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Automated generation of feedforward control using feedback linearization of local model networks

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ABSTRACT

An effective but yet simple approach is introduced to automatically attain a dynamic feedforward control law for non-linear dynamic systems represented by discrete-time local model networks (LMN). In this context, feedback linearization is applied to the generic model structure of LMN and the resulting input transformation is used as model inverse. This general and automated approach for model inversion is applicable even when the overall model complexity may be high. Thus, by representing a non-linear dynamic system by an LMN and applying the proposed feedforward control law generation, a dynamic feedforward control for such a non-linear system can be found automatically with the knowledge of measured input–output data only. However, when feedback linearization is considered, the stability of the internal dynamics plays a key role. This paper analyses the occurring internal dynamics for LMN, which directly result from the chosen model structure in identification, and discusses the effects on the transformed system. Finally, the effectiveness of the proposed data-driven feedforward control is demonstrated by a simulation example as well as by an actual application to the pre-distortion of a microelectromechanical systems (MEMS) loudspeaker with electrostatic actuation.

1. Introduction

The automatic generation of models from measured input and output data is nowadays an established approach in many engineering disciplines (e.g. Sjöberg et al., 1995; Murray-Smith and Johansen, 1997; Norgaard et al., 2000; Nelles, 2001; Ljung, 2010). Commonly, such models are used to simulate the real process for various purposes, such as managing complex traffic networks (McKenney and White, 2013), optimum control of cogeneration heat and power plants (Cerri et al., 2006) or model predictive control in general (Townsend and Irwin, 2001), to name a few. In recent years, significant research efforts have been made to also exploit the structure of non-linear dynamic models in order to facilitate the design of control systems (Hametner et al., 2014; Gao et al., 2002; Deng et al., 2008).

When control tasks are considered, non-linear model structures such as local model networks (LMN) can also be used to determine control laws and their parameters (e.g. Hametner et al., 2013; Hafner et al., 2000). In general, LMN are a well-established multiple-model approach for data-driven modelling of non-linear systems (e.g. Gregorčič and Lightbody, 2007, 2010; Hametner and Jakubek, 2011; Nelles, 2001). This model architecture interpolates between different local models, each valid in a certain operating regime which offers a versatile structure for the identification of non-linear dynamic systems. Each operating regime represents a simple model, e.g. a linear regression model (Murray-Smith and Johansen, 1997), whose parameters are found by identification. Although the complexity of LMN increases with the amount of local linear models to form a sophisticated non-linear model, the model structure still remains generic. This fact is beneficially exploited when automatically generating a dynamic feedforward control law for arbitrarily complex LMN.

To obtain such a dynamic feedforward control law, usually some kind of model inversion has to be performed. Inspired by Silverman (1969), who investigated invertibility for time varying linear systems, Hirschorn (1979) extended the basic principles of system inversion to non-linear systems. Despite numerous research efforts (e.g. Isidori and Byrnes, 1990; Devasia et al., 1996), system inversion still remains a challenging task, which in general requires a thorough analysis and knowledge of the non-linear system under consideration.

However, in the presented approach, by considering the generic model structure of LMN, the application of feedback linearization automatically leads to an output–input relation, which is

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suitable as dynamic feedforward control law for the underlying non-linear process. Thus, a model inverse can directly be found from measured input–output data only.

Originally the concept of feedback linearization has been introduced by Byrnes and Isidori (1984) for the first time. Basically, a non-linear system is linearized exactly by using a non-linear coordinate transformation such that the resulting transformed system consists of an input transformation, linear external dynamics and unobservable internal dynamics. The latter represent a non-linear equivalent to the notion of transmission zeros in linear system theory. A historical perspective of this wide field as well as a detailed review of the feedback linearization technique is given by Isidori (1995) or Slotine and Li (1991). Feedback linearization for discrete-time systems, as it is necessary with LMN, has been addressed for example by Lee et al. (1987), Monaco and Normand-Cyrot (1987) or Grizzle (1986). For continuous-time systems, feedback control using neural networks in combination with feedback linearization approaches has already been applied (He et al., 1998; Chien et al., 2008).

Both, LMN (Murray-Smith and Johansen, 1997; Norgaard et al., 2000; Nelles, 2001; Maass et al., 2009; Novak and Bobal, 2009; Hametner et al., 2014) and the concept of feedback linearization are by themselves well established concepts in academia as well as in industry (e.g. Kotman et al., 2010; Moulin and Chauvin, 2011; Nielsen et al., 2010; Tuan et al., 2013). However, combining both ideas offers the opportunity to provide a substantial tool to dynamically feedforward control any arbitrary non-linear process with knowledge of measured input–output data only. The approach taken in this paper supersedes the need for an in-depth knowledge of the underlying non-linear process as the generic model structure of LMN allows for an automated generation of a feedforward control law. Besides introducing the concept of automatic generation of feedforward control laws, this paper also examines those pitfalls, which are associated with the method, namely the stability of the internal dynamics, respectively, the zero dynamics. According to Isidori (2013), at least "*systems in which the zero dynamics are unstable are still a substantially unexplored and open area of research*". Therefore, in the present contribution an analysis of the more general internal dynamics (as compared to zero dynamics or a minimum phase property) for LMN is given. In addition, an overview of how to choose the architecture of the LMN in order to obtain a model with full relative degree, which is preferable for feedforward control, is given.

