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Discrete-Time Modeling and Control for a Soft Robot Displacements based on Experimental Data

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Abstract. Soft robot applications have recently gained importance over rigid robots for their great maneuverability to work cooperatively with human beings and in unstructured environments. A modified technique for soft-robot actuation is based on rapid liquid evaporation using ultrasonic waves and heat reaction. In any case, the soft robot displacements with rapid actuation contain high non-linearities and uncertainties. Therefore, the classical control techniques based on analytical models become impractical to apply into soft robots. A nonlinear discrete-time model of a soft-robot displacement is proposed from experimental data in this research. In addition, a novel control law is developed applying a neuro-fuzzy network with adaptive stage and a sliding mode surface function as an input to compensate for uncertainties.

Keywords: Soft robot, rapid actuation, discrete-time regression model, sliding mode function, neuro-fuzzy control law.

1 Introduction

During recent years, the soft robot applications have increased notably for their human beings interaction, fragile objects handling and unstructured environments exploration, [1,8]. In addition, the soft robots have a great maneuverability to imitate biological systems, [7,9]. The soft robots are generally performed through pneumatic actuators. The injected fluid into an elastomer chamber covers the robot's volume causing displacements by the pressure on the soft walls.

On the other hand, some conventional soft robot designs are also integrated by heat exchangers to achieve a liquid vaporization at short term. [3] reported the impacts on the soft-robot performance when the phase change rate (liquid-gas) actuation is applied inside of a elastomer chamber. Currently, a novel actuation for soft robots is using a liquid dispersion by ultrasound waves, as is presented by [5]. Rapid actuation evaporates the liquid below its boiling point in a suitable time and without any structural material damage, as is depicted in Figure 1.

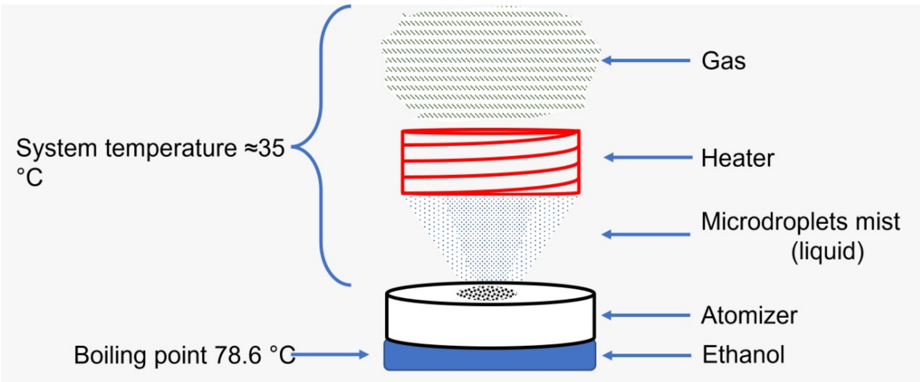

Fig. 1. Schematic of the rapid actuation system. The atomizer is placed directly over the liquid. Once the ultrasonic wave is applied to the atomizer a mist is generated. The mist contacts the heater which produces the evaporation.

In general, the classic control of rigid robots is based on analytical modeling, considering physical and mechanical characteristics of the robot such as: the number and type of degrees of freedom (dof), length of the links, centers of mass and gravity. However, the classic Control Based on Analytical Model (CBAM) is inadequate to deal with flexible robots due to their high nonlinearities and uncertainties during their displacements.

An alternative option to describe the dynamic of the soft robot is applying the data-driven statistical modeling (DDSM) generating a database from experimentation and considering the input and output signals history of the robot [12,13]. The Data-Driven Modeling and Control (DDMC) requires a minimum information of the robotic system in comparison to conventional CBAM, [11].

From the control theory viewpoint, the soft robot is considered as a nonlinear discrete-time system with high uncertainties and disturbance during their performance. Hence, the DDMC can be applied for all kind of robotic systems as manipulators, inertial, and non inertial including flexible robots, see for instance [6]. Consequently, data-driven identification and control are a novel option to apply for unknown nonlinear discrete-time systems as the case of robots, see [2].

The innovations of this work are as follows: (a) the proposal of a discrete-time position model for a soft robot based on DDSM from a phase change (liquid-gas) actuation integrated by a nebulizer and a heat exchanger; (b) the development of a novel control law based on a neuro-fuzzy network with a sliding surface function as input. The control law combines the reasoning-adaptation stage of the neuro-fuzzy network and the robustness against uncertainties of the sliding surface function.

