t_2^i, \dots, t_k^i\}$ is defined for information updates. Each missile cannot access real-time state information from its neighbors and can only update data at triggering times. To compare the differences between time-triggered and event-triggered strategies, the following state measurement errors are defined, measurement error E_{pi}, E_{vi} and event-triggered measurement error $e_{pi}(t_k^i), e_{vi}(t_k^i)$:

$$\begin{cases} e_{pi}(t_k^i) = p_i(t_k^i) - p_{di}(t_k^i) \\ e_{vi}(t_k^i) = v_i(t_k^i) - v_{di}(t_k^i) \end{cases} \quad (12)$$

$$\begin{cases} E_{pi} = e_{pi} - e_{pi}(t_k^i) \\ E_{vi} = e_{vi} - e_{vi}(t_k^i) \end{cases} \quad (13)$$

Considering that actuator saturation may cause the interceptor missile to deviate from its desired trajectory and velocity, it is necessary to replan the missile's trajectory according to the degree of actuator saturation, so that the replanned trajectory can track the desired trajectory and velocity as closely as possible. At this point, the complex kinematic model of the interceptor can be simplified to a simple second-order integrator model:

$$\begin{cases} \dot{p}_i = v_i, \\ \dot{v}_i = \text{Sat}(a_i, a_{Mi}) \end{cases} \quad (14)$$

By integrating the tracking error Formula (11) of the i -th missile, and the dynamic Equation (12) of the virtual intelligent agent, the dynamic Equation (14) describing the tracking error dynamics is derived:

$$\begin{cases} \dot{e}_{pi} = e_{vi}, \\ \dot{e}_{vi} = \text{Sat}(a_i, a_{Mi}) - a_{di} \end{cases} \quad (15)$$

In the formation of multiple missiles, for the i -th missile and its adjacent j -th missile, the local formation tracking errors $\bar{e}_{pi}$ and $\bar{e}_{vi}$ are derived as follows:

$$\begin{cases} \bar{e}_{pi} = \sum_{j \in N} (e_{pi} - e_{pj}) + b_i e_{pi} \\ \bar{e}_{vi} = \sum_{j \in N} (e_{vi} - e_{vj}) + b_i e_{vi} \end{cases} \quad (16)$$

Therefore, by defining $\bar{e}_p = [\bar{e}_{p1}, \bar{e}_{p2}, \dots, \bar{e}_{pN}]^T$ and $\bar{e}_v = [\bar{e}_{v1}, \bar{e}_{v2}, \dots, \bar{e}_{vN}]^T$, it can be obtained that:

$$\begin{cases} \bar{e}_p = (L + B) \otimes I_N \bar{e}_{pi} \\ \bar{e}_v = (L + B) \otimes I_N \bar{e}_{vi} \end{cases} \quad (17)$$

In Equation (17), $\otimes$ denotes the Kronecker product, and L represents the global Laplacian matrix, $B = \text{diag}(b_1, \dots, b_N)$, combined with the measurement error (13) under the triggering condition, the following cooperative triggering error can be defined as:

$$\begin{cases} \tilde{e}_{pi} = \bar{e}_{pi} + \sum_{i \in N} E_{pi} \\ \tilde{e}_{vi} = \bar{e}_{vi} + \sum_{i \in N} E_{vi} \end{cases} \quad (18)$$

To optimize the generation of reference trajectories, the output acceleration reference and the input of position errors need to be designed as saturation functions to avoid abrupt attitude changes and aggressive movements of the missile caused by excessive distance errors. For this purpose, the saturation function and its derivative are defined as follows:

$$\text{Sat}(a_i, a_{Mi}) = a_{Mi} \tanh(a_i) \quad (19)$$

$$\begin{cases} \text{Sat}(\bar{e}_{pi}, e_{piM}) = e_{piM} \tanh(\bar{e}_{pi}) \\ \text{Sat}_d(\bar{e}_{pi}, e_{piM}) = \bar{e}_{vi} e_{piM} \text{sech}^2(\bar{e}_{pi}) \end{cases} \quad (20)$$

where a_{Mi} and e_{piM} are both positive constants, represent the saturated overload of the i -the missile and the maximum allowable tracking error to prevent abrupt attitude changes and aggressive movements of the missile caused by excessive tracking errors. the expression for the virtual sliding surface can be derived as follows:

$$\bar{s}_i = \bar{e}_{vi} + \lambda_{1i} \bar{e}_{pi} = \bar{e}_{vi} + \lambda_{1i} \text{diag}\{\text{Sat}(\bar{e}_{pi}, e_{piM})\} \quad (21)$$

where λ_{1i} is diagonal positive definite matrix, The derivative of the virtual sliding mode surface can be derived as follows:

$$\dot{\bar{s}}_i = \dot{\bar{e}}_{vi} + \Lambda_{1i} \text{diag}\{\text{Sat}_d(\bar{e}_{pi}, e_{piM})\} \quad (22)$$

Then, the expression for the cooperative sliding mode surface under event-triggered mechanisms can be derived as follows:

$$S = \bar{e}_v + \lambda_{1i} \bar{e}_p, \tilde{S}_i = \tilde{e}_{v,i} + \lambda_{1i} \tilde{e}_{p,i}, \tilde{S} = S + A \otimes I_N E_v + \lambda_{1i} A \otimes I_N E_p \quad (23)$$

where $\tilde{S} = [\tilde{S}_1, \tilde{S}_2, \dots, \tilde{S}_N]^T$, $E_v = [E_{v1}, E_{v2}, \dots, E_{vN}]^T$ and $E_p = [E_{p1}, E_{p2}, \dots, E_{pN}]^T$

Based on the preceding designs of the position tracking error, velocity tracking error, and sliding mode quantity, the design of the trajectory reference generator can be derived as follows:

$$a_i^{ref} = a_{di} - q_i \tilde{S}_i - h_i e_{pi} - \lambda_{1i} e_{vi} \text{Sat}_d(e_{pi}, e_{piM}) \quad (24)$$

where q_i, h_i are both diagonal positive definite matrices, the trigger conditions are constructed as follows:

$$t_{k+1}^i = \inf\{t > t_k^i : T_i(E_{pi}, E_{vi}, \Delta u_i, \Delta e_p) - a_{adp,i} > 0\} \quad (25)$$

among them, for $T_i(E_{pi}, E_{vi}, \Delta u_i, \Delta e_p)$, it is defined as:

$$T_i(E_{pi}, E_{vi}, \Delta u_i, \Delta e_p) = \underline{\sigma}(\Upsilon) \underline{\sigma}(q_i) \underline{\sigma}(A) / 2 \|E_{vi}\|^2 + 3 \underline{\sigma}(\Gamma) \underline{\sigma}(h_i) \underline{\sigma}(\lambda_{1i}) \underline{\sigma}(A) \|E_{pi}\|^2 + \underline{\sigma}(\Upsilon) \|\Delta a_i\|^2 / 2 + \underline{\sigma}(Ph_i \lambda_{1i}) / 2 \|\Delta e_p\|^2 \quad (26)$$

among them, for $a_{adp,i}$, it is defined as:

$$\dot{a}_{adp,i} = -\nu a_{adp,i} - T_i(E_{pi}, E_{vi}, \Delta u_i, \Delta e_p) + \vartheta_i \quad (27)$$

where ν and ϑ_i are positive constants, and $\Upsilon = P(L + B)$.

Assumption 1: The local position error variable $\bar{e}_{pi}$, local velocity error variable $\bar{e}_{vi}$, the desired trajectory p_{di} , and its velocity v_{di} for tracking are all bounded and Lipschitz.

Theorem 2. For the reference trajectory generator (24) of the i -th missile, its reference trajectory p_{di} and reference velocity v_{di} satisfy Assumption 1. Through the dynamic event - triggering mechanism (25), (26) and (27), if $\underline{\sigma}(\Upsilon) \underline{\sigma}(q_i) > 3/2$, $\underline{\sigma}(P) \underline{\sigma}(h_i) \underline{\sigma}(\lambda_{1i}) > 1/2$, $\nu > 0$ and (28) holds, then $\bar{S}$, $\bar{e}_x$ and $\bar{e}_v$ are ultimately uniformly ultimately bounded (UUB). which indicates that the design of a_i^{ref} can achieve the convergence of the virtual tracking error.

