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DESIGN OF A FAST ADAPTIVE NEURO-SLIDING MODE CONTROLLER FOR PIEZOELECTRIC ACTUATORS

Ounissi Amor[1,2], Azeddine Kaddouri[1] and Rachid Abdessemed[1]

[1] Department of Electrical Engineering, Faculty of Technology, University Batna 2, Batna, Algeria.
e-mail: amor.ounissi@univ-batna2.dz, e-mail: rachid.abdessemed@gmail.com.
[2] Department of Electrical Engineering University of Moncton, Moncton, Canada
e-mail: azeddine.kaddouri@umoncton.ca
corresponding author

Abstract

In this paper, an adaptive controller is applied to the piezoelectric actuators, PEA, in order to handle them. Our paper deals with the design of a new adaptive neuro-fast terminal sliding mode controller. The new adaptive control law using the terminal attractor concept is used in the finite time control procedure of the non-linear model. The PEA converges to the desired trajectory in a very short time. The controller allows for obtaining good results in terms of trajectory tracking and error minimization. The adaptive scheme is used to reduce the high noise order presented in piezo materials, especially at the micro-positioning level. The results of the simulations undertaken have demonstrated the robustness of the proposed approach and make it possible not only to guarantee the high accuracy of the monitoring but also to maintain the high stability of the piezoelectric actuator.

Keywords: LuGre model, identification with particle swarm optimization (PSO) approach, adaptive neuro-nonsingular terminal fast sliding mode controller, piezo-positioning mechanism.

1. Introduction

Over the past two decades, the performance of stage piezoelectric actuators has dramatically increased in the field of micro/Nano-positioning technology. Much attention has been paid to the problems of controlling these mechanisms to work at their full capacity and often if the precision and performance requirements of the system are too severe. These mechanisms are often subject to significant disturbances and the operating point is no longer fixed at a nominal position (Uchino K. (2019)). Operating a complex system in different regimes requires the controller to be intelligent with adaptive and learning capabilities in the presence of unknown disturbances, unmodelled dynamics, and unstructured uncertainties (Liu et al. (2020), Ho et al. (2021)). In addition, these actuator-driven controllers exhibit severe multiple nonlinearities in terms of friction, dead zone, and time delay (Bai et al. (2018), Uchino K. (2019), Iqbal J et al. (2017)). Intelligent control systems, whose models are inspired by systems, have interesting learning, adaptation, and classification properties (Shin et al. (2018)). The implementation of the algorithms is based on a natural approach highlighting the applicability of the theoretical solutions recommended for the control of complex nonlinear systems (Qian et al. (2020), Bouchiba et al. (2022)). For all recent algorithms, and based on previous scientific work, we have sought an association of robustness and stability criteria leading to the synthesis of efficient control laws. The control algorithms designed cannot, therefore, ensure the robustness of the behavior with respect to uncertainties in the parameters and their variations (Chen et al. (2022)). This has led to a strong interest in the synthesis of robust non-linear control techniques capable of overcoming these problems (Nigam et al. (2022)). One can cite in this situation, the control by sliding mode. In motion control applications, sliding mode control suffers from the main drawbacks that there is always a high-frequency oscillation in the control input and that it is difficult to obtain the system parameters (Ounissi et al. (2022)). The fast terminal sliding mode controller shows a rapid convergence of modeling errors and certain types of external disturbances (Song et al. (2022). This technique inherits the merits of variable structure control theory and terminal attractor techniques which can ensure that error states converge to zero in finite time and avoid the singularity problem and also drive error rate states to zero in finite time in the same way (Shin Chang et al. (2022)). However, all these positive aspects should not overshadow certain disadvantages, namely the development of command theorems in fast terminal sliding mode, where one resort to simplifying assumptions either at the level of the modeling or at the level of the command, thus the numerical simulation cannot reflect all the physical phenomena, because it is difficult, even impossible, to model them. In addition, some technological constraints are not taken into account in the simulation, such as measurement errors due to sensors, sampling time, delays, data processing time, measurement noise, etc. (Jin et al. (2009)). We proposed a new controller based on the concept of combining artificial neural networks with learning rules determined from the design of terminal attractor approaches to build an intelligent control called adaptive neuron fast terminal sliding mode control. The choice of the adaptive linear neuron type neural network is used to estimate the PEA model uncertainties. This type of ADALINE (adaptive linear neuron) is suitable for practical applications, such as prediction or noise suppression (Yildiz et al. (2020)). The new approach speeds up the convergence time and overcomes the problem of unmodelled and/or unknown uncertainties and disturbances, especially with regard to positioning systems. In the next section, the controller design is detailed.