Hence, the application of DDSM approximates the position of the soft robot. In addition, the proposal of an intelligent controller with adaptation stage based on the dynamic system response guarantee a position control through the discrete-time model of the soft robot. The structure of this paper is as follows: Section 2 presents the soft-robot modeling, Section 3 describes the control law design and results, and Section 4 summarizes the conclusion of this work.

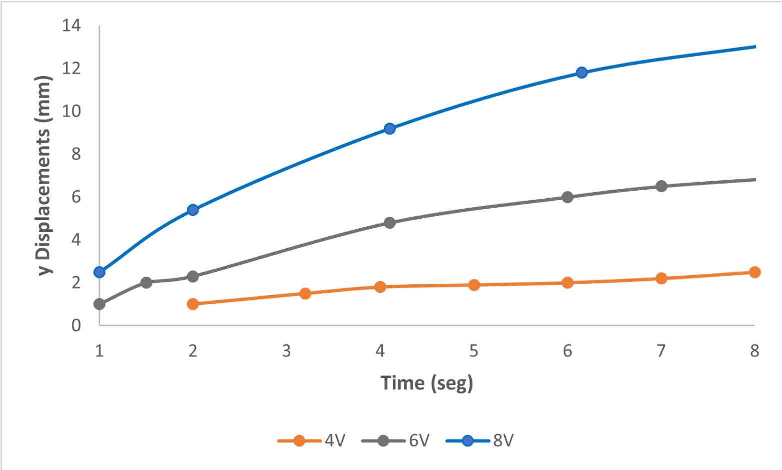

Fig. 2. The experimental data for 8 seconds when the heater was powered by 4, 6 and 8 V.

2 Robotic System

Through this section is presented the strategy to model the dynamic response of the soft- robot displacements applying a regression method from experimental data. Once, the regression model estimates the soft-robot displacements a nonlinear discrete-time function is proposed to validate the dynamic of the system into a closed -loop control. The proposed control is inspired on an intelligent control by an artificial neuro-fuzzy network with a sliding mode function as an input to compensate the nonlinearities and uncertainties during soft-robot displacements.

2.1 Experimental Setup

Remark 1 The proposal of the rapid actuation and the soft robot design have been discussed in [5]. As well, the data set presented in that research is used to obtain the regression model and the discrete-time model of the robot displacements to test the novel control law based on a neuro-fuzzy control in a closed-loop system.

2.2 Soft Robot Modeling

A regression model is presented using the least squares method, which is applied to the experimental results presented by [5]. The proposed regression model requires less data to estimate the displacements of the soft-robot, on the other hand, Artificial Neural Network (ANN) techniques require an extensive database for the training of their parameters. In the case of Fuzzy Logic (FL) the model estimation is based on the human experience, then, a unique model is complicated to obtain. Figure 2 depicts the nonlinear relationship between the soft-robot displacements respect to the voltage input of the heater.

A strategy to obtain a trend-fit approximation function from experimental data is minimizing the residual errors sum of all available data between the measurements $y_{i,\text{measurements}}$ and the estimated $y_{i,\text{computed}}$ as follows:

$$S_r = \sum_{i=1}^{n} (y_{i,\text{measurements}} - y_{i,\text{computed}})^2. \tag{1}$$

Hence, a regression model is proposed based on a power equation in the following equation:

$$y = a_0 t^{a_1} V^{a_2}, \tag{2}$$

where y represents the position, t is the time, V is the input voltage and a_m represents the coefficients to determine by the least squares method. Thus, applying the natural logarithms properties is possible to linearize the equation (2):

$$\ln(y) = \ln(a_0) + a_1 \ln(t) + a_2 \ln(V). \tag{3}$$

The equation (3) fits experimental data for multivariable regressions. Replacing (3) in (1) is found the quadratic error sum function:

$$S_r = \sum_{i=1}^{n} (\ln(y) - \ln(a_0) - a_1 \ln(t) - a_2 \ln(V))^2. \tag{4}$$

The quadratic function in (4) is derived as $\dfrac{\partial S_r}{\partial a_m} = 0$ to find the coefficients a_m and it minimizes the error between the measurements and computed data:

$$\frac{\partial S_r}{\partial a_0} = \frac{2}{a_0} \sum_{i=1}^{n} [\ln(a_0) - a_1 \ln(t_i) - a_2 \ln(V_i)] = 0, \tag{5}$$

$$\frac{\partial S_r}{\partial a_1} = -2 \sum_{i=1}^{n} \ln(t_i) [\ln(a_0) - a_1 \ln(t_i) - a_2 \ln(V_i)] = 0, \tag{6}$$

$$\frac{\partial S_r}{\partial a_2} = -2 \sum_{i=1}^{n} \ln(v_i) [\ln(a_0) - a_1 \ln(t_i) - a_2 \ln(V_i)] = 0. \tag{7}$$

Once, the equations system for the regression model has been solved, the coefficients a_m of the proposed power function are obtained:

$$y = 0.0191\, t^{0.8076}\, V^{2.3752}. \tag{8}$$

Figure 3 shows a comparison between the experimental data and the estimated data according to (8).

