

Lecture 13: Average Sub-Gradient Method in DNN Control (Continuation)

Plan of presentation

- Guidance Control of Underwater Autonomous Vehicle
- 2-4 steps of Backstepping
- Desired dynamics
- DNN version

2-nd step of Backstepping control (1)

- Consider now the situation when the desired control $\mathbf{v}^* = [u^* \ v^* \ w^*]^T$ at the first stage is fixed and equal to \mathbf{u}_1^* , given in the previous theorem.
- Take as the second intermediate pseudo-control $\mathbf{u}_2 = [\tau_u \ q \ r]^T$. Then the equation for \mathbf{v}^* can be represented as

$$\left. \begin{aligned} \dot{\mathbf{v}} &= \mathbf{f}_2(\mathbf{v}^*) + \mathbf{B}_2 \mathbf{u}_2 + \boldsymbol{\zeta}_v, \\ \mathbf{f}_2(\mathbf{v}^*) &:= \begin{bmatrix} -l_1^{-1} d_1 u^* \\ -l_2^{-1} d_2 v^* \\ -l_3^{-1} d_3 w^* \end{bmatrix}, \\ \mathbf{B}_2 &:= \begin{bmatrix} l_1^{-1} & -l_1^{-1} l_3 w^* & l_1^{-1} l_2 v^* \\ 0 & 0 & -l_2^{-1} l_1 u^* \\ 0 & l_3^{-1} l_1 u^* & 0 \end{bmatrix}. \end{aligned} \right\} \quad (1)$$

2-nd step of Backstepping control (2)

- Define then the translation velocity tracking error as $\boldsymbol{\varphi}_2 = \boldsymbol{v} - \boldsymbol{v}^*$. Following the same scheme of representation as at the first stage we are able to formulate the tracking trajectory problem at this stage an optimization, realized by an uncertain controllable dynamic plant:

$$\left. \begin{aligned} J_2(\boldsymbol{\varphi}_2) = \sum_{i=1}^3 |\varphi_{2,i}| \xrightarrow{t \rightarrow \infty} \min_{\mathbf{u}_2(\cdot) \in U_{2,adm}} \\ \text{subjected to (1).} \end{aligned} \right\} \quad (2)$$

The ideal \mathbf{u}_2^* solving the problem (2) denote by $\mathbf{u}_2^* = [\tau_u^* \quad (\boldsymbol{\omega}^*)^\top]^\top$.

2-nd step of Backstepping control (3)

Theorem

Under the accepted assumptions the intermediate pseudo-control \mathbf{u}_2^ , realizing the solution of the problem (2), satisfies the following ODE's*

$$\left. \begin{aligned} \frac{d}{dt} (\mathbf{B}_2 \mathbf{u}_2) + \mathbf{g}_2 &= -k_2 \text{Sign}(\mathbf{s}_2), \quad \mathbf{u}_2^*(0) = \mathbf{u}_{2,0}^*, \quad k_2 > \dot{\zeta}_v^+, \\ \text{Sign}(\mathbf{s}_2) &:= [\text{sign}(s_{2,1}), \text{sign}(s_{2,2}), \text{sign}(s_{2,3})]^\top, \end{aligned} \right\} \quad (3)$$

$$\left. \begin{aligned} \mathbf{g}_2 &:= -\ddot{\mathbf{v}}^* + \frac{\dot{\mathbf{v}} - \dot{\mathbf{v}}^*}{t + \theta} - \frac{\mathbf{v} - \mathbf{v}^* + \boldsymbol{\alpha}_1}{(t + \theta)^2} \\ &\quad - \frac{1}{t + \theta} \Gamma_2 + \frac{1}{t + \theta} \partial J_2(\boldsymbol{\varphi}_2) + \dot{\mathbf{f}}_2(\mathbf{v}^*), \end{aligned} \right\} \quad (4)$$

2-nd step of Backstepping control (4)

Theorem (continuation)

where the integral sliding variable \mathbf{s}_1 is defined as

$$\left. \begin{aligned} \mathbf{s}_2 &= \dot{\boldsymbol{\varphi}}_2 + \frac{\boldsymbol{\varphi}_2 + \boldsymbol{\alpha}_2}{t + \theta} + \boldsymbol{\Gamma}_2, \quad \boldsymbol{\Gamma}_2 = \frac{1}{t + \theta} \int_{\tau=0}^t \partial J_1(\boldsymbol{\varphi}_1) d\tau, \quad t \geq 0, \quad \theta > 0, \\ \partial J_2(\boldsymbol{\varphi}_2) &= [\text{sign}(\varphi_{2,1}), \text{sign}(\varphi_{2,2}), \text{sign}(\varphi_{2,3})]^\top, \\ \boldsymbol{\alpha}_2 &= -\theta \dot{\boldsymbol{\varphi}}_2(0) - \boldsymbol{\varphi}_2(0). \end{aligned} \right\}$$

It guarantees that

$$J_2(\boldsymbol{\varphi}_2(t)) \leq \frac{\Phi_2}{t + \theta} \xrightarrow{t \rightarrow \infty} 0, \quad \Phi_2 = \theta J_2(\boldsymbol{\varphi}_2(0)) + \frac{1}{2} \|\boldsymbol{\alpha}_2\|^2. \quad (5)$$

2-nd step of Backstepping control: proof

Proof.

