Depth control of remotely operated underwater vehicles using an adaptive fuzzy sliding mode controller

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Abstract

Sliding mode control, due to its robustness against modeling imprecisions and external disturbances, has been successfully employed to the dynamic positioning of remotely operated underwater vehicles. In order to improve the performance of the complete system, the discontinuity in the control law must be smoothed out to avoid the undesirable chattering effects. The adoption of a properly designed thin boundary layer has proven effective in completely eliminating chattering, however, leading to an inferior tracking performance. This paper describes the development of a depth control system for remotely operated underwater vehicles. The adopted approach is based on the sliding mode control strategy and enhanced by an adaptive fuzzy algorithm for uncertainty/disturbance compensation. The stability and convergence properties of the closed-loop system are analytically proven using Lyapunov stability theory and Barbalat's lemma. Numerical results are presented in order to demonstrate the control system performance.

Key words: Adaptive algorithms, depth control, fuzzy logic, nonlinear control, remotely operated vehicles, sliding modes.

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1 Introduction

Due to the enormous technological improvements obtained in the last decades it is possible to use robotic vehicles for underwater exploration. These vehicles, often called ROV (Remotely Operated underwater Vehicle), have been substituting for divers in the accomplishment of tasks that may result in risks to human life. In this respect, ROVs have been used thoroughly in the research of subsea phenomena and in the assembly, inspection and repair of offshore structures. During the execution of a certain task with the robotic vehicle, the operator needs to monitor and control a number of parameters. If some of these parameters, as for instance the position and attitude of the vehicle, could be controlled automatically, the teleoperation of the ROV can be enormously facilitated.

A growing number of papers dedicated to the dynamic positioning of unmanned underwater vehicles confirms the necessity of the development of a controller, that could deal with the inherent nonlinear system dynamics, imprecise hydrodynamic coefficients, and external disturbances. It has already been shown [1,2] that, in the case of underwater vehicles, the traditional control methodologies are not the most suitable choice and cannot guarantee the required tracking performance. On the other hand, sliding mode control, due to its robustness to parameter uncertainty and external disturbance, has proven to be a very attractive approach to cope with this problem [3,4,5,6,7,8]. But a known drawback of conventional sliding mode controllers is the chattering effect. To overcome the undesired effects of the control chattering, Slotine [9] proposed the adoption of a thin boundary layer neighboring the switching surface, by replacing the sign function by a saturation function. This substitution can minimize or, when desired, even completely eliminate chattering, but turns *perfect tracking* into a *tracking with guaranteed precision* problem, which actually means that a steady-state error will always remain. In order to enhance the tracking performance inside the boundary layer, some adaptive strategy should be used for uncertainty/disturbance compensation.

Due to the possibility to express human experience in an algorithmic manner, fuzzy logic has been largely employed in the last decades to both control and identification of dynamical systems. In spite of the simplicity of this heuristic approach, in some situations a more rigorous mathematical treatment of the problem is required. Recently, much effort [10,11,12,13] has been made to combine fuzzy logic with sliding mode methodology.

In this paper, an adaptive fuzzy sliding mode controller is proposed to regulate the vertical displacement of remotely operated underwater vehicles. The adopted depth regulator is primarily based on the sliding mode control methodology, but a stable adaptive fuzzy inference system was embedded in the boundary layer to cope with the uncertainties and disturbances that can arise. Using Lyapunov stability theory and Barbalat's lemma, the stability and convergence properties of the closed-loop systems were analytically proven. Some numerical results are also presented in order to demonstrate the control system performance.

2 Dynamic model

An appropriate model to describe the underwater vehicle's dynamical behavior must include the rigid-body dynamics of the vehicle's body, the dynamics of the tether cable and a representation of the surrounding fluid dynamics. In this way, such a model must be composed of a system of ordinary differential equations, to represent rigid-body dynamics, and partial differential equations to represent both tether and fluid dynamics (*Navier–Stokes equations*).