Corollary 1 The polynomial interpolation model could be considered as unsatisfactory estimation, when the analyzed data set shows substantial errors. In contrast, a general approximation of data trend using a power regression is more useful to minimize the sum of the residual errors between the measured-output variable $y_{i,\text{measured}}$ from (8) and its mean $y_{i,\text{mean}}$.

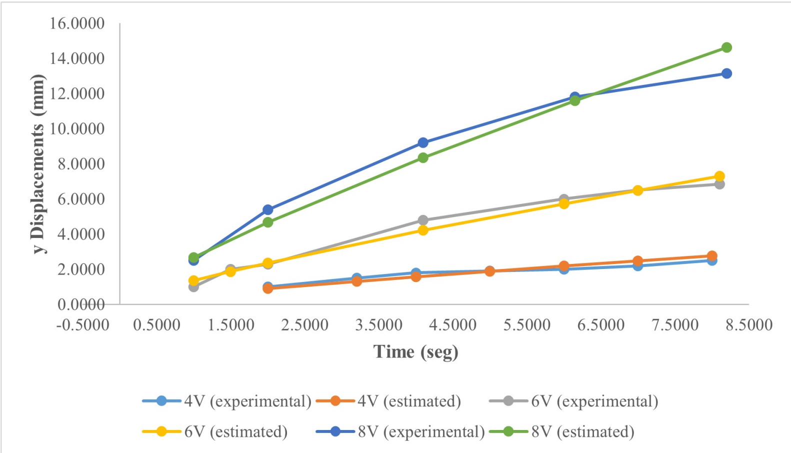

Fig. 3. Comparison between the experimental data and the regression model.

The magnitude of the residual error associated with the dependent variable (y) of the regression model is:

$$S_t = \sum_{i=n}^{n} (y_{i,\text{measured}} - y_{i,\text{mean}})^2. \tag{9}$$

The difference between $S_t - S_r$ quantifies the error between the data and a straight line instead of an average value. Since, the magnitude of this quantity depends on the scale, the difference is normalized respect to S_t to obtain the following form:

$$r^2 = \frac{S_t - S_r}{S_t}, \tag{10}$$

where r^2 and r are the determination and correlation coefficients, respectively. In a perfect fit $S_r \to 0$, therefore $r^2 = 1$. That means, 100% fit of the model according to the experimental data set. The standard error is defined as follows:

$$S_{y/x} = \sqrt{\frac{S_r}{n - (m+1)}}, \tag{11}$$

where $m = 3$ are the degrees of freedom in the power equation (8) and $n = 19$ are the data set numbers for this study in Figure 2. The adjusted coefficient of determination

$r^2_{adjusted}$ demonstrates the degree of effectiveness of the independent variables on the dependent variable:

$$r^2_{\text{adjusted}} = 1 - 1\frac{n-1}{n-m+1}(1-r^2). \tag{12}$$

Table 1 shows the regression model analysis. The results from the experimental data set and the regression model are concluded below. The regression equation (8) for the soft robot displacement has a correlation degree $r = 99.061\%$ between the inputs variables and the output variable.

Tabla 1. Statistical aspects of the regression model as a function of the soft robot displacement.

Parameter	Evaluation
r	0.99061
r^2	0.98131
r^2_{adjusted}	0.97897
$S_{y/x}$	0.53059
m	3
n	19

The regression model $r^2 = 98.131\%$ describes of the phenomenon uncertainties. Furthermore, the variables used for the model represents $r^2_{\text{adjusted}} = 97.7897\%$ of effectiveness. Finally, the standard error estimation is $S_{y/x} = \pm 0.53059$ mm. Once, the regression model is obtained is possible to approximate a nonlinear discrete-time function by the Taylor series expansion, as it is presented below.

