Event-Triggered Composite Learning Finite-Time Trajectory Tracking Control for Underactuated MSVs Subject to Uncertainties

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ABSTRACT

In this paper, a novel event-triggered composite learning finite-time control scheme is presented for underactuated marine surface vehicles (MSVs) trajectory tracking under unknown dynamics and unknown time-varying disturbances. Line-of-sight (LOS) tracking control method is employed to address the underactuation problem of MSVs. The neural networks (NNs) are utilized to approximate unknown dynamics. The serial-parallel estimation model is employed to construct the prediction error, and the prediction errors and tracking errors are fused with construct the NN weights updating. Combining the result of approximation information, the disturbances observers can be created to achieve disturbance estimation. Fractional power technology is artistically introduced to realize the finite-time trajectory tracking control of MSVs based on composite learning. The proposed control scheme ensures the simultaneous realization of high precision tracking performance and unknown information approximation. Moreover, an event-triggered mechanism is introduced to reduce the transmission load and the execution rate of actuators. It is proved that the proposed control scheme ensures all error signals of the MSVs trajectory tracking control system can converge to the neighborhood of zero within a finite time. Finally, the simulation results on an MSV verify the effectiveness and superiority of the proposed control scheme.

INDEX TERMS

Line-of-sight, trajectory tracking, finite-time control, event-triggered, composite learning.

I. INTRODUCTION

Marine surface vehicles (MSVs) have made significant contributions to the growth of the marine economy in recent years. MSVs have a long history of usage in sectors such as maritime cruise, emergency rescue activities, marine transportation, and surveying [1]–[3]. The trajectory tracking control of MSVs plays a critical role in completing these tasks. The kinetics of MSVs unavoidably have uncertain dynamics and unpredictable time-varying environmental disturbances due to the effect of the external environment.

As a result, a variety of control techniques, such as neural network (NN) control [4], [5], fuzzy logic system (FLS) control [6], [7], disturbance observer-based (DOB) control [8]–[10], and finite-time control [11]–[13], have been used for control of MSVs. Uncertain terms, such as unmodeled dynamics and unknown dynamics, are approximated utilizing NNs and FLSs in [4]–[7]. To render the compound uncertainty of parameter perturbations and unknown disturbances, a DOB control method was employed in [8]–[10]. The dynamic uncertainties of MSVs were compensated with using a parameter adaptive approach and a backstepping design tool in [14], [15].

Several control methods are presented to render the underactuation problem of MSVs, including additional control methods [16]–[18], output redefinition control [19], [20], dynamic extension-based dynamic inversion [21], line-of-sight (LOS) [22]–[24], and so on. In [16]–[18], three additional control terms were devised to tackle the underactuation problem of MSVs. The output redefinition control strategy was employed in [19], [20] to handle the

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underactuation problem, as well as the combination of adaptive technique, NNs and Gaussian error function to solve the time-varying disturbances, unknown dynamics, and input saturation, respectively. The LOS technique was introduced to tackle the underactuation problem in [22]–[24], the adaptive technology and NN method were developed to address the unknown disturbances and parameter uncertainties effectively.

The first adopts the traditional dynamic extension technique which views an input as a state to achieve a relative degree, while the second views a state as a virtual input to achieve a relative degree.

Most of the previous studies had focused on the system’s tracking and stability. The precise accuracy of identifying models is rarely discussed in the literature. In practice, the model uncertainties should be estimated as accurately as possible to make the tracking performance of the system reach the expected result. In [25], the prediction error is constructed through the serial-parallel estimation model (SPEM) and the prediction error is introduced to construct the weights updating laws. By introducing the error feedback term into the reference model, [26], [27] obtains better transient performance. The composite learning control scheme was proposed in [28] for strict feedback system, which can obtain better tracking performance than NN control. In [29], both the modified modeling error and tracking error were used to construct the update law of NNs weights. In order to introduce learning performance indicators into update law, some research focuses on constructing composite learning law by introducing auxiliary filters [30], [31] or utilizing time interval data [32], [33].

In recently, finite-time (FT) control has attracted extensive attention from scholars [34], [35]. The FT control has a faster convergence time and strong robustness. A series of FT tracking control schemes using terminal sliding mode control (TSMC) [36], [37], non-singular terminal sliding mode control (NTSMC) [38] and passive sliding mode control [39] are proposed for the robotic manipulators under parameter perturbation. In order to optimize the control performance, the FT control technique is applied to MSV control. By utilizing a power integrator technique, [40] proposed a model-based continuous FT tracking control scheme for underactuated MSVs. The FT trajectory tracking control for MSVs was proposed by using integral sliding-mode techniques in [41] under time-varying disturbances was investigated. In [42], an robust adaptive finite-time tracking control scheme was proposed by using non-smooth and homogeneous tools for MSVs with unknown disturbances.

Although the above methods effectively solve the problems of unknown dynamic and time-varying disturbances, they do not consider how to reduce the mechanical wear of actuators to achieve the purpose of reducing the frequency of actuator failures. Event-triggered control (ETC) schemes have the capabilities of solving this problem, where the control commands are transmitted only if a certain event is triggered [43], [44]. The event-triggered control of unmanned systems has attracted the attention of many scholars [45], [46]. An event-triggered control scheme is presented for trajectory tracking control problem of marine surface vessels [47], which effectively reduces transmitting and computation burdens of control commands. Considering the underactuated MSVs with uncertain dynamics for surrounding a maneuvering target with unknown velocity information, an event-triggered control scheme was developed in [48].

