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A graph search and neural network approach to adaptive nonlinear model predictive control

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ABSTRACT

Systems with *a priori* unknown and time-varying dynamic behavior pose a significant challenge in the field of Nonlinear Model Predictive Control (NMPC). When both the identification of the nonlinear system and the optimization of control inputs are done robustly and efficiently, NMPC may be applied to control such systems. This paper considers stable systems and presents a novel method for adaptive NMPC, called *Adaptive Sampling Based Model Predictive Control (Adaptive SBMPC)*, that combines a radial basis function neural network identification algorithm with a nonlinear optimization method based on graph search. Unlike other NMPC methods, it does not rely on linearizing the system or gradient based optimization. Instead, it discretizes the input space to the model via pseudo-random sampling and feeds the sampled inputs through the nonlinear model, producing a searchable graph. For this discretization, an optimal path is found using Lifelong Planning A*, an efficient graph search method. Adaptive SBMPC is used in simulation to identify and control a simple plant with clearly visualized nonlinear behavior. In these simulations, both fixed and time-varying dynamic systems are considered. Results are compared with an adaptive version of Neural GPC, an existing NMPC algorithm based on Newton–Raphson optimization and a back propagation neural network model. When the cost function exhibits many local minima, Adaptive SBMPC is successful in finding a low-cost solution that appears close globally optimal while Neural GPC converges to a solution that is only locally optimal. This paper presents the method, soundness and completeness theory, and two simulated NMPC examples. The first is a transparent single-input single-output example, and the second considers a more complex power plant combustion process with two inputs and three outputs.

1. Introduction

Model predictive control (MPC) is widely used in industry (Qin and Badgwell, 1997; Janakiraman et al., 2016; Płaczek, 2014), and although most MPC implementations use linear models, nonlinear models allow for better performance over a wider operating range (Berber and Kravaris, 1998; Grancharova and Johansen, 2012; Zhao et al., 2001; Henson, 1998). Furthermore, adaptive implementations of Nonlinear MPC (NMPC), which assume a stable plant as considered in this paper, provide the additional benefit of enabling the model to be updated as plant dynamics change. Several NMPC techniques have been developed by extending existing linear MPC techniques to handle plants with strong nonlinearities (Qin and Badgwell, 1997; Soloway and Haley, 1996; Bemporad and Morari, 1999). Drawbacks of currently used Newton-type methods include the computational expense of computing first and second derivatives, possible convergence to local minima that are globally suboptimal, and a lack of robustness due to overly fine tuning requirements. An adaptive approach to NMPC, Adaptive Sampling Based Model Predictive Control (Adaptive SBMPC) is first presented in Reese and Collins (2014). Here, we go beyond the previous research by providing more algorithm detail, a theoretical derivation of completeness, a comparison to the adaptive form of an existing NMPC method, and new simulation results.

Adaptive SBMPC is not an extension of a linear MPC technique; instead, it applies an optimization method that does not require gradient computations. The method is based on input *sampling* (Dunlap et al., 2010, 2011a,b), which here refers to the pseudorandom or low-correspondence discretization of a continuous set. In input sampling, the space of all valid input vectors is sampled, yielding a set of discrete input vectors that are used to represent the space. Sampling in this sense is not to be confused with the concept of (usually periodic) time sampling in a sampled-data

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system. The method may be used generally with any input–output model and does not inherently prefer linear or nonlinear models. This paper presents a comparison to an adaptive form of Neural GPC (Soloway and Haley, 1996) using both an transparent and simple example (results Cases 1, 2, and 3) and an application to a real world problem, the regulation of emissions for a simulated coal-burning power plant (results Cases 4 and 5).

The Generalized Predictive Control (GPC) method (Clarke, 1987) was the first to merge adaptive control techniques with MPC. GPC handles plants with changing dynamics by using an adaptive linear model and performs well despite unknown time delays, which is in general an advantage of MPC approaches. One particular disadvantage of GPC over other MPC methods is that there is no guarantee that hard input and output constraints will be satisfied. Although Clarke mentions the potential of modification to handle constraints, neither the original GPC nor any of the nonlinear GPC extensions mentioned below guarantee constraint satisfaction.

When implementing MPC, the model that is used for prediction is obtained in one of the several ways. While some take the model to be specified *a priori* (Diehl et al., 2006; Hovorka et al., 2004; Karampoorian and Mohseni, 2010), it is often practical to perform system identification and fit a model from observed input–output behavior (Clarke, 1987).

Linear MPC techniques often use a Least-Squares, Gradient Descent, or Newton method to fit a linear model to observed data (Qin and Badgwell, 1997). Nonlinear MPC techniques, which are far less commonly used, often fit a Neural Network, Neuro-Fuzzy, Nonlinear Polynomial, or other Nonlinear State Space model to predict system behavior (Qin and Badgwell, 2003). This paper focuses on techniques using the neural network pattern recognition paradigm, which is useful for representing general nonlinear system behavior. Neural networks achieve this by using computational building blocks called hidden units or neurons. It is possible to capture the behavior of a nonlinear plant by training and updating a neural network to predict the future response of the system based on past observations.

