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Growth rate maximization in fed-batch processes using high order sliding controllers and observers based on cell density measurement

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ABSTRACT

A novel extremum seeking scheme is proposed for the optimization of the specific growth rate in fed-batch processes with substrate inhibited kinetics. The proposed controller is based on a high order sliding mode algorithm, which uses the gradient of the specific growth rate as switching coordinate. A gradient estimation is obtained through a high order sliding mode observer. Both the control and gradient estimation algorithms are finite-time stable. The stability of the controller is analysed using Lyapunov functions for both the unperturbed and perturbed cases and guidelines for the algorithm tuning are provided. The controller and observer algorithms are numerically assessed and simulation results are obtained for a set of different scenarios.

1. Introduction

In many biotechnological process applications it is important to optimize the reaction rates in order to obtain high productivities or favour metabolic states. For example, the maximization of the specific growth rate allows obtaining the largest amount of biomass for a given process duration. When the microorganism has non-monotonic kinetics (e.g. Haldane) there is a particular substrate concentration which maximizes the specific growth rate.

From the control viewpoint, on-line process optimization consists in regulating the specific growth rate at a given optimal value, or equivalently, in regulating the substrate at the optimal concentration. A wide variety of closed loop algorithms have been reported in the literature aimed at regulating growth rates or concentrations. For instance, closed loop versions of an exponential feeding law are given in [1–3], linearizing control is studied in [4] along with its stability for operating points at both sides of the optimum. Adaptive linearizing control is one of the most developed techniques [5–7], introducing the use of observers to estimate unmeasured variables or parameters. Also, growth rate regulation has been developed in [8,9] based on geometric invariance concepts. These approaches are able to deal with common issues such as parameter uncertainty and lack of on-line measurements. However, a previously known set-point or trajectory is required either for the regulation of the kinetic rates or concentrations.

Extremum-seeking control provides tools to accomplish real time optimization of the process. The basic concept of extremum seeking is to define a control action which allows searching an operating point where a given objective function is maximized (or minimized). A survey on the application of extremum seeking to bioreaction processes was done in [10] where two types of extremum seeking schemes are defined. First, the perturbation-based scheme where the process is treated as black-box and the objective function is not known but measured. The control technique consist in disturbing the input of the process with a dither signal, then an estimate of the gradient is obtained by filtering and modulating the measured output which is later used to define a control action. This type of scheme has been developed in depth in [11] and the application to a continuous tank reactor can be found in [12] for volumetric growth rate maximization. Similarly, in [13] the specific growth rate is maximized but the gradient estimation is obtained with a generalized super-twisting (GST) observer rather than by filtering and modulation. The second scheme is the model-based extremum seeking, where only the objective function structure is known but not the parameters values. These are estimated on-line and the location of the optimum is determined from the estimations resulting in an adaptive algorithm. Many examples can be found in the bibliography as in [7,14–16].

Both the perturbation-based and model-based techniques are equally valid. The first one requires minimum knowledge of the process but the process needs to be persistently disturbed and the final state is likely to oscillate around the optimal operating point. The model-based extremum seeking has the advantage that some degree of transient performance can be guaranteed. However, a

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model structure needs to be assumed and included in the design, moreover, the dither signal is still used to ensure the excitation persistence necessary to estimate the parameters. Also, the resulting algorithms are generally more complex.

More recently, alternative approaches are being developed in the bioprocess control field in an attempt to bring together some of the advantages of the perturbation-based and model-based schemes. The goal is to design algorithms that do not rely vastly in the process models but giving certain guarantees on the transient response. Then, the objective function is unknown but its value can be measured or estimated from the process states. As it is necessary to disturb the plant to locate the optimum position, switched control algorithms like sliding mode control fit suitably for the task. The decision variable which produces the control switch can be in some cases an estimation of the error between the current and optimal substrate concentrations or the gradient of the objective function. In [17] a pseudo-super-twisting controller (PSTC) is proposed to maximize the gas production rate in an activated sludge process, where the substrate error is used as sliding coordinate. The sign of the error is estimated with a state machine analyzing the changes in the measured gas rate and the substrate. However. the magnitude of the error is estimated with a static function rather than with a closed loop algorithm. A similar approach is taken in [18] for the gradient estimation but using an output-feedback two-level controller instead of the PSTC. In [19] specific growth rate maximization is achieved with a first order sliding mode (FOSM) controller using an estimation of the gradient as sliding coordinate. The gradient estimation is obtained by the discrete estimator proposed in [20] using substrate concentration and gas production rate measurements. The growth rate is driven successfully to a neighborhood of the optimal value, however chattering issues are present, at least for gains large enough to reject the studied disturbances. These works have in common that both the control algorithms and decision variable estimations are run with a sample time large enough to let the output show some variation, which also introduces additional dynamics to the loop.