[Proof of Theorem 1]

$$\begin{aligned} \dot{V}(\mathbf{s}_2) &= \mathbf{s}_2^T \dot{\mathbf{s}}_2 = \\ \mathbf{s}_2^T &\left[\ddot{v} - \ddot{v}^* + \frac{\dot{v} - \dot{v}^*}{t + \theta} - \frac{\mathbf{v} - \mathbf{v}^* + \boldsymbol{\alpha}_2}{(t + \theta)^2} - \frac{1}{t + \theta} \Gamma_2 + \frac{1}{t + \theta} \partial J_2(\boldsymbol{\varphi}_2) \right] \\ &= \mathbf{s}_2^T \left[\frac{d}{dt} (\mathbf{B}_2 \mathbf{u}_2) + \dot{\boldsymbol{\zeta}}_v + \mathbf{g}_2 \right] = \mathbf{s}_2^T [-k_2 \text{Sign}(\mathbf{s}_2) + \dot{\boldsymbol{\zeta}}_v], \end{aligned}$$

and then the proof exactly follows the proof of Theorem about the first step. □

3-rd step of Backstepping control (1)

- The orientation dynamics can be represented as

$$\left. \begin{aligned} \dot{\omega} &= \mathbf{f}_3 + \mathbf{B}_3 \mathbf{u}_3 + \zeta_{\omega}, \\ \mathbf{f}_3 &:= f_{\omega}(\mathbf{v}, \omega, \eta) = \\ &\left[\begin{array}{c} I_5^{-1} (I_3 - I_1) u^* w^* - \frac{d_5}{m} q^* - I_5^{-1} m g h s_{\theta^*} \\ I_6^{-1} (I_1 - I_2) u^* v^* - I_6^{-1} d_6 r^* \end{array} \right] \\ &\text{- is a vector measurable (available) on-line,} \\ \mathbf{u}_3 &:= \begin{pmatrix} \tau_q \\ \tau_r \end{pmatrix}, \quad \mathbf{B}_3 := \begin{bmatrix} \frac{1}{I_5} & 0 \\ 0 & \frac{1}{I_6} \end{bmatrix}. \end{aligned} \right\} \quad (6)$$

- In the third stage, consider that the dynamic of the angular velocity is regulated by the pseudocontrol action defined by truster τ_q and τ_r .

3-rd step of Backstepping control (2)

Define the angular velocity tracking error as $\boldsymbol{\varphi}_3 = \boldsymbol{\omega} - \boldsymbol{\omega}^*$, where $\boldsymbol{\omega}^*$ is obtained from the previous stage. The corresponding tracking trajectory problem at this stage may be formulated as an optimization, realized by an uncertain controllable dynamic plant:

$$\left. \begin{aligned} J_3(\boldsymbol{\varphi}_3) = \sum_{i=1}^2 |\varphi_{3,i}| \xrightarrow{t \rightarrow \infty} \min_{\mathbf{u}_3(\cdot) \in U_{3,adm}} \\ \text{subjected to (6).} \end{aligned} \right\} \quad (7)$$

Denote by $\mathbf{u}_3^* = [\tau_q^* \quad \tau_r^*]^T$ the solution of the optimization problem (7).

3-rd step of Backstepping control (3)

Theorem

Under the accepted assumptions the intermediate pseudo-control \mathbf{u}_3^ , realizing the solution of the problem (7), satisfies the following ODE's*

$$\left. \begin{aligned} \frac{d}{dt} (\mathbf{B}_3 \mathbf{u}_3) + \mathbf{g}_3 &= -k_3 \text{Sign}(\mathbf{s}_2), \quad \mathbf{u}_3^*(0) = \mathbf{u}_{3,0}^*, \quad k_3 > \dot{\zeta}_\omega^+ \\ \text{Sign}(\mathbf{s}_3) &:= [\text{sign}(s_{3,1}), \text{sign}(s_{3,2})]^\top, \end{aligned} \right\} \quad (8)$$

$$\begin{aligned} \mathbf{g}_3 &:= -\ddot{\omega}^* + \frac{\dot{\omega} - \dot{\omega}^*}{t + \theta} - \frac{\omega - \omega^* + \alpha_3}{(t + \theta)^2} \\ &\quad - \frac{1}{t + \theta} \Gamma_3 + \frac{1}{t + \theta} \partial J_3(\boldsymbol{\varphi}_3) + \dot{f}_3(\omega^*), \end{aligned} \quad (9)$$

3-rd step of Backstepping control (3)

Theorem (continuation)

where the integral sliding variable \mathbf{s}_3 is defined as

$$\left. \begin{aligned} \mathbf{s}_3 &= \dot{\boldsymbol{\varphi}}_3 + \frac{\boldsymbol{\varphi}_3 + \boldsymbol{\alpha}_3}{t + \theta} + \Gamma_3, \\ \Gamma_3 &= \frac{1}{t + \theta} \int_{\tau=0}^t \partial J_3(\boldsymbol{\varphi}_3) d\tau, \quad t \geq 0, \quad \theta > 0, \\ \partial J_3(\boldsymbol{\varphi}_3) &= \left[\begin{array}{ccc} \text{sign}(\varphi_{3,1}), & \text{sign}(\varphi_{3,2}), & \text{sign}(\varphi_{3,3}) \end{array} \right]^\top \\ \boldsymbol{\alpha}_3 &= -\theta \dot{\boldsymbol{\varphi}}_3(0) - \boldsymbol{\varphi}_3(0). \end{aligned} \right\} \quad (10)$$

It guarantees that

$$J_3(\boldsymbol{\varphi}_3(t)) \leq \frac{\Phi_3}{t + \theta} \xrightarrow{t \rightarrow \infty} 0, \quad \Phi_3 = \theta J_3(\boldsymbol{\varphi}_3(0)) + \frac{1}{2} \|\boldsymbol{\alpha}_3\|^2. \quad (11)$$

3-rd step of Backstepping control (4): proof

Proof.