2. The controller design

Consider a second-order nonlinear system (Tian et al. (2020))

$$\begin{cases} \dot{y}_1 = y_2 \\ \dot{y_2} = F(y,t) + G(y,t) + H(y,t)\,U(t) \end{cases} \tag{1}$$

Where $y_1 = [y_{11}, y_{12}, \dots y_{1n}]^T \in R^n$ and $y_{21} = [y_{21}, y_{22} \dots y_{2n}]^T \in R^n$is the state, $F(y,t)$ is smooth function and $G(y,t)$ represents the disturbances and uncertainties satisfy the $\|G(y,t)\| < L_g$, where $L_g > 0$, $H(y,t)$ represents a non-singular matrix, $U(t)$ is the vector control $\in R^n$.

The global surface variable of the non-singular fast terminal sliding mode for the design is:

$$S_s = Ay_1 + \dot{y_1}^{\Gamma} = Ay_1 + y_2^{\Gamma} \tag{2}$$

Where $A = diag(\mu_1, \dots, \mu_n)$, $\mu_i > 0$, $\Gamma = diag(\rho_1, \dots, \rho_n)$, $1 < \rho_i < 2$, for $i = 1, \dots, n$ and is represented as $y_1^T = (y_{11}^{\rho}, \dots, y_{1n}^{\rho n})^T$. We also adopt the notion that:

$$y_2^{\Gamma} = \frac{d(y_{1)}^T}{dt} = \Gamma\, diag\left(y_{11}^{\rho}, \dots, y_{1n}^{\rho n}\right) \dot{y}_1 \tag{3}$$

The derivative of equation (3) gives:

$$\dot{y}_2^{\Gamma} = \Gamma\, diag\left(\dot{y}_{11}^{\rho}, \dots, \dot{y}_{1n}^{\rho n}\right) \ddot{y}_1 \tag{4}$$

Consider the Lyapunov candidate function:

$$V = \frac{1}{2}\, S_s {S_s}^T \tag{5}$$

The time derivative of (5):

$$\dot{V} = \dot{S}_s {S_s}^T \tag{6}$$

The derivative of equation (2):

$$\dot{S_s}^T = A\dot{y}_1 + \dot{y}_2^{\Gamma} \tag{7}$$

Replacing (7), and (4) in (6), one can get:

$$\begin{aligned} \dot{V} &= {S_s}^T (A\dot{y}_1 + \Gamma\, diag\left(\dot{y}_{11}^{\rho}, \dots, \dot{y}_{1n}^{\rho n}\right)\ddot{y}_1) \\ &= {S_s}^T (A\dot{y}_1 + \Gamma\, diag\left(\dot{y}_{11}^{\rho}, \dots, \dot{y}_{1n}^{\rho n}\right)\dot{y_2}) \end{aligned} \tag{8}$$

$$\dot{V} = {S_s}^T (A\dot{y}_1 + \Gamma\, diag\left(\dot{y}_{11}^{\rho}, \dots, \dot{y}_{1n}^{\rho n}\right)(F(y,t) + G(y,t) \; + H(y,t)\, U(t))$$

The control law U is obtained as:

$$U = \frac{1}{H(y,t)} \left[K \frac{S_s}{\|S_s\|} + F(y,t) + G(y,t)\Gamma^{-1} A\, \dot{y}_1^{(2I-\Gamma)} \right] \tag{9}$$

where K is a positive defined gain. The substitution of (9) in (8) leads to:

$$\dot{V} = -K \sum_{i=1}^{n} |\dot{y}_{i1}|^{\rho_i - 1} \frac{S_s^2}{\|S_s\|} < 0 \tag{10}$$

We conclude from equations (8) and (2) that the system is stable in finite time and the sliding function will converge to zero in finite time. The non-singular fast terminal sliding mode controller approach is proposed for tracking the PEA displacement trajectory, and it is assumed that the precise upper bound of the uncertainty is known. In practice, obtaining the upper limit of the precise uncertainty information is usually difficult. The controller performances are based on the accuracy of the LuGre model parameters. The next section is dedicated to the identification of the LuGre model based on PSO algorithm.

