Trajectory tracking control of a seesaw-propeller system using a feedback-feedforward approach and artificial neural network

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Abstract: A controller for a nonlinear dynamic system is proposed in this work. This system is composed of a propeller driven seesaw, whose angular position must be controlled. For this purpose, the ordinary differential equation that describes the system dynamics is shown and the control strategy was developed through a feedback-feedforward configuration combined with neural networks. The approach consists in the Radial Bases Function artificial neural network application in a feedforward compensator, to estimate and predict plant disturbances, and to overcome the feedback linearization technique limitations. Results obtained by numerical simulation of the controller with and without the performance of the feedforward with the neural network compensator are presented and discussed to demonstrate the effectiveness of the approach presented in the project in promoting an approximate state of robustness.

Keywords: control of nonlinear system, feedback linearization, feedforward compensator, artificial neural network.

INTRODUCTION

There is a growing tendency for intelligent mechatronics to become an integral part of people's everyday life in line with Harari's (2016) expectations. In practice, the dynamics of most of these systems present a high degree of non-linearity and uncertainties (Farrel and Polycarpou, 2006), which makes their control a challenging situation, corroborating the effervescence of this research area. Thus, in this work, a controller of the angular position of a propeller driven seesaw, a mechatronic system with multiple sources uncertainties was conceived.

Because there are the uncertainties associated with friction, external vibrations and perturbations, incomplete modeling of the system dynamic behavior may occur, in addition to unexpected disturbances in the plant, which implies the impossibility of removing nonlinearities through conventional techniques, such as feedback linearization (FB) exclusively (Bessa, 2017). As pointed out by Slotine and Li (1991), the adoption of these techniques without a compensator promotes an increase in tracking error. Thus, in order to control nonlinear systems, with uncertainties, abrupt changes in operational parameters and information imperfections, computational techniques such as fuzzy logic and artificial neural networks (ANN) are widely used (Akbarzadeh et al., 2000; Ibrahim, 2016).

Considering mobile devices mechanical systems, subject to vibration, either because of their low rigidity or disturbances, the position reading error, for example, is increased (Ren, Lewis and Zhang, 2009). A solution to this case was proposed by Pannu and Horowitz (1997), who presented an adaptive feedforward (FF) controller. Among the computational techniques mentioned above, artificial neural networks have received more attention for the control of nonlinear systems due to their learning capacity and the approximation of nonlinearities (Ge and Wang, Lewis, Yesildirek and Liu 1996, Lewis, Jagannathan and Yesildirek, 1999, Polycapou and Mears, 1998). As an example of the use of neural networks in a feedforward system for compensation of disturbances, Gorinevsky and FeldKamp (2001) designed a car engine speed controller, in which the external loads change constantly. Ren, Lewis and Zhang (2009) present a neural network approach in a feedback-feedforward compensator for a mobile device hard disk system.

Therefore, for the controller proposed in this paper, the radial-based neural networks (RBF) are applied in a uncertainties, associated with both nonlinearities and disturbances, estimation and prediction strategy, in order to overcome the limitations of the linearization technique feedback and improve controller performance. The approach is the application of neural networks in a feedforward compensator allied to system feedback. The control technique efficiency is evaluated in the angular position control of a seesaw actuated by propeller as to contributions to an approximate state of robustness.

SYSTEM ANGULAR POSITION CONTROL

The feedback linearization method is a control technique whose limitations are related to uncertainties and unmodulated dynamics of the plant. Despite this, it has been widely used in practical problems of industrial robots control, helicopters and aircraft (Slotine and Li, 1991). Then, a mechanical system with propellant to be controlled was designed.

System Dynamics

It consists in a 2 l length seesaw with two masses (M_A and M_B), both opposite and at the l distance of the seesaw rotation axis, which is located in its center of mass. The seesaw angular position must be controlled by the action of a propeller coupled at one of its ends.

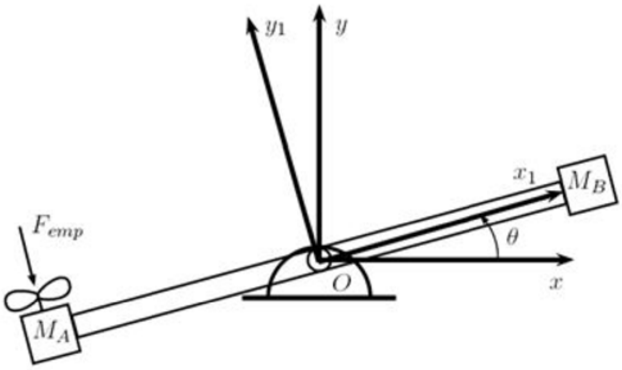


Figure 1: Seesaw-propeller system.

Using the Newton-Euler equations, it was possible to determinate the expression that describes the system dynamics:

$$I_{zz}\ddot{\theta} = (M_A - M_B)gl\cos\theta + F_{emp}l \tag{1}$$

in wich θ is the angle between the mobile base and the inertial frame, g corresponds to gravitational acceleration, I_{zz} is the bar inertia moment, and F_{emp} is the thrust force.

