Intelligent control for accurate position tracking of electrohydraulic actuators

J. D. B. dos Santos and W. M. Bessa

This letter presents a novel intelligent control scheme for accurate position tracking of electrohydraulic servo actuators. The proposed control law is designed by means of a nonlinear control approach and includes an adaptive neural network to provide the basic intelligent features. Online learning, instead of off-line supervised training, is proposed to update the weight vector of the neural network. Moreover, the adoption of a composite error signal as the only input to the neural network allows a significant reduction in the computational complexity of the algorithm. Rigorous proofs for the boundedness and convergence properties of the closed-loop signals are provided. Experimental results obtained with an electrohydraulic system demonstrate the efficacy of the proposed controller, even considering the highly nonlinear and uncertain plant dynamics.

Introduction: In view of the growing demand for more precise manufacturing processes, the design of control schemes that improve the tracking performance of servomechanisms is of broad and current interest. On this basis, nonlinear control methods in combination with computational intelligence techniques, such as artificial neural networks, has proved to be a promising approach to deal with electrohydraulic actuators [1, 2, 3]. Nevertheless, it should be emphasized that, considering that external disturbances may also occur, the adoption of an off-line supervised training algorithm might not be the most appropriate choice. In addition, in order to avoid the curse of dimensionality and allow the adoption of an online learning procedure, the number of input neurons should be kept as small as possible.

In this work, a novel intelligent approach is designed for precise motion control with electrohydraulic servo systems. Feedback linearization is employed as the main framework and an adaptive neural network is incorporated into the control law to deal with modeling inaccuracies. Experimental results obtained with an electrohydraulic test bench show that the adopted scheme is able to automatically recognize the unmodeled dynamics and compensate for it, leading to an accurate position tracking.

Intelligent Controller: An electrohydraulic servo actuator is mainly composed by a proportional valve, a hydraulic cylinder, a position sensor, and control electronics, as depicted in Fig. 1. Its dynamic behavior can be mathematically represented by a set of two ordinary differential equations (ODEs): a 2nd order ODE governing the load motion and a 1st order equation for the pressure drop variation with respect to time. For control purposes, the nonlinear system can be conveniently written as a 3rd order ODE [4]:

$$\dddot{x} = f(\boldsymbol{x}) + b(\boldsymbol{x})[u + d], \tag{1}$$

where $\boldsymbol{x} = [x\ \dot{x}\ \ddot{x}]^\top$ represents the state vector, x stands for the position of the load, $\dot{x}$, $\ddot{x}$, and $\dddot{x}$ are the derivatives of x with respect to time, $f : \mathbb{R}^3 \to \mathbb{R}$ and $b : \mathbb{R}^3 \to \mathbb{R}^+$ are both nonlinear functions, u is the control signal, and d represents a disturbance term that comprises not only the eventual external disturbances but also all neglected dynamics, including the the dead-zone effect due to valve spool overlap [4].

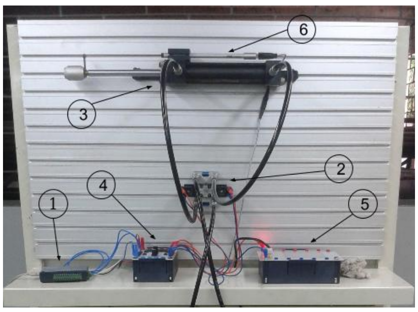


Fig. 1 *Electrohydraulic test bench: (1) 12 Bit AD/DA card; (2) 4/3-way proportional valve; (3) Single-rod hydraulic cylinder; (4) Proportional amplifier; (5) Power supply unit; (6) Linear potentiometer.*

The control task is to ensure that even in the presence of modeling inaccuracies the state vector $\boldsymbol{x} = [x\ \dot{x}\ \ddot{x}]^\top$ will follow a desired reference $\boldsymbol{x}_\mathrm{d} = [x_\mathrm{d}\ \ \dot{x}_\mathrm{d}\ \ \ddot{x}_\mathrm{d}]^\top$, i.e. the error vector $\tilde{\boldsymbol{x}} = [\tilde{x}\ \ \dot{\tilde{x}}\ \ \ddot{\tilde{x}}]^\top = [x - x_\mathrm{d}\ \ \dot{x} - \dot{x}_\mathrm{d}\ \ \ddot{x} - \ddot{x}_\mathrm{d}]^\top \to \mathbf{0}$ as $t \to \infty$.