The purpose of the fusion of composite neural network and NDO is to achieve faster and more accurate approximation of unknown information. The finite-time control scheme can guarantee the finite-time stability of systems. Therefore, the composite learning finite-time control scheme can further improve the control performance of the system. To reduce the transmission frequency of control commands and the execution rate of actuators, the event-triggered control is introduced to control law design.

Motivated by the review on previous works, an event-triggered composite learning finite-time control scheme for the trajectory tracking control of MSVs under time-varying disturbances and unknown dynamics is presented. This is the first attempt to propose an event-triggered finite time control scheme based on composite learning, while ensures the high-precision tracking control of the MSVs and the execution rate of the actuator are drastically reduced.

The main contributions can be summarized as follows.

- Different from traditional NN that only use tracking error to constructing the update of NN weights, the prediction error is introduced to construct the weights updating laws. The proposed control scheme ensures the simultaneous realization of higher tracking precision and more accurate approximation to unknown information than the control scheme based on NN.
- Compared with the prediction error construction method in [28], [29], the fractional power technology is artistically introduced into the SPEM to design the prediction error, which realizes the finite-time control under the composite learning scheme.
- The combination of ETC and composite learning scheme ensures the high-precision tracking control of the MSVs, while the transmission frequency of the control commands and the execution rate of the actuator are drastically reduced.

The rest of this paper is arranged as follows. In Section 2, the mathematical model of MSVs and the problem formulation are introduced. In Section 3, the principle of intelligent approximation using NN is presented. In Section 4, proposes the details of controller design procedures. In Section 5, the simulation results are given to show the effectiveness of the controller. In Section 6, the entire work is summarized.
II. PROBLEM FORMULATION AND PRELIMINARIES
A. MSV KINEMATIC AND DYNAMIC MODELS
The kinematics and dynamics of underactuated MSVs can be described as
\[
\begin{align*}
\dot{x} &= u \cos \varphi - v \sin \varphi \\
\dot{y} &= u \sin \varphi + v \cos \varphi \\
\dot{\varphi} &= r
\end{align*}
\]
where \((x, y)\) denote the ship position and \(\varphi\) is the yaw angle in the earth-fixed frame. \(u, v\) and \(r\) are surge, sway and yaw velocities in the body-fixed frame, \(m_{11}, m_{22}\) and \(m_{33}\) stand for inertia mass parameters, \(d_{11}, d_{22}\) and \(d_{33}\) represent hydrodynamic damping parameters, \(\Delta f_u, \Delta f_v\) and \(\Delta f_r\) are unknown dynamics of MSVs. \(\tau_u\) and \(\tau_r\) are control inputs of surge force and yaw moment, and \(d_u, d_v\) and \(d_r\) denote environmental disturbances.

**Assumption 1:** The unknown environmental disturbances \(d_j, j = u, v, r\) are unknown bounded and first differentiable, i.e.,
\[
|\dot{d}_j| \leq L
\]
where \(L < \infty\).

**Assumption 2:** The reference trajectory \(x_d, y_d\) and its first two time derivatives are bounded.

The position errors can be expressed in the body-fixed frame
\[
\begin{align*}
x_e &= (x - x_d) \cos \varphi + (y - y_d) \sin \varphi \\
y_e &= -(x - x_d) \sin \varphi + (y - y_d) \cos \varphi
\end{align*}
\]
According to (4a) and (4b), we have
\[
\begin{align*}
\dot{x}_e &= u + r y_e - \dot{x}_d \cos \varphi - \dot{y}_d \sin \varphi \\
\dot{y}_e &= v - r x_e + \dot{x}_d \sin \varphi - \dot{y}_d \cos \varphi
\end{align*}
\]
The position error \(\rho_s\) and yaw angle error \(\theta\) can be expressed
\[
\begin{align*}
\rho_s &= \rho_e - \rho_0 = \sqrt{x_e^2 + y_e^2} - \rho_0 \\
\theta &= \arctan(2(y_e, x_e))
\end{align*}
\]
According to (4a)-(4b) and (6a)-(6b), we have
\[
\begin{align*}
x_e &= \rho_e \cos \theta \\
y_e &= \rho_e \sin \theta
\end{align*}
\]
In order to avoid the singularity of the virtual control law subsequently designed, a positive constant \(\rho_0\) is introduced. The control objective in this paper is to construct the control law for MSVs suffering from unknown dynamic and time-varying disturbances satisfying Assumption 1-2 based on event-triggered mechanism to ensure the \(\rho_s\) and \(\theta\) can converge to the neighbor of zero within a finite time.