In this work, a new extremum seeking scheme is proposed to maximize the specific growth rate in fed-batch processes. The scheme is based on a high order sliding mode (HOSM) controller where the sliding coordinate is an estimation of the specific growth rate gradient with respect to the substrate. The gradient estimation is obtained from a HOSM observer after setting the problem into the form of a parameter estimation problem. In contrast with the model-based techniques, the proposed extremum seeking scheme does not require the inclusion of the kinetic model structure in its design. Only some bounds on its curvature are required to guarantee stability. Hence, only a partial model is required, involving only yields and influent substrate concentrations. Moreover, no dither signal is added to the process input like in the perturbation and model-based schemes, instead, it is replaced by the switched nature of the controller with the advantage that the switching action becomes zero in the desired operating point. Another advantage of the HOSM control over the FOSM, like the one in [19], is that the control action (dilution rate) is continuous and hence the chattering, usually associated to this kind of controller, is significantly reduced. Also, the integral term, which is not present in the previous case, allows to reject any constant disturbance. In this work, finite-time stability proofs are also given for the proposed controller (for the first time), first for the nominal case and then considering bounded disturbances. In previous contributions, like [21,22], the stability problem was solved numerically, in this work a Lyapunov function is derived for the HOSM controller. A stable operating region is derived from the stability proofs, and tuning guidelines are given for the case in which an approximate kinetic model is available. The proposed gradient estimation is performed in continuous time rather than with the (slow) sampling time of the controller, like in [17–19]. The advantage in this is that the estimation converges in finite-time and no additional dynamics are added to the closed loop. Another significant difference with many of the works reported in the bibliography is that the proposed control and gradient estimation scheme is based solely in the measurement of cell concentration. This constitutes and advantage in many cases, for example in industrial processes were waste or impure substrates are used. Carbon source or nitrogen on-line measurement may be possible in some cases, but is generally expensive and affine to certain specific substances. On the other hand, cell density can measured by optical density methods or even dielectric spectroscopy in a range of different processes and conditions.

Table 1
Variables and parameters.

Name	Description
x	Cell concentration
s	Substrate concentration
s_f	Fed substrate concentration
v	Volume
D	Dilution rate
y_{xs}	Substrate to biomass yield
μ	Specific growth rate
$\omega(s)$	Gradient of $\mu(s)$ w.r.t. s
$h(s)$	Hessian of $\mu(s)$ w.r.t. s

2. Problem formulation

The model for fed-batch processes in terms of concentrations is obtained from mass balance equations:

$$\dot{x} = (\mu - D)x \tag{1}$$

$$\dot{s} = -\frac{\mu x}{y_{xs}} + D(s_f - s) \tag{2}$$

$$\dot{v} = Dv \tag{3}$$

where all the variables and parameters are referenced in Table 1. It is assumed that an excess of substrate concentration has an inhibiting effect on the specific growth rate, hence, the kinetic of the microorganism is non-monotonic and holds a maximum μ^* at an optimal substrate concentration s^*. It is also assumed that neither the kinetic model or its structure are known, either by uncertainty or lack of identification, therefore the location of the optimal operating point (s^*, μ^*) is unknown.

At this point it is convenient to define some other variables that are important for the proposed control and estimation scheme. Supposing that the specific growth rate is a function of the limiting substrate s only, the gradient of μ can be defined as

$$\nabla\mu = \frac{\partial \mu(s)}{\partial s} = \omega(s), \tag{4}$$

which in this case is scalar because it was supposed that μ depends on a single variable. The gradient is the slope of the kinetic map and indicates the direction in the s axis for which μ increases. Another important variable is the Hessian defined as

$$\nabla^2\mu = \frac{\partial^2 \mu}{\partial s^2} = h(s), \tag{5}$$

which is also scalar and describes the curvature of the kinetic map. It is a necessary condition for the the operating point (s^*, μ^*) to be an extreme that $\omega(s^*) = 0$. Particularly, it is a sufficient condition for that point to be a maximum that $h(s^*) < 0$ [23].

Having defined both the gradient $\omega(s)$ and Hessian $h(s)$ of the map (ω and h from now on) it is possible to extend the process