Proof. Consider a Lyapunov candidate as follows:

$$V_1 = \frac{1}{2} \tilde{S}^T P \otimes I_3 \tilde{S} + \frac{1}{2} \bar{e}_p^T (PH) \otimes I_3 \bar{e}_p + a_{adp}$$

Taking the derivative with respect to V_1 , we obtain:

$$\begin{aligned}
\dot{V}_1 &= \tilde{S}^T P \otimes I_3 \dot{\tilde{S}} + \bar{e}_p^T (Ph_i) \otimes I_3 \dot{\bar{e}}_p + \sum_{i=1}^N \dot{a}_{adp,i} \\
&= \tilde{S}^T P \otimes I_3 (\dot{\bar{e}}_p + \lambda_{1i} \otimes I_3 \text{diag}\{\text{Sat}_d(\bar{e}_{pi}, e_{piM})\} \bar{e}_v) + \bar{e}_p^T (Ph_i) \otimes I_3 (\tilde{S} - (\lambda_{1i} \otimes I_3) \text{Sat}(\bar{e}_{pi}, e_{piM})) + \sum_{i=1}^N \dot{a}_{adp,i} \\
&= \tilde{S}^T (P(L+B)) \otimes I_3 (\dot{\bar{e}}_p + \lambda_{1i} \otimes I_3 \text{diag}\{\text{Sat}_d(\bar{e}_{pi}, e_{piM})\} \bar{e}_v) + \bar{e}_p^T (Ph_i) \otimes I_3 \tilde{S} - \bar{e}_p^T (Ph_i \lambda_{1i}) \otimes I_3 \text{Sat}(\bar{e}_{pi}, e_{piM}) + \sum_{i=1}^N \dot{a}_{adp,i} \\
&= \tilde{S}^T (P(L+B)) \otimes I_3 (a_i^{ref} - a_{di} + \lambda_{1i} \otimes I_3 \text{diag}\{\text{Sat}_d(\bar{e}_{pi}, e_{piM})\} \bar{e}_v) + \bar{e}_p^T (Ph_i) \otimes I_3 \tilde{S} - \bar{e}_p^T (Ph_i \lambda_{1i}) \otimes I_3 \text{Sat}(\bar{e}_{pi}, e_{piM}) + \sum_{i=1}^N \dot{a}_{adp,i} \\
&= \tilde{S}^T (P(L+B)) \otimes I_3 (-q_i \tilde{S} - q_i A \otimes I_3 E_{vi} - q_i A \lambda_{1i} \otimes I_3 E_{pi} - e_p - \Delta u) + \bar{e}_p^T (Ph_i) \otimes I_3 \tilde{S} - \bar{e}_p^T (Ph_i \lambda_{1i}) \otimes I_3 \text{Sat}(\bar{e}_{pi}, e_{piM}) + \sum_{i=1}^N \dot{a}_{adp,i} \\
&= -\tilde{S}^T \Upsilon q_i \tilde{S} - \tilde{S}^T \Upsilon q_i A E_v - \tilde{S}^T \Upsilon q_i A \lambda_{1i} E_p - \tilde{S}^T \Upsilon \Delta u + \bar{e}_p^T (Ph_i) \otimes I_3 \tilde{S} - \bar{e}_p^T (Ph_i \lambda_{1i}) \otimes I_3 \text{Sat}(\bar{e}_{pi}, e_{piM}) + \sum_{i=1}^N \dot{a}_{adp,i}
\end{aligned}$$

Where $\Delta u = a^{ref} - a_d$, $a^{ref} = [a_1^{ref}, a_2^{ref}, \dots, a_N^{ref}]^T$ and $a_d = [a_{d1}, a_{d2}, \dots, a_{dN}]^T$, according to Young's inequality, it can be obtained that:

$$\begin{aligned}
\tilde{S}^T \Upsilon Q A E_v &\leq \|\tilde{S}\|^2 / 2 + \|\Upsilon Q A E_v\|^2 / 2 \\
\tilde{S}^T \Upsilon Q A \lambda_{1i} E_p &\leq \|\tilde{S}\|^2 / 2 + \|\Upsilon Q A \lambda_{1i} E_p\|^2 / 2 \\
\tilde{S}^T \Upsilon \Delta u &\leq \|\tilde{S}\|^2 / 2 + \|\Upsilon \Delta u\|^2 / 2
\end{aligned}$$

This is to verify whether the nominal controller can ensure the uniform ultimate boundedness of $\bar{e}_p$. Considering the cooperative tracking error in event triggering $\tilde{e}_{pi} = \bar{e}_{pi} + \sum_{i=1}^N E_{pi}$, it can be obtained that:

$$\begin{aligned}
&-\bar{e}_p^T (Ph_i \lambda_{1i}) \otimes I_3 \text{Sat}(\bar{e}_{pi}, e_{piM}) \leq -(\bar{e}_p^T (Ph_i \lambda_{1i}) \otimes I_3 \bar{e}_p - \bar{e}_p^T (Ph_i \lambda_{1i}) \otimes I_3 \Delta e_p) \\
&\leq -Ph_i \lambda_{1i} \|\bar{e}_p\|^2 + \|\bar{e}_p\|^2 / 2 + \|Ph_i \lambda_{1i} \Delta e_p\|^2 / 2 \\
&\leq -(Ph_i \lambda_{1i} - 1/2) \|\bar{e}_p + A \otimes I_3 E_p\|^2 + \|Ph_i \lambda_{1i} \Delta e_p\|^2 / 2 \leq (Ph_i \lambda_{1i} - 1/2) A (2 \|\tilde{e}_p^T E_p\| + \|E_p\|^2) \\
&\quad - (Ph_i \lambda_{1i} - 1/2) \|\bar{e}_p\|^2 + \|Ph_i \lambda_{1i} \Delta e_p\|^2 / 2 \\
&\leq -(Ph_i \lambda_{1i} - 1/2) \|\tilde{e}_p\|^2 + 3(Ph_i \lambda_{1i} - 1/2) A \|E_p\|^2 + \|Ph_i \lambda_{1i} \Delta e_p\|^2 / 2
\end{aligned}$$

where $\Delta e_p = \bar{e}_{pi} - e_{piM}$, and thus $\dot{V}_1$ can be transformed into:

$$\begin{aligned}
\dot{V}_1 &\leq 3\|S_i\|^2 / 2 + \|\Upsilon q_i A E_v\|^2 / 2 + \|\Upsilon q_i A \lambda_{1i} E_p\|^2 / 2 + \|\Upsilon \Delta a_i\|^2 / 2 - (Ph_i \lambda_{1i} - 1/2) \|\tilde{e}_p\|^2 \\
&\quad + 3(Ph_i \lambda_{1i} - 1/2) A \|E_p\|^2 + \|Ph_i \lambda_{1i} \Delta e_p\|^2 / 2 - \Upsilon q_i \|S_i\|^2 + \sum_{i=1}^N \dot{a}_{adp,i} \\
&\leq \underline{\sigma}(\Upsilon q_i A) / 2 \|E_v\|^2 + \underline{\sigma}(\Upsilon) \|\Delta a_i\|^2 / 2 - (\underline{\sigma}(\Upsilon q_i) - 3/2) \|S_i\|^2 \\
&\quad + 3(\underline{\sigma}(Ph_i \lambda_{1i}) - 1/2) \underline{\sigma}(A) \|E_p\|^2 - (\underline{\sigma}(Ph_i \lambda_{1i}) - 1/2) \|\tilde{e}_p\|^2 + \underline{\sigma}(Ph_i \lambda_{1i}) / 2 \|\Delta e_p\|^2 \\
&\quad + \sum_{i=1}^N (-\nu a_{adp,i} - T_i(E_{pi}, E_{vi}, \Delta u_i, \Delta e_p) + \vartheta_i) \\
&= -(\underline{\sigma}(\Upsilon q_i) - 3/2) \|S_i\|^2 - (\underline{\sigma}(Ph_i \lambda_{1i}) - 1/2) \|\tilde{e}_p\|^2 + \sum_{i=1}^N -\nu a_{adp,i} + N\vartheta_i
\end{aligned}$$

It can be derived that:

$$\vartheta_i < (\underline{\sigma}(\Upsilon q_i) - 3/2) S_{Max,i}^2 + (\underline{\sigma}(Ph_i \lambda_{1i}) - 1/2) \tilde{e}_{Max,i}^2 + \sum_{i=1}^N -\nu a_{Max,adp,i} \quad (28)$$

where $\|S_i\| \leq S_{Max,i}$, $\|\tilde{e}_p\| \leq \tilde{e}_{Max,i}$ and $a_{adp,i} \leq a_{Max,adp,i}$.

Subsequently, to prove that the dynamic event-triggered mechanism does not induce Zeno behavior (i.e., the phenomenon where trigger events occur infinitely densely), for the trigger time interval from t_k^i to t_{k+1}^i , which is the time required for $T_i(E_{pi}, E_{vi}, \Delta u_i, \Delta e_p)$ to rise from 0 to $a_{adp,i}$, we can obtain:

$$\begin{aligned} T_i(E_{pi}, E_{vi}, \Delta u_i, \Delta e_p) &\leq \hbar_p \|E_{pi}\|^2 + \hbar_v \|E_{vi}\|^2 + \hbar_a \|\Delta a_i\|^2 + \hbar_{ep} \|\Delta e_p\|^2 \\ &\leq \left(\sqrt{\hbar_p} \|E_{pi}\| + \sqrt{\hbar_v} \|E_{vi}\| + \sqrt{\hbar_a} \|\Delta a_i\| + \sqrt{\hbar_{ep}} \|\Delta e_p\| \right)^2 \end{aligned}$$

according to Equation (25), it can be obtained that:

$$\int_{t_k^i}^{t_{k+1}^i} \left(\sqrt{\hbar_p} \|E_{pi}\| + \sqrt{\hbar_v} \|E_{vi}\| + \sqrt{\hbar_a} \|\Delta a_i\| + \sqrt{\hbar_{ep}} \|\Delta e_p\| \right) d\tau = \sqrt{\frac{\vartheta_i}{1+\nu_i}}$$

thus, the minimum trigger interval is:

$$t_{k+1}^i - t_k^i \geq t_{low}^i = \sqrt{\frac{\vartheta_i}{1+\nu_i}} / \left(\sqrt{\hbar_p} V_{Max,i} + \sqrt{\hbar_v} a_{Max,i} + \sqrt{\hbar_a} a_{Max,i} + \sqrt{\hbar_{ep}} e_{pMax,i} \right) > 0$$

where $a_{Max,i}$, $e_{pMax,i}$ are positive constants satisfying $\Delta a_i \leq a_{Max,i}$ and $\Delta e_p \leq e_{pMax,i}$, within the time interval $[t_k^i, t_{k+1}^i]$, it is necessary to analyze the characteristics of the time derivatives of E_{pi}, E_{vi}

$$\begin{cases} \frac{d}{dt} \|E_{v,i}\| \leq \|\dot{v}_i - \dot{v}_i(t_k^i)\| \leq \|a_i\| \leq \|a_{Max,i}\| \\ \frac{d}{dt} \|E_{p,i}\| \leq \|\dot{p}_i - \dot{p}_i(t_k^i)\| \leq \|v_i\| \leq \|V_{Max,i}\| \end{cases}$$

So the design of this dynamic event-triggered mechanism can rule out the existence of Zeno behavior.