Following the feedback linearization method, the control law may be designed as follows

$$u = \hat{b}^{-1}(-\hat{f} + \dddot{x}_\mathrm{d} - 3\lambda\ddot{\tilde{x}} - 3\lambda^2\dot{\tilde{x}} - \lambda^3\tilde{x}) - \hat{d}, \tag{2}$$

with λ being a strictly positive constant and $\hat{f}$, $\hat{b}$, and $\hat{d}$ representing estimates of f, b, and d, respectively.

Considering that all uncertainties with respect to f and b, i.e. Δf and Δb, are properly incorporated in d, and applying the proposed control law (2) to the electrohydraulic servo (1), the closed-loop dynamics becomes

$$\dddot{\tilde{x}} + 3\lambda\ddot{\tilde{x}} + 3\lambda^2\dot{\tilde{x}} + \lambda^3\tilde{x} = b\,(d - \hat{d}). \tag{3}$$

Eq. (3) shows that if $\hat{d} = d$ the error vector will exponentially converge to zero. Otherwise, the tracking error will be driven by the approximation error $d - \hat{d}$. In order minimize the approximation error and enhance the tracking performance, an adaptive neural network is proposed to estimate $\hat{d}$. However, instead of adopting the states or the tracking errors, we propose a composite error signal to be the only input variable to the network:

$$\sigma(\tilde{\boldsymbol{x}}) = \ddot{\tilde{x}} + 2\lambda\dot{\tilde{x}} + \lambda^2\tilde{x}\,. \tag{4}$$

It is important to note that, by defining the composite error according to (4), the closed-loop dynamics (3) becomes $\dot{\sigma} + \lambda\sigma = b\,(d - \hat{d})$.

At this point, considering that neural networks can perform universal approximation, i.e. $d = \hat{d}^* + \varepsilon$, with $\hat{d}^*$ being the optimal estimate and ε the minimum approximation error, a single-hidden layer network is adopted to estimate the neglected dynamics:

$$\hat{d} = \boldsymbol{w}^\top \boldsymbol{\varphi}(\sigma)\,, \tag{5}$$

where $\boldsymbol{w} = [w_1\ \ w_2\ \ \ldots\ \ w_n]^\top$ is the weight vector, $\boldsymbol{\varphi}(\sigma) = [\varphi_1\ \varphi_2\ \ldots\ \varphi_n]^\top$ represents the vector with the activation functions φ_i, $i = 1, \ldots, n$, and n is the total number of neurons in the hidden layer.

It should be highlighted that if either three states or three tracking errors, instead of the single composite error signal, have been adopted as input to the neural network, the computational complexity would grow from n to n^3.

Now, by means of a Lyapunov-like stability analysis, the boundedness and convergence properties of the error signals are investigated. Thus, let a positive-definite function V be defined as

$$V(t) = \frac{1}{2}\sigma^2 + \frac{1}{2\nu}\boldsymbol{\delta}^\top\boldsymbol{\delta}\,, \tag{6}$$

where ν is a strictly positive constant and $\boldsymbol{\delta} = \boldsymbol{w} - \boldsymbol{w}^*$, with $\boldsymbol{w}^*$ being the optimal weight vector that minimizes the approximation error.

