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Sliding mode observer for biomass estimation in a biohydrogen production process

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ABSTRACT

This work deals with the problem of estimation of biomass concentration and specific growth rate in a biohydrogen production process. A photo-fermentation process with the photosynthetic bacteria *Rhodobacter capsulatus* is considered. The reaction dynamics is represented with a Monod law while the hydrogen production rate is modeled with a Luedeking-Piret expression. A sliding mode observer is proposed and designed, which gives an estimate of both biomass concentration and specific growth rate from measurements of the produced hydrogen volume. The proposed observer is completely robust against the growth kinetic model, and it presents a first-order reduced dynamics. Numerical simulation results are presented for a batch biohydrogen production process.

1. Introduction

Hydrogen is considered a promising energy carrier as an alternative to fossil fuels. Besides being renewable, its combustion generates no pollution and provides an amount of energy per unit weight higher than the energy obtained from hydrocarbon fuels.

In the last years there has been an increasing interest in obtaining hydrogen from biological processes (biohydrogen), as these processes are environment friendly. Biological hydrogen production is basically based on either bio-photolysis, photo-fermentation or dark fermentation [1].

Diverse experiments have been carried out, using pure and mixed cultures of microorganism, for a large variety of substrates and under different operating conditions. Both the hydrogen yield and the specific production rate have been shown to be strongly dependent on the carbon source and the physiological conditions [2]. Although the utilization of organic wastes as substrate could help to waste minimization and cost reduction, biohydrogen production has not yet entered bulk markets mainly because of its comparatively high costs and low production rates.

In this work we consider a photo-fermentation process, which has been found to be the most promising bioproduction process due to its high substrate to product conversion yield [3]. In such a process, a photoheterothrophic bacteria reduces organic acids into H_2 and CO_2 mainly through nitrogenase enzyme. In addition to hydrogen generation, the photo-fermentation provides the possibility of organic waste treatment at industrial scale by using mixed culture of microorganisms [4].

On the other hand, photo-fermentation processes are affected by physicochemical conditions in which microorganism grows such as: C/N ratio, light intensity, temperature, pH and operating mode [3]. Another important constraint is that during the photo-fermentation process, only a few measurements are available online.

In order to make progress towards an economically viable biohydrogen production process, it is essential to apply advanced control strategies which can optimize the process

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and significantly improve the production rates. Since any control strategy which can be applied will require as much information as possible, the implementation of state observers (or software sensors) for the estimation of those variables which are not accesible becomes a crucial task.

In this direction, one of the earliest contributions to state estimation in bioprocesses was proposed in [5], where a specific growth rate estimation was performed assuming that it is a bounded time-varying parameter. More recently [6], proposed a high-gain state observer, while [7] proposed a hybrid observer which combines high-gain with asymptotic estimation properties. A special class of nonlinear observers is that one which operates under sliding mode (SM) regime. Particularly [8], proposed an SM observer for specific growth rate estimation from biomass measurements. Regarding biohydrogen generation, there are just a few works published dealing with state estimation. Among them [9], presents a model predictive control strategy using an asymptotic observer, whereas [10] proposes a moving horizon state estimator to be applied to biohydrogen process control.

This work deals with the problem of estimation of biomass concentration and specific growth rate in a biohydrogen production process. The photo-fermentation process with purple non-sulfur bacteria *Rhodobacter capsulatus* is considered. The reaction dynamics is represented with a Monod law, while hydrogen production rate is modeled with a Luedeking-Piret expression. An SM observer is designed which provides an estimation of microorganisms (biomass) concentration and specific growth rate from measurements of the produced hydrogen volume. Some distinctive features of this observer are that it presents a reduced-order dynamics and it is independent of the growth kinetics (provided it is bounded).

The work is organized as follows. Section 2 introduces the photo-fermentation bioprocess model and some necessary assumptions. The SM observer for biomass concentration and specific growth rate is described in Section 3. Section 4 presents numerical results, which are discussed in Section 5. Finally, conclusions are given in Section 6.