3. Modeling and identification of LuGre model

The dynamic equation from the motion stage mechanism positioning piezo actuated PEA can be described by the following set of equations (Ounissi et al. (2022)).

$$\begin{cases} \dot{y}_1 = y_2 \\ \dot{y}_2 = \frac{K_e U}{m} - \frac{1}{m}\left[C_0 G(y_2) \frac{y_2}{|y_2|} + (B + C_3) y_2 + C_2 y_1 + F_L \right] \end{cases} \tag{11}$$

Where m denotes the equivalent mass of the PEA; the y is the displacement of the mechanism; B is the linear friction coefficient of PEA. K_e is the voltage to force ratio, F_L is the external load; C_0, C_2 are positive constants and can be equivalently interpreted as the bristle, and viscous damping coefficient respectively, $G(y_2)$ denote the Stribeck effect. With $K_1 = \frac{K_e}{m}$, $K_2 = \frac{B+C_3}{m}$, $L(t) = \frac{1}{m}\left[C_0 G(y_2) \frac{y_2}{|y_2|} \right]$ and $K_3 = \frac{C_2}{m} K_1$, just as $L(t)$ is unknown and bounded by K_4.

$$\begin{cases} \dot{y}_1 = y_2 \\ \dot{y}_2 = K_1 U - L(t) - K_2 y_2 - K_3 y_1 + F_L \end{cases} \quad (12)$$

(Ounissi A et al. (2022) validates the experimental configuration used for identifying the LuGre model on the piezo-actuator positioning mechanism. The hysteresis comparison of experimental and simulation results when a sinusoidal input signal is used to drive the piezoelectric positioning stage is shown in Fig. 1. Figure 1 shows the experimental results of the hysteresis response and the simulated results for a frequency of 1.0 Hz for validation from the parameters obtained. In Fig. 2, the simulated and experimental outputs are compared; the difference between the simulation and experimental models is between 4.49 nm and 144.65 nm. We find that the two results are in good agreement.

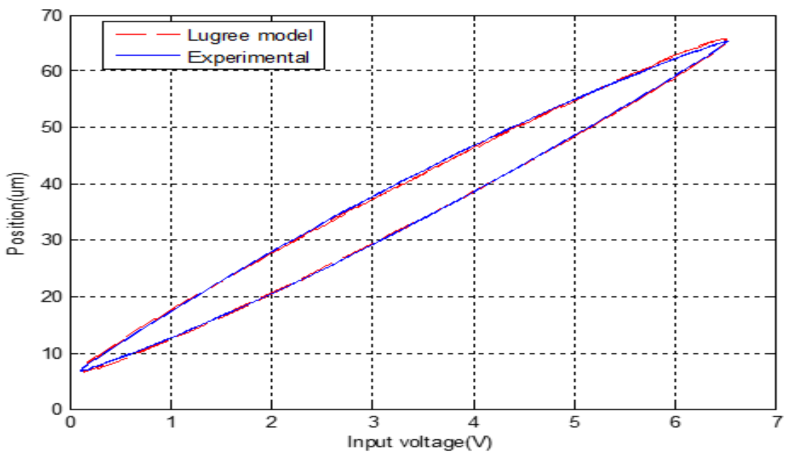

Fig. 1. Hysteresis cycle obtained by PSO and by experiment.