To overcome the computational problem of solving a system with this degree of complexity, in the majority of publications [14,15,16,8] a lumped-parameters approach is employed to approximate vehicle's dynamical behavior.

In the range of velocities in which remotely operated underwater vehicles typically operate, never exceeding 2 m/s, the hydrodynamic forces (F_h) can be approximated using the *Morison equation* [17]:

$$F_h = C_D \frac{1}{2} \rho A v |v| + C_M \rho \nabla \dot{v} + \rho \nabla \dot{v}_w \tag{1}$$

where v and $\dot{v}$ are, respectively, the relative velocity and the relative acceleration between rigid-body and fluid, $\dot{v}_w$ is the acceleration of underwater currents, A is a reference area, ρ is the fluid density, ∇ is the fluid's displaced volume, C_D and C_M are coefficients that must be experimentally obtained.

The last term of equation (1) is the so-called *Froude-Kryloff force* and will not be considered in this work due the fact, that at normal working depths, the acceleration of the underwater currents is negligible. In this way, the coefficient $C_M \rho \nabla$ of the second term will be called *hydrodynamic added mass*. The first term represents the nonlinear hydrodynamic quadratic damping.

For control purposes, the dynamic model of underwater vehicles are commonly expressed with respect to the inertial reference frame by the position/attitude vector $\mathbf{x} = [x, y, z, \alpha, \beta, \gamma]^{\mathrm{T}}$. In the particular case of remotely operated vehicles, the distance between buoyancy and gravity centers is usually large enough to keep the roll (α) and pitch (β) angles small, i.e., $\alpha \approx 0$ and $\beta \approx 0$. Besides the self-stabilizing property, this design characteristic allows the vertical motion (heave) of the vehicle to be considered decoupled from the motion in the horizontal plane. So, with this in mind and considering Morison equation, the vertical motion along z-axis can be described by

$$m\ddot{z} + c\dot{z}|\dot{z}| + d = u \tag{2}$$

where u is the control input (thrust force), d the disturbance caused by external forces, $c = \frac{1}{2}C_D\rho A$ the coefficient of the hydrodynamic quadratic damping and m represents vehicle's mass plus the hydrodynamic added mass.

With respect to the dynamic model, the following physically motivated assumptions can be made:

Assumption 1 *The parameter $m(t)$ is time-varying and unknown but positive and bounded, i.e., $0 < m_{\min} \leq m(t) \leq m_{\max}$.*

Assumption 2 *The parameter $c(t)$ is time-varying and unknown but bounded, i.e., $c_{\min} \leq c(t) \leq c_{\max}$.*

Assumption 3 *The disturbance $d(t)$ is time-varying and unknown but bounded by a known function of z, $\dot{z}$ and t, i.e., $|d(t)| \leq \delta(t, z, \dot{z})$.*

3 Depth control

Let $S(t)$ be a sliding surface defined in the state space by the equation $s(\tilde{z}, \dot{\tilde{z}}) = 0$, with the function $s : \mathbb{R}^2 \to \mathbb{R}$ satisfying

$$s(\tilde{z}, \dot{\tilde{z}}) = \dot{\tilde{z}} + \lambda\tilde{z} \tag{3}$$

where $\tilde{z} = z - z_d$ is the tracking error, $\dot{\tilde{z}}$ the time derivative of $\tilde{z}$, z_d the desired trajectory and λ a strictly positive constant.