B. PRELIMINARIES

**Lemma 1:** (Yu, Yu, Shirinzadeh, Man, 2005) For the dynamical control system \(\dot{X} = G(X), \ g(0) = 0, \ X \in \mathbb{R}^n\), if Lyapunov function \(V(X)\) can be described by the following.
\[
\dot{V}(X) \leq -\delta_1 V(X) - \delta_2 V^2(X)
\]
where \(\delta_1 > 0(i = 1, 2)\) and \(0 < J < 1\) are positive parameters. Then, the nonlinear control system is finite-time stable, and the setting time function \(T_v\) satisfies
\[
T_v \leq \frac{1}{\delta_1(1 - J)} \ln \frac{\delta_1 V^{1-J}(X_0) + \delta_2}{\delta_2}
\]
**Lemma 2:** For any real number \(a_i, (i = 1, \ldots, n)\) and \(0 < \delta < 1\), the following inequality holds.
\[
(\sum_{i=1}^{n} |a_i|)^\delta \leq \sum_{i=1}^{n} |a_i|^\delta
\]
**Lemma 3:** For any real \(\phi, \lambda \in \mathbb{R}\) and positive constants \(c, d, f\), the following inequality holds.
\[
|\phi| |\lambda|^d \leq \frac{c}{c + d f} |\phi| |\lambda| + \frac{d}{c + d f} |\lambda|^d
\]
C. RADIAL BASIS FUNCTION NEURAL NETWORK (RBFNN) APPROXIMATION

Due to its inherent approximation characteristics, NNs are frequently used to approximate nonlinear terms. There exist an unknown continuous function \(f(Z)\) can be expressed as follows:
\[
\begin{align*}
f(Z) &= \omega^T \psi(Z) + \varepsilon \\
\psi(Z) &= \exp(-(Z - c_j)^T(Z - c_j)/b_j^2), \quad j = 1, 2, \ldots l
\end{align*}
\]
where \(Z \in \mathbb{R}^m\) is the input vector, \(\omega^*\) denotes the optimal weight vector that minimizes \(\|\varepsilon\|\) as expressed satisfies
\[
\omega^* = \arg \min_{\omega \in \mathbb{R}^n} \left\{ \sup_{Z \in \mathbb{R}^m} |f(Z) - \omega^T \psi(Z)| \right\}
\]
where \(\omega^* \in \mathbb{R}^n\) is a positive constant. The inherent approximation error \(\varepsilon\) is bounded, there exists an positive constant satisfying \(\|\varepsilon\| \leq \varepsilon_m\) and \(b_j\) and \(l\) are the center and the width of the Gaussian function, respectively, \(b\) is the number of the node.

III. CONTROL LAW DESIGN

The time derivative of \(\rho_s\) is obtained as
\[
\dot{\rho}_s = u \cos \theta + v \sin \theta + \cos \theta \xi_1 + \sin \theta \xi_2
\]
where \(\xi_1\) and \(\xi_2\) are defined as follows
\[
\begin{align*}
\xi_1 &= -\dot{x}_d \cos \varphi - \dot{y}_d \sin \varphi \\
\xi_2 &= \dot{x}_d \sin \varphi - \dot{y}_d \cos \varphi
\end{align*}
\]
From (13a), the virtual control law \(\alpha_u\) can be designed as
\[
\alpha_u = \frac{1}{\cos \theta} \left( -k_{\rho 1}(\rho_e - \rho_0)^2 - k_{\rho 2}(\rho_e - \rho_0) \\
- v \sin \theta - \cos \theta \xi_1 - \sin \theta \xi_2 \right)
\]
where \(k_{\rho 1}\) and \(k_{\rho 2}\) are positive design parameters.
Therefore, the (13a) can be rewritten as
\[
\dot{\hat{z}} = -k_p \rho \hat{z} + u_\epsilon \cos \theta \tag{16}
\]
Combining (2a) and (15), the equation as follows can be obtained
\[
m_{11} \dot{u}_e = m_{22} vr - d_{11} u + \tau_u + \Delta f_u + d_u - m_{11} \dot{u}_u \tag{17}
\]
According to the inherent approximation characteristics of NNs. We can get \(m_{22} vr - d_{11} u + \Delta f_u = \omega_\psi^T \psi_u + \hat{e}_u\). Further, define \(D_u = \hat{e}_u + d_u\). The \(\hat{e}_u\) is the approximation error of NNs and the time derivative of \(\hat{e}_u\) is bound.
From Assumption 1, we can get
\[
|D_u| \leq \chi_d \mu, |\dot{D}_u| \leq \chi_u \tag{18}
\]
where \(\chi_d\mu\) and \(\chi_u\) are unknown positive constants.
Then, the control law in the surge direction can be designed as
\[
\mu_u = -k_n u_{1,1} \hat{z}_u - k_n u_{2,2} u_{1,1} - \omega_\psi^T \psi_u - \hat{D}_u + m_{11} \dot{u}_u \tag{19}
\]
where \(\hat{\omega}_{1,1}\) and \(\hat{\omega}_{2,2}\) are positive parameters.
Then, \(\hat{\dot{z}}_u\) can be obtained
\[
\dot{\hat{z}}_u = \frac{1}{m_{11}} (\hat{\omega}_\psi^T \psi_u + \hat{D}_u + \tau_u + \phi_{u1} \hat{z}_u - \hat{\phi}_{u1} \hat{\omega}_1) \tag{20}
\]
The weight updating can be constructed as
\[
\hat{\dot{\omega}}_{11} = \gamma_{u1} (u_e + \gamma_{1u} \hat{z}_u) - \omega_{u1} \hat{z}_u - \phi_{u1} \hat{\omega}_{1,1} \tag{21}
\]
where \(\gamma_{1u}\) and \(\kappa_{u1}\) are the positive constants to be designed.
Combining with the approximation information, the nonlinear disturbance observer can be constructed as the following form:
\[
\dot{D}_u = m_{11} u - \sigma_u \tag{24a}
\]
\[
\dot{\sigma}_u = \hat{\omega}_\psi^T \psi_u + \hat{D}_u + \tau_u - (u_e + \gamma_{1u} \hat{z}_u) \tag{24b}
\]
According to (2a), (24a)-(24b) and \(\dot{D}_u = D_u - \hat{D}_u\), the derivative of \(D_u\) can be calculated as
\[
\dot{\hat{D}}_u = \hat{D}_u - (\hat{\omega}_\psi^T \psi_u + \hat{D}_u) - u_e - \gamma_{1u} \hat{z}_u \tag{25}
\]
The time derivative of \(\dot{\theta}\) is expressed as
\[
\dot{\theta} = -r + \frac{1}{\rho_e} (u_\psi \sin \theta + v \cos \theta - \sin \theta \xi_1 + \cos \theta \xi_2) \tag{26}
\]
From (26), the virtual control law \(\alpha_r\) can be designed as
\[
\alpha_r = k_1 \dot{\theta} + k_2 \dot{\theta} + \frac{1}{\rho_e} (\rho_e \sin \theta + v \cos \theta - \sin \theta \xi_1 + \cos \theta \xi_2) \tag{27}
\]
where \(k_1\) and \(k_2\) are positive design parameters.