Remark 1. For the aforementioned dynamic event-triggering mechanism and the parameters designed in its update laws (25), (26) and (27), the event-triggering interval and convergence speed can be adjusted by tuning these parameters: The variation of ν affects the convergence speed of $a_{adp,i}$. Thus, increasing ν can lead to more trigger events; ϑ_i is used to adjust the trigger threshold, and when ϑ_i increases, it results in a reduction in the number of trigger events.

3.2. RBFNN-Based Finite-Time Disturbance Observer

Lemma 2 ([26]). For a vector X and its associated continuous Lyapunov function $V(X)$, if $\dot{V}(X) \leq -nV^\iota(X) + \Delta$, where $n > 0$, $0 < \iota < 1$ and $\Delta > 0$, then is finite-time bounded.

For the dynamic model (4) of the i -th missile, by combining d_i and E_i and treating them as the disturbance to be observed, we can obtain:

$$w_i = -E_i + d_i \quad (29)$$

Since w_i is an unknown disturbance. To effectively compensate for and suppress the disturbance in the controller design, we propose a sliding mode disturbance observer based on the Radial Basis Function Neural Network (RBFNN). First, a virtual second-order observation system is constructed based on the actual system (30):

$$\begin{cases} \dot{\hat{p}}_i = \hat{v}_i \\ \dot{\hat{v}}_i = B_i u_i + w_i \end{cases} \quad (30)$$

where $\hat{u}_i$ is the virtual control input, and the vectors $\hat{p}_i$ and $\hat{v}_i$ represent the estimated values of the state variables p_i and v_i , respectively. Since u_i is the controller to be designed and the term B_i is regarded as the known dynamics of the virtual system. By comparing the differences between the virtual system and the actual dynamics Equation (4), the following tracking error dynamic equations of the virtual system are derived:

$$\begin{cases} \dot{\delta}_{pi} = \delta_{vi} \\ \dot{\delta}_{vi} = w_i - \hat{w}_i \end{cases} \quad (31)$$

where $\delta_{pi} = p_i - \hat{p}_i$ and $\delta_{vi} = v_i - \hat{v}_i$ are applied. we define sliding surface as:

$$\tilde{s}_i = \delta_{vi} + \tilde{\lambda}_i \delta_{pi} + \tilde{\lambda}_i \delta_{pi}^\rho \quad (32)$$

we have the derivative of sliding surface as:

$$\dot{\tilde{s}}_i = \tilde{\lambda}_i \delta_{vi} + w_i - \hat{w}_i \quad (33)$$

Based on the previous discussion regarding the estimation of w_i using artificial RBF neural network, the following design of a neural adaptive sliding - mode controller for the virtual system is presented:

$$\hat{w}_i = \hat{W}_i^T \sigma(p_i, v_i) + \mu_i(\sigma(p_i, v_i)) + \tilde{\lambda}_i \delta_{vi} + \kappa_i \tilde{s}_i + \kappa_i \tilde{s}_i^\rho + r_i \delta_{pi} \quad (34)$$

where $\tilde{\lambda}_i$, κ_i and r_i are diagonal positive definite matrices and the update law of the RBFNN is:

$$\dot{\hat{W}}_i = \ell \sigma(x_i, v_i) \tilde{s}_i^T - \chi \hat{W}_i - \chi \hat{W}_i^\rho \quad (35)$$

where ℓ and χ are both positive constants.

Theorem 3. For the observer designed in (34) and the update law designed in (35), where the condition in (36) is satisfied, the error states δ_{pi} , sliding mode variables $\tilde{s}_i$, and neural network weight $\hat{W}$ are all semi-globally uniformly ultimately bounded.

Proof. Consider the following Lyapunov candidate

$$V_2 = \frac{1}{2} \tilde{s}_i^T \tilde{s}_i + \frac{1}{2\ell_i} \hat{W}_i^T \hat{W}_i + \frac{1}{2} \delta_{pi}^T r_i \delta_{pi}$$

Then we have the derivative of V_2 as follows:

$$\begin{aligned} \dot{V}_2 &= \tilde{s}_i^T \dot{\tilde{s}}_i + \frac{1}{\ell_i} \hat{W}_i^T \dot{\hat{W}}_i + r_i \delta_{pi}^T \dot{\delta}_{pi} \\ &= \tilde{s}_i^T (w_i - \hat{w}_i + \tilde{\lambda}_i \delta_{vi}) + \frac{1}{\ell_i} \hat{W}_i^T \dot{\hat{W}}_i + p_i \delta_{pi}^T (\tilde{s}_i - \tilde{\lambda}_i \delta_{pi} - \tilde{\lambda}_i \delta_{pi}^\rho) \\ &= \tilde{s}_i^T (w_i - \hat{W}_i^T \sigma(p_i, v_i) - \mu(\sigma(p_i, v_i)) - \kappa_i \tilde{s}_i - \kappa_i \tilde{s}_i^\rho - r_i \delta_{pi}) \\ &\quad + \frac{1}{\ell_i} \hat{W}_i^T (\ell_i \sigma(p_i, v_i) \tilde{s}_i^T - \chi_i \hat{W}_i - \chi_i \hat{W}_i^\rho) + r_i \delta_{pi}^T \tilde{s}_i - r_i \tilde{\lambda}_i \delta_{pi}^T \delta_{pi} - r_i \delta_{pi}^T \delta_{pi}^\rho \\ &= -\kappa_i \tilde{s}_i^T \tilde{s}_i - \kappa_i \tilde{s}_i^T \tilde{s}_i^\rho - \tilde{\lambda}_i r_i \delta_{pi}^T \delta_{pi} - \tilde{\lambda}_i r_i \delta_{pi}^T \delta_{pi}^\rho - \tilde{s}_i^T \mu(\sigma(p_i, v_i)) \\ &\quad + \tilde{s}_i^T w_i - \frac{\chi_i}{\ell_i} \hat{W}_i^T (\hat{W}_i + \hat{W}_i^\rho) \\ &\leq -\kappa_i \|\tilde{s}_i\|^2 - \kappa_i \|\tilde{s}_i\|^{1+\rho} - \tilde{\lambda}_i r_i \|\delta_{pi}\|^2 - \tilde{\lambda}_i r_i \|\delta_{pi}\|^{1+\rho} - \|\tilde{s}_i\| \sigma_{Max} + \|\tilde{s}_i\| w_{Max} \\ &\quad - \frac{\chi_i}{\ell_i} \|\hat{W}_i\|^2 - \frac{\chi_i}{\ell_i} \|\hat{W}_i\|^{1+\rho} \end{aligned}$$

Thus, we can obtain that:

$$\dot{V}_2 \leq -\tau^T Z \tau + \Xi \tau$$

where $\tau = \left[\|\tilde{s}_i\|, \|\tilde{s}_i\|^{(1+\rho)/2}, \|\tilde{x}_i\|, \|\tilde{x}_i\|^{(1+\rho)/2}, \|\hat{W}_i\|, \|\hat{W}_i\|^{(1+\rho)/2} \right]^T \in \mathbb{R}^6$

$$Z = \text{diag}(\kappa_i, \kappa_i, \tilde{\lambda}_i r_i, \tilde{\lambda}_i r_i, \frac{\chi_i}{\ell_i}, \frac{\chi_i}{\ell_i})$$

$$\Xi = [-\|\tilde{s}_i\| \mu_{\text{Max}} + \|\tilde{s}_i\| w_{\text{Max}}, 0, 0, 0, 0, 0]$$

If $\dot{V}_2$ is kept negative at all times, then we can obtain that:

$$\|\tau\| > \frac{-\|\tilde{s}_i\| \mu_{\text{Max}} + \|\tilde{s}_i\| w_{\text{Max}}}{\underline{\sigma}(Z)} \quad (36)$$

By Theorem 3, we can conclude that the observation errors δ_{vi} , δ_{pi} , and $\tilde{s}_i$ eventually converge to zero. According to Lyapunov stability theory, it can be concluded that $\hat{w}_i$ is semi-globally uniformly ultimately bounded.

$$\begin{aligned} \dot{V}_2 &\leq -\kappa_i \|\tilde{s}_i\|^2 - \kappa_i \|\tilde{s}_i\|^{1+\rho} - \tilde{\lambda}_i r_i \|\tilde{\delta}_{pi}\|^2 - \tilde{\lambda}_i r_i \|\tilde{\delta}_{pi}\|^{1+\rho} - \|\tilde{s}_i\| \sigma_{\text{Max}} + \|\tilde{s}_i\| w_{\text{Max}} \\ &\quad - \frac{\chi_i}{\ell_i} \|\hat{W}_i\|^2 - \frac{\chi_i}{\ell_i} \|\hat{W}_i\|^{1+\rho} \\ &\leq -\kappa_i \|\tilde{s}_i\|^{1+\rho} - \tilde{\lambda}_i r_i \|\tilde{\delta}_{pi}\|^{1+\rho} - \frac{\chi_i}{\ell_i} \|\hat{W}_i\|^{1+\rho} + \|\tilde{s}_i\| (w_{\text{Max}} - \mu_{\text{Max}}) \end{aligned}$$

From the Young's inequality, it can be obtained that:

$$\|\tilde{s}_i\| (w_{\text{Max}} - \mu_{\text{Max}}) \leq \frac{\|\tilde{s}_i\|^{1+\rho}}{1+\rho} + \frac{\rho}{1+\rho} (w_{\text{Max}} - \mu_{\text{Max}})^{\frac{1+\rho}{\rho}}$$