Control Law

The controller was conceived by means of the following proposition: there is ideal performance, represented by feedforward in the trajectory tracking problem, the actual system performance, known by the angular position feedback, and the difference between them, given by uncertainties, which must be estimated and compensated by the artificial neural networks. Therefore, it was proposed the technique in which a trajectory tracking feedforward and the neural networks compensator are used to overcome the limitations of the feedback linearization method and a RBF that, in turn, is used to estimate the uncertainties and adjust the compensator.

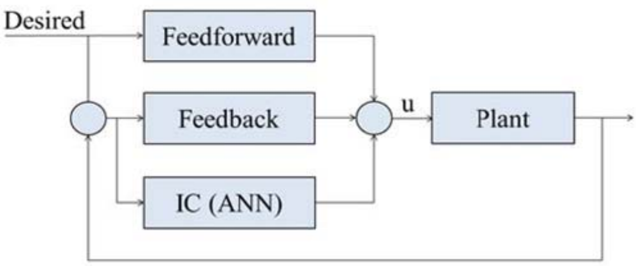


Figure 2: Proposed topology for the controller.

Thus, knowing the system dynamics, by the method of feedback linearization has:

$$u = \frac{1}{l}(-f_d - \hat{d} + I_{zz}(\ddot{\theta}_d - 2\lambda\dot{\tilde{\theta}} - \lambda^2\tilde{\theta})) \tag{2}$$

where $fd = f(\theta = \theta_d; \dot{\theta} = \dot{\theta}_d)$; is the term of the expected known dynamics evaluated in the desired state (feedforward contribution) and $\hat{d}$ is the estimated disturbance (RBF contribution) of the difference between the real and the ideal dynamics.

Replacing (2) in (1):

$$I_{zz}(\ddot{\tilde{\theta}}_d - 2\lambda\dot{\tilde{\theta}} - \lambda^2\tilde{\theta}) = f - f_d + d - \hat{d} \tag{3}$$

in (3), if $f - f_d + d = h$ and $\hat{d} = h$, the expression becomes a linear Ordinary Differential Equation for the error dynamics and, therefore, implies convergence to the null value. Consider that the calculation of $\hat{d}$ is done by means of the following neural network of type RBF:

$$\hat{d} = \boldsymbol{\omega}^\top \boldsymbol{\varphi}(\sigma) \tag{4}$$

where $\sigma = \dot{\tilde{\theta}} + \lambda \tilde{\theta}$ Finally, the adjustment of weights is performed based on the methodology presented by Bessa et al. (2017), so that the following expression is presented for updating the weights:

$$\dot{\boldsymbol{\omega}} = \eta \sigma \boldsymbol{\varphi} \tag{5}$$

SIMULATION RESULTS

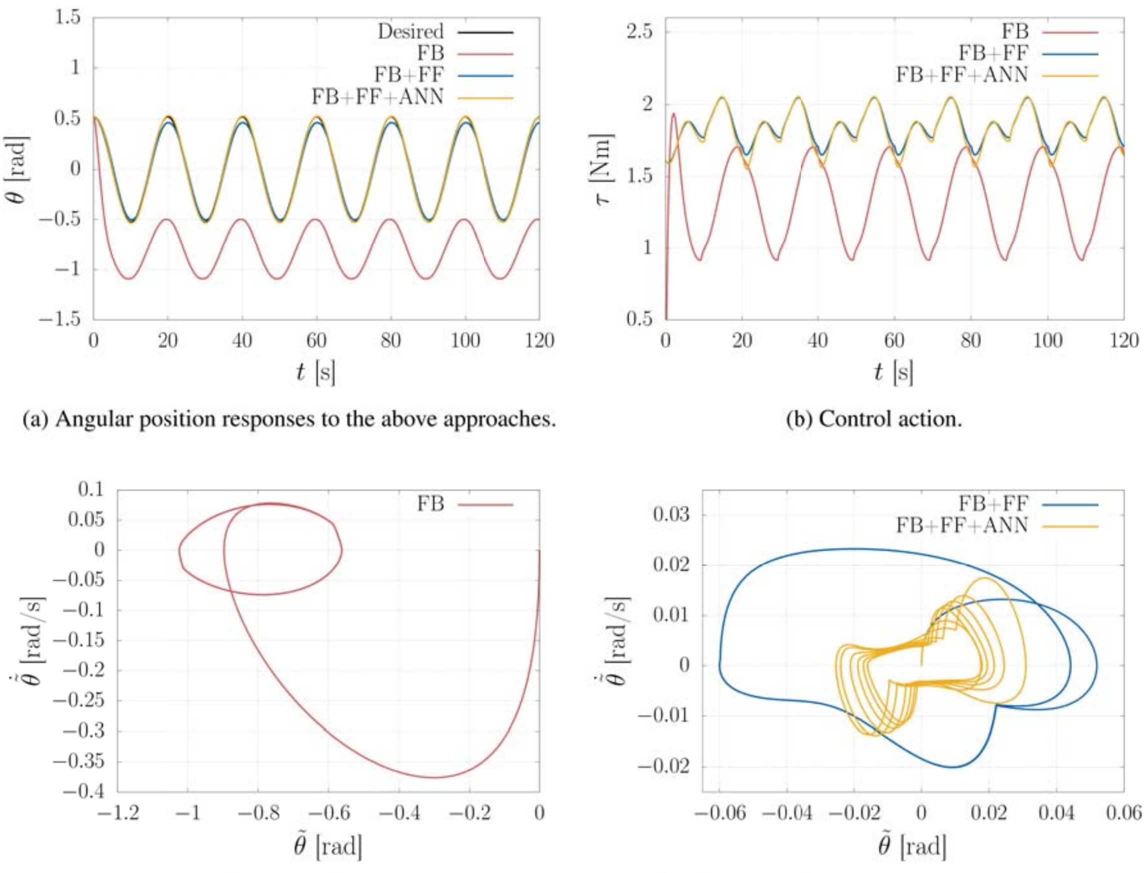
In this section we present the computational results of the control approach adopted for the dynamic non-linear system presented with the purpose of evaluating the efficiency of the feedback-feedforward model with RBF.