**Remark 1:** The positive parameter \(\rho_0\) is introduced to (27), such that \(\rho_0 - \rho_0\) can be guaranteed converge to the neighbor of zero. It means that \(\rho_0\) can converge to the neighbor of \(\rho_0\). Therefore, the singularity of \(\alpha_r\) can be effectively avoided. By setting \(k_01 \gg k_02, k_02 \gg k_02\), \(\theta\) is forced to approach to zero very faster than \(\rho_0 - \rho_0\), the singularity of \(\alpha_u\) is avoidable.
Therefore, the (26) can be rewritten as
\[
\dot{\theta} = -r - k_1 \dot{\theta} + k_2 \dot{\theta} \tag{28}
\]
Combining (2c) and (27), the equation as follows can be obtained
\[
m_{33} \dot{r}_e = (m_{11} - m_{22}) vr - d_{33} r + \tau_r + \Delta f + d_r - m_{33} \dot{u}_r \tag{29}
\]
According to the inherent approximation characteristics of NNs. We can get \((m_{11} - m_{22}) vr - d_{33} r + \Delta f + d_r - m_{33} \dot{u}_r\). Further, define \(D_r = \xi_z + d_r\). The \(\xi_z\) is the approximation error of NNs and the time derivative of \(\xi_z\) is bound.
From Assumption 1, we have
\[
|D_r| \leq \chi_r, |\dot{D}_r| \leq \chi_r \tag{30}
\]
where \(\chi_{r0}\) and \(\chi_r\) are positive constants.
Then, the control law in the yaw direction can be designed as
\[
\mu_r = -k_r r_{1,1} \hat{z}_r - k_r r_{2,2} r_{1,1} - \omega_\psi^T \psi_r - \hat{D}_r + m_{33} \dot{u}_r \tag{31}
\]
where \(\hat{\omega}_1 \) and \(\hat{\phi}_{u1} \) are positive parameters.
Then, \(\hat{\dot{z}}_r\) can be obtained
\[
\dot{\hat{z}}_r = \frac{1}{m_{33}} (\hat{\omega}_\psi^T \psi_r + \hat{D}_r + \tau_r + \phi_{r2} \hat{z}_r + \phi_{r1} \hat{z}_r) \tag{32}
\]
where \(\hat{\phi}_{r1} \) and \(\kappa_{r2} \) are the positive constants to be designed.
Combining with the approximation information, the nonlinear disturbance observer can be constructed as the following form:
\[
\dot{D}_r = m_{33} r - \sigma_r \tag{36a}
\]
\[
\dot{\sigma}_r = \hat{\omega}_\psi^T \psi_r + \hat{D}_r + \tau_r - (r_e + \gamma_{1r} \hat{z}_r) \tag{36b}
\]
According to (2c), (36a)-(36b) and \(\dot{D}_r = D_r - \hat{D}_r\), the derivative of \(\dot{D}_r\) can be calculated as
\[
\dot{\hat{D}}_r = \hat{D}_r - (\hat{\omega}_\psi^T \psi_r + \hat{D}_r) - (r_e + \gamma_{1r} \hat{z}_r) \tag{37}
\]
\[
\dot{\hat{D}}_r = \hat{D}_r - (\hat{\omega}_\psi^T \psi_r + \hat{D}_r) - (r_e + \gamma_{1r} \hat{z}_r) \tag{37}
\]
Remark 2: From (23) and (35), the composite NN weight updating is constructed by the tracking error and prediction error. The extra information is introduced through SPEM for constructing the weight updating to approximated the uncertain term of MSVs. Thus, the tracking performance of the system is further improved.

Remark 3: Compared with the prediction error construction method in [28], [29], the fractional power technology is artistically introduced into the SPEM to design the prediction error, which realizes the finite-time control under the composite learning scheme.