2. Process model and problem statement

The following model represents the photo-fermentation process for biohydrogen production with *R. capsulatus* in a batch culture, under anaerobic condition and nitrogen-limiting substrate [11]. Variation of biomass and substrate concentration is expressed as:

$$\frac{dX}{dt} = \mu(S)X \tag{1}$$

$$\frac{dS}{dt} = -\frac{1}{Y_{XS}}\mu(S)X, \tag{2}$$

where X is biomass concentration (g L^{-1}) and S substrate concentration (g L^{-1}). $\mu(S)$ is the specific growth rate (h^{-1}) and Y_{XS} substrate on biomass yield (g g^{-1}).

Specific growth rate is represented with a Monod law

$$\mu(S) = \mu_{max}\frac{S}{K_S + S}, \tag{3}$$

where μ_{max} is the maximum growth rate (h^{-1}) and K_S the substrate saturation constant (g L^{-1}).

The specific production rate of biohydrogen is expressed with a Luedeking-Piret model:

$$\frac{dP}{dt} = \alpha\frac{dX}{dt} + \beta X. \tag{4}$$

The first term in the right side of Eq. (4) takes into account the growth associated production rate and the second term the non-growth associated production rate. Whilst Eq. (4) was first proposed to describe acid lactic fermentation [12], it has also been applied to fit experimental data from biohydrogen production with photosynthetic bacteria [13,14]. Furthermore, modified models have been presented to take into account inhibition effect of substrate, product and light intensity [15]. In [11] the authors consider the produced hydrogen volume as state variable and the effect of light intensity into the growth associated term. In this manner, regarding Eqs. (1)–(4), they propose:

$$\frac{dP}{dt} = \frac{1}{Y_{XP}}\phi(I)\mu(S)X + \beta X, \tag{5}$$

where P (mL) is the produced hydrogen, Y_{XP} the biomass on product yield and $\phi(I)$ a function of light intensity. Given a level of light intensity I_0, and using Eq. (4): $\alpha = \phi(I_0)/Y_{XP}$.

In this context, the following assumptions are made for the development of an SM state observer:

A.1 It is assumed that the photo-fermentation process can be properly described by Eqs. (1)–(4).
A.2 A continuous measurement of biohydrogen volume, P, is assumed available.
A.3 The specific growth rate $\mu(\cdot)$ is bounded, i.e. there exists $\overline{\mu}_{max}$ such that $|\mu(\cdot)| \le \overline{\mu}_{max}$.
A.4 State variables are bounded and positive. This can be assumed because these variables represent concentrations in the bioreactor.

Note that none of the assumptions are actually restrictive. Hence, given the listed assumptions, the problem is to determine an estimation of biomass concentration X and specific growth rate $\mu(\cdot)$ from the measurement P.

3. The proposal

3.1. SM estimation in a class of nonlinear system

Consider a class of nonlinear system that can be represented by the following model:

$$\frac{dx_1}{dt} = \varepsilon(x,t)x_1 \tag{6}$$

$$\frac{dx_2}{dt} = k_{10}x_1 + k_{20}x_2 + k_{11}\frac{dx_1}{dt} \tag{7}$$

$$y = x_2 \tag{8}$$

where x_1, $x_2 \in \mathbb{R}^+$, $\varepsilon(x,t)$ is a scalar bounded function, and $k^T = [k_{10}\ k_{20}]$ a constant vector. Then, in order to obtain estimates of x_1 and $\varepsilon(x,t)$ using measurement of $y = x_2$, the following observer is proposed:

$$\frac{d\hat{x}_1}{dt} = \hat{\varepsilon}(y,\hat{x})\hat{x}_1 \tag{9}$$

$$\frac{d\hat{x}_2}{dt} = k_{10}\hat{x}_1 + k_{20}\hat{x}_2 + k_{11}\hat{\varepsilon}(y,\hat{x})\hat{x}_1 \tag{10}$$

$$\hat{y} = \hat{x}_2 \tag{11}$$

$$\hat{\varepsilon}(y,\hat{x}) = M\,\mathrm{sign}(y - \hat{x}_2) \tag{12}$$

where $\hat{x}_1$ and $\hat{x}_2$ are the state estimates, $\hat{\varepsilon}(y,\hat{x})$ an estimation of $\varepsilon(x,t)$, sign(.) the sign function and M a constant gain. It is worth noting that the dynamics of $\hat{x}_1$ and $\hat{x}_2$ are affected by a discontinuous term.