Numerical Results

In order to simulate the plant dynamic behavior, the fourth order Runge-Kutta method is implemented for the numerical solution of the ODE. The sampling rates for the control system and the dynamic model are respectively: 80 Hz and 100 Hz. The model parameters are set to $M_A = 0.1$ kg, $M_B = 0.11$ kg and $l = 0.3$ m. The parameters setted for the controller are: $\lambda = 0.7$, $\eta = 8$. It should be noted that were added to the ideal model two terms of viscous and dry in the values of 0.1 Nm.s and 0,01 Nm respectively.

In relation to the adopted neural network, the weight vector is initialized in $\boldsymbol{\omega} = 0$ and updated in each iteration according to equation (5). The adaptation rate defined for $\eta = 8$. For the RBF activation functions are used Gaussian functions, in addition, the network have seven neurons in the hidden layer, whose defined centers are error phase space partitions where the feedback linearization method loses its efficiency in relation convergence of the error to the null value.

The limitations of the feedback linearization technique are visible when analyzing the phase space of the error, because even when the feedback-feedforward approach is used, the uncertainties provoke its non-convergence. Thus, the RBF is used to compensate for these uncertainties and incompletely modeled dynamics (Fig. 3).



(a) Angular position responses to the above approaches.

(b) Control action.

(c) Phase portrait, FF.

(d) Phase portrait, FB + FF, FB + FF + ANN.

Figure 3: FB, FB + FF and FB + FF + ANN approaches numerical results.

As observed in Fig. 3a and Fib. 3b, the feedback linearization was not able to promote convergence to the desired trajectory. Thus, it is possible to observe the feedforward contribution to the controller in Fig. 3a. Despite this, the feedback-feedforward approach was note able to compensate the uncertainties in the control action, as it can be observed in the error phase portrait (Fig. 3c). Thus, based on these responses, the use of the neural network not only promoted a soft stabilization (Fig. 3a and Fig. 3b), but also minimized the residual error significantly (Fig. 3d). Fig. 3 shows the performance of controllers designed for a trajectory described by the function:

$$\theta_d = \frac{\pi}{6}\cos\left(\frac{2\pi t}{20}\right) \tag{6}$$

In all three situations, the initial condition is for $\theta_0 = \theta_d = \pi/6$ and $\dot{\theta}_0 = \dot{\theta}_d = 0$. The simulation time was 120 seconds. From the ability to follow the trajectory, the time taken to perform this activity and the control action employed, it is possible to evaluate the performance of the controllers implemented through the techniques approached. The results confirm that the proposed control strategy was able to regulate and stabilize the dynamics behavior of the seesaw-propeller system. The feedback-feedforward approach (FF + FB) presented a residual error, while the feedback-feedforward with the neural network compensator approach presented better convergence in addition to a significantly faster convergence for the desired trajectory, despite the initial overshot in the control action.

CONCLUSION

In this paper, an angular position controller of a propeller-actuated seesaw was proposed in a feedback-feedforward approach with an RBF neural network to estimate the uncertainties. A comparison was made between controller performances by feedback only, feedback-feedforward and feedback-feedforward with compensatory neural network techniques. The objective was to evaluate the efficiency of these techniques based on error state spaces, the ability of the stem to follow the desired trajectory and the control effort in the form of thrust. The simulations show that the intelligent controller neural network significantly improved the controller performance in relation to feedback-feedforward approach, contributing to an approximate state of robustness. For future work, it is suggested to experimentally validate the obtained results and implement another neural network that acts in a complementary way, so that one has a coarse and a fine adjustment.

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