Considering that $\dot{\boldsymbol{\delta}} = \dot{\boldsymbol{w}}$, the time derivative of V is

$$\begin{aligned}
\dot{V}(t) &= \sigma\,\dot{\sigma} + \nu^{-1}\boldsymbol{\delta}^\top\dot{\boldsymbol{w}} = -[\lambda\sigma - b\,(d - \hat{d})]\sigma + \nu^{-1}\boldsymbol{\delta}^\top\dot{\boldsymbol{w}} \\
&= -[\lambda\sigma - b\,(\hat{d}^* + \varepsilon - \hat{d})]\sigma + \nu^{-1}\boldsymbol{\delta}^\top\dot{\boldsymbol{w}} \\
&= -(\lambda\sigma - b\,\varepsilon + b\,\boldsymbol{\delta}^\top\boldsymbol{\varphi})\sigma + \nu^{-1}\boldsymbol{\delta}^\top\dot{\boldsymbol{w}} \\
&= -(\lambda\sigma - b\,\varepsilon)\sigma + \nu^{-1}\boldsymbol{\delta}^\top(\dot{\boldsymbol{w}} - b\,\nu\sigma\boldsymbol{\varphi}).
\end{aligned} \tag{7}$$

Since both b and ν are positive, they can be combined into a single learning rate $\eta = b\,\nu$. Thus, by updating $\boldsymbol{w}$ according to $\dot{\boldsymbol{w}} = \eta\sigma\boldsymbol{\varphi}$, the time derivative of V becomes $\dot{V}(t) = -(\lambda\sigma - b\,\varepsilon)\sigma \leq -(\lambda|\sigma| - \epsilon)|\sigma|$, with $\epsilon \geq b\,|\varepsilon|$ being an upper bound related to the approximation error. Considering that $\dot{V}$ is negative semi-definite when $|\sigma| > \epsilon/\lambda$, the bounds of $\boldsymbol{w}$ cannot be guaranteed with $\dot{\boldsymbol{w}} = \eta\sigma\boldsymbol{\varphi}$ when $|\sigma| \leq \epsilon/\lambda$. To overcome this issue, the projection algorithm is evoked to ensure that $\boldsymbol{w}$ will always remains within a convex region $\mathcal{W} = \{\boldsymbol{w} \in \mathbb{R}^n \mid \boldsymbol{w}^\top\boldsymbol{w} \leq \mu^2\}$:

$$\dot{\boldsymbol{w}} = \begin{cases} \eta\sigma\boldsymbol{\varphi} & \text{if } \|\boldsymbol{w}\|_2 < \mu \text{ or} \\ & \text{if } \|\boldsymbol{w}\|_2 = \mu \text{ and } \eta\sigma\boldsymbol{w}^\top\boldsymbol{\varphi} \leq 0 \\ \left(I - \dfrac{\boldsymbol{w}\,\boldsymbol{w}^\top}{\boldsymbol{w}^\top\boldsymbol{w}}\right)\eta\sigma\boldsymbol{\varphi} & \text{otherwise,} \end{cases} \tag{8}$$

with μ representing the desired upper bound for $\|\boldsymbol{w}\|_2$.

Hence, by adopting (8) along with $\|\boldsymbol{w}(0)\|_2 \leq \mu$, it follows that $|\sigma(\tilde{\boldsymbol{x}})| \leq \epsilon/\lambda$ and $\|\boldsymbol{w}(t)\|_2 \leq \mu$ as $t \to \infty$.

Recalling that $\sigma(\tilde{\boldsymbol{x}}) = \ddot{\tilde{x}} + 2\lambda\dot{\tilde{x}} + \lambda^2\tilde{x}$, $|\sigma(\tilde{\boldsymbol{x}})| \leq \lambda^{-1}\epsilon$ becomes

$$-\lambda^{-1}\epsilon \leq \ddot{\tilde{x}} + 2\lambda\dot{\tilde{x}} + \lambda^2\tilde{x} \leq \lambda^{-1}\epsilon\,. \tag{9}$$

Multiplying (9) by $e^{\lambda t}$ yields

$$-\lambda^{-1}\epsilon\, e^{\lambda t} \leq \frac{\mathrm{d}^2}{\mathrm{d}t^2}(\tilde{x}e^{\lambda t}) \leq \lambda^{-1}\epsilon\, e^{\lambda t}\,. \tag{10}$$

Integrating (10) between 0 and t leads to

$$-\lambda^{-2}\epsilon\, e^{\lambda t} - \kappa_1 \leq \frac{\mathrm{d}}{\mathrm{d}t}(\tilde{x}e^{\lambda t}) \leq -\lambda^{-2}\epsilon\, e^{\lambda t} + \kappa_1\,, \tag{11}$$

with $\kappa_1 = \lambda^{-2}\epsilon + \dot{\tilde{x}}(0) + \lambda\tilde{x}(0)$ being a constant value.