Remark 4: γ_u and γ_r in (23) and (35) are introduced to improve learning competence. If γ_u and γ_r are selected smaller, the γ_u and γ_r mainly adjustment depends on prediction errors, while if γ_u and γ_r are selected smaller, the γ_u and γ_r mainly adjustment depends on tracking errors.

Remark 5: Combining the approximation information of the unknown dynamics, the adaptive neural disturbance observers were constructed to compensate the external disturbances and approximation errors of NNs. The proposed control scheme ensures the simultaneous realization of high precision tracking performance and unknown information approximation performance.

Remark 6: Through a series of simulation trial and error, we firstly select the appropriate design parameters k^1, k^2, k^1, k^2, k^1, k^2, k^1 and k^2 and k^1 to ensure that the system is stable. Furthermore, we properly regulate the other design parameters γ_u, γ_r, θ, φ, and ω to obtain the satisfactory control performance. In many cases, a large number of simulations validate that γ_u, γ_r, θ, φ, and ω are the MSVs can obtain higher tracking accuracy.

The compounded uncertain terms composed of unknown dynamics and disturbances are denoted as \( m_{22r}v - d_{11u} + Δ_u + d_u = \Sigma_u \) (38a) \( m_{11} - m_{22}uv - d_{33r} + Δ_r + τ = \Sigma_r \) (38b)

Remark 7: The NDO and NN have a close intersection of information between each other. If the compounded uncertain terms are perfectly compensated by \( \hat{ω}_u^Tψ_u + \hat{D}_u \) and \( \hat{ω}_r^Tψ_r + \hat{D}_r \), the identification of system uncertainty information is more accurate. The purpose of the combination of composite NN and NDO is effectively realized.

To reduce the frequency of the execution of actuators, an event-triggered mechanism is introduced in this paper. The event triggering mechanism is designed as

\[
τ_g(t) = μ_g(t_k) \quad \forall t \in [t_k, t_{k+1}]
\]

where \( e_g(t) = μ_g(t) - τ_g(t) \) \( g = u, r \) is the measurement error, \( ζ_u = \frac{1}{2}e_u^2 - \frac{1}{2}u^2 \) and \( ζ_r = \frac{1}{2}e_r^2 - \frac{1}{2}r^2 \).

Theorem: Considering the MSVs system (1a)-(1c) and (2a)-(2c) with unknown dynamics and time-varying disturbances under Assumption 1-2, by using virtual control law (15), (27), control law (19), (31), the NN updating laws (23), (35), NDOs (24a)-(24b), (36a)-(36b) and event-triggered mechanism (39a)-(39b). It is guaranteed that all the error signals in (40) can converge to the neighborhood of zero within a finite time.

Proof: The Lyapunov function can be selected as

\[
V = \frac{1}{2}\rho_s^2 + m_{11}uu^2 + \frac{1}{γ_u}\hat{ω}_u^T\hat{ω}_u + \hat{D}_u^2 + m_{11}\gamma_u u^2 + \theta^2 + m_{33r}r^2 + \frac{1}{γ_r}\hat{ω}_r^T\hat{ω}_r + \hat{D}_r^2 + m_{33r}z_r^2
\] (40)

The time derivative of (40) can obtain as

\[
\dot{V} = ρ_s\hat{ρ}_s + m_{11}uu\hat{u}_e + \frac{1}{γ_u}\hat{ω}_u^T(-\hat{ω}_u) + \hat{D}_u(-\hat{D}_u) + m_{11}\gamma_u u\hat{u}_e + \theta\hat{θ} + m_{33r}r\hat{r}_e + \frac{1}{γ_r}\hat{ω}_r^T(-\hat{ω}_r) + \hat{D}_r(-\hat{D}_r) + m_{33r}z_r\hat{z}_r
\] (41)

Combining (16), (28) and Young’s inequality, we have

\[
ρ_s\hat{ρ}_s = -k\rho_1\rho_s^2 - k\rho_2\rho_s^2 < u_ee^2 < -k\rho_1\rho_s^2 - (k\rho_2 - \frac{1}{2})ρ_s^2 + \frac{1}{2}u_ee^2
\] (42)

\[
\theta\hat{θ} < -k\theta\hat{θ}^2 - (k\theta_2 - \frac{1}{2})\theta^2 + \frac{1}{2}u_ee^2
\] (43)

Invoking equations (19), (31) and (39a)-(39b)

\[
m_{11}uu\hat{u}_e = u_e(-k\mu_1\alpha_2u_e - k\mu_2\alpha_2e_u + \alpha_u^T\psi_u + \hat{D}_u - e_u)
\] (44)

\[
m_{33r}r\hat{r}_e = r_e(-k\mu_1\alpha_2\hat{r}_e - k\mu_2\alpha_2r_e + \alpha_r^T\psi_r + \hat{D}_r - e_r)
\] (45)

According to (23) and (35), we have

\[
\frac{1}{γ_u}\hat{ω}_u^T\hat{ω}_u = -\hat{ω}_u^T[(u_e + γ_u\z_u)\psi_u - k\mu_1\hat{ω}_u] - k\mu_2\hat{ω}_u
\] (46)

\[
\frac{1}{γ_r}\hat{ω}_r^T\hat{ω}_r = -\hat{ω}_r^T[(u_e + γ_r\z_r)\psi_r - k\mu_1\hat{ω}_r] - k\mu_2\hat{ω}_r
\] (47)