Let the estimation error be $\tilde{x}_i \triangleq x_i - \hat{x}_i$, then for x_1 and x_2 we have:

$$\frac{d\tilde{x}_1}{dt} = \varepsilon(x,t)\tilde{x}_1 + (\varepsilon(x,t) - \hat{\varepsilon}(y,\hat{x}))\hat{x}_1, \tag{13}$$

$$\frac{d\tilde{x}_2}{dt} = k_{10}\tilde{x}_1 + k_{20}\tilde{x}_2 + k_{11}\frac{d\tilde{x}_1}{dt}. \tag{14}$$

Now consider the following function of the estimation error: $\phi(\tilde{x}) = \tilde{x}_2$. Wherever

$$M \geq \left|\frac{k^T\tilde{x}}{k_{11}\hat{x}_1} + \frac{x_1\varepsilon}{\hat{x}_1}\right|, \tag{15}$$

the discontinuous term in $\frac{d\tilde{x}_2}{dt}$ enforces that

$$\frac{d\phi}{dt} > 0 \text{ when } \phi < 0, \tag{16}$$

$$\frac{d\phi}{dt} < 0 \text{ when } \phi > 0. \tag{17}$$

Under these conditions, ϕ vanishes ($\phi = 0$) in finite time. From then on, the discontinuous term switches at an ideally infinite frequency constraining the state trajectory on the surface

$$\phi\left(\tilde{x}\right) = \tilde{x}_2 = 0. \tag{18}$$

It is said that a sliding mode regime is established, where the invariance condition

$$\phi = \tilde{x}_2 = 0, \tag{19}$$

$$\frac{d\phi}{dt} = \frac{d\tilde{x}_2}{dt} = 0, \tag{20}$$

holds [16].

Eqs. (19) and (20) imply that:

$$\hat{x}_2 = y, \tag{21}$$

$$k_{10}\tilde{x}_1 + k_{11}\frac{d\tilde{x}_1}{dt} = 0. \tag{22}$$

Therefore, from (22) we have the following reduced-order dynamics for the observer error:

$$\frac{d\tilde{x}_1}{dt} = -\frac{k_{10}}{k_{11}}\tilde{x}_1. \tag{23}$$

The dynamics of $\tilde{x}_1$ converges to zero with a time constant $\tau = k_{11}/k_{10}$. From the invariance condition (19)–(20), it can be interpreted that the discontinuous signal $\hat{\varepsilon}(y,\hat{x})$ behaves like a fictitious continuous signal $\varepsilon_{eq}(t)$ which enforces the system to operate on $\phi(\tilde{x}) = 0$ [16]. Using (13) and (23), it follows that

$$\varepsilon_{eq}(t) = \left(\varepsilon(x,t) + \frac{k_{10}}{k_{11}}\right)\frac{\tilde{x}_1}{\hat{x}_1} + \varepsilon(x,t). \tag{24}$$

Then, as $\tilde{x}_1 \to 0$, according to (23) we have

$$\varepsilon_{eq}(t) \to \varepsilon(x,t). \tag{25}$$

The results (23)–(25) are useful to estimate biomass concentration and specific growth rate as we discuss in the next subsection.

