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Identification of a nonlinear model for a glucoregulatory benchmark problem

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ABSTRACT

Recently, a novel identification method for a nonlinear dynamic model, called nonlinear Linear Fractional Representation (NL-LFR) model, has been developed. The model, composed of a static nonlinearity (SNL) surrounded by linear dynamics, can account for both nonlinear feed-forward and nonlinear feedback effects. Using two classical frequency response measurements, the SNL is automatically recovered in a user-friendly and efficient (non-iterative) way. In this contribution, the method is illustrated on a glucoregulatory benchmark dataset (insulin–glucose relationship of the human body). The research on insulin–glucose models is essential to develop methodologies to control the blood glucose level in diabetes patients. The obtained results outperform earlier results on the same benchmark data, while providing an excellent accuracy-complexity tradeoff.

1. Introduction

To be able to describe measured data with an increased accuracy, e.g. over a wide amplitude range, it is important to explicitly incorporate nonlinearities into the model. Until now, a range of nonlinear models have been proposed [1–9]. However, most of them either require a (typically) quite large number of parameters (i.e., they are not parsimonious enough) or are not well suited to represent ubiquitous nonlinear feedback effects, such as amplitude-dependent resonance frequencies and dampings (i.e., they are not flexible enough). The *nonlinear Linear Fractional Representation* (NL-LFR) model belongs to the popular class of nonlinear block-oriented models. It offers a good flexibility-parsimony tradeoff, and is therefore applicable to a wide range of scientific domains. Block-oriented nonlinear models [1,7] can be defined as interconnections of linear dynamic elements (a.k.a. Linear Time Invariant parts or LTI blocks) and static nonlinear elements (a.k.a. Static NonLinearities or SNL blocks). The most studied block-oriented model structures are cascade structures of the form LTI-SNL, SNL-LTI and LTI-SNL-LTI (known as Wiener, Hammerstein and Wiener–Hammerstein model, respectively).

The NL-LFR model, to be discussed in Section 3, is more general than these cascades and surrounds the SNL by arbitrary dynamics. We refer to [10] for a complete description of these matters and of the benefits of the model. In this paper, an insulin–glucose benchmark problem (see Section 2) is presented as an application of the NL-LFR model. The results and comparison to earlier results with different model structures are shown in Sections 4–6. Section 7 concludes the paper.

2. Insulin–glucose modelling problem

2.1. Aim

To enhance the lives of (type 1) diabetes (mellitus) patients, research is conducted on the regulation of the blood glucose level [11]. E.g., glucose control schemes for an artificial pancreas have been developed for the insulin–glucose metabolism [12], based on a Wiener (LTI-SNL) model and nonlinear sliding mode control. More sophisticated simulation insulin–glucose models built from first principles exist [13,14], but are avoided for control due to a large computational effort involved with the implementation and model parameters are very difficult to estimate from the available patient data. In this work, as in [15], simplified nonlinear models, for use in control in a later stage, represent the system as a replacement

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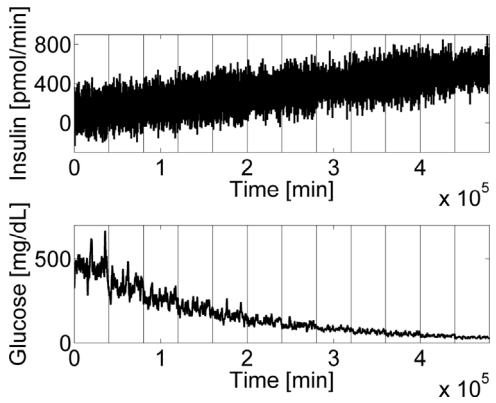

Fig. 1. (Concatenated) input and output signals for estimation (dataset A): random-phase multisines at 12 operating points.

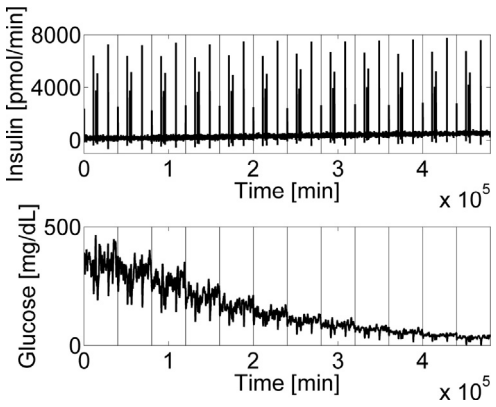

Fig. 2. (Concatenated) input and output signals for estimation (dataset B): band-limited pulses superimposed on a random-phase multisine at 12 operating points.