[Proof of Theorem 3]

$$\begin{aligned} \dot{V}(\mathbf{s}_3) &= \mathbf{s}_3^T \dot{\mathbf{s}}_3 = \\ \mathbf{s}_3^T &\left[\ddot{\omega} - \ddot{\omega}^* + \frac{\dot{\omega} - \dot{\omega}^*}{t + \theta} - \frac{\omega - \omega^* + \alpha_3}{(t + \theta)^2} - \frac{1}{t + \theta} \Gamma_3 + \frac{1}{t + \theta} \partial J_3(\varphi_3) \right] \\ &= \mathbf{s}_2^T \left[\frac{d}{dt} (\mathbf{B}_3 \mathbf{u}_3) + \mathbf{g}_3 + \dot{\zeta}_\omega \right] = \mathbf{s}_2^T [-k_3 \text{Sign}(\mathbf{s}_3) + \dot{\zeta}_\omega], \end{aligned}$$

and then the proof follows the proof of Theorem concerning the 1-st step. □

4-th step of Backstepping control (1): torque tracking

- The dynamic actuators model is

$$\dot{t} = Z_E \mathbf{g} + \mathbf{B}_4 \mathbf{u}_4, \mathbf{B}_4 := Z_E \quad (12)$$

- Here

$$\mathbf{u}_4 = [\mathbf{v}_u \quad \mathbf{v}_q \quad \mathbf{v}_r]^T$$

is the last intermediate control affecting the general dynamics.

- Define the last tracking error as $\varphi_4 = \tau - \tau^*$, where τ^* are obtained from the previous stages.
- Then the corresponding tracking problem at the last stage may be formulated as an optimization, realized by an uncertain controllable dynamic plant:

$$J_4(\boldsymbol{\varphi}_4) = \left. \begin{array}{l} \sum_{i=1}^3 |\varphi_{4,i}| \xrightarrow{t \rightarrow \infty} \min_{\mathbf{u}_4(\cdot) \in U_{4,adm}} \\ \text{subjected to (12).} \end{array} \right\} \quad (13)$$

Denote by $\mathbf{u}_4^* = [\mathbf{v}_u^* \quad \mathbf{v}_q^* \quad \mathbf{v}_r^*]^T$ the solution of the problem (13).

4-th step of Backstepping control (2): torque tracking

Theorem

Under the accepted assumptions the intermediate pseudo-control \mathbf{u}_4^ , realizing the solution of the problem (13), satisfies the following ODE's*

$$\left. \frac{d}{dt} (\mathbf{B}_4 \mathbf{u}_4) + \mathbf{g}_4 = -k_4 \text{Sign}(\mathbf{s}_4), \mathbf{u}_4^*(0) = \mathbf{u}_{4,0}^*, k_4 > \|Z_E\| \dot{g}^+, \right\}$$

$$\text{Sign}(\mathbf{s}_4) := [\text{sign}(s_{4,1}), \text{sign}(s_{4,2}), \text{sign}(s_{4,3})]^\top,$$

$$\mathbf{g}_4 := -\ddot{\tau}^* + \frac{\dot{\tau} - \dot{\tau}^*}{t + \theta} - \frac{\tau - \tau^* + \alpha_4}{(t + \theta)^2} - \frac{1}{t + \theta} \Gamma_4 + \frac{1}{t + \theta} \partial J_4(\boldsymbol{\varphi}_4),$$

(14)

4-th step of Backstepping control (3): torque tracking

Theorem (continuation)

where the integral sliding variable \mathbf{s}_3 is defined as

$$\left. \begin{aligned} \mathbf{s}_4 &= \dot{\boldsymbol{\varphi}}_4 + \frac{\boldsymbol{\varphi}_4 + \boldsymbol{\alpha}_4}{t + \theta} + \Gamma_4, \\ \Gamma_4 &= \frac{1}{t + \theta} \int_{\tau=0}^t \partial J_4(\boldsymbol{\varphi}_4) d\tau, \quad t \geq 0, \quad \kappa > 0, \\ \partial J_4(\boldsymbol{\varphi}_4) &= \left[\text{sign}(\varphi_{4,1}), \text{sign}(\varphi_{4,2}), \text{sign}(\varphi_{4,3}) \right]^\top, \\ \boldsymbol{\alpha}_4 &= -\theta \dot{\boldsymbol{\varphi}}_4(0) - \boldsymbol{\varphi}_4(0). \end{aligned} \right\} \quad (15)$$

It guarantees that

$$J_4(\boldsymbol{\varphi}_4(t)) \leq \frac{\Phi_4}{t + \theta} \xrightarrow{t \rightarrow \infty} 0, \quad \Phi_4 = \theta J_4(\boldsymbol{\varphi}_4(0)) + \frac{1}{2} \|\boldsymbol{\alpha}_4\|^2. \quad (16)$$

4-th step of Backstepping control (4): proof

Proof.

[Proof of Theorem 5]

$$\left. \begin{aligned} \dot{V}(\mathbf{s}_4) &= \mathbf{s}_4^T \dot{\mathbf{s}}_4 = \\ \mathbf{s}_4^T &\left[\ddot{t} - \ddot{t}^* + \frac{\dot{t} - \dot{t}^*}{t + \theta} - \frac{\tau - \tau^* + \alpha_4}{(t + \theta)^2} - \frac{1}{t + \theta} \Gamma_4 + \frac{1}{t + \theta} \partial J_4(\boldsymbol{\varphi}_4) \right] \\ &= \mathbf{s}_4^T \left[\frac{d}{dt} (\mathbf{B}_4 \mathbf{u}_4) + \mathbf{g}_4 + Z_E \mathbf{g} \right] \leq \\ &- k_4 \mathbf{s}_4^T \text{Sign}(\mathbf{s}_4) + \|\mathbf{s}_4\| \|Z_E\| \dot{g}^+ \leq \\ &- \|\mathbf{s}_4\| (k_4 - \|Z_E\| \dot{g}^+), \end{aligned} \right\}$$