Regarding the development of the control law the following assumptions must be made:

Assumption 4 *The states z and $\dot{z}$ are available.*

Assumption 5 *The desired trajectory z_d is C^1. Furthermore z_d, $\dot{z}_d$ and $\ddot{z}_d$ are available and with known bounds.*

Now, let the problem of controlling the vertical motion of a remotely operated underwater vehicle, governed by equation (2), be treated in a Filippov's way

[18], defining a control law composed by an equivalent control $\hat{u} = \hat{c}\dot{z}|\dot{z}| + \hat{d} + \hat{m}(\ddot{z}_d - \lambda\dot{\tilde{z}})$ and a discontinuous term $-K\text{sgn}(s)$:

$$u = \hat{c}\dot{z}|\dot{z}| + \hat{d} + \hat{m}(\ddot{z}_d - \lambda\dot{\tilde{z}}) - K\text{sgn}(s) \tag{4}$$

where $\hat{m}$, $\hat{c}$ and $\hat{d}$ are estimates of m, c and d, respectively, K is the control gain and $\text{sgn}(\cdot)$ is defined as

$$\text{sgn}(x) = \begin{cases} -1 \text{ if } & x < 0 \\ 1 \text{ if } & x > 0 \end{cases} \tag{5}$$

Based on Assumptions 1–2, the estimates $\hat{m}$ and $\hat{c}$ can be properly chosen such that $|\hat{c} - c| \leq \zeta$ and $\mu^{-1} \leq \hat{m}/m \leq \mu$, where $\mu = \sqrt{m_{\max}/m_{\min}}$.

Therefore, if we choose the control gain according to

$$K \geq \hat{m}\mu\eta + \zeta\dot{z}^2 + \delta + |\hat{d}| + \hat{m}(\mu - 1)|\ddot{z}_d - \lambda\dot{\tilde{z}}| \tag{6}$$

where η is a strictly positive constant related to the reaching time, it can be easily verified that (4) is sufficient to impose the sliding condition

$$\frac{1}{2}\frac{d}{dt}s^2 \leq -\eta|s| \tag{7}$$

and, consequently, the finite time convergence to the sliding surface $S(t)$.

In order to obtain a good approximation to the disturbance $d(t)$, the estimate $\hat{d}$ will be computed directly by an adaptive fuzzy algorithm.

The adopted fuzzy inference system was the zero order TSK (Takagi–Sugeno–Kang), whose rules can be stated in a linguistic manner as follows:

$$\textit{If } s \textit{ is } S_r \textit{ then } \hat{d}_r = \hat{D}_r \; ; \; r = 1, 2, \cdots, N$$

where S_r are fuzzy sets, whose membership functions could be properly chosen, and $\hat{D}_r$ is the output value of each one of the N fuzzy rules.

Considering that each rule defines a numerical value as output $\hat{D}_r$, the final output $\hat{d}$ can be computed by a weighted average:

$$\hat{d}(s) = \frac{\sum_{r=1}^{N} w_r \cdot \hat{d}_r}{\sum_{r=1}^{N} w_r} \tag{8}$$

or, similarly,

$$\hat{d}(s) = \hat{\mathbf{D}}^{\mathrm{T}} \mathbf{\Psi}(s) \tag{9}$$

where, $\hat{\mathbf{D}} = [\hat{D}_1, \hat{D}_2, \dots, \hat{D}_N]^{\mathrm{T}}$ is the vector containing the attributed values $\hat{D}_r$ to each rule r, $\mathbf{\Psi}(s) = [\psi_1(s), \psi_2(s), \dots, \psi_N(s)]^{\mathrm{T}}$ is a vector with components $\psi_r(s) = w_r / \sum_{r=1}^{N} w_r$ and w_r is the firing strength of each rule.

To ensure the best possible estimate $\hat{d}(s)$ to the disturbance d, the vector of adjustable parameters can be automatically updated by the following adaptation law:

$$\dot{\hat{\mathbf{D}}} = -\varphi s \mathbf{\Psi}(s) \tag{10}$$

where φ is a strictly positive constant related to the adaptation rate.

It's important to emphasize that the chosen adaptation law, equation (10), must not only provide a good approximation to disturbance d but also assure the convergence of the state variables to the sliding surface $S(t)$, for the purpose of trajectory tracking.