By combining (25) and (37), we can obtain

\[
\hat{D}_u\hat{D}_u = \hat{D}_u\hat{D}_u - \hat{D}_u\hat{ω}_u^T\psi_u + \hat{D}_u(u_e + γ_u\z_u))
\] (48)

\[
\hat{D}_r\hat{D}_r = \hat{D}_r\hat{D}_r - \hat{D}_r\hat{ω}_r^T\psi_r + \hat{D}_r(r_e + γ_r\z_r))
\] (49)

From (22) and (34), we have

\[
m_{11}γ_u\z_u\hat{z}_u = γ_u\z_u\hat{z}_u(\alpha_u^T\psi_u + \hat{D}_u - \phi_2\z_u - \phi_1\z_u
\] (50)

\[
m_{33}γ_r\z_r\hat{z}_r = γ_r\z_r\hat{z}_r(\alpha_r^T\psi_r + \hat{D}_r - \phi_2\z_r - \phi_1\z_r
\] (51)
The (41) can be rearranged as
\[
\dot{V} \leq -k_{\rho_1}l_{\rho_1}^2 - (k_{\rho_2} - \frac{1}{2}) \rho_2 - k_{u1}u_e^2
\]
\[-(k_{\alpha_2} - \frac{1}{2})u_e^2 - \hat{D}_{u}^2 - \gamma_{\alpha u}\phi_{u1}z_\alpha^4 - \gamma_{\alpha u}\phi_{u2}z_\alpha^2
\]+\kappa_{u1}\tilde{\phi}_{u1}\tilde{z}_\alpha + \kappa_{u2}\tilde{\phi}_{u2}\tilde{z}_\alpha + \kappa_{u1}\tilde{\phi}_{u1}\psi_{u}
\[-k_{\alpha_1}\theta_\alpha - (k_{\alpha_2} - \frac{1}{2})\theta_\alpha^2 - (k_{\alpha_2} - \frac{1}{2})\theta_\alpha^2
\]-\hat{D}_{r}^2 - \gamma_{\alpha r}\phi_{r1}\tilde{z}_\alpha^4 - \gamma_{\alpha r}\phi_{r2}\tilde{z}_\alpha^2 + \kappa_{r1}\tilde{\phi}_{r1}\tilde{z}_\alpha + \kappa_{r2}\tilde{\phi}_{r2}\tilde{z}_\alpha
\[+\frac{1}{2}\kappa_{u1}\tilde{w}_u^2 + \frac{1}{2}\kappa_{u2}\tilde{w}_u^2 + \frac{2}{3}\kappa_{u2}\tilde{w}_u^2 + \frac{3}{4}\kappa_{u2}\tilde{w}_u^2
\](52)

Considering the following fact
\[
\kappa_{g1}\tilde{\omega}_g^T\tilde{\omega}_g^p = -\kappa_{g1}(-\tilde{\omega}_g)^T(-\tilde{\omega}_g + \omega_g)^p
\]
\[\leq -\kappa_{g1} \frac{1-g}{1+p}(\tilde{\omega}_g)^T \tilde{\omega}_g + \kappa_{g1} \frac{g}{1+p}
\](53)
\[\frac{1}{4}\hat{D}_{r}^2 \tilde{r}_g \leq \frac{1}{12}\tilde{\omega}_g + \frac{1}{12}\tilde{\omega}_g^T \tilde{\omega}_g
\](54)
\[-\tilde{D}_{r}\tilde{D}_{r}^T \tilde{r}_g \leq \frac{1}{2}\tilde{\omega}_g + \frac{1}{2}\tilde{\omega}_g^T \tilde{\omega}_g
\](55)
\[\tilde{D}_{r}\tilde{D}_{r} \leq \frac{1}{2}\hat{D}_{r}^2 + \frac{1}{2}\kappa_{g1} \frac{g}{1+p}
\](56)
\[\tilde{D}_{r}\tilde{D}_{r}^T \tilde{r}_g \leq \frac{1}{2}\tilde{\omega}_g + \frac{1}{2}\tilde{\omega}_g^T \tilde{\omega}_g
\](57)

where \(\omega_g\), \(\kappa_{g1}\) and \(\kappa_{g2}\) are positive user-defined parameter, \(\|\psi_g\| \leq \sigma_g\), \(\|\tilde{D}_r\| \leq \kappa_{g1}\), \(g = u, r\).