and then the proof follows the proof of Theorem from the previous lecture. □

Diagram of control structure

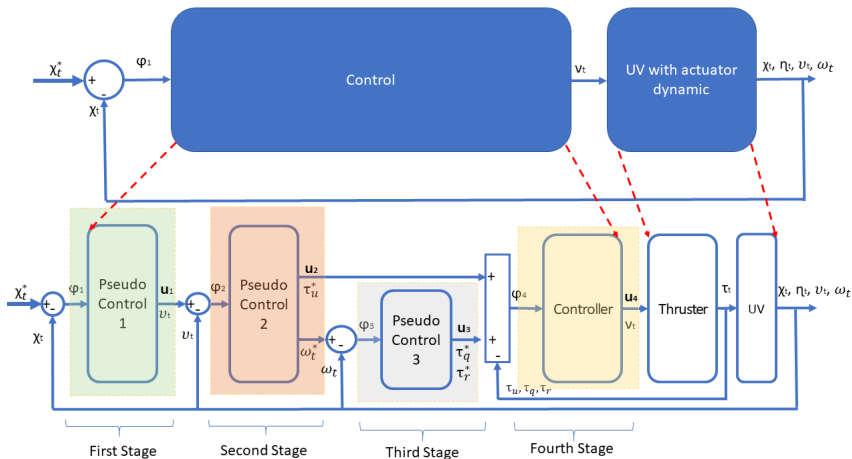


Figure 1: Diagram of control structure

DNN model

Recall the model of UAV: $\mathbf{v} = \begin{bmatrix} \mathbf{v}_1^T & \mathbf{v}_2^T \end{bmatrix}^T \in \mathbb{R}^5$ where $\mathbf{v}_1 = \begin{bmatrix} u & v & w \end{bmatrix}^T$ the translation velocity and $\mathbf{v}_2 = \begin{bmatrix} q & r \end{bmatrix}^T$ is angular velocity. The dynamic model of the state vectors of the UAV is given by

$$\left. \begin{aligned} \frac{d}{dt} \mathbf{x}_t &= \Theta(\mathbf{x}_t) \mathbf{v}_t + \mathbf{f}_1(\mathbf{x}_t, \mathbf{v}_t), \\ \frac{d}{dt} \mathbf{v}_t &= \mathbf{f}_v(\mathbf{x}_t, \mathbf{v}_t) + \mathbf{B}_v \boldsymbol{\tau}_t + \mathbf{f}_2(\mathbf{x}_t, \mathbf{v}_t, \boldsymbol{\tau}_t). \end{aligned} \right\} \quad (17)$$

Define the state $\hat{\zeta}_t = \begin{bmatrix} \hat{\mathbf{x}}_t^T & \hat{\mathbf{v}}_t^T \end{bmatrix}^T \in \mathbb{R}^{10}$ of DNNO:

$$\left. \frac{d}{dt} \hat{\zeta}_t = \Sigma(\zeta_t, \hat{\zeta}_t, \mathbf{y}_t^* | \hat{W}_t), \quad \frac{d}{dt} \hat{W}_t = \Omega(\zeta_t, \hat{\zeta}_t). \right\} \quad (18)$$

Here $\hat{\zeta}_t$ is treated as the current estimation of the vector $\zeta_t = \begin{bmatrix} \mathbf{x}_t^T & \mathbf{v}_t^T \end{bmatrix}^T$ with the structure dynamics Σ containing the adaptive parameters \hat{W}_t which are adjusted on-line to provide a "good quality" of the identification process. Only the state \mathbf{x}_t is observable on-line.

DNNO model: open format

Define the dynamics of DNNO as

$$\left. \begin{aligned} \frac{d}{dt} \hat{\zeta}_t &= A \hat{\zeta}_t + F(\hat{\zeta}_t) + \hat{W}_{1,t} \sigma_1(\hat{\zeta}_t) + \\ &\hat{W}_{2,t} \sigma_2(\hat{\zeta}_t) \mathbf{v}_t + \hat{W}_{3,t} \sigma_3(\hat{\zeta}_t) \mathbf{u}_t + L(\mathbf{x}_{1,t} - \mathbf{x}_{1,t}^*), \\ \hat{\zeta}_t &= [\mathbf{x}_t^\top \quad \mathbf{v}_t^\top]^\top, \quad F(\hat{\zeta}_t) = \begin{bmatrix} \ominus(\mathbf{x}_t) \mathbf{v}_t \\ 0 \end{bmatrix}. \end{aligned} \right\} \quad (19)$$

Here $\hat{\zeta}_t \in \mathbb{R}^{10}$ is the state of DNNO, while $\hat{W}_{1,t} \in \mathbb{R}^{10 \times p_{21}}$, $\hat{W}_{2,t} \in \mathbb{R}^{10 \times p_{11}}$ and $\hat{W}_{3,t} \in \mathbb{R}^{10 \times p_{22}}$ are the time varying matrix weights parameters. The vector $\mathbf{v}_t \in \mathbb{R}^5$ is the estimate of \mathbf{v}_t and

$$\left. \begin{aligned} \mathbf{x}_t &= C_0 \zeta_t, \quad C_0 = \begin{bmatrix} I_{5 \times 5} & 0_{5 \times 5} \end{bmatrix}, \\ \mathbf{x}_{1,t} &= C \mathbf{x}_t = (x_t, y_t, z_t)^\top = C C_0 \zeta_t \in \mathbb{R}^3. \end{aligned} \right\} \quad (20)$$

DNNO model: error of tracking

The error of tracking:

$$\delta_t = \mathbf{x}_{1,t} - \mathbf{x}_{1,t}^* = CC_0 (\zeta_t - \zeta_t^*) \quad (21)$$

Notice that

$$\begin{aligned} \|\delta_t\| &= \|CC_0 (\zeta_t - \zeta_t^*)\| = \left\| CC_0 \left([\zeta_t - \hat{\zeta}_t] + [\hat{\zeta}_t - \zeta_t^*] \right) \right\| \\ &\leq \left\| CC_0 (\zeta_t - \hat{\zeta}_t) \right\| + \left\| CC_0 (\hat{\zeta}_t - \zeta_t^*) \right\|, \end{aligned}$$