Theorem 1 *Let the underwater vehicle be represented by equation (2). Then, subject to Assumptions 1–5, the controller defined by (4), (6), (9) and (10) ensures the convergence of the states to the sliding surface $S(t)$ and the desired trajectory tracking.*

Proof: Let a Lyapunov function candidate V be defined as

$$V(t) = \frac{1}{2} s^2 + \frac{1}{2m\varphi} \mathbf{\Delta}^{\mathrm{T}} \mathbf{\Delta} \tag{11}$$

where $\mathbf{\Delta} = \hat{\mathbf{D}} - \hat{\mathbf{D}}^*$ and $\hat{\mathbf{D}}^*$ is the optimal parameter vector, associated to the optimal estimate $\hat{d}^*(s)$, i.e., the ideal estimate that represents the better compensation to every disturbance and uncertainty that can arise.

Thus, the time derivative of V is

$$
\begin{aligned}
\dot{V}(t) &= s\dot{s} + (\varphi m)^{-1}\boldsymbol{\Delta}^{\mathrm{T}}\dot{\boldsymbol{\Delta}} \\
&= (\ddot{z} - \ddot{z}_d + \lambda\dot{\tilde{z}})s + (\varphi m)^{-1}\boldsymbol{\Delta}^{\mathrm{T}}\dot{\boldsymbol{\Delta}} \\
&= \Big[(u - d - c\dot{z}|\dot{z}|)m^{-1} - \ddot{z}_d + \lambda\dot{\tilde{z}}\Big]s + (\varphi m)^{-1}\boldsymbol{\Delta}^{\mathrm{T}}\dot{\boldsymbol{\Delta}}
\end{aligned}
$$

Defining the minimum approximation error as $\varepsilon = \hat{d}^{*}(s) - d$ and noting that $\dot{\boldsymbol{\Delta}} = \dot{\hat{\mathbf{D}}}$, then

$$
\begin{aligned}
\dot{V}(t) =& -\Big[K\mathrm{sgn}(s) - \varepsilon - (\hat{d} - \hat{d}^{*}) - (\hat{c} - c)\dot{z}|\dot{z}| - (\hat{m} - m)(\ddot{z}_d + \lambda\dot{\tilde{z}})\Big]m^{-1}s \\
&+ (\varphi m)^{-1}\boldsymbol{\Delta}^{\mathrm{T}}\dot{\hat{\mathbf{D}}} \\
=& -\Big[K\mathrm{sgn}(s) - \varepsilon - \boldsymbol{\Delta}^{\mathrm{T}}\boldsymbol{\Psi}(s) - (\hat{c} - c)\dot{z}|\dot{z}| - (\hat{m} - m)(\ddot{z}_d + \lambda\dot{\tilde{z}})\Big]m^{-1}s \\
&+ (\varphi m)^{-1}\boldsymbol{\Delta}^{\mathrm{T}}\dot{\hat{\mathbf{D}}} \\
=& -\Big[K\mathrm{sgn}(s) - (\hat{c} - c)\dot{z}|\dot{z}| - (\hat{m} - m)(\ddot{z}_d + \lambda\dot{\tilde{z}}) - \varepsilon\Big]m^{-1}s \\
&+ (\varphi m)^{-1}\boldsymbol{\Delta}^{\mathrm{T}}\Big[\dot{\hat{\mathbf{D}}} + \varphi s\boldsymbol{\Psi}(s)\Big]
\end{aligned}
$$

By applying the adaptation law, equation (10), to $\dot{\hat{\mathbf{D}}}$, $\dot{V}(t)$ becomes:

$$
\dot{V}(t) = -\Big[K\mathrm{sgn}(s) - (\hat{c} - c)\dot{z}|\dot{z}| - (\hat{m} - m)(\ddot{z}_d + \lambda\dot{\tilde{z}}) - \varepsilon\Big]m^{-1}s \tag{12}
$$

Furthermore, considering Assumptions 1–3, defining K according to (6) and verifying that $|\varepsilon| = |\hat{d}^{*} - d| \leq |\hat{d}^{*}| + |d| \leq |\hat{d}| + \delta$, we get

$$
\dot{V}(t) \leq -\eta|s| \tag{13}
$$

which implies $V(t) \leq V(0)$ and that s and $\boldsymbol{\Delta}$ are bounded. Considering Assumption 5 and equation (3), it can be easily verified that $\dot{s}$ is also bounded.

