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A framework for the development of intelligent mechanical systems

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Abstract

From autonomous vacuum cleaners to self-driving cars, intelligent mechanical systems are becoming an intrinsic part of our daily lives. In this work, a framework for the development of intelligent mechanical systems is presented. Considering that in this scenario the adopted control approach plays an essential role, I show that the proposed scheme should be able to not only adapt itself to changes in the environment, but also learn from its own experience.

Keywords: Intelligent control, Neural networks, Adaptive algorithms, Nonlinear systems.

INTRODUCTION

Intelligent control is usually defined as the discipline where control schemes are developed in order to emulate certain competencies of human intelligence [1], [2]. However, even among psychologists and neuroscientists there is no consensus on what intelligence really means. Some researchers suggest that prediction is the foundation of intelligence [3], [4]; another widely assumed definition is the ability to adapt oneself adequately to new situations [5]–[7]; and it has also been characterized as the capacity to learn or to profit by experience [8]–[10].

Of course intelligence can have many other higher attributes, such as emotion [11], creativity [12] and consciousness [13], but the abilities to predict, adapt itself, and learn are the most basic ones, and can be found in all intelligent biological systems. They are also very convenient, from the control theory perspective, since they can provide a structured way to the development of intelligent schemes. On this basis, within the proposed framework, an intelligent controller should present at least the following three competencies:

Prediction It should be able to incorporate some prior knowledge of the plant, in order to make plausible predictions about the expected dynamic behavior;

Adaptation It must adapt itself to changes in the plant and in the environment;

Learning It have to learn by experience as well as acquire knowledge by interacting with the environment, in order to improve the capacity to predict the dynamics of the plant.

In this work, in order to comply with the ability to predict, a feedback linearization approach is used. Moreover, a single hidden layer neural network is embedded within the control law to fulfill with adaptation and learning. The main details of the resulting scheme is presented in the next section.

INTELLIGENT FEEDBACK LINEARIZATION

Intelligent control has proven to be a very attractive approach to cope with uncertain nonlinear systems [14]–[26]. By combining nonlinear control techniques, such as feedback linearization or sliding modes, with adaptive intelligent algorithms, for example fuzzy logic or artificial neural networks, the resulting intelligent control strategies can deal with the nonlinear characteristics as well as with modeling imprecisions and external disturbances that can arise.

Now, Consider a class of n^{th} -order nonlinear systems:

$$x^{(n)} = f(\mathbf{x}, t) + b(\mathbf{x}, t)u + d \tag{1}$$

where u is the control input, the scalar variable x is the output of interest, $x^{(n)}$ is the *n*-th time derivative of x, $\mathbf{x} = [x, \dot{x}, \dots, x^{(n-1)}]$ is the system state vector, $f, b : \mathbb{R}^n \to \mathbb{R}$ are both nonlinear functions and d is assumed to represent all uncertainties and unmodeled dynamics regarding system dynamics, as well as any external disturbance that can arise.

In respect of the disturbance-like term d, the following assumption will be made:

Assumption 1. The disturbance d is unknown but continuous and bounded, i. e. $|d| \leq \delta$.

Let me now define an appropriate control law based on conventional feedback linearization scheme that ensures the tracking of a desired trajectory $\mathbf{x}_d = [x_d, \dot{x}_d, \dots, x_d^{(n-1)}]$, *i. e.* the controller should assure that $\tilde{\mathbf{x}} \to 0$ as $t \to \infty$, where $\tilde{\mathbf{x}} = \mathbf{x} - \mathbf{x}_d = [\tilde{x}, \dot{\tilde{x}}, \dots, \tilde{x}^{(n-1)}]$ is the related tracking error.

On this basis, assuming that the state vector x is available to be measured and system dynamics is perfectly known, *i. e.* there is no modeling imprecision nor external disturbance (d = 0) and the functions f and b are well known, with $|b(\mathbf{x}, t)| > 0$, the following control law:

$$u = b^{-1}(-f + x_d^{(n)} - k_0 \tilde{x} - k_1 \dot{\tilde{x}} - \dots - k_{n-1} \tilde{x}^{(n-1)})$$
(2)

guarantees that $\mathbf{x} \to \mathbf{x}_d$ as $t \to \infty$, if the coefficients k_i (i = 0, 2, ..., n - 1) make the polynomial $p^n + k_{n-1}p^{n-1} + \cdots + k_0$ a Hurwitz polynomial [27].

The convergence of the closed-loop system could be easily established by substituting the control law (2) in the nonlinear system (1). The resulting dynamical system could be rewritten by means of the tracking error:

$$\tilde{x}^{(n)} + k_{n-1}\tilde{x}^{(n-1)} + \ldots + k_1\dot{\tilde{x}} + k_0\tilde{x} = 0$$
(3)

where the related characteristic polynomial is Hurwitz.

However, since in real-world applications the nonlinear system (1) is often not perfectly known, the control law (2) based on conventional feedback linearization is not sufficient to ensure the exponential convergence of the tracking error to zero.

Considering that neural networks can perform universal approximation [28], I propose the adoption of a single hidden layer feedforward neural network within the control law, in order to compensate for d and to enhance the feedback linearization controller. The chosen network architecture is presented in Fig. 1, with Gaussian functions as neural basis functions, φ_i , and a filtered tracking error, s, as input.

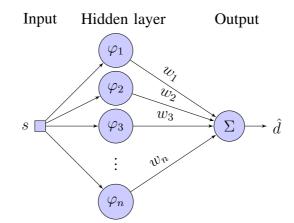


Figure 1: Single hidden layer feedforward neural network.

Therefore, the control law with the fuzzy compensation scheme can be stated as follows

$$u = b^{-1} \left[-f + x_d^{(n)} - k_0 \tilde{x} - k_1 \dot{\tilde{x}} - \dots - k_{n-1} \tilde{x}^{(n-1)} - \hat{d}(\tilde{\mathbf{x}}) \right]$$
(4)

and the related closed-loop system is:

$$\tilde{x}^{(n)} + k_{n-1}\tilde{x}^{(n-1)} + \ldots + k_1\dot{\tilde{x}} + k_0\tilde{x} = \tilde{d}$$
 (5)

with $\tilde{d} = \hat{d} - d$.

Now, defining $\mathbf{k}^{\mathrm{T}} \tilde{\mathbf{x}} = k_{n-1} \tilde{x}^{(n-1)} + \ldots + k_1 \dot{\tilde{x}} + k_0 \tilde{x}$, where $\mathbf{k} = [c_0 \lambda^n, c_1 \lambda^{n-1}, \ldots, c_{n-1} \lambda]$, λ is a strictly positive constant and c_i states for binomial coefficients, *i. e*.

$$c_i = \binom{n}{i} = \frac{n!}{(n-i)! \, i!}, \quad i = 0, 1, \dots, n-1$$
 (6)

the convergence of the closed-loop signals to a bounded region is assured.

More details about the boundedness and convergence properties of the resulting controller, as well as some numerical simulations to illustrate the overall system performance, should be presented in the final version of the manuscript.

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