Integrating (11) between 0 and t results in

$$-\lambda^{-3}\epsilon\, e^{\lambda t} - \kappa_1 t - \kappa_0 \leq \tilde{x}e^{\lambda t} \leq \lambda^{-3}\epsilon\, e^{\lambda t} + \kappa_1 t + \kappa_0\,, \tag{12}$$

with $\kappa_0 = \lambda^{-3}\epsilon + \tilde{x}(0)$.

Dividing (12) by $e^{\lambda t}$, it can be verified for $t \to \infty$ that

$$-\lambda^{-3}\epsilon \leq \tilde{x} \leq \lambda^{-3}\epsilon\,. \tag{13}$$

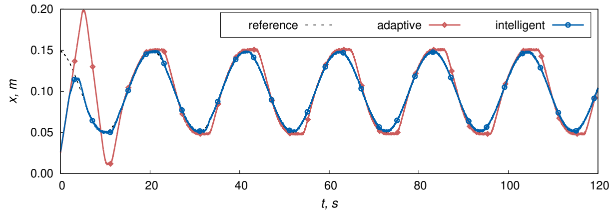
Applying (13) to (11) and dividing it by $e^{\lambda t}$, gives, for $t \to \infty$,

$$-2\lambda^{-2}\epsilon \leq \dot{\tilde{x}} \leq 2\lambda^{-2}\epsilon\,. \tag{14}$$

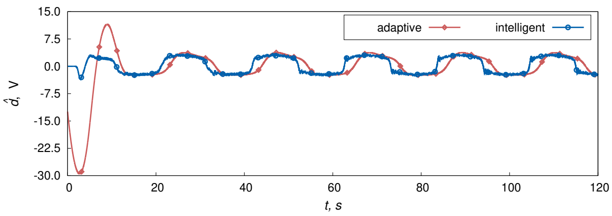
Furthermore, by imposing (13) and (14) to (9), one has

$$-6\lambda^{-1}\epsilon \leq \ddot{\tilde{x}} \leq 6\lambda^{-1}\epsilon\,. \tag{15}$$

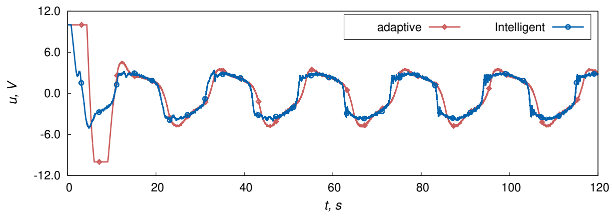
Thus, one can conclude that the proposed controller defined by (2), (5), and (8) ensures the exponential convergence of the tracking error to the closed region $\mathcal{X} = \big\{\tilde{\boldsymbol{x}} \in \mathbb{R}^3 \;\big|\; |\tilde{x}^{(i)}| \leq (i+1)!\lambda^{i-3}\epsilon\,,\ i = 0, 1, 2\big\}$.



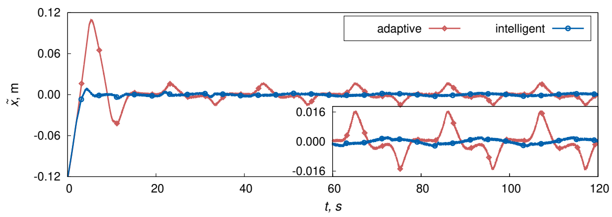
(a) Position tracking.



(b) Compensation signal.



(c) Control signal.



(d) Tracking error.

Fig. 2. Experimental results.