GPC has been extended to nonlinear systems using neural network models, yielding one of the first and most widely used adaptive NMPC algorithms, Neural GPC (Soloway and Haley, 1996). As illustrated in Fig. 1, this method consists of an identification phase, using a Back Propagation Network (BPN), and an MPC optimization phase using Newton's method. The cost function J is minimized, using computed gradient and Hessian values to seek a locally optimal sequence of inputs. Constraint and damping terms are added to the GPC cost function to penalize input constraint violations and avoid potential instability of the Newton's method solver.

Neural GPC enables control of a multiple-input multiple-output (MIMO) plant. However, in prior publications, each implementation fixed the neural network parameters after the learning phase ends. Hence, although the formulation of Neural GPC allows for adaptation, the research in published literature did not perform adaptive control. Neural GPC has been applied experimentally to a single-input single-output (SISO) nonlinear magnetic levitation system using a network with only three computational units in the hidden layer (Haley et al., 1999). For this paper, Neural GPC is implemented for comparison to the proposed algorithm. In this

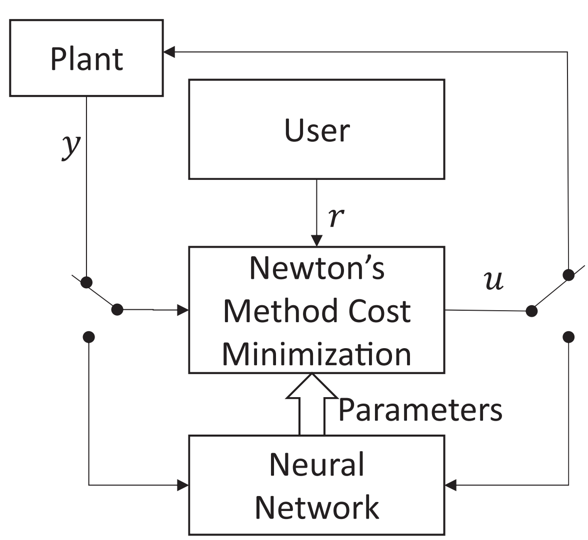

Fig. 1. Block diagram of Neural GPC. The control task is to provide inputs u to the plant such that outputs y match a reference trajectory r. The two way switch allows the neural network model to be identified online and the MPC control optimization to be recomputed at each time step using the latest model parameters.

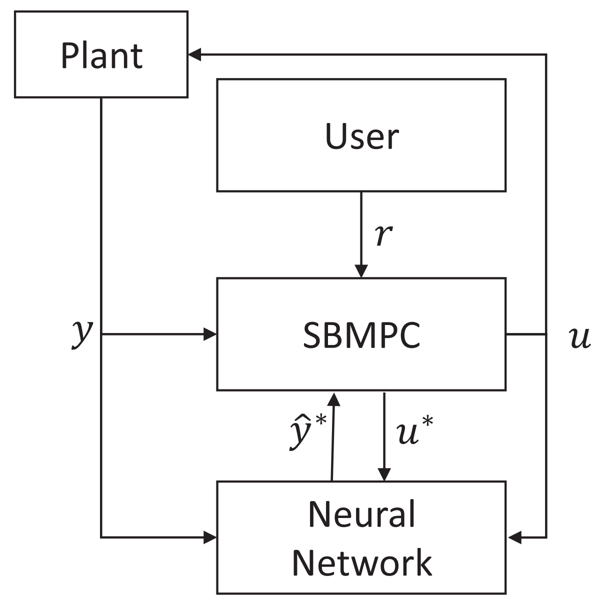

Fig. 2. Block diagram of Adaptive SBMPC. The control task is to provide inputs u to the plant such that outputs y match a reference trajectory r. The neural network model is identified online, and as candidate input trajectories u^* are provided by SBMPO to the neural network, their corresponding predicted outputs $\hat{y}^*$ are returned.

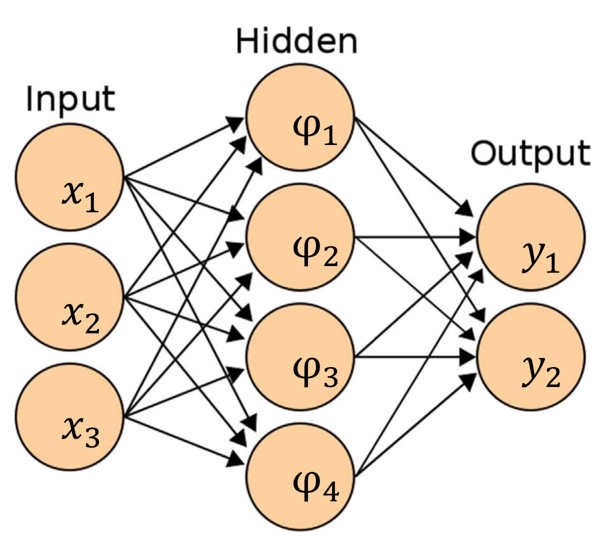

Fig. 3. The structure of an RBF Neural Network with four hidden units. Each hidden unit ϕ_j evaluates a Gaussian function centered at basis vector μ_j, which has dimension equal to the vector x of network inputs. Each output y_i is an affine function of the ϕ_j.