To characterize the quality of the tracking process $\hat{\delta}_t = \hat{\mathbf{x}}_{1,t} - \mathbf{x}_{1,t}^* \in R^3$ let us use the loss function

$$J(\hat{\delta}_t) := \sum_{i=1}^3 |\hat{x}_{1i,t} - x_{1i,t}^*|. \quad (22)$$

DNNO model: sliding variable

Introduce also for all $t \geq t_0$ the auxiliary vector function $\mathbf{s}_t \in R^3$ which below is referred to as "*sliding variable*":

$$\left. \begin{aligned} \mathbf{s}_t &= \frac{d}{dt} \hat{\delta}_t + \frac{\hat{\delta}_t + \boldsymbol{\eta}}{t + \theta} + \tilde{\mathbf{G}}_t, \quad \boldsymbol{\eta} \in \mathbb{R}^3, \\ \tilde{\mathbf{G}}_t &:= \frac{1}{t + \theta} \int_{\tau=t_0}^t \mathbf{a}(\hat{\delta}_\tau) d\tau, \quad \theta > 0, \end{aligned} \right\} \quad (23)$$

where $\mathbf{a}(\hat{\delta}_t) = \partial J(\hat{\delta}_t)$ is the subgradient of the function $J(\hat{\delta}_t)$ (22) in the point $\hat{\delta}_t$. Suppose that

$$\mathbf{s}_t = 0 \text{ for all } t \geq t_0. \quad (24)$$

Then the following result holds.

Lemma

If (24) holds, then we may guarantee the functional convergence

$$J(\hat{\delta}_t) \leq \frac{\Phi_{t_0}}{t + \theta} \xrightarrow{t \rightarrow \infty} 0, \quad \Phi_{t_0} = (t_0 + \theta) F(\hat{\delta}_{t_0}) + \frac{1}{2} \|\eta\|^2. \quad (25)$$

Remark

To have $\mathbf{s}_{t_0} = 0$ at time $t_0 = 0$, namely,

$$\mathbf{s}_{t_0} = \frac{d}{dt} \hat{\delta}_{t_0=0} + \frac{\hat{\delta}_{t_0=0} + \eta}{\theta} + \tilde{\mathbf{G}}_{t_0=0} = \frac{d}{dt} \hat{\delta}_0 + \frac{\hat{\delta}_0 + \eta}{\theta} = 0$$

it is sufficient to take

$$\eta = -\theta \frac{d}{dt} \hat{\delta}_0 - \hat{\delta}_0, \quad (26)$$

Let us represent the DNNI dynamics (19) the short following format:

$$\left. \begin{aligned} \frac{d}{dt} \hat{\zeta}_t &= \mathbf{g}_t + \mathcal{B}_t \mathbf{u}_t, \quad \hat{\zeta}_t = \begin{bmatrix} \hat{\mathbf{x}}_t^\top & \hat{\mathbf{v}}_t^\top \end{bmatrix}^\top, \\ \mathbf{g}_t &:= A \hat{\zeta}_t + F(\hat{\zeta}_t) + \hat{W}_{1,t} \sigma_1(\hat{\zeta}_t) \\ &\quad + \hat{W}_{2,t} \sigma_2(\hat{\zeta}_t) \mathbf{v}_t + L(\mathbf{x}_{1,t} - \mathbf{x}_{1,t}^*), \\ \mathcal{B}_t &:= \hat{W}_{3,t} \sigma_3(\hat{\zeta}_t), \quad F(\hat{\zeta}_t) = \begin{bmatrix} \ominus(\hat{\mathbf{x}}_t) \hat{\mathbf{v}}_t \\ 0 \end{bmatrix}. \end{aligned} \right\} \quad (27)$$

DNNO model: dynamics of sliding variable

In view of (23), we have

$$\begin{aligned} \dot{s}_t = & \frac{d^2}{dt^2} \left[CC_0 \left(\hat{\zeta}_t - \zeta_t^* \right) \right] + \frac{1}{t+\theta} \frac{d}{dt} \left[CC_0 \left(\hat{\zeta}_t - \zeta_t^* \right) \right] \\ & - \frac{\hat{\delta}_t + \eta}{(t+\theta)^2} - \frac{1}{(t+\theta)^2} \int_{\tau=t_0}^t \mathbf{a} \left(\hat{\delta}_\tau \right) d\tau + \frac{\mathbf{a} \left(\hat{\delta}_t \right)}{t+\theta} = \\ & CC_0 \frac{d}{dt} \left[\frac{d}{dt} \hat{\zeta}_t - \dot{\zeta}_t^* \right] + \frac{CC_0}{t+\theta} \left[\frac{d}{dt} \hat{\zeta}_t - \dot{\zeta}_t^* \right] + \\ & \frac{1}{t+\theta} \left(\mathbf{a} \left(\hat{\delta}_t \right) - \left[\frac{\hat{\delta}_t + \eta}{t+\theta} + \tilde{\mathbf{G}}_t \right] \right) = \\ & CC_0 \frac{d}{dt} \left[\mathbf{g}_t + \mathcal{B}_t \mathbf{u}_t \right] + \frac{CC_0}{t+\theta} \left[\mathbf{g}_t + \mathcal{B}_t \mathbf{u}_t \right] + \\ & CC_0 \ddot{\zeta}_t^* + \frac{1}{t+\theta} \left(\mathbf{a} \left(\hat{\delta}_t \right) - \left[\frac{\hat{\delta}_t + \eta}{t+\theta} + \tilde{\mathbf{G}}_t \right] - CC_0 \dot{\zeta}_t^* \right) = \\ & CC_0 \left[\mathcal{B}_t \dot{\mathbf{u}}_t + \left(\dot{\mathcal{B}}_t + \frac{1}{t+\theta} \mathcal{B}_t \right) \mathbf{u}_t \right] + \mathbf{p}_t, \end{aligned}$$