Integrating both sides of (13) shows that

$$
\lim_{t\to\infty}\int_0^t \eta|s|\,d\tau \leq \lim_{t\to\infty}\left[V(0) - V(t)\right] \leq V(0) < \infty
$$

Therefore, it follows from Barbalat's lemma that $s \to 0$ as $t \to \infty$, which ensures the convergence of the states to the sliding surface $S(t)$ and the desired trajectory tracking. □

However, the presence of a discontinuous term in the control law leads to the well known chattering effect. In order to avoid these undesirable high-frequency oscillations of the controlled variable, the sign function can be replaced by a saturation function [9], defined as:

$$\text{sat}(x) = \begin{cases} \text{sgn}(x) & \text{if} \quad |x| \geq 1 \\ x & \text{if} \quad |x| < 1 \end{cases} \tag{14}$$

This substitution smoothes out the control discontinuity and introduces a thin boundary layer in the neighborhood of the switching surface. A major drawback of this strategy is that a steady-state error will always remain. According to Slotine [9], the tracking error will exponentially converge to a closed region $\Phi = \{(\tilde{z}, \dot{\tilde{z}}) \in \mathbb{R}^2 \mid |\tilde{z}| \leq \lambda^{-1}\phi \text{ and } |\dot{\tilde{z}}| \leq 2\phi\}$. In this way, the adoption of the proposed adaptive scheme enhance the tracking performance inside the boundary layer by compensating uncertainties and disturbances that can occur.

Thus, considering a thin boundary layer, the resulting control law can be stated as follows

$$u = \hat{c}\dot{z}|\dot{z}| + \hat{d} + \hat{m}(\ddot{z}_d - \lambda\dot{\tilde{z}}) - K\text{sat}\left(\frac{s}{\phi}\right) \tag{15}$$

where ϕ is a strictly positive constant that represents the boundary layer thickness.

4 Simulation results

The simulation studies were performed with an implementation in C, with sampling rates of 500 Hz for control system and 1 kHz for dynamic model. The differential equations of the dynamic model were numerically solved with a fourth order Runge-Kutta method. Concerning the fuzzy system, triangular and trapezoidal membership functions were adopted for S_r, with the central values defined as $C = \{-5.0; -1.0; -0.5; 0.0; 0.5; 1.0; 5.0\} \times 10^{-3}$ (see Fig. 1). It is also important to emphasize, that the vector of adjustable parameters was initialized with zero values, $\hat{\mathbf{D}} = \mathbf{0}$, and updated at each iteration step according to the adaptation law, equation (10).

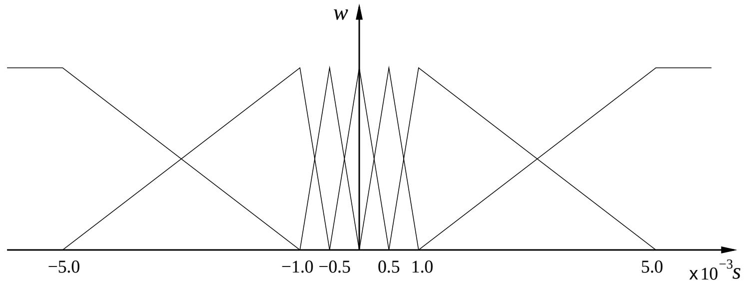


Figure 1. Adopted fuzzy membership functions.