3.2. *SM observer for biohydrogen production*

In order to apply the previous development to the process model (1)–(4), let $x_1 = X$, $x_2 = P$, $\varepsilon(x,t) = \mu(\bullet)$, $k^T = [\beta\ 0]$, $k_{11} = \alpha$ and $\hat{\varepsilon}(y,\hat{x}) = \hat{\mu}$. With the objective of estimating biomass concentration and specific growth rate, the following SM state observer is proposed:

$$\frac{d\hat{X}}{dt} = \hat{\mu}\hat{X} \tag{26}$$

$$\frac{d\hat{P}}{dt} = \alpha\hat{\mu}\hat{X} + \beta\hat{X} \tag{27}$$

$$\hat{\mu} = M\ \mathrm{sign}(P - \hat{P}) \tag{28}$$

$$\hat{X}(0) = \hat{X}_0 \tag{29}$$

$$\hat{P}(0) = P(0) \tag{30}$$

where $\hat{X}$ and $\hat{P}$ are states of the observer which estimate X and P respectively, $\hat{\mu}$ the estimated specific growth rate, $\hat{X}(0) > 0$ and $\hat{P}(0)$ the initial conditions, and K a constant.

Since the produced hydrogen volume P is available and measured, the comparison $P - \hat{P}$ can be done. Then the observer is initialized with the first sample, that is $\hat{P}(0) = P(0)$. We define the estimation error as in the previous section:

$$\tilde{X} = X - \hat{X}, \tag{31}$$

$$\tilde{P} = P - \hat{P}. \tag{32}$$

From Eqs. (1), (4), (26) and (27), it is straightforward to show that the error dynamics results:

$$\frac{d\tilde{X}}{dt} = \mu\tilde{X} + \left(\mu - M\,\mathrm{sign}\left(\tilde{P}\right)\right)\hat{X}, \tag{33}$$

$$\frac{d\tilde{P}}{dt} = \alpha\frac{d\tilde{X}}{dt} + \beta\tilde{X}. \tag{34}$$

Now consider the following switching function:

$$\phi\left(\tilde{X},\tilde{P}\right) = \tilde{P}. \tag{35}$$

Table 1 – Value of parameters describing biohydrogen production with *R. capsulatus* [10,11]. (*) Units according to expression (5).

Parameter	Value	Unit
μ_{max}	0.4	h^{-1}
K_S	10	$g\,L^{-1}$
Y_{XS}	0.7	$g\,g^{-1}$
Y_{XP}	1	$g\,L^{-1}$
α	5	*
β	16	*

It can be easily verified that the relative degree of the switching function ϕ with respect to the discontinuous signal $sign(\tilde{P})$ is equal to one, which is a necessary condition for the existence of sliding regime [17]. The sliding domain, i.e the region of the sliding surface $\phi = 0$ where sliding mode exists can be determined from Eq. (15).

Note that for the observer to evolve in sliding mode towards $\tilde{X} = 0$, $M > \overline{\mu}_{max}$ must be selected.

During sliding mode operation, the invariance condition (19) and (20) holds, i.e:

$$\phi = \tilde{P} = 0, \tag{36}$$

$$\frac{d\phi}{dt} = \frac{d\tilde{P}}{dt} = 0. \tag{37}$$

Then,

$$\hat{P} = P, \tag{38}$$

$$\alpha\frac{d\tilde{X}}{dt} + \beta\tilde{X} = 0. \tag{39}$$

Note that (38) implies that the estimation $\hat{P}$ matches the measured volume of biohydrogen P. Furthermore, from Eq. (39) we have the reduced-order dynamics

$$\frac{d\tilde{X}}{dt} = -\frac{\beta}{\alpha}\tilde{X}. \tag{40}$$

This means that the dynamics of the biomass estimation error converge to zero with a time constant $\tau = \alpha/\beta$. From the invariance condition (36) and (37), the discontinuous signal $\hat{\mu}(t)$ behaves like a fictitious continuous signal $\mu_{eq}(t)$ which perfectly estimates $\mu(t)$. The fictitious $\mu_{eq}(t)$ is (see (24))

$$\mu_{eq}(t) = \left(\mu(t) + \frac{\beta}{\alpha}\right)\frac{\tilde{X}}{\hat{X}} + \mu(t). \tag{41}$$

Then, as $\tilde{X} \to 0$, we have

$$\mu_{eq}(t) \to \mu(t). \tag{42}$$

Since $\hat{\mu}(t)$ is discontinuous, an estimate $\hat{\mu}_{eq}(t)$ of $\mu_{eq}(t)$ can be obtained by using a low-pass filter which removes the high frecuency component of $\hat{\mu}(t)$.

