ADAPTIVE FUZZY CONTROL FOR TRANSFER CHANNELS IN PARTICLE ACCELERATORS

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Abstract

Long-term objective of this work is to develop a fuzzy technology based control framework to be applied in particle accelerators. Main motivation for this is the promise of fuzzy systems to exploit the tolerance for imprecision, un-certainty, and partial truth to achieve tractability, robustness, and low solution cost. Intended areas of application are manifold: we think on automatic operation, optimization of the operating conditions and yields; applied to various stages in the processing of circular and linear accelerators. As a first step towards this goal a fuzzy control system for a transfer channel in a particle accelerator has been developed. For it we built up the machinery, i.e. algorithms, data structures, integration in the existing control system and did a first proof-of-concept. Special emphasis is given on handling high dimensional data streams and the immanent challenges as sparsity and equidistance of the data.

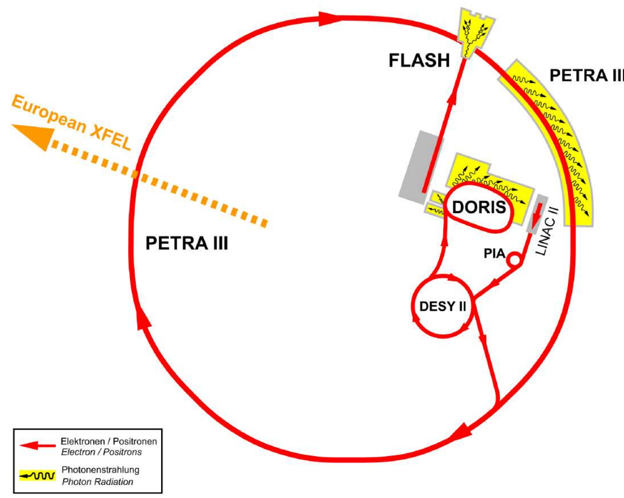

Figure 1: Particle accelerators at DESY.

INTRODUCTION

Model-based techniques for process control can provide valuable advantage over conventional approaches. They may yield a better understanding of the underlying system behavior than pure black box models and offer the opportunity to directly include expert knowledge. Such models, however, are costly to build and maintain when manually designed. Furthermore, they usually need to be continuously adapted since process conditions may change dynamically. Because of that evolving data-driven models with automatic adaptation techniques are becoming more and more attractive since they reduce maintenance costs while keeping high precision and interpretability.

Such a system that learns and evolves with every single sample from the data stream shall be developed for the use in a particle accelerator. A special problem here is the high dimensionality and homogeneity of the incoming data. For it, an additional projection step is implemented to reduce the dimensionality and filter out the most interesting ones.

Key ideas of the algorithm and the state of the work in progress are to be presented in the following. First we outline the current area of application within the DESY particle accelerator complex and sketch the algorithm's overall structure. In the following sections essentials of adaptive, i.e. evolving fuzzy systems are introduced and the projection mechanism is presented.

AREA OF APPLICATION

As a sandbox for its initial release the 450 MeV electron/positron transfer line between the accelerators PIA and DESY II within the pre-accelerator chain for PETRA III has been chosen. This decision was motivated by the ideal test condition, since tests can be carried out parasitically to the regular operation at a quite high beam transfer frequency of 6 Hz. For a short overview over the DESY facility (Fig. 1) and its accelerators see [1]. The fuzzy control algorithms were integrated into the TINE-based accelerator control system via MATLAB codes.

OVERALL STRUCTURE OF THE CONTROL ALGORITHM

A modern method for the control of complex processes is *model predictive control* (MPC), also referred to as *receding horizon control* (RHC)[2, 3]. Model predictive control uses a time-discrete dynamic model of the process to be controlled to calculate its future states and output values as a function of the input signals. Using this prediction, in particular suitable input signals for desired output values can be found. While the model behavior will be predicated several steps ahead till a certain time frame, the input signal is usually only searched for the next time step and then the optimization is repeated. For the calculations of the next time step then the actual measured state is used, resulting in a feedback and thus a closed loop. Model predictive control technology offers a number of advantages that have made it one of the most widely used advanced control methods in the process industry. It can calculate control variables where classical nonlinear control techniques fail, is easily extended to multivariable problems, can take restrictions on the actuators into account, permits the operation near the constraints, allows a flexible specification of the objective function, delivers optimum control devices and is last not least model based. A typical controller structure to build a

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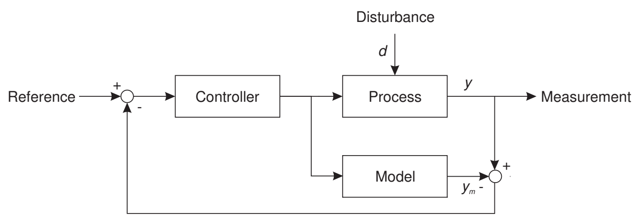

Figure 2: Internal model control scheme.

model predictive controller is shown in Figure 2.