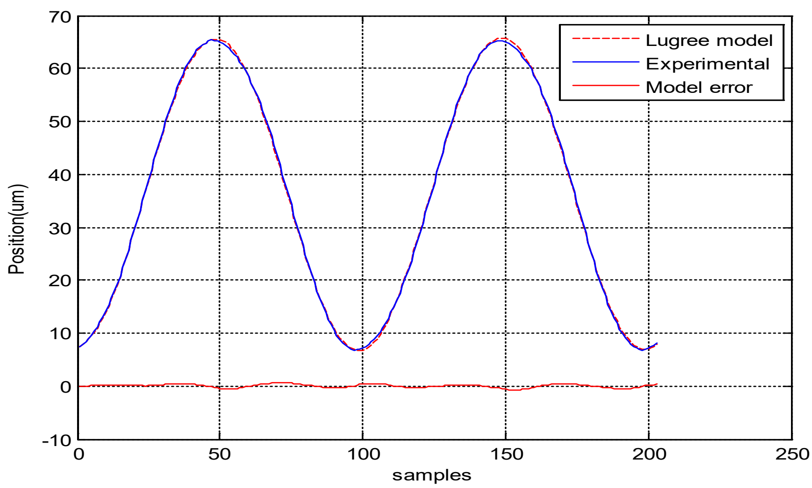

Fig. 2. Trajectory tracking the position.

4. Application of the adaptive neuro-nonsingular terminal fast sliding mode controller

More specifically, the objective of our paper is to propose an adaptive linear neuron (ADALINE) structure based on the online learning procedure. Indeed, our proposal is to take advantage of the linear and adaptive characteristics of ADALINE and introduce it in the control system, in order to take into the account the uncertainties in the real mechanism, using the backpropagation gradient descent algorithm.

To account for the uncertainties in the real system, the ADALINE is intended for the approximation Q which can be expressed as follows:

$$Q = w^T K_4 + \varepsilon_m \tag{13}$$

Where w is the optimal weight, K_4 is positive gain, ε_m is the approximation error.

Then the output vector of NN is:

$$\hat{Q} = \hat{w}_j^T K_4 \tag{14}$$

The network expression consists of adapting the weights w_j in such a way that the error function tends toward zero [19]. This function is chosen as follows:

The error function is defined by the following equation:

$$E = \frac{1}{2}(\dot{S}_s + \varepsilon_0 S_s)^2 \tag{15}$$

where ε_0 is closed loop positive gain.

The weight adaptation algorithm is performed, using gradient descent:

$$\dot{w}_j = -K_0 \frac{dE}{dw_j} \tag{16}$$

where K_0 is the learning gain $0 < K_0 < 1$.

The derivative of the error function can be calculated as follows:

$$\frac{dE}{dw_j} = \frac{dE}{dU}\frac{dU}{dw_j} \tag{17}$$

Substituting (16) into (17), we get:

$$\frac{dE}{dw_j} = (\dot{S}_s + \varepsilon_0 S_s) \quad \frac{d\dot{S}_s}{d\,U} e^{j-1} \tag{18}$$

The aim is to track a given reference signal y_d in finite time from any initial state. The tracking error is defined as:

$$e = y - y_d = [(y_1 - y_{1d})(y_2 - y_{2d}), \dots, ((y_n - y_{nd})]^T = [e_1, e_2, \dots, e_n]^T \tag{19}$$

The goal is to design an adaptive control by terminal sliding mode such that the resulting tracking error satisfies:

$$\lim_{t\to\infty} |e(t)| = \lim_{t\to\infty} |y - y_d| \to 0 \tag{20}$$

Furthermore, from (19) we can obtain:

$$\frac{dE}{dw_j} = -(\dot{S}_s + \varepsilon_0 S_s) \; K_4 \; |\dot{e}| \tag{21}$$

Finally, the expression of the adaptation law is:

$$\dot{w}_j = -(\dot{S}_s + \varepsilon_0 S_s) K_4 |\dot{e}| \quad (22)$$

Based on equations (20) and (1), the control law in equation (9) is rewritten as follows:

$$U = \frac{1}{H(y,t)} \left[K \frac{S_S}{\|S_S\|} + F(y,t) + \hat{Q} + G(y,t)\Gamma^{-1} A\, \dot{y}_1^{(2I-\Gamma)} \right] \quad (23)$$

5. Simulation results and discussion

The goal of the simulations is to examine the performance of the adaptive neuron rapid terminal control mode. Figure 3 depicts the simulation results with a reference of one-micron meter and a frequency of 1.0 Hertz. Figures 3a and b show that the trajectory of the system states follows their required reference and the control signal applied to achieve this performance. Figure 4 illustrates the convergence of the adaptive weight gains of the neural network control (of w_1, w_2 and w_3). It is clear that the adaptive neuro terminal fast sliding mode controller can converge very quickly.