So, we have

$$\dot{\mathbf{s}}_t = CC_0 \left[\mathcal{B}_t \dot{\mathbf{u}}_t + \left(\dot{\mathcal{B}}_t + \frac{1}{t+\theta} \mathcal{B}_t \right) \mathbf{u}_t \right] + \mathbf{p}_t, \quad (28)$$

where

$$\left. \begin{aligned} \mathbf{p}_t := CC_0 \left(\ddot{\zeta}_t^* - \frac{1}{t+\theta} \dot{\zeta}_t^* + \dot{\mathbf{g}}_t + \frac{1}{t+\theta} \mathbf{g}_t \right) \\ + \frac{1}{t+\theta} \left(\mathbf{a}(\hat{\delta}_t) - \left[\frac{\hat{\delta}_t + \eta}{t+\theta} + \tilde{\mathbf{G}}_t \right] \right) \end{aligned} \right\} \quad (29)$$

DNNO model: Dynamic Controller

Let the control action \mathbf{u}_t satisfies the following ODE:

$$CC_0 \left[\mathcal{B}_t \dot{\mathbf{u}}_t + \left(\dot{\mathcal{B}}_t + \frac{1}{t+\theta} \mathcal{B}_t \right) \mathbf{u}_t \right] + \mathbf{p}_t = -k \text{Sign}(\mathbf{s}_t), \quad k > 0, \quad (30)$$

or in the resolving format

$$\begin{aligned} \dot{\mathbf{u}}_t &= \mathcal{B}_t^+ \left[- (CC_0)^+ [\mathbf{p}_t + k \text{Sign}(\mathbf{s}_t)] - \left(\dot{\mathcal{B}}_t + \frac{1}{t+\theta} \mathcal{B}_t \right) \mathbf{u}_t \right] \\ &= -\mathcal{B}_t^+ (CC_0)^+ [\mathbf{p}_t + k \text{Sign}(\mathbf{s}_t)] - \mathcal{B}_t^+ \left(\dot{\mathcal{B}}_t + \frac{1}{t+\theta} \mathcal{B}_t \right) \mathbf{u}_t, \end{aligned}$$

$$\begin{aligned} \mathcal{B}_t^+ (CC_0)^+ &= \left[\hat{W}_{3,t} \sigma_3 \left(\hat{\boldsymbol{\zeta}}_t \right) \right]^+ \begin{bmatrix} I_{3 \times 3} & O_{3 \times 2} \end{bmatrix} \begin{bmatrix} I_{5 \times 5} & O_{5 \times 5} \end{bmatrix} \\ \bar{W}_3 &= B_1 W_3 \quad (\bar{W}_3 \in \mathbb{R}^{10 \times p_{22}}), \quad B_1 = \begin{bmatrix} O_{5 \times 5} & I_{5 \times 5} \end{bmatrix}^\top \end{aligned}$$

DNNO model: Lyapunov function analysis

The Lyapunov function $V(\mathbf{s}) = \frac{1}{2} \|\mathbf{s}\|^2$ we have

$$\begin{aligned}\dot{V}(\mathbf{s}_t) &= \mathbf{s}_t^T \dot{\mathbf{s}}_t = \mathbf{s}_t^T \left(CC_0 \left[\mathcal{B}_t \dot{\mathbf{u}}_t + \left(\dot{\mathcal{B}}_t + \frac{1}{t+\theta} \mathcal{B}_t \right) \mathbf{u}_t \right] + \mathbf{p}_t \right) \\ &= -k \mathbf{s}_t^T \text{Sign}(\mathbf{s}_t) = -k \sum_{i=1}^3 |s_{i,t}| \leq -k \|\mathbf{s}_t\| = -k\sqrt{2} \sqrt{V(\mathbf{s}_t)},\end{aligned}$$

implying

$$0 \leq \|\mathbf{s}_t\| = \sqrt{V(\mathbf{s}_t)} \leq \sqrt{V(\mathbf{s}_0)} - \frac{k}{\sqrt{2}} t = \frac{1}{\sqrt{2}} (\|\mathbf{s}_0\| - kt)$$

which means that for all $t \geq t_{reach} = \frac{\|\mathbf{s}_0\|}{k}$ we obtain the desired regime

$$\mathbf{s}_t = 0 \text{ for all } t \geq t_{reach}.$$

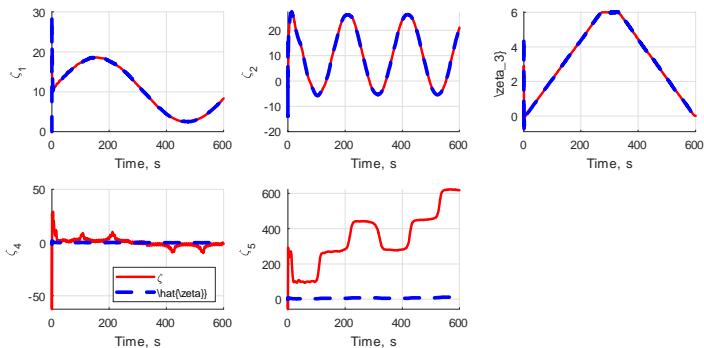


Figure 2: The position and velocity of the underwater vehicle model and by the neural network model

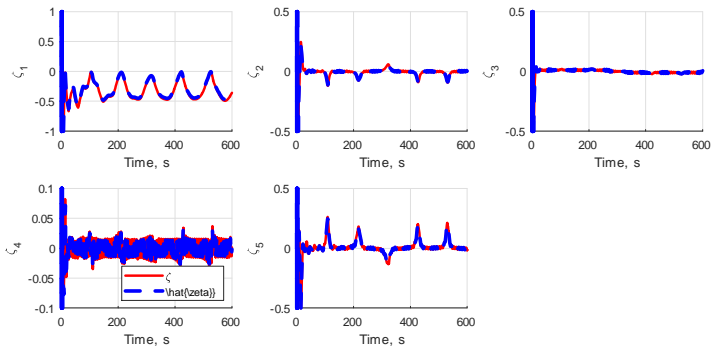


Figure 3: Translation velocity and angular velocity state by the underwater vehicle and the neural network model