Experimental results: The intelligent controller is now evaluated by means of the experimental results obtained with the electrohydraulic test bench presented in Fig. 1. Considering that the proposed scheme requires full state feedback, a 2^{nd}-order sliding mode differentiator [5] is used to estimate both $\dot{x}$ and $\ddot{x}$. It has recently been shown [6] that higher-order sliding mode observers are among the best options for state estimation in the case of electrohydraulic systems. Regarding the adaptive neural network, Gaussian functions are adopted for the neurons: $\varphi(\sigma; c_i, a_i) = \exp\{-0.5[(\sigma - c_i)/a_i]^2\}$. Six neurons are defined with centers $c_i = \{-0.6, -0.1, -0.02, 0.02, 0.1, 0.6\}$ and widths $a_i = \{1, 10, 30, 30, 10, 1\}$. The weight vector is initialized as $\boldsymbol{w} = \boldsymbol{0}$ and updated according to Eq. (8). By setting $\hat{f} = 0$, we assume that no previous knowledge about f is required and that $\hat{d}$ is able to cope with all neglected dynamic effects. The remaining control parameters are chosen as follows $\hat{b} = 1$, $\eta = 2$, and $\lambda = 5$. For comparison purposes, the proposed intelligent approach is confronted with a common adaptive controller. The intelligent scheme can be easily converted to the adaptive law by computing $\hat{d}$ according to $\hat{d}_{k+1} \leftarrow \hat{d}_k + \eta\sigma\Delta t$, with Δt being the sampling period, $\hat{d}_k$ standing for the estimation at the k^{th} step, and $\hat{d}_0 = 0$. Fig. 2 shows the obtained results. As observed in Fig. 2(a), the proposed scheme is able to provide accurate position tracking, while the adaptive controller shows a degraded performance. Moreover, the intelligent approach allows a much faster convergence to the reference, without overshooting. The overshoot of the adaptive controller is caused by the exaggerated response of its compensation scheme, Fig. 2(b), which in fact also leads to the saturated control signal observed in Fig. 2(c). The intelligent compensation approach, on the other hand, shows a smoother and faster accommodation response. The tracking error, Fig. 2(d), confirms the improved performance of the proposed controller. By means of the Mean Absolute Error (MAE), it can be verified that the intelligent scheme provides a tracking error almost three times smaller: $\text{MAE}_{\text{INT}} = 4.22$ mm and $\text{MAE}_{\text{ADA}} = 11.94$ mm.

Conclusion: In this letter, a novel intelligent approach is introduced for precise motion control of electrohydraulic servo actuators. It is shown that the adoption of an adaptive neural network with only a single input, namely the proposed composite error signal, is able to cope with a high degree of uncertainty and provide an accurate position tracking. The low computational complexity of the proposed scheme allows the development of high-precision servo drives with embedded intelligence.

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J. D. B. dos Santos and W. M. Bessa (*Federal University of Rio Grande do Norte, Campus Universitário Lagoa Nova, Natal – RN, Brazil*)

E-mail: wmbessa@ct.ufrn.br

References

1 Guo, Q., Shi, G., Wang, D., and He, C.: ‘Neural network-based adaptive composite dynamic surface control for electrohydraulic system with very low velocity’, *Proc. Inst. Mech. Eng. I J. Syst. Control Eng.*, 2017, **231**, p. 867-880

2 Yang, Y., Balakrishnan, S. N., Tang, L., and Landers, R. G.: ‘Electrohydraulic control using neural MRAC based on a modified state observer’, *IEEE/ASME Trans. Mechatronics*, 2013, **18**, p. 867-877

3 Knohl, T. and Unbehauen, H.: ‘Adaptive position control of electrohydraulic servo systems using ANN’, *Mechatronics*, 2000, **10**, p. 127-143

4 Bessa, W. M., Dutra, M. S., and Kreuzer, E.: ‘Sliding mode control with adaptive fuzzy dead-zone compensation of an electrohydraulic servo-system’, *J Intell Robot Syst*, 2010, **58**, pp. 3-16

5 Levant, A.: ‘Higher-order sliding modes, differentiation and output-feedback control’, *Int. J. Control*, 2003, **76**, p. 924-941

6 Palli, G., Strano, S., and Terzo, M.: ‘Sliding-mode observers for state and disturbance estimation in electrohydraulic systems’, *Control Eng. Pract.*, 2018, **74**, p. 58-70