for the sophisticated models. To estimate a simplified nonlinear model, a data-driven, measurement point of view is taken here: the insulin is treated as a measured input and the glucose concentration as a measured output of the glycoregulatory system. In this paper, estimation results for the NL-LFR model are presented, and are compared with the Wiener and other nonlinear models. The data from which the simplified nonlinear models are estimated, are priorly generated through the Dalla-Man model [14]. The same data as in [15] are used: partly with a multisine[1] insulin input (dataset A) and partly a multisine input with band-limited pulses superimposed, intended to simulate a more realistic situation (dataset B). The data are available at 5 multisine amplitudes and 12 DC-levels. Please note that the estimation of a (simplified) nonlinear model is based on simulated data. The simple reason is that performing real measurements on patients can be very expensive, and that high-quality results on simulated data may be required to convince the medical experts that performing a real measurement campaign makes sense.

2.2. Benchmark datasets

The benchmark datasets used consist of steady-state[2] measurements of the glucose response of the Dalla-Man model to an insulin input at different basal (DC) glucose levels, while keeping the meal input zero [15].

Note that, for both datasets, only the data at a single input std[3]-value is taken as estimation data and another (slightly lower) std-value is taken as validation data, only intended to assess the model quality. The input (insulin[4]) and output (glucose) signals for datasets A and B are depicted in Figs. 1 and 2, respectively.

The properties of both datasets are listed in Table 1.

To compare the results, the following measure for the fit quality is used on the validation data:

$$\text{Fit\%} = \left(1 - \frac{\|y - \hat{y}\|_2}{\|y - \bar{y}\|_2}\right) \times 100$$

with y, $\hat{y}$, and $\bar{y}$ the steady-state measured output signal, the steady-state simulated model output signal and the mean value of the measured output (constant signal), respectively. Distinct values for the fit quality for the different operating points will be considered.

3. Nonlinear LFR model

The focus of this paper is to identify an NL-LFR model on the insulin–glucose benchmark data. The model's input and output are represented by u and y, as shown in Fig. 3. The SNL has an input z and output v. It has no memory effects, and can therefore be considered as a simple nonlinear mapping $f_{\text{SNL}} : \mathbb{R} \to \mathbb{R}$ operating on each input sample $z(k)$ (with discrete time index k):

$$v(k) = f_{\text{SNL}}(z(k)) \tag{1}$$

The linear part (LTI) connects the SNL and the model's input and output: the MIMO LTI converts the two inputs, u and v, to two outputs, y and z. Signals v and z are internal and not accessible for measurement.

The MIMO-LTI part can, in general, be described as:

$$x(k+1) = Ax(k) + \boldsymbol{B}\boldsymbol{u}(k) \tag{2}$$

$$\boldsymbol{y}(k) = \boldsymbol{C}x(k) + \boldsymbol{D}\boldsymbol{u}(k)$$

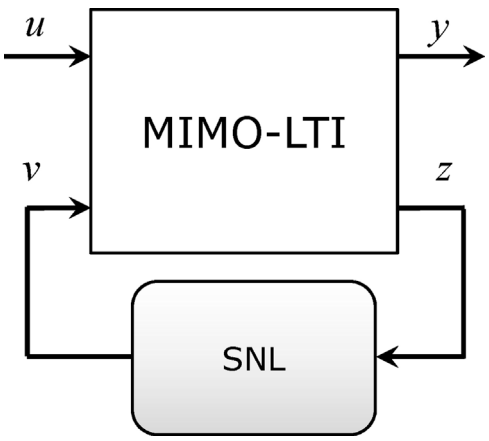

Fig. 3. The NL-LFR model. The signals u, y, z and v represent the model input and output and the SNL's input and output, respectively (the identification method has no access to measurements of z and v).

[1] The use of multisine signals (among other types of variations), to represent low amplitude slow fluctuations around a basal insulin level is known in the field of artificial pancreas, mainly for the identification of control-relevant models [16]. The use of such signals taking into account patients safety limits, would be possible.

[2] In the context of this paper, "steady-state" means "after die-out of the transient phenomena", i.e. the periodic regime response is considered.

[3] std = standard deviation

[4] It can be remarked that, at some places, negative insulin values are visible. This is not realistic. However, the idea behind using negative values is to implement fluctuations below the basal (viz., average) insulin levels.