EVOLVING TAKAGI-SUGENO FUZZY MODEL

In the present work, the model shown in Figure 2 is a fuzzy one. Fuzzy set theory provides structured ways of handling uncertainties, ambiguities, and contradictions which made systems based on fuzzy set theory the approach of choice in many situations. Since its introduction in 1965 [4], fuzzy set theory has found applications in a wide variety of disciplines. Modeling and control of dynamic systems belong to the fields in which fuzzy set techniques have received considerable attention, not only from the scientific community but also from industry. Their effectiveness together with their ease of use compared to systems based on classical two-valued logic paved the way to countless practical applications of fuzzy systems.

Compared with other control strategies, e.g. based on neural networks, the use of fuzzy models offers significant advantages: Already existing expertise can be directly fed into the system, in contrast to neural networks the knowledge is explicitly, thus self-explanatory and the acceptance of the procedure higher.

The modeling and control of nonlinear systems using fuzzy concepts is described in [5]. Current methods for identification are data-extraction techniques on the one hand and expertise on the other, but also mixed forms of both approaches. Basis of the data-driven approach is a clustering algorithm whereby fuzzy models are derived, preferably of the Takagi-Sugeno (TS) type [6].

A Takagi-Sugeno fuzzy model is characterized by its crisp, most often linear functions in the consequent part. Thus, it combines linguistic and mathematical regression modeling in one. The antecedents describe fuzzy regions in the input space in which the consequent functions are valid. The TS rules take the following form:

$$R_i\text{: If } \vec{x} \text{ is } A_i \text{ then } \hat{y}_i = \hat{\mathrm{f}}_i(\vec{x}); \qquad i = 1, \ldots, C. \tag{1}$$

Formally, the underlying Takagi-Sugeno fuzzy system with its multiple input variables $(x_1, \ldots, x_p)$, one single output variable y, and C rules can be defined as follows:

$$\hat{\mathrm{f}}(\vec{x}) = \hat{y} = \sum_{i=1}^{C} l_i \Psi_i(\vec{x}) \tag{2}$$

with normalized Gaussian membership functions

$$\Psi_i(\vec{x}) = \frac{\exp\left(-\frac{1}{2}\sum_{j=1}^{p}\frac{(x_j-c_{ij})^2}{\sigma_{ij}^2}\right)}{\sum_{k=1}^{C}\exp\left(-\frac{1}{2}\sum_{j=1}^{p}\frac{(x_j-c_{kj})^2}{\sigma_{kj}^2}\right)} \tag{3}$$

and consequent functions

$$l_i = w_{i0} + w_{i1}x_1 + \cdots + w_{ip}x_p, \tag{4}$$

where x_j denotes the jth input variable, c_{ij} the center, and σ_{ij} the width of the Gaussian fuzzy set in the jth premise part of the ith rule.

In principal, learning in this setting can be implemented in two places: a) fuzzy-rule-based structure design and b) parameter identification of the rules consequents. The rule base may evolve in the number of rules C and the number of fuzzy sets per input dimension, each premise in turn in its center c_{ij} and width σ_{ij}. Consequent parameter estimation is realized via the output weights $w_{i0}, \ldots, w_{ip}$.

Evolving Fuzzy Model

As already mentioned, the fuzzy model in the kernel of the controller shall evolve over time as data samples arrive from the data stream. Several algorithms have been proposed for this use case, e.g. the FLEXFIS model [7] or the eSensor approach [8]. Generally speaking – while varying in details – all of these approaches follow the same main idea to partition the learning problem into the subproblems structure identification and consequent-parameter estimation. The first subproblem is usually approached using some clustering technique in the data space. This partitioning creates basic information granules, described linguistically by fuzzy sets, that transform the raw data into primitive forms of knowledge. For the second subproblem typically some form of weighted recursive least squares algorithm (WRLS) is applied to estimate the output weights per rule. In general, our implementation is inspired by the eSensor approach with some major modifications in the data preprocessing phase (see next Section).