Combining (53)-(57) and (39a)-(39b), the (41) can be further rearranged as
\[
\dot{V} \leq -k_{\rho_1}l_{\rho_1}^2 - (k_{\rho_2} - \frac{1}{2}) \rho_2 - k_{u1}u_e^2
\]
\[-(k_{\alpha_2} - \frac{1}{2})u_e^2 - (1 - \frac{1}{4}\tilde{\omega}_g^T \tilde{\omega}_g)^2
\]-\gamma_{\alpha u}\phi_{u1}z_\alpha^4 - \gamma_{\alpha u}\phi_{u2}z_\alpha^2
\[-k_{\alpha_1}\theta_\alpha - (k_{\alpha_2} - \frac{1}{2})\theta_\alpha^2 - (k_{\alpha_2} - \frac{1}{2})\theta_\alpha^2
\]-\hat{D}_{r}^2 - \gamma_{\alpha r}\phi_{r1}\tilde{z}_\alpha^4 - \gamma_{\alpha r}\phi_{r2}\tilde{z}_\alpha^2 + \kappa_{r1}\tilde{\phi}_{r1}\tilde{z}_\alpha + \kappa_{r2}\tilde{\phi}_{r2}\tilde{z}_\alpha
\[+\frac{1}{2}\kappa_{u1}\tilde{w}_u^2 + \frac{1}{2}\kappa_{u2}\tilde{w}_u^2 + \frac{2}{3}\kappa_{u2}\tilde{w}_u^2 + \frac{3}{4}\kappa_{u2}\tilde{w}_u^2
\](58)
\[\dot{V} \leq -aV - hV^{2/3} + b
\](59)

From (59), we can get
\[
\dot{V} \leq -agV - a(1-g)V - hV^{2/3} + b
\](60)

From (60), if \(V > \frac{h}{ag}\) we have
\[
\dot{V} \leq -a(1-g)V - hV^{2/3}
\](61)

According to Lemma 1, V could converge to the neighborhood of \(\frac{h}{ag}\) within a finite time
\[
T_V \leq \frac{3}{a(1-g)} \ln \frac{(1-a)h^{V^{1/3}}(0) + h}{h}
\](62)

Next, we will prove that the Zeno behavior can be avoided by the proposed algorithm.

There exists \(t^* > 0\) such that \(t_{k+1}^* - t_k^* > t^*\), the control command generated by the control law \(\tau_{g1}(t)\) is held as a constant. From the measurement error \(e_g(t) = \mu_g(t) - \tau_{g1}(t)\), we can get \(\frac{d}{dt} |e_g(t)| = \text{sgn}(e_g(t)) |\dot{e}_g(t)| \leq |\dot{\mu}_g(t)|\).

From (20), (27) and (34), it can be seen that \(\mu_g(t)\) is a differentiable function and \(\dot{\mu}_g(t)\) is bounded. Therefore, \(\left[\mu\right]_{t_{k+1}^*-t_k^*} \leq \dot{\theta}_t, \exists \theta_t \in R^+\). And initial condition \(e_i(\theta_t) = 0\), we have \(\lim_{t \rightarrow t_{k+1}^*} |e_g(t)| = \hat{h}_g = |g_e(t)|\). It is easy to get \(t^* \geq \hat{h}_g / \dot{\theta}_t\).

This concludes the proof.

IV. SIMULATION RESULTS

In order to validate the effectiveness and superiority of the proposed control scheme, we conduct the simulation on an MSV.

The model parameters in [8] are described as follows: \(m_{11} = 25.8\) kg, \(m_{22} = 33.8\) kg, \(m_{33} = 2.76\) kg \cdot m². \(d_{11} = 0.725\) kg/s, \(d_{22} = 0.89\) kg/s, \(d_{33} = 1.9\) kg/m².

The proposed control scheme in this paper is marked as \(\tau_{tec-ct}\). The control scheme under the time-triggered (with a sampling interval of 0.01) is denoted as \(\tau_{time-ct}\). The control scheme without considering the prediction error under the time-triggered is denoted as \(\tau_{time-nv}\).

The reference trajectory is selected as \(x_d = 4 \sin(0.02\pi t), y_d = 4 \cos(0.02\pi t)\).

Case 1: Unknown dynamics are given as \([\Delta u, \Delta v, \Delta f_r]^T = [(-0.2d_{11} |u|)u, (-0.2d_{22} |v|)v, (-0.2 |r|)r]^T\]. The external disturbances are given as \([d_{du}, d_{dv}, d_{dr}]^T = [5 \sin(0.2t - \pi/3) + 5 \cos(0.2t - \pi/4), 3 \sin(0.2t - \pi/3) + 3 \cos(0.2t - \pi/4), 6 \sin(0.2t - \pi/3) + 6 \cos(0.2t - \pi/4)]^T\).

The initial condition is given as \([x(0), y(0), w(0), u(0), v(0), r(0)] = [1, 3.5, -0.02\pi, 0, 0, 0]\).

The user-defined parameters of the control laws are designed as \(\rho_0 = 0.2, k_{\rho_1} = 0.1, k_{\alpha_1} = 1, k_{\alpha_2} = 2, k_{\eta_2} = 5, k_{\alpha_1} = k_{\alpha_2} = 0.12, k_{\alpha_2} = 25, k_{\eta_2} = 15, \phi_{u1} = \phi_{r1} = 0.2, \phi_{u2} = \phi_{r2} = 10, \kappa_{u1} = \kappa_{r1} = 0.00001, \kappa_{u2} = \kappa_{r2} = 0.01, \gamma_{u1} = \gamma_{r1} = 10, \gamma_u = 5, \gamma_r = 10\).

