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Engine control unit PID controller calibration by means of local model networks

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ABSTRACT

In this work a new approach for a fully automated calibration of nonlinear PID controllers and feedforward maps is introduced. Controller design poses a particularly challenging task in the application to internal combustion engines due to the nonlinear controller structure, which is usually prescribed by the manufacturer of the engine control unit (ECU). A dynamic local model network is used to represent the actual physical process as its architecture can beneficially be adopted for scheduling of the nonlinear controller parameters. The presented calibration technique uses a genetic algorithm to calibrate the nonlinear PID controller and a static model inversion to determine the feedforward map. Closed-loop stability is taken into account by incorporating a Lyapunov function. Finally, an example demonstrates the effectiveness of the proposed method.

1. Introduction

In engine control units (ECUs) usually discrete-time, nonlinear PID controllers with a specific structure are used for many control tasks such as the actuator position in a variable-turbine geometry (VTG) turbocharger for intake manifold pressure control. Basically, the controller gains are retrieved from nonlinear maps, which depend on engine load and speed. Further, there are additional parameters to distinguish between small and large control errors. Usually calibration engineers determine the parameters and maps within the ECU structure manually with testbed runs, test drives and a lot of expert knowledge. Thus, as it will be demonstrated in the last section, a model-based calibration method will help to increase the efficiency of the calibration workflow whenever conflictive objectives, such as stability and performance, are considered.

In the setting of internal combustion engines, PID control has become increasingly complex due to the large amount of degrees of freedom in calibration. Current production ECUs usually implement fixed PID controller structures where several thousand parameter values, parameter maps and look-up tables describe gains, time delays or correction factors. Therefore, under the condition that the controller structure is prescribed by the ECU, the ambition of the new calibration approach is that it can be implemented into the established workflow straightaway while exploiting the already existing knowledge most efficiently.

Usual approaches from linear theory are insufficient because of the mutual influence of numerous parameters. Merely in combination with lots of expert knowledge the calibration task can be tackled sufficiently at the moment. In this context, the presented method achieves a base calibration by optimization considering stability as well as performance at the same time.

In the future, control strategies will most likely changeover to model-predictive control (MPC). Clearly, this is a very promising and innovative approach, which has already been applied to the calibration of internal combustion engines, e.g. Ferreau, Ortner, Langthaler, del Re, and Diehl (2007), El Hadef (2013), and Zhao et al. (2014). Control performance as well as disturbance rejection will be improved by using MPC as compared to (even nonlinear) PID control. Nevertheless, MPC represents a complex approach in the automotive technology, which also requires suitable models and stability criteria. Further, to establish MPC as a standard method in ECUs not only scientific progress has to be made but also the implementation of new standard operating procedures, the buildup of expert knowledge of calibration engineers as well as an ECU hardware suitable for serial production is needed. Thus, PID control still is the current industrial standard. It fits very well in the well-established technology development processes, allows

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for division of the control task into smaller subproblems (i.e. modularity) and provides the opportunity for locally recalibrating a controller in a particular operating region with a limited impact on the global behavior (Cieslar, 2013).

For an integrated model-based controller design scheme it is reasonable to use local model networks (LMN), which approximate even strongly nonlinear dynamic processes by a network of locally linear dynamic submodels. Their approximation capabilities allow for, or at least facilitate, the design of PID controllers for nonlinear systems. LMN from the family of multiple-model approaches (e.g. Murray-Smith & Johansen, 1997) are a qualified approach because of their transparent structure and the possibility to incorporate prior (physical) knowledge (Jakubek & Hametner, 2009). LMN interpolate between different local models, each valid in a certain operating regime. Each of these operating regimes represents a simple model, e.g. a linear regression model, describing the local dynamics.

This paper introduces a method for calibration of nonlinear PID controllers in ECUs using LMN. In this context three main tasks have to be solved:

- *Automatically determine feedforward maps.* In ECUs there are two-dimensional feedforward maps, which usually depend on load and speed.
- *Automatically determine nonlinear PID maps.* The gains of PID controllers (usually P, I, D and T_1 of the DT_1-Part) are two-dimensional maps, which, very much like the feedforward maps, usually depend on load and speed.
- *Parameterize error signal adaption.* In ECU PID control scheduling of the controller parameters is usually not only carried out along load and speed. In addition to these quite obvious scheduling variables, the control error itself is often used as a means for parameter scheduling. This approach is commonly understood as error signal adaption. It is noteworthy, that this introduces an additional nonlinearity into the closed-loop system.