Corollary 2 Taylor serie approximates the model through a polynomial function as:

$$y(x) = a_0 + a_1(x-c) + a_2(x-c)^2 + a_3(x-c)^3 + ... + a_n(x-c)^n. \tag{13}$$

The compact form from is:

$$y(x) = \sum_{n=0}^{\infty} a_n(x-c)^n, \tag{14}$$

where $x = c$ and (14) is derived successively:

$$\frac{d^n y(c)}{dx^n} = n! a_n. \tag{15}$$

Then, the approximation of the function by the Taylor serie is:

$$y(x) = \sum_{0}^{\infty} \frac{1}{n!}\frac{d^n y(c)}{dx_n}(x-c)^n. \tag{16}$$

The forward finite differences calculate a value in front of a reference point, where $x = x_{i+1}$, $x = c$, $\Delta x = x_{i+1} - x_i$ and $y(x_i) = y_i$, then the Taylor series is:

$$y_{i+1} = \frac{1}{0!} y_i + \frac{1}{1!} \frac{dy_i}{dx} \Delta x + \frac{1}{2!} \frac{d^2 y_i}{dx^2} \Delta x^2 + ... + \frac{1}{n!} \frac{d^n y_i}{dx^n} \Delta x^n \tag{17}$$

$$= y_i + \frac{dy_i}{dx} \Delta x + \frac{1}{2} \frac{d^2 y_i}{dx^2} \Delta x^2 + ... + \frac{1}{n!} \frac{d^n y_i}{dx^n} \Delta x^n. \tag{18}$$

For the case of backward finite differences, the Taylor series is obtained as follows, where $x = x_{i-1}$, $x = c$, $-\Delta x = x_{i-1} - x_i$ and $y(x_i) = y_i$, then Taylor serie is:

$$y_{i-1} = \frac{1}{0!} y_i - \frac{1}{1!} \frac{dy_i}{dx} \Delta x + \frac{1}{2!} \frac{d^2 y_i}{dx^2} (-\Delta x^2) + ... + \frac{1}{n!} \frac{d^n y_i}{dx^n} (-\Delta x^n) \tag{19}$$

$$= y_i - \frac{dy_i}{dx} \Delta x + \frac{1}{2} \frac{d^2 y_i}{dx^2} (-\Delta x^2) + ... + \frac{1}{n!} \frac{d^n y_i}{dx^n} (-\Delta x^n). \tag{20}$$

This series calculate a value behind of a reference point. Therefore, the expansion of Taylor series approximate the position function obtained with the regression model in (8) as follows:

$$y(k+1) = y(k) + \frac{\partial y}{\partial t} T_s + \frac{1}{2} \frac{\partial^2 y}{\partial t^2} T_s^2. \tag{21}$$

2.3 Transition from Regression Model to Discrete Model

The first derivative considers the coefficients and the regression model in (8) in order to approximate the discrete model as follows:

$$\frac{\partial y}{\partial t} \approx 0.01545 k^{-0.1924} (V(k))^{2.3752} \left[\frac{\mathrm{mm}}{\mathrm{s}} \right]. \tag{22}$$

This term is associated to the velocity of the system, where k is the discrete time index and V is the input voltage. The second derivative is related to the acceleration of the system:

$$\frac{\partial^2 y}{\partial t^2} \approx -0.00297 (V(k))^{2.3752} k^{-1.924} \left[\frac{\mathrm{mm}}{\mathrm{s}^2} \right]. \tag{23}$$

From the Taylor series is obtained:

$$y(k+1) = y(k) + \frac{\partial y}{\partial t} T_s + \frac{1}{2} \frac{\partial^2 y}{\partial t^2} T_s^2. \tag{24}$$

Substituting (23) and (24) in (22) is obtained the discrete-time function:

$$\begin{aligned} y(k+1) = y(k) &+ 0.01545 k^{-0.1924} (u(k))^{2.3752} T_s \\ &- \tfrac{1}{2} (-0.00297 (u(k))^{2.3752} k^{-1.924}) T_s^2. \end{aligned} \tag{25}$$

The expression in (25) approximates the nonlinear system dynamic of the soft robot working within discrete-time in order to apply a novel neurofuzzy control.

3 Control Law

This section presents a novel intelligent controller inspired by an artificial neuro-fuzzy network considering the nonlinear discrete-time function in (25), which describes the displacement of the soft robot. The input signal to the nonlinear discrete-time function is the voltage (control variable) applied to the heater during the soft-robot actuation, and the output signal is the displacement (controlled variable) generated by the soft-robot. Therefore, the following assumptions should be satisfied for the control law design.