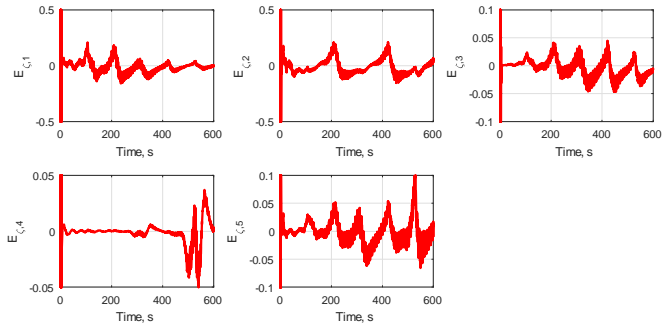


Figure 4: Error estimation by the Neural Network model in position and orientation

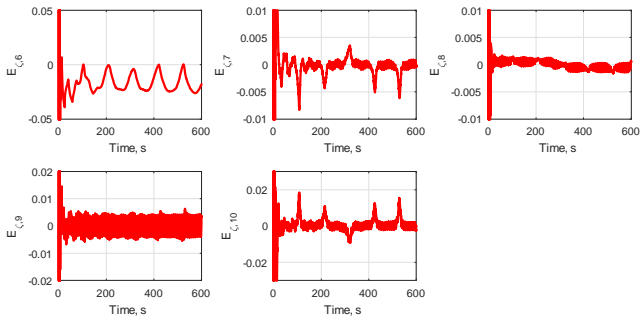


Figure 5: Estimation error by the Neural Network model in translation and angular velocity

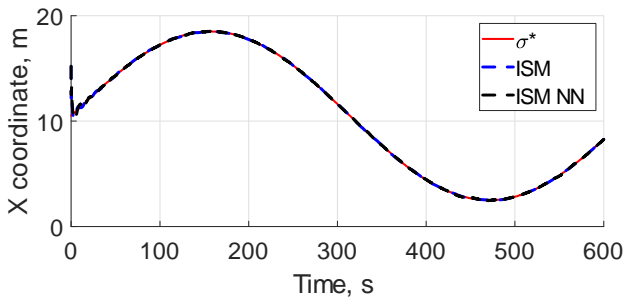


Figure 6: Tracking trajectory in x axis by ISM and ISM-NN controllers

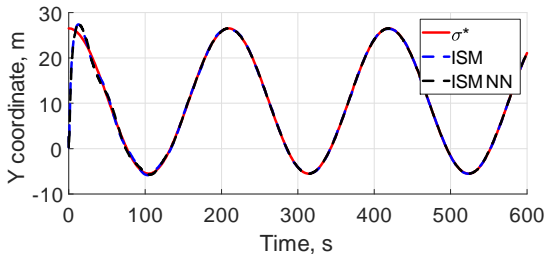


Figure 7: Tracking trajectory in Y axis by ISM and ISM-NN controllers

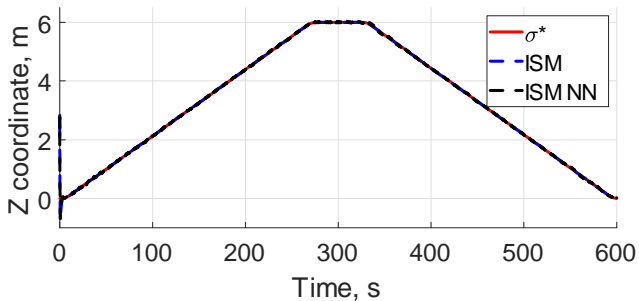


Figure 8: Tracking trajectory in z axis by PD, ISM and ISM-O controllers

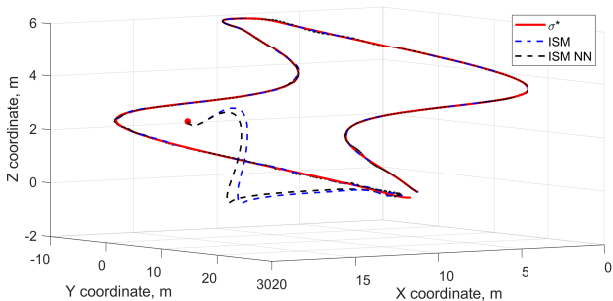


Figure 9: Tracking trajectory in 3D space by ISM and ISM-NN controllers

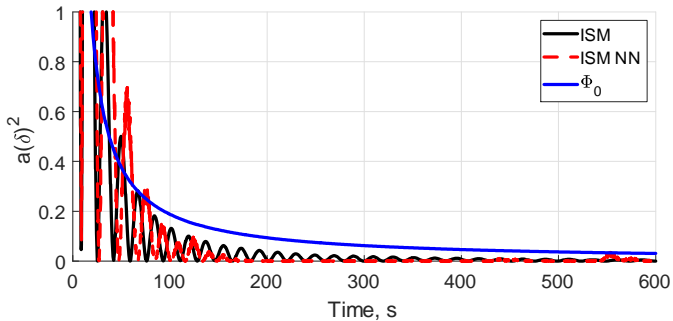


Figure 10: Cost function of the tracking error δ

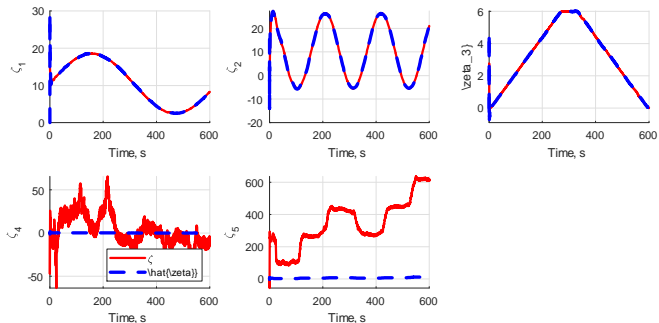


Figure 11: The position and velocity of the underwater vehicle model and by the neural network model