By adjusting the inequality, it can be obtained that:

$$\begin{aligned} \dot{V}_2 &\leq -\kappa_i \|\tilde{s}_i\|^{1+\rho} - \tilde{\lambda}_i r_i \|\tilde{\delta}_{pi}\|^{1+\rho} - \frac{\chi_i}{\ell_i} \|\hat{W}_i\|^{1+\rho} + \frac{\|\tilde{s}_i\|^{1+\rho}}{1+\rho} + \frac{\rho}{1+\rho} (w_{\text{Max}} - \mu_{\text{Max}})^{\frac{1+\rho}{\rho}} \\ &\leq -(\kappa_i - \frac{1}{1+\rho}) \|\tilde{s}_i\|^{1+\rho} - \tilde{\lambda}_i r_i \|\tilde{\delta}_{pi}\|^{1+\rho} - \frac{\chi_i}{\ell_i} \|\hat{W}_i\|^{1+\rho} + \frac{\rho}{1+\rho} (w_{\text{Max}} - \mu_{\text{Max}})^{\frac{1+\rho}{\rho}} \\ &\leq -\xi V_2 + \frac{\rho}{1+\rho} (w_{\text{Max}} - \mu_{\text{Max}})^{\frac{1+\rho}{\rho}} \end{aligned}$$

where $\xi = \min[(\kappa_i - \frac{1}{1+\rho}) 2^{(1+\rho)/2}, \frac{\chi_i}{\ell_i} (2\ell_i)^{(1+\rho)/2}, \tilde{\lambda}_i r_i (\frac{2}{r_i})^{(1+\rho)/2}]$,

From Lemma 2, it can be concluded that the error states δ_{pi} , sliding mode variables $\tilde{s}_i$, and neural network weight $\hat{W}$ are finite-time bounded.

3.3. A Trajectory Tracker Based on Dynamic Event-Triggered Mechanism

In the reference trajectory generator, the desired trajectory p_{di} and the desired velocity v_{di} are converted into an executable reference trajectory p_i^{ref} and a reference velocity v_i^{ref} , and the reference acceleration a_i^{ref} is provided. For the trajectory tracking controller, the tracking errors $e_{pi,l}$ and $e_{vi,l}$ for the reference trajectory and the reference velocity are defined as follows:

$$\begin{cases} e_{pi,l} = p_i - p_i^{ref} \\ e_{vi,l} = v_i - v_i^{ref} \end{cases} \quad (37)$$

To compare the differences between time-triggered and event-triggered strategies, the following state measurement errors are defined, measurement error $E_{pi,l}, E_{vi,l}$ and event-triggered measurement error $e_{pi,l}(t_k^i), e_{vi,l}(t_k^i)$:

$$\begin{cases} e_{pi,l}(t_k^i) = p_i(t_k^i) - p_i^{ref}(t_k^i) \\ e_{vi,l}(t_k^i) = v_i(t_k^i) - v_i^{ref}(t_k^i) \end{cases} \quad (38)$$

$$\begin{cases} E_{pi,l} = e_{pi,l} - e_{pi,l}(t_k^i) \\ E_{vi,l} = e_{vi,l} - e_{vi,l}(t_k^i) \end{cases} \quad (39)$$

The tracking error dynamics are as follows:

$$\begin{cases} \dot{e}_{pi,l} = e_{vi,l} \\ \dot{e}_{vi,l} = B_i u_i + \hat{w}_i - a_i^{ref} \end{cases} \quad (40)$$

The sliding surface is constructed as follows:

$$s_{i,l} = e_{vi,l} + \lambda_{2i} e_{pi,l} \quad (41)$$

The sliding surface under event-triggered conditions is expressed as:

$$\tilde{s}_{i,l} = s_{i,l} + E_{pi,l} + \lambda_{2i} E_{vi,l} \quad (42)$$

where λ_{2i} is diagonal positive definite matrix.

The time derivative of the sliding surface is given as:

$$\dot{s}_{i,l} = \dot{e}_{vi,l} + \lambda_{2i} e_{vi,l} = B_i u_i + \hat{w}_i - a_i^{ref} + \lambda_{2i} e_{vi,l} \quad (43)$$

Through the design of the disturbance observer mentioned above, we can observe $\hat{w}_i$ as the uncertainty of the system. Based on the expression of the sliding surface, we can derive the trajectory tracking controller under the event-triggered mechanism:

$$u_i = B_i^{-1} (a_i^{ref} - \hat{w}_i - \lambda_{2i} e_{vi,l}(t_k^i) - k_i e_{pi,l}(t_k^i) - c_i s_{i,l}) \quad (44)$$

where k_i and c_i are both diagonal positive definite matrices.

The trigger conditions are constructed as follows:

$$t_{k+1}^i = \inf\{t > t_k^i : T_{i,l}(E_{pi,l}, E_{vi,l}, \hat{w}_i) - u_{adp,i} > 0\} \quad (45)$$

among them, for $T_{i,l}(E_{pi,l}, E_{vi,l}, w_i)$, it is defined as:

$$T_{i,l}(E_{pi,l}, E_{vi,l}, \hat{w}_i) = \|\hat{w}_i\|^2 / 2 + \sigma(c_i) \|E_{xi,l}\|^2 / 2 + \sigma(c_i) \sigma(\lambda_{2i}) \|E_{vi,l}\|^2 / 2 \quad (46)$$

among them, for $u_{adp,i}$, it is defined as:

$$\dot{u}_{adp,i} = -\nu_l u_{adp,i} - T_{i,l}(E_{xi,l}, E_{vi,l}, \hat{w}_i) + \vartheta_{i,l} \quad (47)$$

where ν_l and $\vartheta_{i,l}$ are positive constants.

Theorem 4. For the trajectory tracking controller (44) of the i -th missile, the dynamic event - triggering mechanism (45), if $\sigma(c_i) > 3/2, \sigma(k_i) \sigma(\lambda_{2i}) > 0, \nu_l > 0$ and (48) holds, then $s_{i,l}, e_{pi,l}$ and $e_{vi,l}$ are ultimately

uniformly ultimately bounded (UUB). which indicates that the design of u_i can achieve the convergence of the tracking reference error.

Proof. Consider the following Lyapunov candidate:

$$V_3 = \frac{1}{2} s_{i,l}^T s_{i,l} + \frac{1}{2} e_{pi,l}^T k_i e_{pi,l} + u_{adp}$$

the time derivative of the Lyapunov candidate is:

$$\begin{aligned} \dot{V}_3 &= s_{i,l}^T \dot{s}_{i,l} + k_i e_{pi,l}^T \dot{e}_{pi,l} + \dot{u}_{adp,i} \\ &= s_{i,l}^T (\dot{e}_{vi,l} + \lambda_{2i} e_{vi,l}) + k_i e_{pi,l}^T (s_{i,p} - \lambda_{2i} e_{pi,l}) + \dot{u}_{adp,i} \\ &= s_{i,l}^T (B_i u_i + \hat{w}_i - a_i^{ref} + \lambda_{2i} e_{vi,l}) + k_i e_{pi,l}^T (s_{i,p} - \lambda_{2i} e_{pi,l}) + \dot{u}_{adp,i} \\ &= s_{i,l}^T (\hat{w}_i - k_i e_{pi,l} - c_i s_{i,l} - c_i E_{pi,l} - c_i \lambda_{2i} E_{vi,l}) - k_i \lambda_{2i} e_{pi,l}^T e_{pi,l} + k_i e_{pi,l}^T s_{i,l} + \dot{u}_{adp,i} \\ &= s_{i,l}^T \hat{w}_i - s_{i,l}^T c_i s_{i,l} - c_i s_{i,l}^T E_{pi,l} - c_i s_{i,l}^T \lambda_{2i} E_{vi,l} - e_{pi,l}^T k_i \lambda_{2i} e_{pi,l} + \dot{u}_{adp,i} \end{aligned}$$

according to Young's inequality, it can be obtained that:

$$\begin{aligned} s_{i,l}^T \hat{w}_i &\leq \|s_{i,l}\|^2 / 2 + \|\hat{w}_i\|^2 / 2 \\ c_i s_{i,l}^T E_{pi,l} &\leq \|s_{i,l}\|^2 / 2 + \|c_i E_{pi,l}\|^2 / 2 \\ c_i s_{i,l}^T \lambda_{2i} E_{vi,l} &\leq \|s_{i,l}\|^2 / 2 + \|c_i \lambda_{2i} E_{vi,l}\|^2 / 2 \end{aligned}$$

thus, we can obtain this form:

$$\begin{aligned} \dot{V}_1 &\leq -(\sigma(c_i) - 3/2) \|s_{i,l}\|^2 - \|\hat{w}_i\|^2 / 2 - \|\sigma(c_i) E_{xi,l}\|^2 / 2 - \|\sigma(c_i) \sigma(\lambda_{2i}) E_{vi,l}\|^2 / 2 - \sigma(k_i) \sigma(\lambda_{2i}) \|e_{xi,l}\|^2 \\ &\quad - \nu_l u_{adp,i} - T_{i,l} (E_{xi,l}, E_{vi,l}, \hat{w}_i) + \vartheta_{i,l} \\ &\leq -(\sigma(c_i) - 3/2) \|s_{i,l}\|^2 - \sigma(k_i) \sigma(\lambda_{2i}) \|e_{xi,l}\|^2 + -\nu_l u_{adp,i} + \vartheta_{i,l} \end{aligned}$$

where $\|s_{i,l}\| \leq s_{Max,i}$, $\|e_{pi,l}\| \leq e_{Max,i}$ and $u_{adp,i} < u_{Max,adp,i}$ simplifying the above inequality yields:

$$\vartheta_{i,l} < (\sigma(c_i) - 3/2) S_{Max,i} + -\sigma(k_i) \sigma(\lambda_{2i}) \tilde{e}_{Max,i} + \sum_{i=1}^N -\nu_l u_{Max,adp,i} \quad (48)$$

According to Theorem 4, $s_{i,l}$, $e_{pi,l}$ and $e_{vi,l}$ are ultimately uniformly ultimately bounded (UUB), the proof of this stability is completed.