Typically, feedforward control is used as an enhancement of common feedback control strategies. In Fig. 1 a so-called two-degrees-of-freedom control scheme is depicted where the design of the feedforward part $\hat{\Sigma}_{\mathrm{ol}}^{-1}$ and the feedback part Σ_{C} is independent of each other. If parameter uncertainties or model errors occur in $\hat{\Sigma}_{\mathrm{ol}}$ and $\hat{\Sigma}_{\mathrm{ol}}^{-1}$, respectively (e.g. due to measurement noise on the identification data), the feedback part will still track the desired trajectory and try to compensate for the inaccuracies. However, only stable plants should be considered in a control scheme including a feedforward part.

Feedforward control of LMN has been considered in the literature before. Karer et al. (2011) applied feedforward control to a dynamic hybrid fuzzy model of a batch reactor with both discrete and continuous states. Therein the partitioning considers the output only and the validity functions are triangular. In the present contribution also the input can be used as a dimension of the partition space, which is an important prerequisite for the partitioning of many non-linearities where off-equilibrium conditions arise (Johansen et al., 2000). In addition, a hierarchical discriminant tree, which is determined from input–output data only (Hametner and Jakubek, 2011; Jakubek and Hametner, 2009), yields the validity functions instead of utilizing fuzzy rules. Nentwig and Mercorelli (2008) proposed an algorithm for a combined analytical/numerical inversion of a static fuzzy neural network applied to a throttle valve control. In contrast, the presented approach in this paper also holds for dynamic LMN and in addition directly incorporates non-linear validity functions of arbitrary shape into the automatic feedforward control law generation. Hagan et al. (2002) propose NARMA-L2 control, which incorporates an approximation of a non-linear autoregressive-moving average (NARMA) model found by non-linear identification. The resulting NARMA-L2 model contains two separate subnetworks such that the next controller input $u(k)$ is not contained inside the non-linearity and can therefore be used to solve for a reference tracking control input. However, a specific model structure is required in the identification. Boukezzoula et al. (2003, 2007) analytically invert a Takagi–Sugeno fuzzy model by feedback linearization for designing a fuzzy controller, although the submodels are inverted locally and an additional criterion has to be considered in each time step to choose from multiple solutions.

In a direct data-driven design approach such as direct inverse control (e.g. Norgaard et al., 2000; Hunt et al., 1992) depicted in Fig. 2(b), the inverse model is identified from input–output data directly. In contrast, in the presented approach outlined in Fig. 2 (a), the inverse is found from an existing plant model. The latter procedure offers the opportunity to exploit the existing and generic model structure of local model networks. By evaluating the relative degree and the resulting internal dynamics, this approach allows a far deeper insight and a methodology to analyse and understand the resulting feedforward control law. In addition, no dedicated identification procedure or special model structure is required.

Numerous applications in various branches of the industry benefit from the presented approach as merely adequately measured input–output data are required to identify a model (i.e. an LMN) of almost any arbitrary non-linear dynamic process. To automatically obtain a feedforward control law for such a process, the LMN is represented in discrete-time state space form, which is then transformed into a feedback linearized normal representation. To determine the required feedforward input value for the desired reference trajectory, an input transformation is utilized. Therein the current and past model outputs are replaced by the desired reference values. Besides an illustrative example, an application of the presented approach, a microelectromechanical

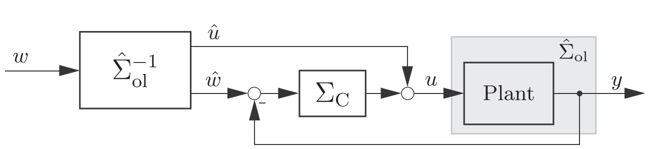

Fig. 1. Two-degrees-of-freedom control scheme.

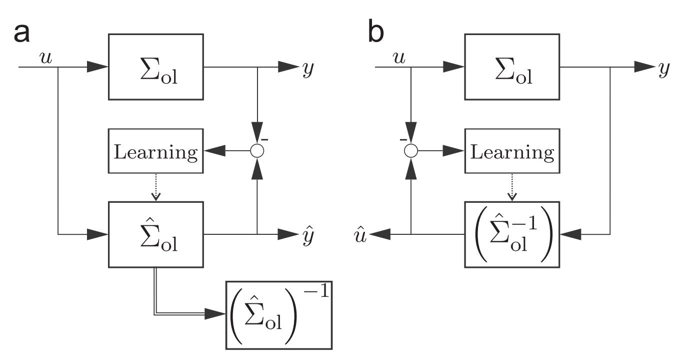

Fig. 2. Comparison of (a) the feedforward control law generation using feedback linearization of a LMN plant model and (b) a direct data-driven control approach.