4. Numerical results

Numerical simulation results for a batch biohydrogen production process are presented in this section to illustrate the proposed observer performance. The initial conditions are $X(0) = 0.13\ g\,L^{-1}$, $S(0) = 4.19\ g\,L^{-1}$ and $P(0) = 0$ mL [10], the

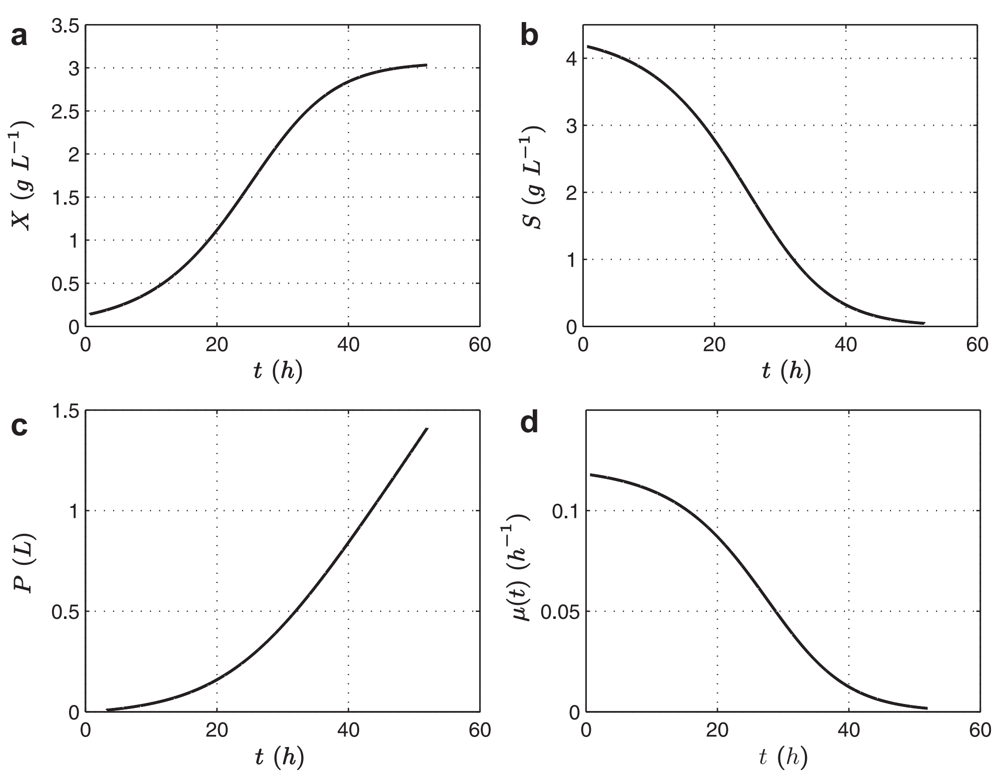

Fig. 1 – Bioprocess simulation: a) biomass, b) substrate, c) biohydrogen, d) specific growth rate.

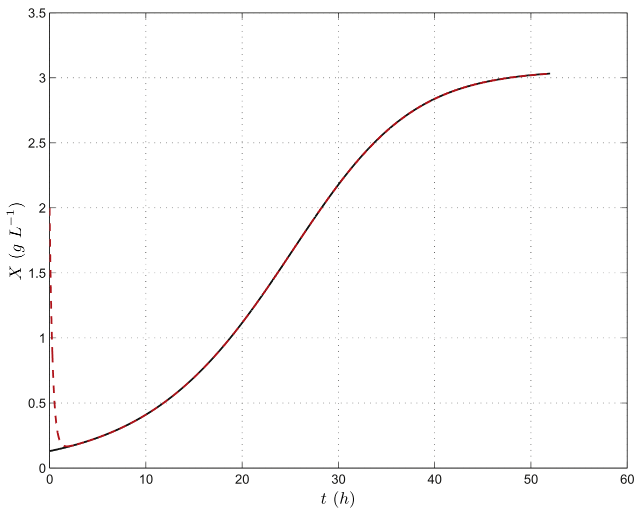

Fig. 2 – Evolution of biomass X (solid) and estimated biomass $\hat{X}$ (dashed).

batch run is 52 h. The model parameters are presented in Table 1.