Simulation results under the three control schemes as shown in Fig. 1(a)-(g). In addition, the tracking control performance of underactuated MSV under three control schemes is quantitatively analyzed. IAE = \(\int_0^{100} |L|dt_L\) = \(\rho_1, \theta_1\). IAE represents the integrated absolute of the tracking error. \(E_f = \max_{t \in [0, 100]} |L(t)|\). \(E_f\) represents the final accuracy of the trajectory tracking error in the last 5 s in
FIGURE 1. Simulation results under \( \tau_{time-\text{nn}}, \tau_{time-cl} \) and \( \tau_{etc-cl} \)incase 1. (a) Reference and actual trajectories of the MSV. (b) Tracking position error and yaw angle error. (c) \( \sum u \) and its estimation. (d) \( \sum r \) and its estimation. (e) 2-norms \( \| \hat{\omega}_u \|, \| \hat{\omega}_r \| \) of parameter estimates \( \hat{\omega}_u \) and \( \hat{\omega}_r \). (f) Control signals \( \tau_u \) and \( \tau_r \). (g) Triggering instants, triggering time and the numbers of events for \( \tau_u \) and \( \tau_r \).

As shown in Fig. 1(a) that the MSV can track the reference trajectory suffering from under three control methods. The performance indices of \( \rho_s \) and \( \theta \) are presented in Table 1. 

simulation. The performance indices of \( \rho_s \) and \( \theta \) are presented in Table 1.
result in Fig. 1(b) and Table 1 demonstrate the MSV can obtain higher tracking performance under composite learning scheme. The tracking control accuracy of the continuous control scheme is slightly better than ETC scheme.
TABLE 1. Comparison of the control performance in case 1.

| Index | Settling time | IAE | $E_f$ |
|-------|--------------|-----|------|
| $\theta$ | $\tau_{time-nn}$ | 4.906 | 1.15 | 0.0041 |
|        | $\tau_{time-cl}$ | 1.287 | 0.9413 | 0.0018 |
|        | $\tau_{etc-cl}$ | 1.721 | 1.076 | 0.0022 |

TABLE 2. Comparison of the control performance in case 1.

| Index | Settling time | IAE | $E_f$ |
|-------|--------------|-----|------|
| $\rho_s$ | $\tau_{time-nn}$ | 4.936 | 1.212 | 0.0223 |
|        | $\tau_{time-cl}$ | 2.462 | 1.048 | 0.0043 |
|        | $\tau_{etc-cl}$ | 2.481 | 2.258 | 0.0050 |
| $\theta$ | $\tau_{time-nn}$ | 4.895 | 0.88 | 0.0099 |
|        | $\tau_{time-cl}$ | 3.487 | 0.7824 | 0.0001 |
|        | $\tau_{etc-cl}$ | 3.502 | 0.76 | 0.0018 |

This conclusion is further supported by the approximation of unknown information in Fig. 1(c) and Fig. 1(d). It is clearly more sensitive under the “composite learning”. Therefore, composite learning can make a faster and more sensitive response to uncertain information. The estimates of 2-norms weights are bound as illustrated in Fig. 1(e).

The control inputs $\tau_u$ and $\tau_r$ are presented in Fig. 1(f). From Fig. 1(g), it can be observed the proposed ETC control scheme can reduces the transmission load and execution rate drastically. The continuous execution of actuators is avoided and thus the energy consumption is reduced.

Case 2: The unknown dynamics of MSV are raised $1.1 \times \Delta f_m$. The control law’s initial conditions and design parameters are the same as in Case 1, and the larger time-varying disturbances can be chosen as $[d_u, d_v, d_x]^T = [8 \sin(0.2t - \pi/3) + 8 \cos(0.2t - \pi/4), 5 \sin(0.2t - \pi/3) + 5 \cos(0.2t - \pi/4), 9 \sin(0.2t - \pi/3) + 9 \cos(0.2t - \pi/4)]^T$.

Simulation results are presented in Fig. 2(a)-(g) under the three control schemes. The tracking control performance can be clearly shown in Table 2. It is obvious that the developed tracking control scheme has almost similar control performance to case 1, which means the developed tracking control scheme has good robustness to unknown dynamic and time-varying disturbance. It can be seen from Fig. 2(a)-(g) and Table 2, the MSV can track desired trajectory under three control schemes, and the MSV can obtain higher control performance under composite learning control scheme. The tracking control performance under $\tau_{time-cl}$ is slightly better than under $\tau_{etc-cl}$. This result is confirmed further by the Figs. 2(c) and 2(d). The estimates of 2-norms weights are bound as illustrated in Fig. 2(e). The same conclusion can be obtained as case 1. The control inputs $\tau_u$ and $\tau_r$ are presented in Fig. 2(f). From Fig. 2(g), It can be shown that the proposed ETC control scheme significantly decreases transmission burden and execution rate.

V. CONCLUSION

This paper develops an event-triggered composite learning FT trajectory tracking control scheme for underactuated MSVs under unknown dynamics and time-varying disturbances. The LOS approach was introduced to handle the underactuation of the MSV. The composite NN is employed to approximate the unknown dynamics. Both of the prediction errors and the tracking errors are fused to design the NN weight updating. Combining approximation information, the disturbance observers are created to estimates unknown disturbances. Fractional power technology is artistically introduced to achieve the FT trajectory tracking control of MSVs based on composite learning. The execution rate of the actuator was reduced though the ETC mechanism. The stability of the closed-loop system of MSVs trajectory tracking was proof by Lyapunov method. Simulation results validate the effectiveness and superiority of the proposed control scheme.

Furthermore, the fixed time control can be further considered. The control scheme in this paper can be easily combined with formation control.

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