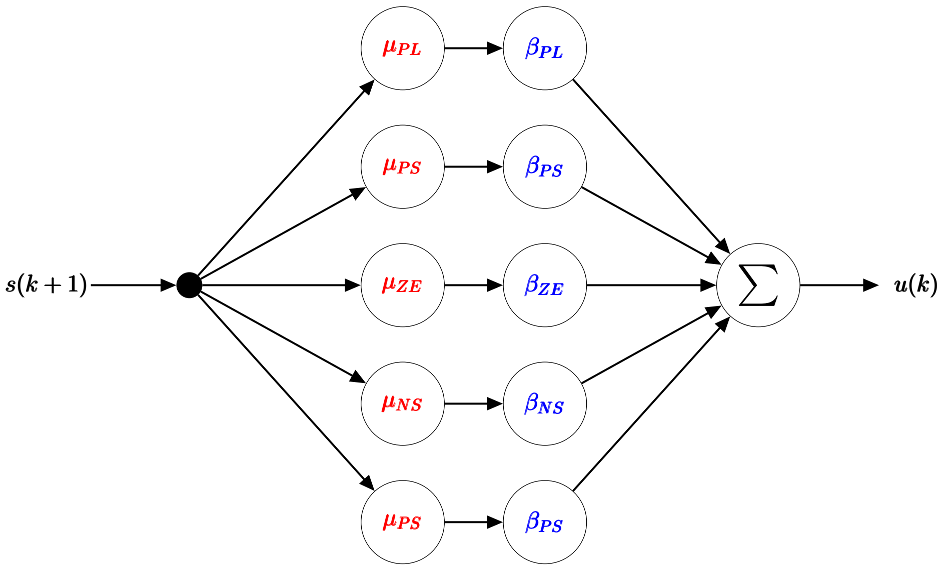

Fig. 4. NFN architecture and $s(k+1)$ as input signal.

Assumption 1 The robot is considered Lipschitz and exists a positive constant L that defines the direct relationship between system input-output $\| y(k+1) \| \leq L \| u(k) \|$. that means, a change of the system output imposes a change of the system input.

Assumption 2 The output of the robotic system is observable, *i.e.*, $y(k+1) = \hat{\Phi}(k)u(k)$ $\forall k > 0$. It is possible to know the equivalent model of the system from the measured output signals.

The artificial neuro-fuzzy network is characterized by an adaptive stage based on a human experience and the intuitive initial parameters selection. The adaptation stage adjusts its parameters using the descending gradient technique. The neuro-fuzzy network considers the plant as an unknown nonlinear system working in the discrete-time domain.

Therefore, the neuro-fuzzy network only requires to know the input and output signals from the system to control the plant. The structure of Neuro-Fuzzy Network (NFN) is based on the human knowledge and the intuitive initialization of its parameters [10] as is referred Figure 4. A sliding mode surface function $s(k+1)$ in (26) is proposed as input to the NFN:

$$s(k+1) = C_1 e(k+1) + C_2 e(k), \tag{26}$$

where $C_1,\ C_2 \in \mathbb{R}^+$ and the position error is defines as:

$$e(k+1) = y_d(k+1) - y(k+1), \tag{27}$$

where $y(k+1)$ is the current position and $y_d(k+1)$ is the desired position.

3.1 Proposed NFN Architecture

NFN structure has 4 layers and 5 nodes.

– Layer 1. This layer is considered as the input to the artificial neural network $s(k+1)$, also this signal is sent to each node in the next layer.

– Layer 2. This layer contains the membership functions. Each node in this layer is a membership function corresponding to the design of the linguistic variables. The output of each node is calculated as follows:

$$\phi(k) = \mu(s(k)). \tag{28}$$

– Layer 3. This layer is the adaptation stage where the parameters $\beta(k+1)$ are adjusted.

– Layer 4. This layer is the output of the NFN:

$$O(k) = \sum_{i=1}^{N} \phi(k)\beta(k), \tag{29}$$

where N represents the number of linguistic variables.