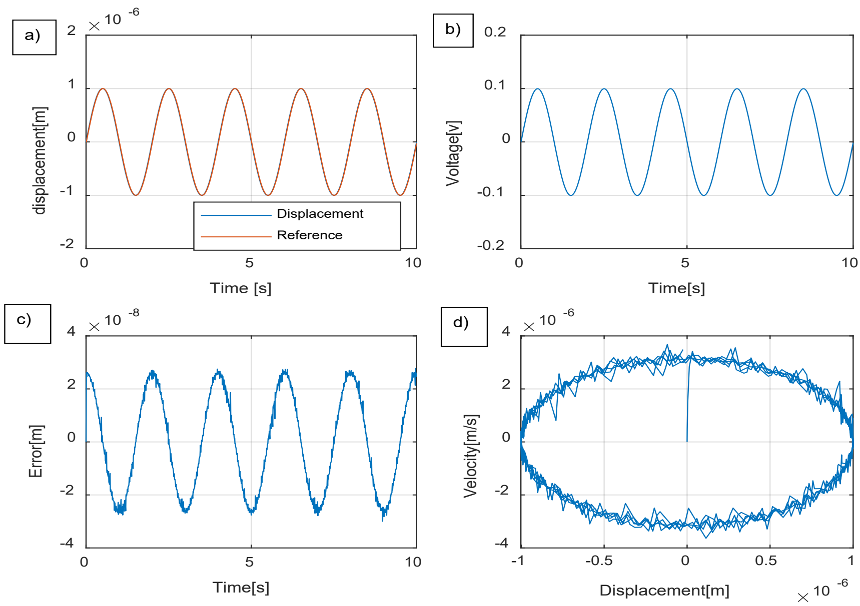

Fig. 3. Results simulation of the adaptive neuron terminal fast sliding mode controller: a) Trajectory tracking response of the position, b) Control voltage, c) Tracking error, d) the phase plane (velocity, displacement).

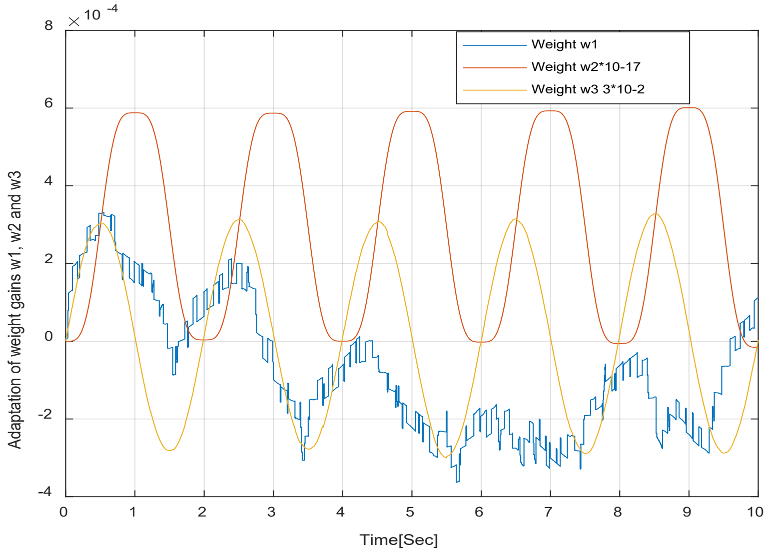

Fig. 4. Evolution of parameters w_1, w_2 and w_3.