Subsequently, to prove that the dynamic event-triggered mechanism does not induce Zeno behavior, for the trigger time interval from t_k^i to t_{k+1}^i , which is the time required for $T_{i,l}(E_{pi,l}, E_{vi,l}, w_i)$ to rise from 0 to $u_{adp,i}$, we can obtain:

$$\begin{aligned} T_{i,l}(E_{pi,l}, E_{vi,l}, w_i) &\leq \bar{h}_{p,l} \|E_{pi,l}\|^2 + \bar{h}_{v,l} \|E_{vi,l}\|^2 + \bar{h}_w \|w_i\|^2 \\ &\leq \left(\sqrt{\bar{h}_{p,l}} \|E_{pi,l}\| + \sqrt{\bar{h}_{v,l}} \|E_{vi,l}\| + \sqrt{\bar{h}_w} \|w_i\| \right)^2 \end{aligned}$$

according to Equation (45), it can be obtained that:

$$\int_{t_k^i}^{t_{k+1}^i} \left(\sqrt{\bar{h}_{x,l}} \|E_{xi,l}\| + \sqrt{\bar{h}_{v,l}} \|E_{vi,l}\| + \sqrt{\bar{h}_w} \|\hat{w}_i\| \right) d\tau = \sqrt{\frac{\vartheta_{i,l}}{1 + \nu_l}}$$

thus, the minimum trigger interval is:

$$t_{k+1}^i - t_k^i \geq t_{low}^i = \sqrt{\frac{\vartheta_{i,l}}{1 + \nu_l}} / \left(\sqrt{\bar{h}_{x,l}} V_{Max,i} + \sqrt{\bar{h}_{v,l}} a_{Max,i} + \sqrt{\bar{h}_w} w_{Max,i} \right) > 0$$

where $w_{Max,i}$ is a positive constant satisfying $\hat{w}_i \leq w_{Max,i}$, within the time interval $[t_k^i, t_{k+1}^i]$, it is necessary to analyze the characteristics of the time derivatives of $E_{xi,l}, E_{vi,l}$

$$\begin{cases} \frac{d}{dt} \|E_{vi,l}\| \leq \|\dot{v}_{i,l} - \dot{v}_{i,l}(t_k^i)\| \leq \|a_{i,l}\| \leq a_{Maxi,l} \\ \frac{d}{dt} \|E_{pi,l}\| \leq \|\dot{p}_{i,l} - \dot{p}_{i,l}(t_k^i)\| \leq \|v_{i,l}\| \leq V_{Maxi,l} \end{cases}$$

So the design of this dynamic event-triggered mechanism can rule out the existence of Zeno behavior.

As shown in Figure 1. Control framework diagram, the design of this paper is fully described in the control framework diagram. The hierarchical framework achieves the on - demand allocation of communication and computing resources through the “dynamic event - triggered mechanism” (only updating the trajectory at critical moments), resists model and environmental uncertainties via the “RBFNN disturbance observer”, and reduces the design complexity by means of “hierarchical decoupling” (each layer focuses on a single function). From the generation of the reference trajectory to the terminal execution, a closed loop of “cooperative planning - disturbance compensation - precise tracking” is formed.

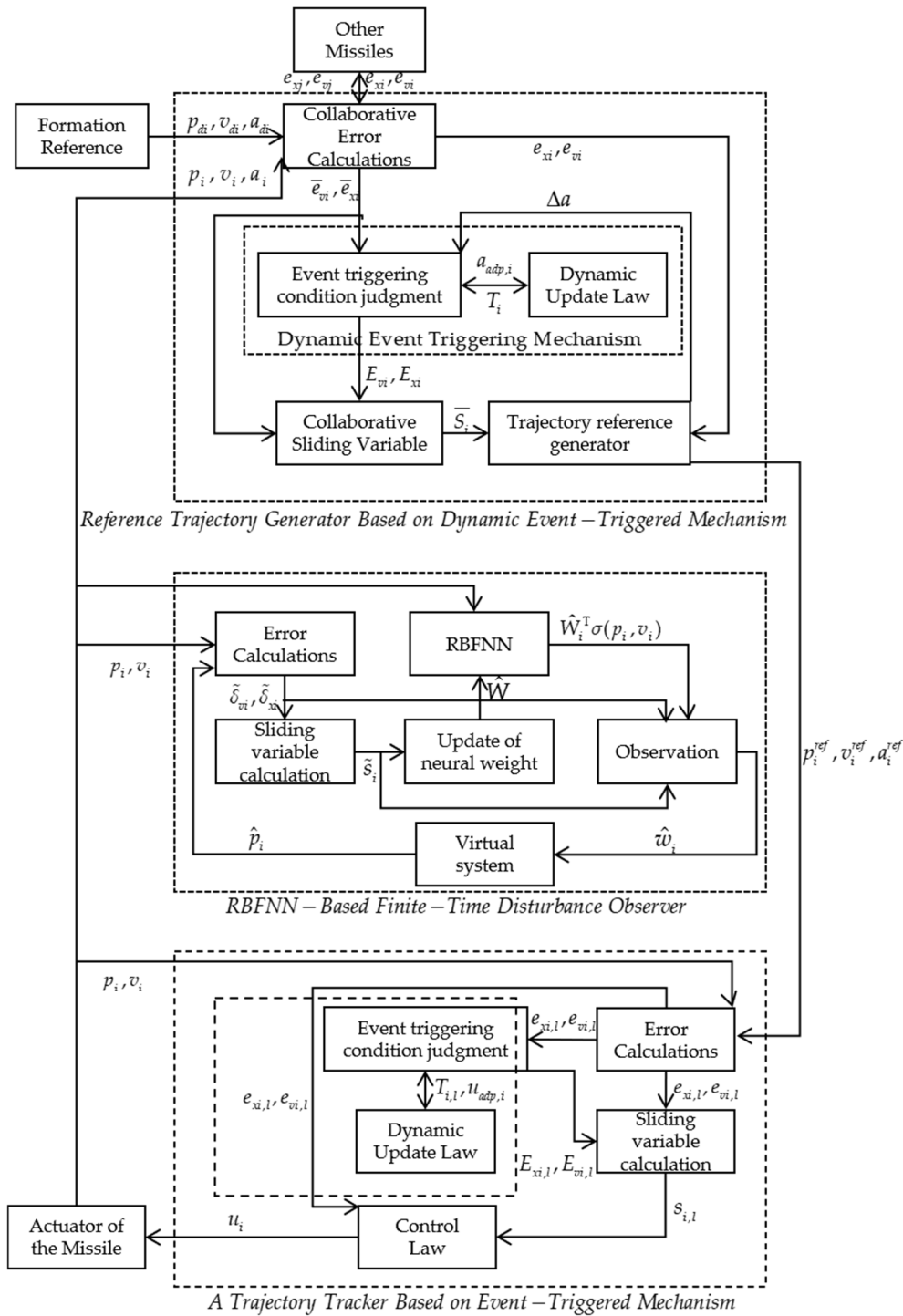


Figure 1. Control framework diagram.

4. Simulation Results and Discussion

In order to verify the performance of the proposed formation tracking controller design and RBFNN-based sliding mode disturbance observer, simulation experiments based on multi missiles are carried out.

Consider a multi-missile formation consisting of four heterogeneous interceptors, whose dynamic model is given by Equation (4). The parameters of this system are listed in Table 1. Its communication topology graph is shown in Figure 2

Table 1. Parameters of multi missile formation.

Missile number	x-direction position	y-direction position	z-direction position	velocity	flight path angles	flight path angles
1	8	8	0	0.1	0.5	0.5
2	8	-8	0	0.1	0.5	0.5
3	-8	8	0	0.1	0.5	0.5
4	-8	-8	0	0.1	0.5	0.5

The masses of the i -th missiles are 400, 402, 398, and 400 respectively. The gravitational constant g is set to $g = 9.8$, the simulation step size is selected as 0.1 seconds.

The position reference and velocity reference of the i -th missile are shown:

$$\begin{aligned} p_{d1} &= [1.5\sin(0.08t) + 5t^2 + 6, 1.5\sin(0.08t) + 5t^2 + 6, 0.5t - 2] \\ p_{d2} &= [1.5\sin(0.08t) + 5t^2 + 6, 1.5\sin(0.08t) + 5t^2 - 6, 0.5t] \\ p_{d3} &= [1.5\sin(0.08t) + 5t^2 - 6, 1.5\sin(0.08t) + 5t^2 + 6, 0.5t] \\ p_{d4} &= [1.5\sin(0.08t) + 5t^2, 1.5\sin(0.08t) + 5t^2, 0.5t] \\ v_{d1} &= [0.24\cos(0.08t) + 10t, 0.24\cos(0.08t) + 10t, 0.5] \\ v_{d2} &= [0.24\cos(0.08t) + 10t, 0.24\cos(0.08t) + 10t, 0.5] \\ v_{d3} &= [0.24\cos(0.08t) + 10t, 0.24\cos(0.08t) + 10t, 0.5] \\ v_{d4} &= [0.24\cos(0.08t) + 10t, 0.24\cos(0.08t) + 10t, 0.5] \end{aligned}$$

The system uncertainties and disturbances are selected as shown :

$$\begin{aligned} d_{ix} &= 0.3\sin(0.3t + i\pi / 6) \\ d_{iy} &= 0.4\cos(0.4t + i\pi / 4) \\ d_{iz} &= 0.4\sin(0.4t + i\pi / 6) \end{aligned}$$

In this paper, the parameter selections for the reference trajectory generator, RBFNN disturbance observer, tracking controller, and dynamic event-triggered mechanism are shown in Table 2.