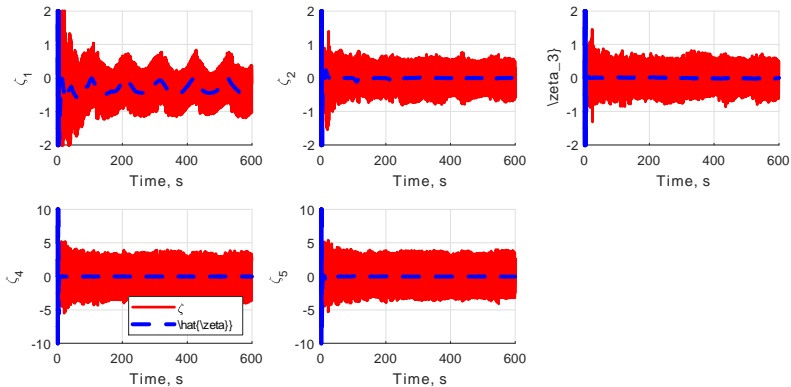


Figure 12: Translational velocity and angular velocity state by the underwater vehicle and the neural network model

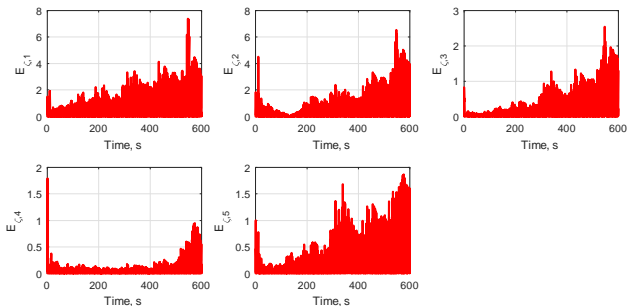


Figure 13: Error estimation by the Neural Network model in position and orientation

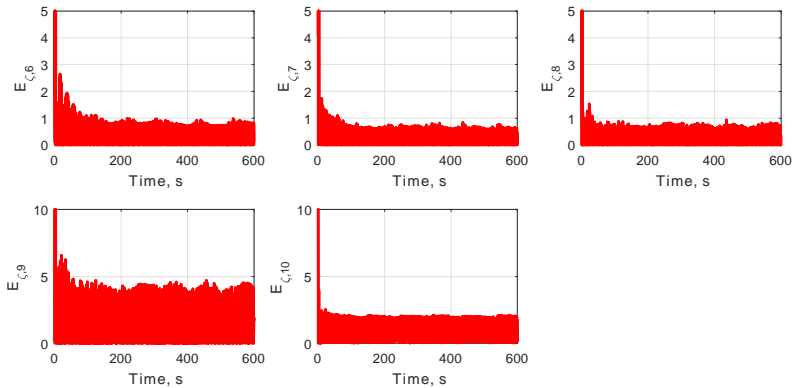


Figure 14: Estimation error by the Neural Network model in translation and angular velocity

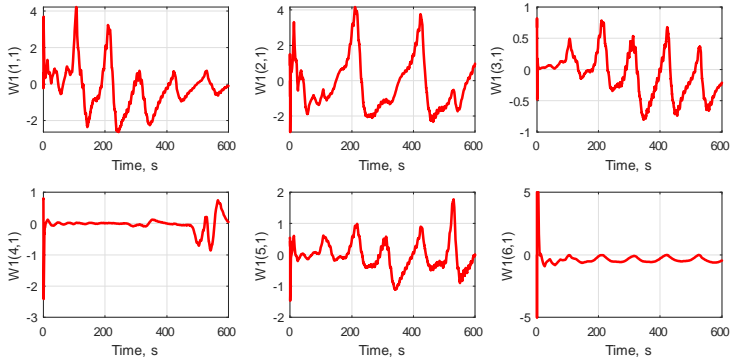


Figure 15: Weights of matrix W_1

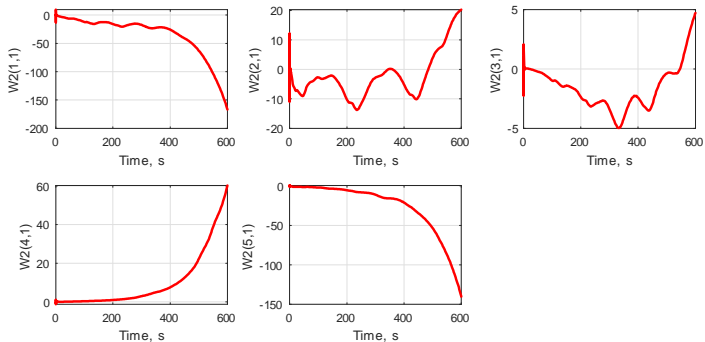


Figure 16: Weights of matrix W_2

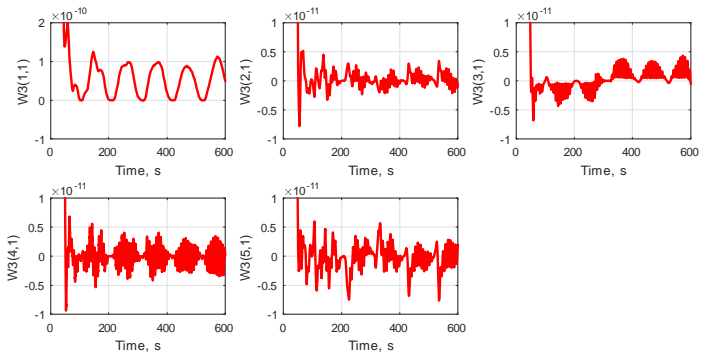


Figure 17: Weights of matrix W_1