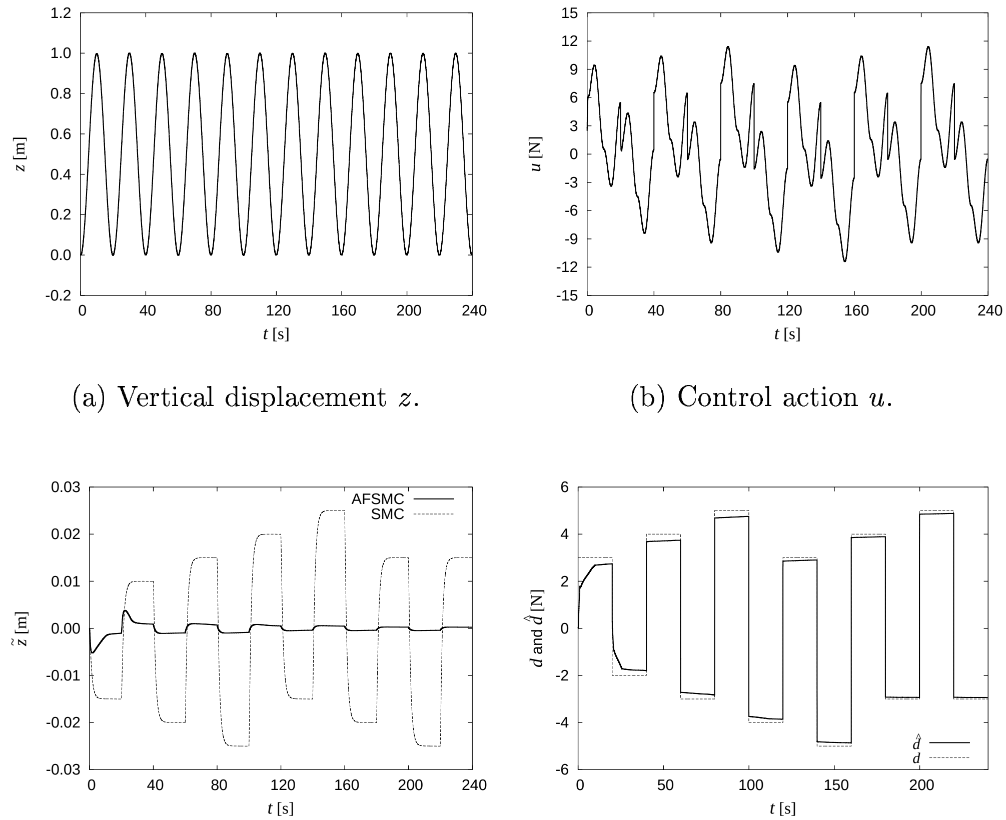
In order to evaluate the control system performance, three different numerical simulations were performed. The obtained results were presented from Fig. 2 to Fig. 5.

In the first case, it was considered that the model parameters, m and c, were perfectly known. Regarding controller and model parameters, the following values were chosen $\hat{m} = m = 50$ kg, $\hat{c} = c = 250$, $\mu = 1$ and $\zeta = 0$. The disturbance force was chosen to vary in the range of ± 5 N, as will be seen further in Fig. 2(d) and Fig. 3(d). The other used parameters were $\delta = 5$, $\lambda = 0.6$, $\eta = 0.1$, $\phi = 0.01$ and $\varphi = 150$. Fig. 2 gives the corresponding results for the tracking of $z_d = 0.5[1 - \cos(0.1\pi t)]$, considering that the initial state coincides with the initial desired state, $\tilde{\mathbf{z}}(0) = [\tilde{z}(0), \dot{\tilde{z}}(0)]^{\mathrm{T}} = \mathbf{0}$.

As observed in Fig. 2, even in the presence of external disturbances, the adaptive fuzzy sliding mode controller (AFSMC) is able to provide trajectory tracking with a small associated error and no chattering at all. It can be also verified that the proposed control law provides a smaller tracking error when compared with the conventional sliding mode controller (SMC), Fig. 2(c). The improved performance of AFSMC over SMC is due to its ability to recognize and compensate the external disturbances, Fig. 2(d). The AFSMC can be easily converted to the classical SMC by setting the adaptation rate to zero, $\varphi = 0$.