The feedforward map is determined by a point-wise static inversion of the local model network. To determine the nonlinear PID maps, a multi-objective genetic algorithm (multiGA) is used, which considers closed-loop stability and performance. For closed-loop stability a Lyapunov criterion from Takagi–Sugeno (TS) fuzzy models is adopted and extended by a decay rate to get a scalar stability measure, which is required for the multiGA (Hametner, Mayr, Kozek, & Jakubek, 2013). The adoption of the Lyapunov stability criterion is justified, because similarities between TS fuzzy models and LMN exist, if the number of if–then rules in the TS fuzzy model equals the number of local models in an LMN (Gregorcic & Lightbody, 2008). The stability criterion results in linear matrix inequalities (LMIs), which are solved by a specialized solver, e.g. Nemirovskii and Gahinet (1994). However, a state-space system of the closed-loop (LMN and PID controller) is introduced, because Lyapunov stability criteria require a state-space notation. For an efficient handling, the presented state-space system strictly discriminates between parameters of the system and the controller; there is no matrix, which includes parameters of both the LMN *and* the controller. The performance of the control system is determined by simulating the closed-loop with proper input/reference signals. The performance is measured by the summation of the quadratic offset of the output from an expected output in each time-step. Parameters of the error signal adaption are determined by a performance criterion similar to the nonlinear PID maps. The difference lies in the performance sequence, which is designed with stronger transients to obtain larger control errors.

Well known model-based, characteristics-based or rule-based methods for the autotuning of PID controllers (Åström & Hägglund, 2006; Leva, Cox, & Ruano, 2002) mostly account for simple linear process models of low order only. Such methods could be applied to each local linear model in the LMN individually, but the stability and performance of the overall closed-loop would remain unconsidered. To obtain good initial conditions for the optimization, the local application of such an autotuning method is reasonable.

This paper is organized as follows. First, the nonlinear PID controller of ECUs is investigated in Section 2. The architecture of local model networks is described in Section 3. Subsequently, the state-space model of the closed-loop is introduced in Section 4. Section 5 presents the methodology to design nonlinear ECU PID controllers for turbochargers. Next, in Section 6 the effectiveness of the proposed method is shown by means of an example, where the VTG position of a turbocharger is used for controlling the intake manifold pressure. Finally, the paper is concluded by some remarks in Section 7.

2. Architecture of PID controllers used in ECUs

This section describes the architecture as well as the control algorithm of common PID controllers in ECUs. Fig. 1 gives an overview of the architecture, which employs a PID controller with a DT_1-Part. The reference map, the controller gains as well as the feedforward map to determine the reference signal w, the actuating variable u_{fb} and the feedforward signal u_{ff} respectively, depend on engine load q (in mg/stroke) and speed n (in rpm). In contrast to the feedforward and the controller gain maps, the reference map is largely determined from emission limits beforehand and is usually prescribed for calibration engineers.

In addition to the above control architecture ECUs employ error signal adaption, which is applied to the control error e within each controller part individually and results in a nonlinearly modified error signal. For example, the adaption in the P-Part leading to the modified control error $\bar{e}_p$ is shown in Fig. 2. All three gradients

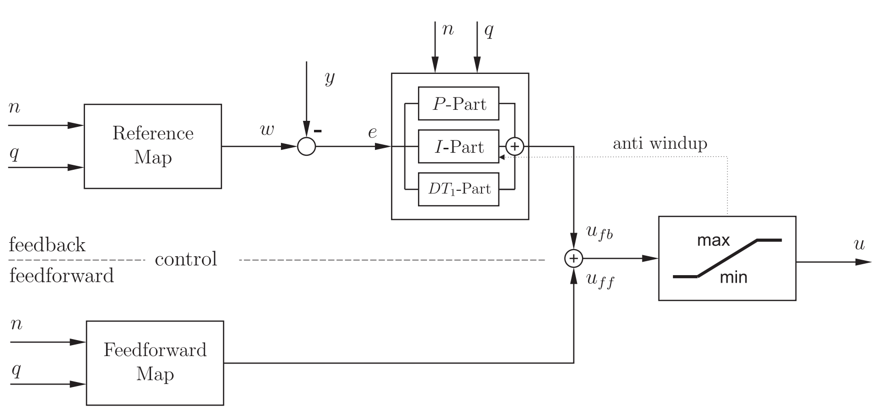

Fig. 1. Scheme of a nonlinear PID controller used in ECUs.