Table 2. The parameters in the observer, controller, and triggering conditions.

parameters				value			
a_{M1}	a_{M2}	a_{M3}	a_{M4}	3	0.5	0.5	0.5
e_{p1M}	e_{p2M}	e_{p3M}	e_{p4M}	0.5	0.5	0.5	0.5
λ_{1i}	λ_i	λ_{2i}		$diag(2,2,2)$	$diag(1,1,1)$	$diag(1.5,1.5,1.5)$	
q_i	h_i			$diag(1,1,1)$	$diag(2,2,2)$		
κ_i	r_i			$diag(2,2,2)$	$diag(2,2,2)$		
k_i	c_i			$diag(0.75,0.75,0.75)$	$diag(0.25,0.25,0.25)$		
ℓ	χ			0.1	0.5		
ν	ϑ_i	ν_l	$\vartheta_{i,l}$	1	0.5	1	0.5

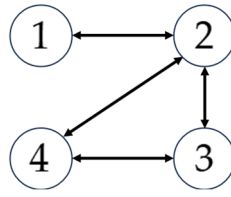


Figure 2. Communication topology diagram.

To demonstrate the effectiveness of the reference trajectory generator, Figures 3 and 4, as well as the error between the generated reference velocity and the actual reference velocity. Figure 5 shows the generated reference acceleration under actuator saturation, i.e., when the acceleration in each direction is constrained. The simulation results show that the position and velocity tracking errors of all four missiles converge rapidly within the time interval of 20-30 seconds, indicating that the reference trajectory generator can plan the missile reference trajectories to quickly approach the reference trajectories, and the convergence speed meets the requirements of formation coordination. After convergence, the errors are stabilized within a very small range (e.g., the position error $e_{pi} \leq \pm 0.2$ and the velocity error $e_{vi} \leq \pm 0.1$), verifying that the algorithm has high-precision tracking capability and can maintain low steady-state errors even in the presence of overload saturation. In the design of the dynamic event-triggered mechanism, the simulation curves converge stably rather than diverge despite the reduced communication frequency. This finding validates that the event-triggered mechanism can effectively reduce communication overhead without compromising tracking accuracy, thus verifying the rationality of the proposed algorithm architecture.

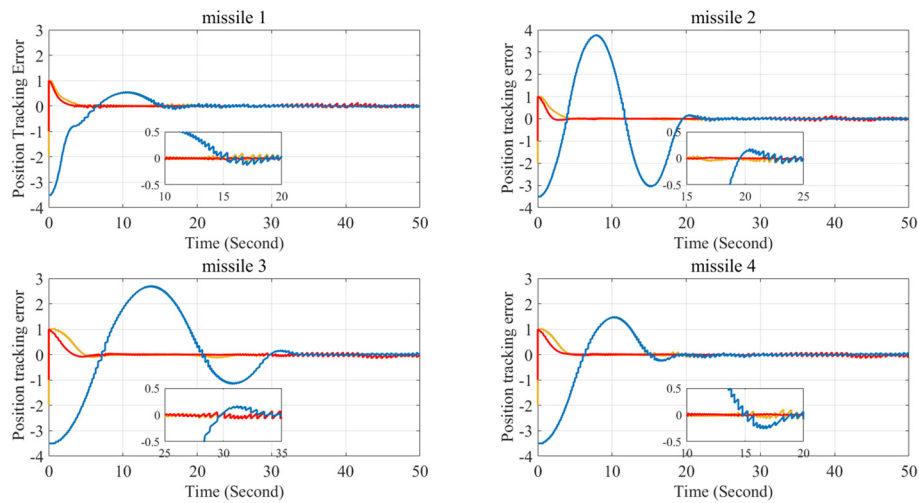


Figure 3. The position error in the reference trajectory generator.

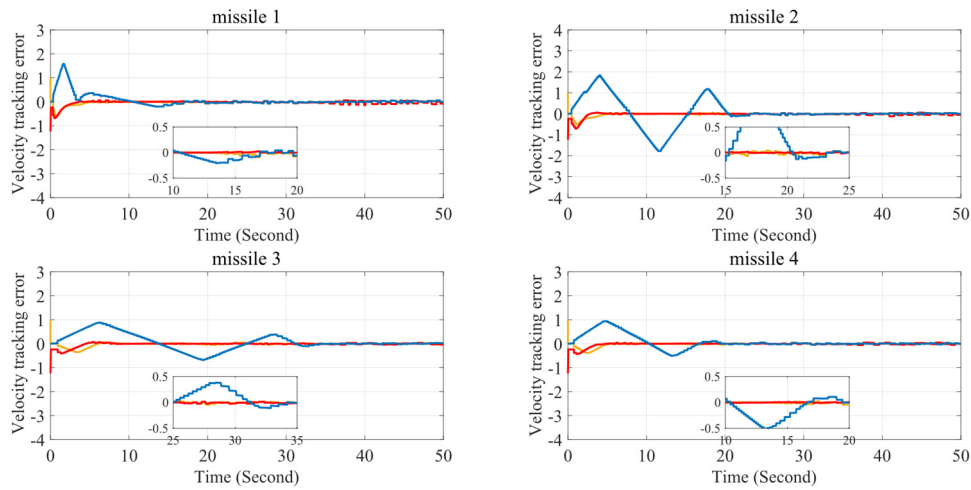


Figure 4. The velocity error reference trajectory generator.

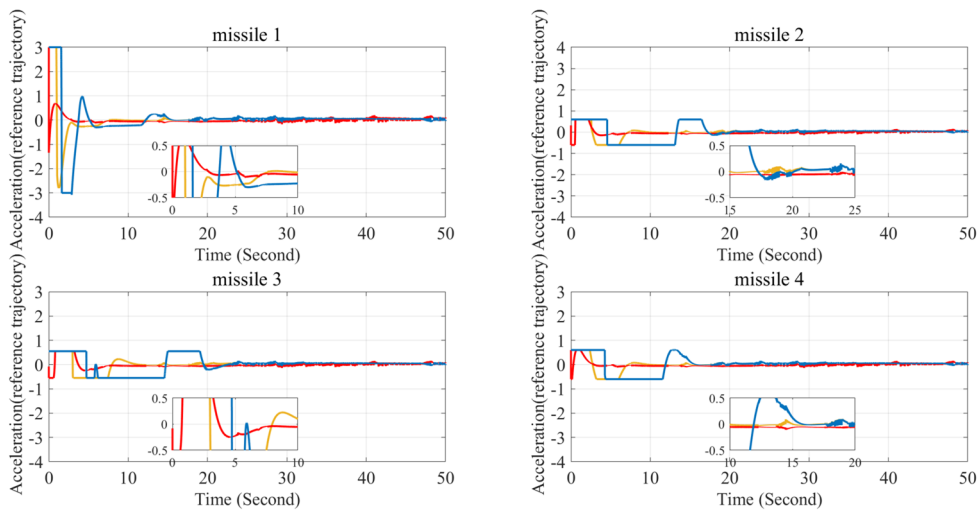


Figure 5. The reference acceleration in the reference trajectory generator.

To illustrate the dynamic cooperative event-triggered mechanism designed in Equations (25), (26) and (27), Figures 6 and 7 show the event-triggered intervals and the total number of event triggers for four missiles on the trajectory generator. For Figures 6 and 7, the trigger intervals of the four missiles all exhibit obvious fluctuations over time. This indicates that the dynamic event - triggered mechanism can adjust the trigger frequency in real - time according to the system state, enabling flexible adaptation between communication load and control performance. The trigger intervals of the four missiles are generally relatively low in the early stage and show an upward trend in the later stage; the number of triggers of the four missiles grows rapidly in the early stage, and the growth trend slows down in the later stage; the trigger intervals of the four missiles are generally relatively low in the early stage and show an upward trend in the later stage. This shows that the dynamic event - triggered mechanism can dynamically allocate communication resources according to the characteristics of the missiles at that moment — Missiles with frequent triggering generate more events to ensure control accuracy, and the number of triggers is reduced to save resources by cutting down on triggers. It verifies that the dynamic event - triggered mechanism has good self - adaptability: It can not only flexibly adjust the trigger frequency according to the real - time state of the missiles, allowing the system to operate efficiently under the condition of limited communication resources; but also adapt to the differences among heterogeneous missiles in the formation and balance “control accuracy” and “communication load”.

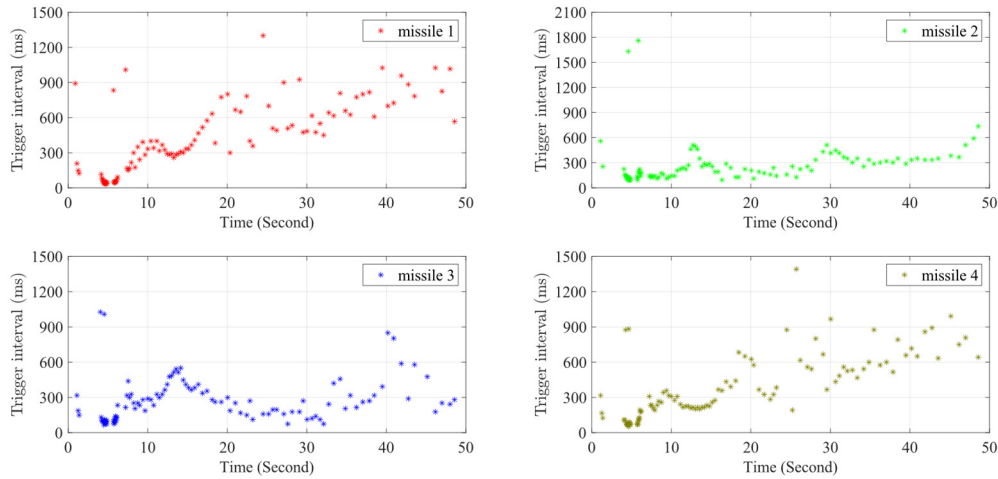


Figure 6. Trigger intervals in the reference trajectory generator.