In the second simulation study, the parameters for the controller were chosen based on the assumption that exact values are not known but with a maximal uncertainty of $\pm 10\%$ over previous adopted values, $\hat{m} = 49.75$ kg, $\hat{c} = 250$, $\mu = 1.1$ and $\zeta = 25$. For the dynamic model, it was selected $m = 55$ kg and $c = 275$. The other parameters, as well as the disturbance force and the desired trajectory, were defined as before. Fig. 3 shows the obtained results.

Despite the external disturbance forces and uncertainties with respect to model parameters, the AFSMC allows the underwater robotic vehicle to track the desired trajectory with a small tracking error (see Fig. 3). As before, the undesirable chattering effect was not observed, Fig. 3(b). Through the comparative analysis showed in Fig. 3(c), the improved performance of the AFSMC over the uncompesated counterpart can be clearly ascertained.



(a) Vertical displacement z.

(b) Control action u.

(c) Tracking error $\tilde{z}$.

(d) Disturbance d and estimate $\hat{d}$.

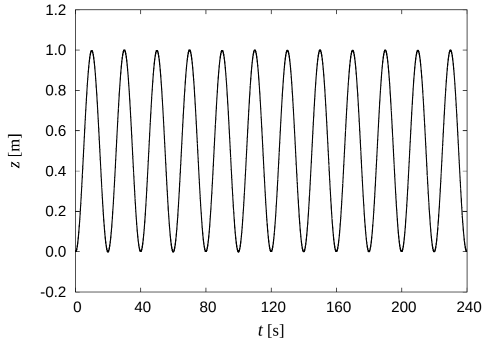
Figure 2. Tracking with known parameters and $\tilde{\mathbf{z}}(0) = \mathbf{0}$.

In the last simulation the initial state and initial desired state are not equal, $\tilde{\mathbf{z}}(0) = [0.6, 0.0]^{\mathrm{T}}$. The controller and model parameters, the disturbance force and the desired trajectory were defined as before. Fig. 4 shows the corresponding results. Only the first 60 seconds are displayed in order to emphasize the time required to reach the desired trajectory.

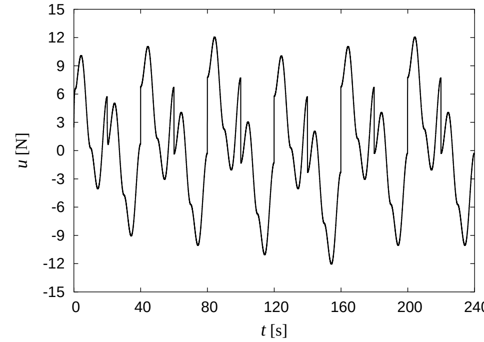
The phase portrait associated with the last simulation is shown in Fig. 5(a). For comparison purposes, the phase portrait obtained with the conventional sliding modes is also presented, Fig. 5(b). Note that in both situations the steady-state tracking error remains on the convergence region Φ, but the improved performance of the AFSMC can be easily observed.

5 Concluding remarks

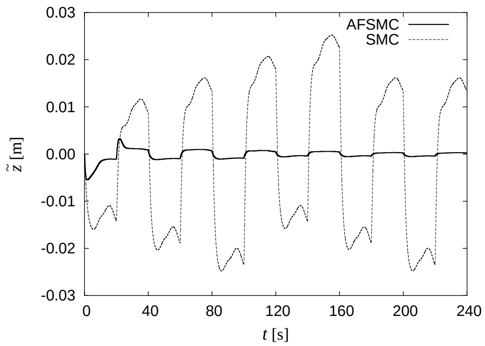
In this paper, an adaptive fuzzy sliding mode controller was proposed to deal with the depth regulation of underwater robotic vehicles. To enhance the track-



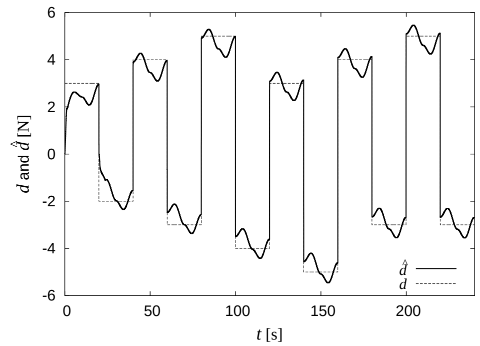
(a) Vertical displacement z.