3.2 Adaptation Algorithm

An adaptive technique based on the descending gradient method is proposed to adjust NFN parameters. First, an objective function is defined to achieve the optimal value of the network parameters. The parameters are adjusted at each time step through a quadratic function $\xi(k+1)$ in terms of the control error:

$$\xi(k+1) = \frac{1}{2} s^2(k+1). \tag{30}$$

According to the descending gradient method, the adaptation of the parameters $\beta(k+1)$ is computed as follows:

$$\beta(k+1) = \beta(k) - \eta \frac{\partial \xi(k+1)}{\partial \beta(k)}, \tag{31}$$

where η is the learning rate and applying the chain rule:

$$\frac{\partial\xi(k+1)}{\partial\beta(k)} = \frac{\partial\xi(k+1)}{\partial s(k+1)}\frac{\partial s(k+1)}{\partial e(k+1)}\frac{\partial e(k+1)}{\partial y(k+1)}\frac{\partial y(k+1)}{\partial u(k)}\frac{\partial u(k)}{\partial O(k)} \quad (32)$$

$$= \qquad s(k+1)C_1[-1]\hat{\Phi}(k)\mu(s(k)), \quad (33)$$

When substituting (33) in (31) is found the adaptation law:

$$\beta(k+1) = \beta(k) + \eta s(k+1)C_1\hat{\Phi}(k)\mu(s(k)). \quad (34)$$

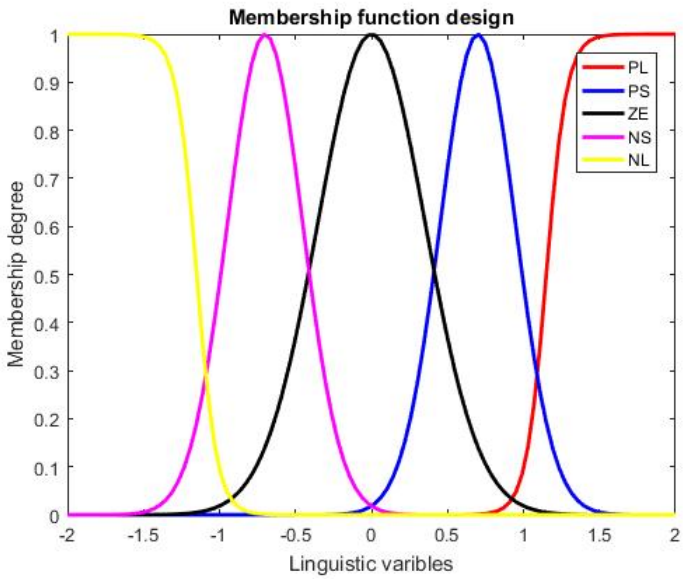

Fig. 5. Design of the membership functions for SMC-NFN.

Remark 2 where $\hat{\Phi}(k) = y(k+1)/u(k)$ denotes the approximated input and output relationship of the system in (25), therefore the representation of the ideal system $\Phi^*(k)$ is given by:

$$\Phi^*(k) = \hat{\Phi}(k) + \epsilon(k), \quad (35)$$

where $\epsilon(k)$ is the estimation error and the control law is:

$$u(k) = \mu(s(k))\beta_s(k). \quad (36)$$

Remark 3 The novelties in the proposed neuro-fuzzy-control are:

– The five membership functions are designed according to the robot displacement as is shown in Figure 5.

- The sliding surface function $s(k+1)$ improves the tracking control and robustness.
- The adaptation law (34) permits to update the neuro-fuzzy parameters $\beta(k+1)$ and it captures instantaneous changes on the system.

3.3 Simulations

The five linguistic variables are designed according to the physical characteristics of the robot. Therefore, the linguistic variables are μ_i : P_L is positive large, P_S is positive small, Z_E is zero, N_S is negative small and N_L es negative large. Figure 5 shows the membership function design and the Table 2 shows the control setting parameters. The IF-THEN rules are established by the input function $s(k+1)$ and the output $u(k)$:

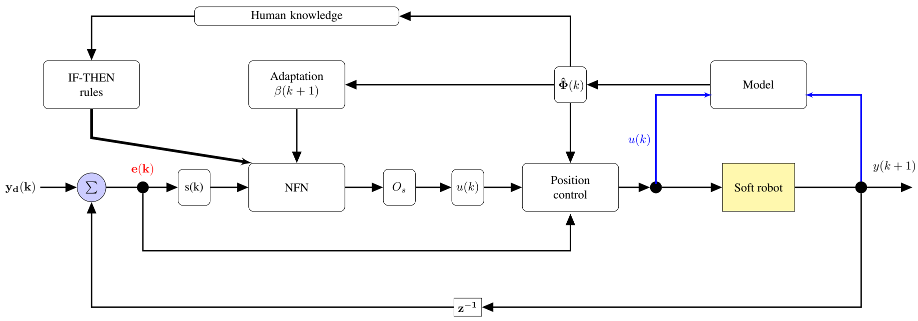

Fig. 6. Block diagram of the closed-loop system.