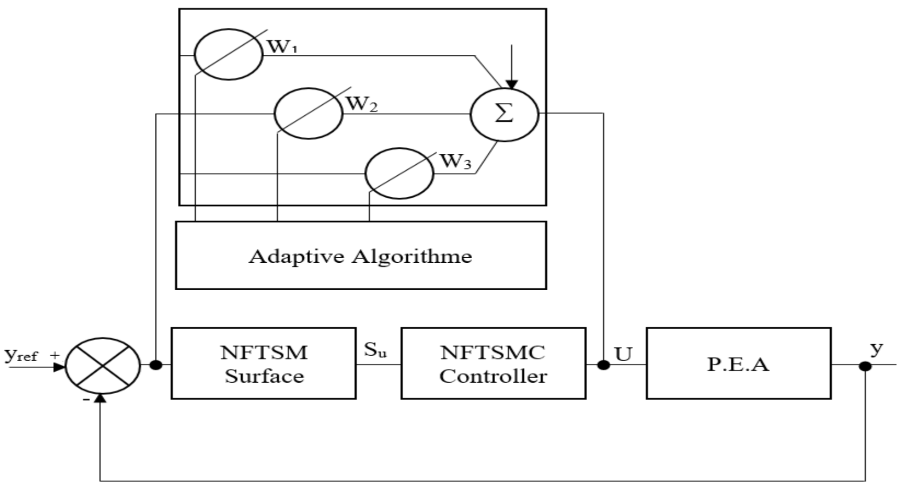

Fig. 5. The block diagram of adaptive neuron fast terminal sliding mode controller for PEA.

6. Comparative analysis

The comparison is based on the observation of the results of simulations obtained by the application of the two different control techniques developed on the PEA, with the sampling period and simulation time fixed.

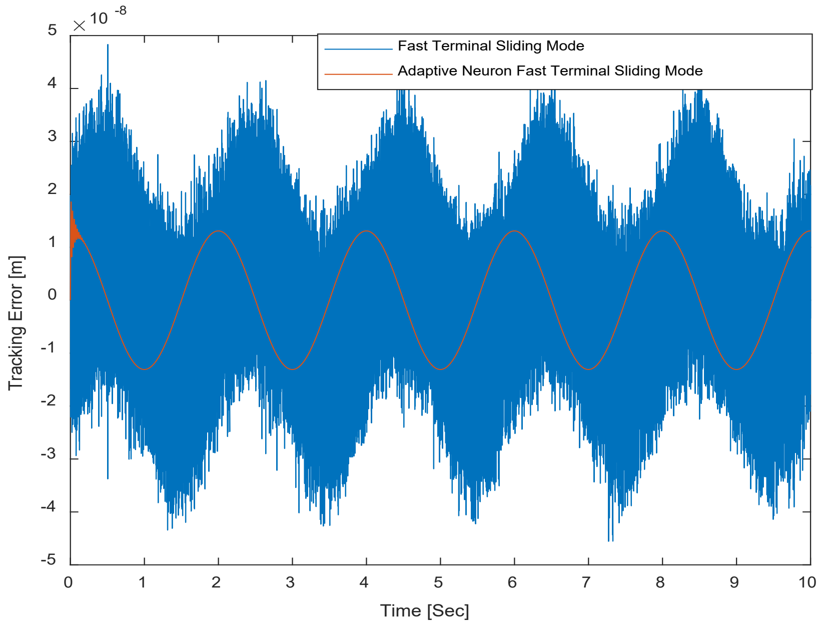

Fig. 6. Evolution of the tracking error of two control techniques.

Through Fig. 6, we can conclude that the terminal fast neural adaptive control by sliding mode is more efficient control on the PEA, compared to the fast terminal control by sliding mode. It represents the performance of the tracking error better than the terminal fast control by sliding mode and without chattering phenomenon in the control signal. Figure 5 represents the proposed control's block diagram.

7. Conclusions

To support a class of uncertain and perturbed nonlinear systems for finite-time global position tracking of PEA, adaptive neuro-fast terminal sliding mode controller was developed. We have presented this approach for the development of control structures, where the uncertainties of the system are not only the unknown functions but also the unmodulated dynamics and the dynamical uncertainties. The proposed controller handles well the high-frequency chattering of the tracking error signal (see Fig. 5). The adaptive scheme is used to reduce the high noises order presented in piezo materials especially in micro-positioning stages. Considering the results obtained and the comparative study carried out, we can say that the terminal fast neural adaptive control by sliding mode gives better results in terms of robustness, tracking quality, and fast stability in a finite time of an uncertain system.

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