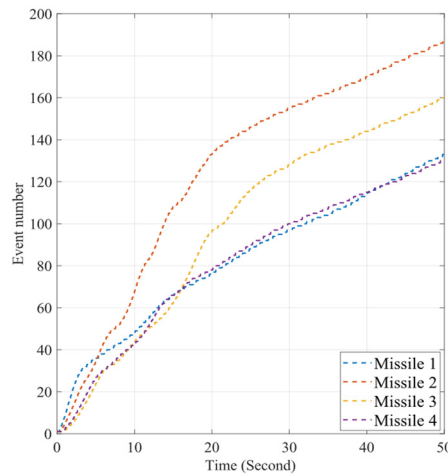


Figure 7. Event numbers in the reference trajectory generator.

In the subsequent experimental simulations of the finite-time sliding mode observer based on RBFNN (Radial Basis Function Neural Network)

Figure 8 illustrates the training process of the RBFNN, The approximation curve of the RBFNN highly coincides with the curve of the real nonlinear interference. Moreover, the approximation error on the right converges rapidly to a value close to 0. This indicates that the RBFNN has excellent nonlinear interference approximation capability and can accurately learn and compensate for unknown interferences in the system. The approximation error curve drops rapidly from the peak value to approach 0 within an extremely short time (about 5 seconds), verifying the fast convergence of the RBFNN — it can stably track the interference after the transient state, providing reliable interference compensation for subsequent control algorithms.

According to Equations (31), (33) and (34), the norms of $\tilde{\delta}_{vi}$ for each disturbance observer are selected, and their fast convergence verifies the rapid estimation of disturbances, As shown in Figure 9.

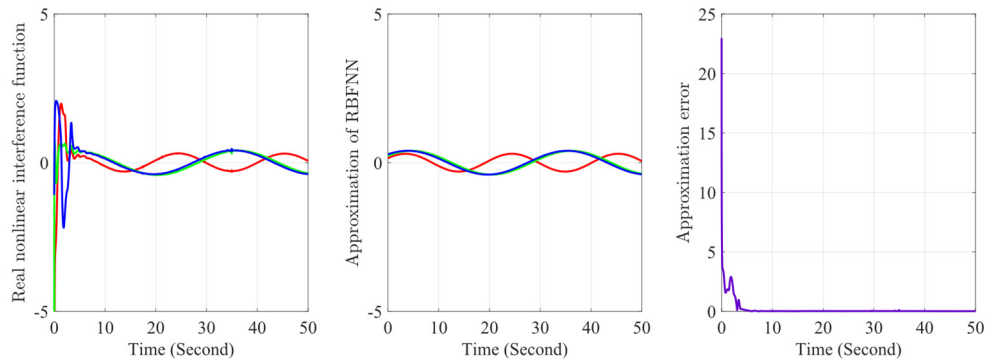


Figure 8. RBFNN training results for nonlinear functions.

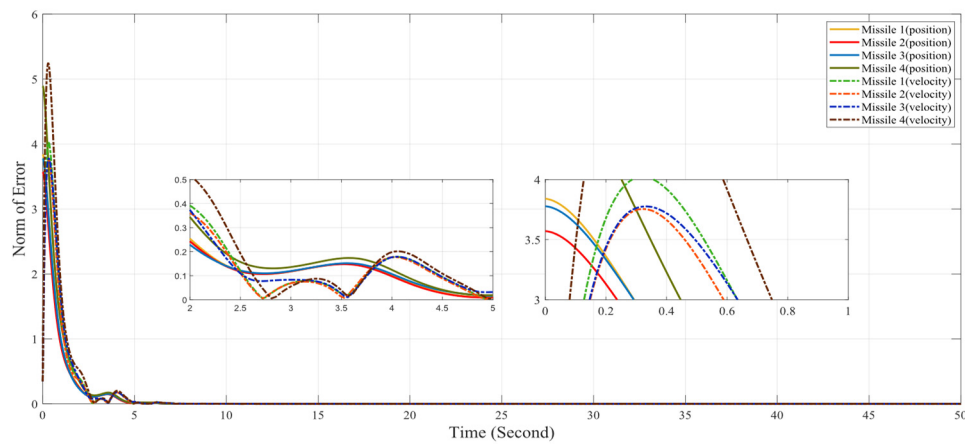


Figure 9. Effectiveness of the RBFNN observer.

To validate the effectiveness of the trajectory tracking controller, Figures 10 and 11 respectively depict the temporal evolution of errors between the generated reference trajectory and the actual flight trajectory, as well as those between the generated reference velocity and the actual flight velocity. Figure 12 further demonstrates the controller's output. The position tracking errors and velocity tracking errors of the four missiles all rapidly converge to extremely small values close to 0 within 10 seconds, which indicates that the control algorithm can drive the positions and velocities of the missiles to accurately approach the reference trajectories, satisfying the position constraint requirements and velocity constraint requirements for formation coordination. The control output curves show peaks in the initial stage (0 - 5 seconds) due to error adjustment, and then quickly drop back and remain stable, which shows that the control algorithm can rapidly suppress initial disturbances.

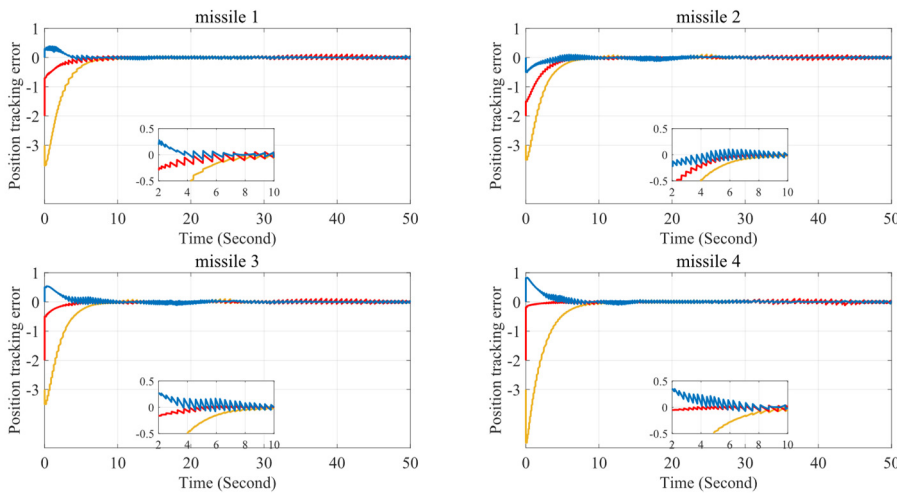


Figure 10. The position error in the trajectory tracking controller.

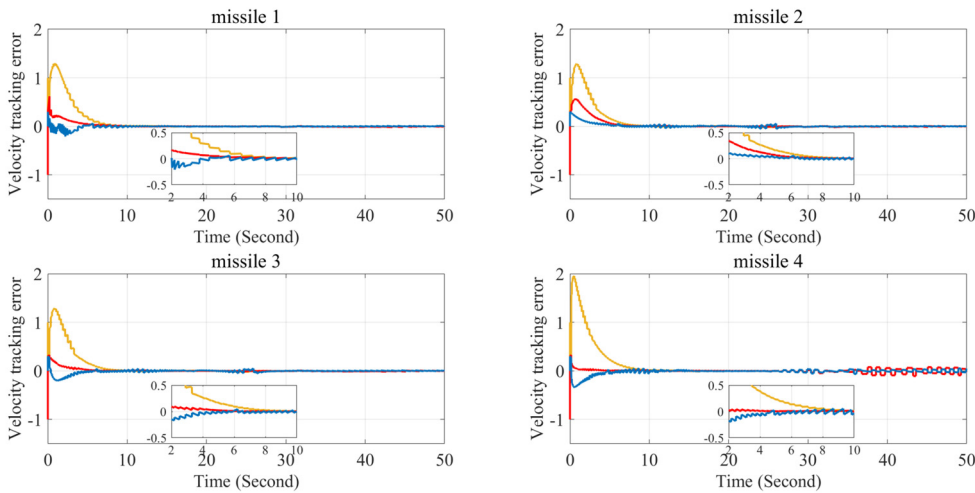


Figure 11. The velocity error in the trajectory tracking controller.

To illustrate the dynamic cooperative event-triggered mechanism designed based on Equations (45)–(47), Figures 13 and 14 present the event-triggered intervals, total number of event triggers for four missiles on the trajectory generators, as well as their comparison with the conventional static event-triggered mechanism. The results of the comparison are presented in Table 3. Among them, the trigger intervals of the dynamic event - triggered mechanism (DETM) are generally larger than those of the static event - triggered mechanism (SETM). The sparse trigger intervals of DETM, in contrast to the dense ones of SETM, verify that DETM can still stably reduce the trigger frequency in a heterogeneous missile formation. Additionally, the much lower growth rate of the trigger count for DETM compared to SETM further validates this ability of DETM to stably reduce the trigger frequency in such a formation.

Table 3. Comparison of communication times and percentage reduction.