Tabla 2. Control setting parameters values.

Parameters	Value
$\beta_{PL}(0)$	2.25
$\beta_{NL}(0)$	1.85
$\beta_{ZE}(0)$	0.5
$\beta_{NS}(0)$	-1.65
$\beta_{NL}(0)$	-1.85
C_1	1.45
C_2	0.55
η	0.85

- IF $s(k+1)$ Is positive large (P_L), THEN $u(k)$ Is positve large (P_L).

– IF $s(k+1)$ is positive small (P_S), THEN $u(k)$ is positve small (P_S).
– IF $s(k+1)$ is zero (Z_E), THEN $u(k)$ Is Zero (Z_E).
– IF $s(k+1)$ is negative small (N_S), THEN $u(k)$ Is negative small (N_S).
– IF $s(k+1)$ is negative large (N_L), THEN $u(k)$ Is negative large (N_L).

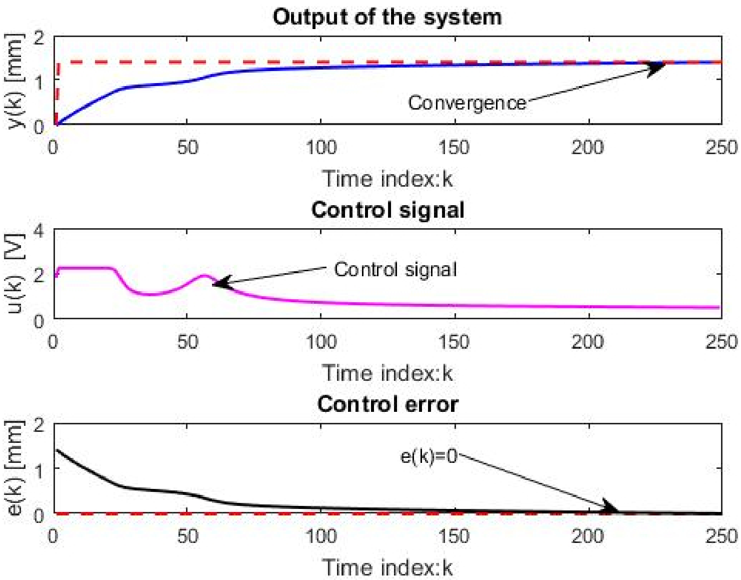

Fig. 7. SMC-NFN controller with adaptive parameters $\beta(k+1)$.

Figure 6 depicts the closed-loop system. The control law in (36) represents the system input, the nonlinear discrete-time function in (25) represents the system output, and the adaptation law is in (34). NFN guarantees the adaptation and learning stages based on the plant empirical knowledge, as well the sliding mode function in (26) provides robustness against uncertainties inside of the NFN structure.

Figure 7 shows the simulation of the controller for a regulation position task where the control law design remedies the control error convergence to zero, successfully. Figure 8 depicts the parameters $\beta(k+1)$ for the the proposed adaptive law in (34). Moreover, the proposed controller is compared to a conventional PID controller in order to review its advantages.

The conventional PID controller is:

$$u(k) = K_p e(k) + K_d \left[e(k) - e(k-1)\right] T_s + K_i \left[\frac{e(k) - e(k-1)}{T_s}\right]. \qquad (37)$$

where the proportional, integral and derivative gains are $K_p = 3.95$, $K_i = 0.01$ and $K_d = 0.01$, respectively. Figure 10 depicts the simulation results applied to the discrete-time model in (25). The comparison bewteen the proposed control and the conventional

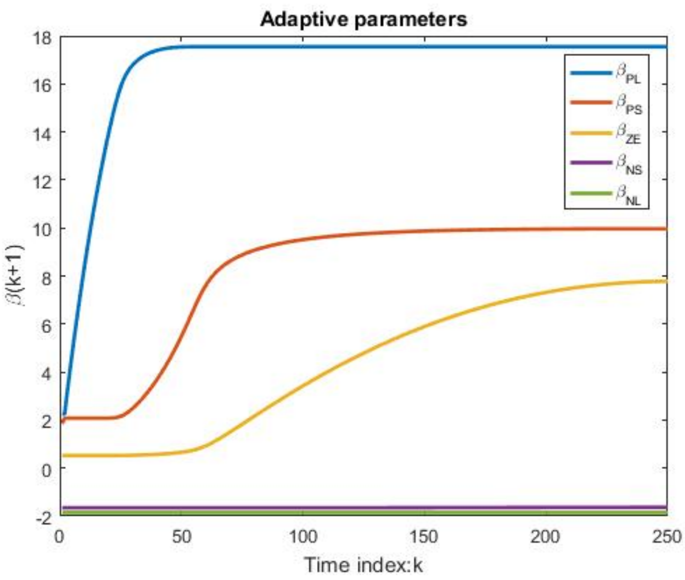

Fig. 8. Adaptive law for $\beta_i(k+1)$.