Fig. 1 shows the state evolution for the photo-fermentation process. The initial substrate concentration is consumed by biomass for biomass growth and product formation. Hydrogen is produced according to model (5), with a rate proportional to biomass concentration and biomass growth rate.

According to Eq. (40), the error dynamics of biomass estimation is stable and it asymptotically converges to zero. This is verified by Fig. 2, where it is shown how the biomass estimation effectively converges to the real biomass concentration from an initial condition $\hat{X}(0) = 2$ g L^{-1} with the time constant $\alpha/\beta = 0.3125$ h.

In turn, Fig. 3 reveals the observer potentials to estimate the specific growth rate, as stated by (42). To this end, $\hat{\mu}_{eq}(t)$ is obtained by filtering the discontinuous specific growth rate estimation $\hat{\mu}(t)$ with a second-order low-pass Butterworth filter with cut-off frequency of 0.5 Hz, so as to remove the high-frequency component. As can be appreciated, after a relatively short transient caused by the filter and the dynamic of $\tilde{X}$, the signal $\hat{\mu}_{eq}(t)$ satisfactorily estimates the actual specific growth rate $\mu(t)$.

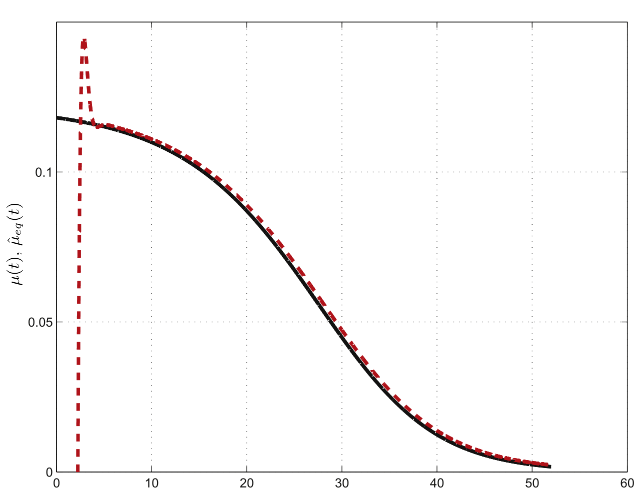

Fig. 3 – Specific growth rate: $\mu(t)$ (solid) and filtered estimation $\hat{\mu}_{eq}(t)$ (dashed).

5. Discussion

As was verified in the previous section, the sliding mode regime enforces the observer to operate on the surface $\tilde{P} = 0$. Because of the SM reduced-order dynamics, the error $\tilde{X}$ tends to zero with a first-order dynamics, and then an estimation of biomass concentration is achieved.

It is worthy to remark that the development of the observer does not require any model (Monod, Haldane, etc.) for specific growth rate $\mu(t)$. Indeed, an upper bound $\overline{\mu}_{max}$ is only required. This allows the utilization of the observer without having identified the parameters of the μ model. Furthermore, the resultant observer can be applied to any other bioprocess in which the product formation rate can be associated to biomass growth and biomass concentration, that is, when a model with the structure of (4) is applicable.

6. Conclusions

An SM observer of biomass concentration and specific growth rate was designed for a biohydrogen production process. The convergence of the observer was verified by numerical simulation in a photo-fermentation process with the bacteria *R. capsulatus*. The proposed observer assumes no particular model for $\mu(\cdot)$, only requiring the growth rate to be bounded.

This algorithm could be employed both for online monitoring of the biohydrogen production process and for the application of advanced control strategies in order to optimize the operating conditions.

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