Formation member	Missile 1	Missile 2	Missile 3	Missile 4
Without ETM	501	501	501	501
SETM	346	250	371	359
DETM	109	100	135	136
Percentage reduction	78.24%	80.03%	73.05%	72.85%

Finally, considering the global reference trajectory p_{ref} , global trajectory replanning p_d , and global actual trajectory p , Figure 15 illustrates the norms of errors including:

- (1) the norm of the error between global trajectory replanning and global reference trajectory;
- (2) the norm of the error between global trajectory replanning and global actual trajectory;
- (3) the norm of the error between global reference trajectory and global actual trajectory. The definitions of the quantities are as follows.

Among them, $\|p_d - p_{ref}\|$ gradually converges from the initial deviation, which indicates that the reference trajectory generation can maintain the approximation to the reference trajectory during dynamic adjustment. The rapid convergence of $\|p - p_{ref}\|$ proves that the designed trajectory tracking controller can quickly track the reference trajectory $\|p - p_d\|$ shows that the hierarchical control framework designed in this paper is effective and meets the actual control requirements.

$$\|p - p_{ref}\| = \sqrt{\sum_{i=1}^N \|p_i - p_{ref,i}\|^2}$$

$$\|p - p_d\| = \sqrt{\sum_{i=1}^N \|p_i - p_{d,i}\|^2}$$

$$\|p_d - p_{ref}\| = \sqrt{\sum_{i=1}^N \|p_{d,i} - p_{ref,i}\|^2}$$

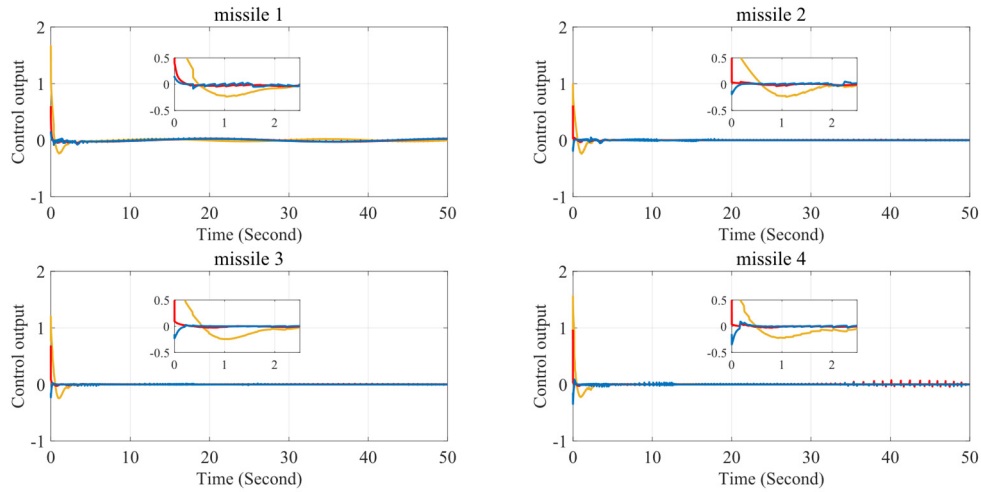


Figure 12. The control output in the trajectory tracking controller.

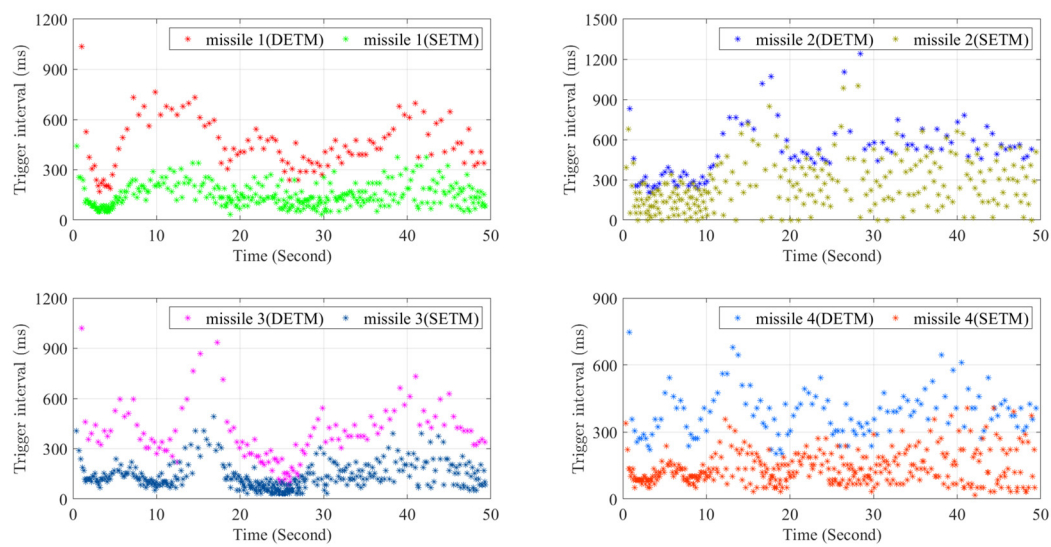


Figure 13. Trigger intervals in the trajectory tracking controller.

The trajectories of all missiles are shown in Figure 16 to illustrate the movement and formation status of the entire system.

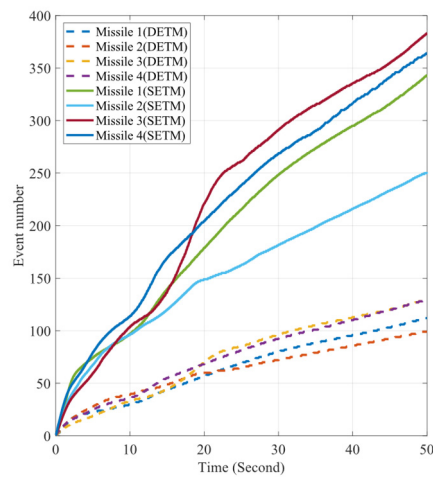


Figure 14. Event numbers in the trajectory tracking controller.

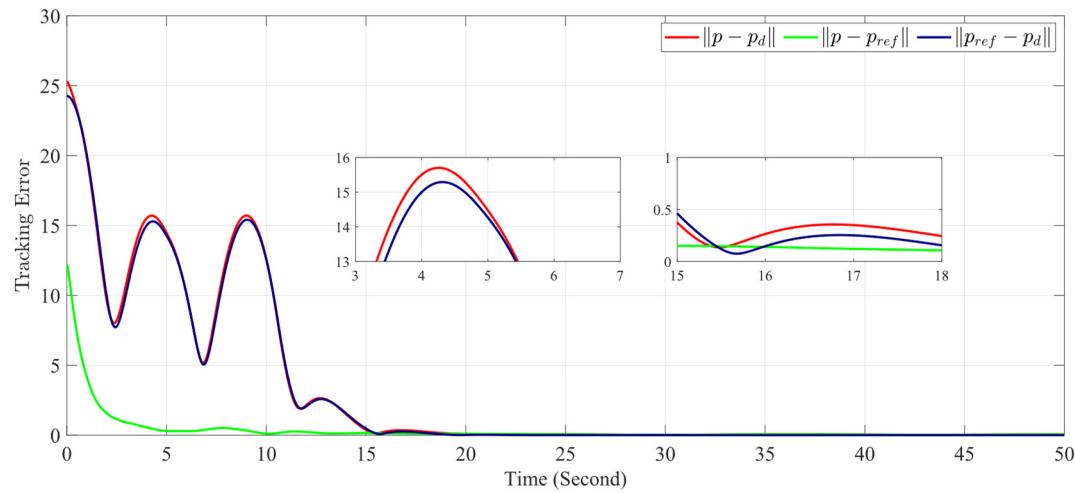


Figure 15. Norm of the tracking error.

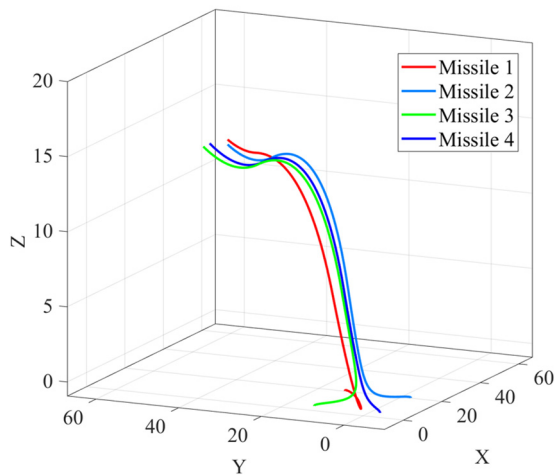


Figure 16. individual trajectory.

5. Conclusions

This paper investigates the formation tracking control problem of multiple missiles subject to overload saturation and system uncertainties. A hierarchical structure comprising a reference trajectory generator and a trajectory tracking controller is designed. The reference trajectory generator, by introducing a dynamic event - triggered mechanism and combining the communication cooperation among multiple interceptors and saturation constraints, generates executable reference trajectories, which effectively suppresses the violent maneuvers caused by overload saturation. The trajectory tracking controller, based on the generated reference trajectories and combined with the radial basis function neural network and the sliding mode disturbance observer, realizes the estimation and compensation of unknown disturbances and model uncertainties. It ensures the trajectory tracking accuracy and, meanwhile, proves its finite - time convergence property. Then, under the condition of generating reference trajectories, a missile tracking controller with a dynamic event - triggered condition is designed to reduce the number of communications among adjacent missiles. Theoretical analysis and comparative simulations are conducted. The simulation results show that, compared with the traditional static event - triggered mechanism, the dynamic mechanism can reduce the number of communications by 72.85% - 80.03%, significantly reducing the system communication and computational burdens, and verifying the effectiveness of the proposed formation control scheme.

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