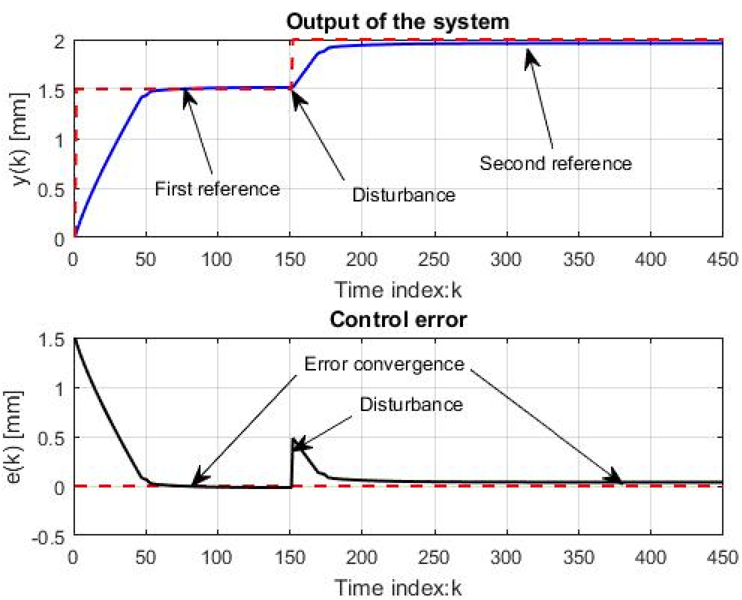

Fig. 9. SMC-NFN controller with disturbance response.

control is observed directly on the error convergence, meanwhile the control error $e(k) = 0$ [mm] in the neuro-fuzzy control, and the control error

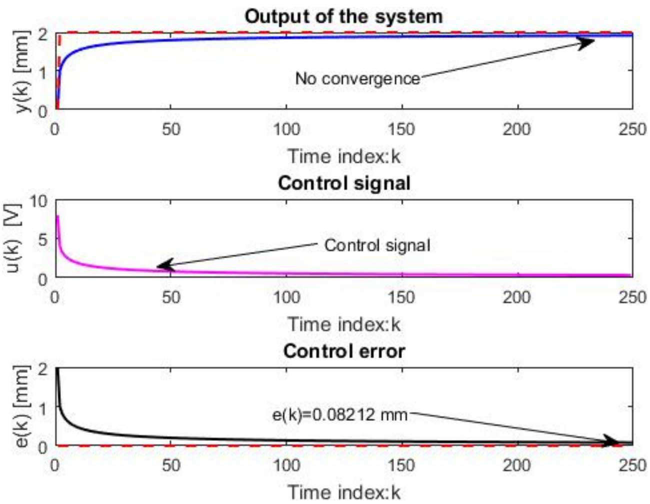

Fig. 10. PID controller.

$e(k) = 0.08212$ [mm] in PID is not enough to converge.

Additional simulation of the control system is presented at Figure 9 in order to validate the proposed neuro-fuzzy control, a disturbance was included in the simulation to demonstrate the adaptation and the response against sudden changes in the system.

4 Conclusions

An statistical data regression model is proposed to describe the displacements of a soft robot based on the historical response (experimentation) of the input and output signals. Hence, the expansion of multi-variable Taylor series approximated a nonlinear discrete-time model from the SDDM.

A novel control law for the nonlinear discrete-time model of the robot was proposed based on the concept of NFN and a sliding surface function as input. The adaptive law permits to capture instantaneous changes in the closed loop system. Moreover, the sliding surface function improves the tracking control. The control law presented combines the adaptive stage and human experience knowledge of the system from NFN and the uncertainties compensation from the sliding surface function.

As well, the proposed control law guarantee the control error convergence in comparison to a conventional PID controller that does not compensate the non-linearities of the system. As future work, the research is led to test a Data-Driven Model and Control (DDMC) in an experimental setup only using the association of the input signal (heater voltage) and the output signal (soft-robot displacement). Moreover, the stability analysis will be developed to guarantee the control error convergence.

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