Abstract

There are three major directions in the design of discrete time control systems based on artificial neural network (NN) techniques, namely model predictive controllers (MPCs) [1], adaptive control techniques [2] and inverse model-based control methodologies [3]. Incorporating NNs in MPC design is the most popular approach, in which neural network methodologies are applied on historical dynamic input-output data to construct a nonlinear dynamic predictive model of the system [4]. Usually, ANN models are developed due to lack of first principle models, by applying training algorithms on the historical dynamic input – output data of the process.

The main obstacle in the application of nonlinear MPC is that the nonlinear optimization problem that is formulated at each discrete time instant must be solved in real time [5]; nevertheless, the available time between two subsequent time instants may not be sufficient even for satisfying the requirements of suboptimal MPC [6]. To overcome this problem and extend the applicability of MPC to systems with fast dynamics, the concept of explicit MPC was coined, under which the computational burden of MPC is moved offline, by pre-computing the optimal MPC control law as a function of the current state. The exact solution offered by explicit MPCs for linear systems is guaranteed [7], but unfortunately, only approximate explicit MPC methods have been developed for nonlinear systems [8]. Another disadvantage of the explicit MPC is that it suffers from the curse of dimensionality: especially for problems of high dimensionality, the process of finding the correct region where the current state belongs can be more computationally demanding than solving the online optimization problem. Improving the computational speed is the most important research issue today in the MPC literature [5], but the development of customized fast optimization algorithms [9] is restricted to linear systems, or systems iteratively linearized online [10].

This work presents a novel nonlinear control scheme based on approximating the inverse system dynamics, employing a radial basis function (RBF) neural network model. The RBF network is trained with the fuzzy means (FM) algorithm [11, 12] using solely historical dynamic input – output data obtained during the normal operation of the system under control; the trained network can then be applied as an explicit control law. On the subject of the computational burden, the direct inverse control methodology is very efficient, since it only requires the calculation of a nonlinear function.

The neural controller employing the inverse system model is prone to extrapolation, an issue affecting every black-box modeling technique. This phenomenon results in producing unreliable predictions, for areas of the input space which are not fully covered by experimental input – output data and, thus, can significantly impair the controller performance. In order to avoid extrapolation in the RBF model predictions, a concept borrowed from chemometrics, namely the applicability domain [13], is incorporated to the proposed framework. The applicability domain is expressed, using the leverage value, which is proportional to the Hotelling T^2 statistic and to the Mahalanobis distance. More precisely, the AD concept is used to define upper and lower bounds on the setpoint value that guarantee reliable interpolation.

In order to account for inaccuracies in the training data, the limits defining the AD can be tightened by using a narrowing parameter. The later also serves as a tuning parameter, offering the ability for more conservative or, if desired, more aggressive actions while the controller tries to track the setpoint value. Moreover, an error correction term is added, allowing the inverse neural controller to account for modeling errors and process uncertainty and reject external disturbances, eliminating steady state offset in every case. The error correction term relies on a principal similar to the integral action used by PID controllers, which use the integral of the error to properly correct the output value. Employing previous errors forces the controller to continuously change its actions, until the offset is eliminated.

The proposed approach is applied to the control of two different nonlinear systems, namely a DC motor and a Continuous Stirred Tank Reactor (CSTR) exhibiting multiple equilibrium points, including an unstable one. A comparison with other control schemes on various tests, including set-point tracking, unmeasured disturbance rejection and process uncertainty, highlights the advantages of the proposed controller, which clearly outperforms its rivals in terms of response time, overshoot and settling time.

This thesis resulted to a publication in the Journal of Process Control [14]. Future research plans include the extension of the proposed approach in order to design an inverse neural controller suitable for Multiple-Input-Multiple-Output (MIMO) systems.

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