As can be seen in Figure 3 the fuzzy rule base of the controller works in two main modes, the calibration and estimation mode depending on the kind of data sent to the model. If the input data comes with measured output data the evolving fuzzy model uses both to recalibrate the actual model. In case of input data coming alone, the output is estimated by the fuzzy model.

PROJECTED CLUSTERING OF HIGH DIMENSIONAL DATA

The input data stream of the given problem consists of measurements of the several devices in the accelerator and is hence high-dimensional in nature. High-dimensional data however is inherently more complex in clustering, classification, and similarity search. Among others this is because of the sparsity of the data in the high-dimensional case. Moreover, in high-dimensional space, all pairs of

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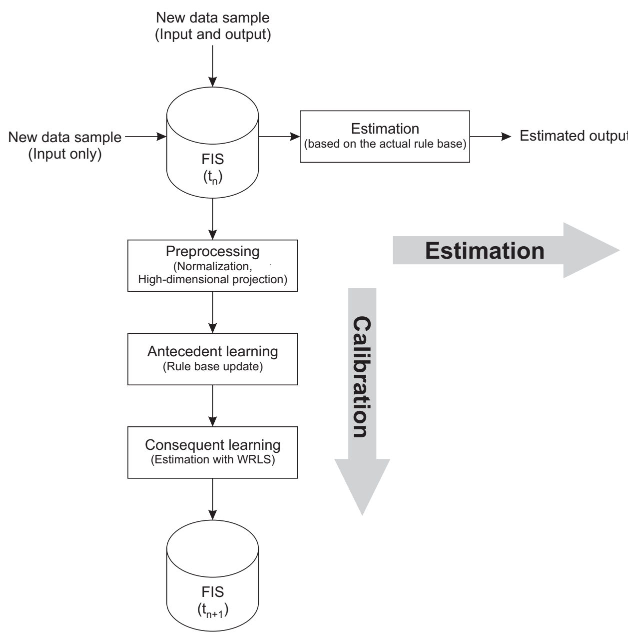

Figure 3: Calibration and estimation flowchart of the evolving Takagi-Sugeno fuzzy model.

points tend to be almost equidistant from one another. This makes it difficult for common distance-based clustering algorithms to find meaningful clusters.

An algorithm tailored to this domain is the HPStream algorithm [9]. It implements a high-dimensional projected stream clustering by continuous refinement of the set of projected dimensions during the progression of the stream. Dimensions to be projected are selected depending on the variance of the data in it. Those with the smallest variance are chosen. The updating of the set of dimensions associated with each cluster is performed in such a way that the points and dimensions associated with each cluster can effectively evolve over time.

We use a methodology inspired by the HPStream algorithm to preprocess the high dimensional data stream. It differs in one essential way from its model in that it prefers dimensions with high to small variance. This is due to the rather unconventional environment the algorithm is used in. Measurements are in most dimensions more or less constant. Since the original projection mechanism clusters data samples with the highest similarity it would mask out the few dimensions in which variations happen. The modification aims at finding the dimensions with high 'liveliness'.

CURRENT STATUS

Currently the core algorithms with its data structures have been developed and integrated in the existing control system. Critical turned out to be the model building due to the special nature of the data. With the eSensor concept no meaningful model could be achieved. Either only one single cluster was created for all incoming data samples or every sample made up a new own cluster. Transition between both states turned out to be extreme sharp. Configuring the algorithms parameter such that a meaningful number of clusters is maintained was not possible.

Because of this the projection mechanism has been integrated. With it a configurable number of fuzzy clusters can be supported. The problem than has shifted to the poor extrapolation quality of the model. The optimization algorithm that evaluates the model in order to find the next control variables is miss leaded by the linear consequent functions to the borders of the domain. For this reason the current work focuses on the integration of a confidence factor in the blending procedure of the consequent functions.

CONCLUSION

Presented has been an architecture that addresses the design of an adaptive fuzzy model predictive control system, comprising a data stream driven evolving fuzzy model with data projection mechanism to reduce the input dimensionality and an optimization component to find optimal control quantities.

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