(b) Control action u.

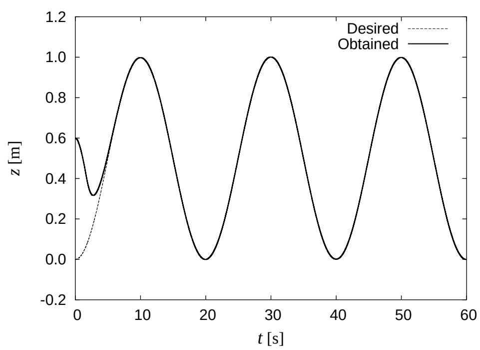


(c) Tracking error $\tilde{z}$.

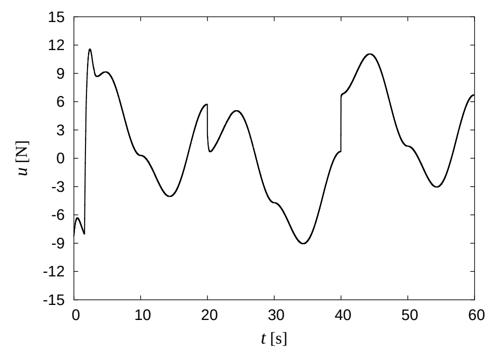


(d) Disturbance d and estimate $\hat{d}$.

Figure 3. Tracking with uncertain parameters and $\tilde{\mathbf{z}}(0) = \mathbf{0}$.



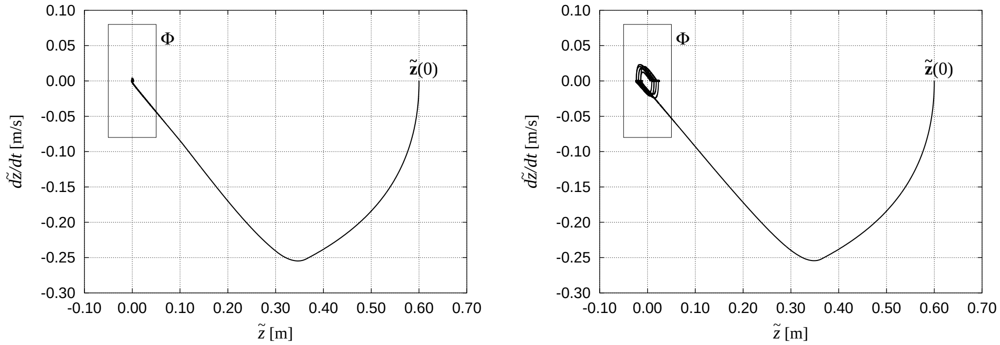
(a) Vertical displacement z.



(b) Control variable u.

Figure 4. Tracking with uncertain parameters and $\tilde{\mathbf{z}}(0) = [0.6, 0.0]^{\mathrm{T}}$.

ing performance inside the boundary layer, the adopted strategy embedded an adaptive fuzzy algorithm within the sliding mode controller for uncertainty/disturbance compensation. The stability and convergence properties of the closed-loop systems were analytically proven using Lyapunov stability



(a) With the proposed AFSMC. (b) With the conventional SMC.

Figure 5. Phase portrait of the trajectory tracking.

theory and Barbalat's lemma. Through numerical simulations, the improved performance over the conventional sliding mode controller was demonstrated.

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