Nonlinear Observer for Applications of Fermentation Process in Stirred Tank Bioreactor

Hak Kyeong Kim, Tan Tien Nguyen and Sang Bong Kim

Abstract: This paper proposed a modified observer based on Busawon's high gain observer using an appropriate time depended function, which can be chosen to make each estimated state converge faster to its real value. The stability of the modified observer is proved by using Lyapunov function. The modified nonlinear observer is applied to estimate the states in stirred tank bioreactor: output substrate concentration, output biomass concentration and the specific growth rate of the process. The convergences of the modified observer and Busawon's observer are compared through simulation results. As the results, the modified observer converges faster to its real value than the well-known Busawon's observer.

Keywords: non-linear observer, bioreactor, parameter estimation

I. Introduction

Fermentation is an important process for cultivating microorganisms. Fermentation can be run as a batch, fed-batch and continuous process. In a continuous system, the substrate is supplied to the bioreactor and extracted from the bioreactor. Fermentation process is so complex, time varying and highly nonlinear. Due to pH, dissolved oxygen, temperature, antifoam addition, biomass accumulation, production formation and nutrient depletion during fermentation process, the dynamic behavior is significantly changed. So it is difficult to make a model and control for fermentation process exactly. Specially, the exact estimate of the specific growth rate is so uncertain because it depends on parameters such as biomass concentration, substrate concentration, production formulation and temperature, etc. Despite the intensive effort spent in developing new biological sensors in recent years, the sensors are not much exact. To overcome these problems, observers, software sensors, for on-line monitoring biological variables has been developed.

The observer is expected to produce the estimate $\hat{x}(t)$ of the state of $x(t)$ of the original system. One of the reasons of using observer is that full state measurement of a process is generally not available. The construction of observers is very interesting and there are some available methods have been introduced in literatures. For a linear system, a standard solution is given by the classical Lubenburger observer. For a nonlinear system, the list of references at the end of the paper cover part of recent works done in the area. Gauthier et al.[11] proposed a simple observer for nonlinear system application to bioreactor under general technological assumptions. Farza et al.[6] proposed simple nonlinear observer for estimation in fermentation process. Martinez-Guerra et al.[2] proposed parametric and state estimation using high-gain nonlinear observers applied to bioreactor. Olivera et al.[9] solved the tuning problem of an observer-based algorithm for the on-line estimation of reaction rates in stirred tank bioreactors. Tonambe[12] reduced the estimation of the unknown parameters of a nonlinear system to the estimation of its state variables by a state space immersion using asymptotic high-gain observers. Busawon et al.[3-5] proposed simple high gain observer for a class of nonlinear systems in a special canonical observable form for state and parameter estimation in bioreactor. Among the above papers, the Busawon's high gain observer attained good performance and agreed well with the experimental results. However in some cases, the estimated state of the system is not converged to its real value as fast as required.

This paper proposed a modified observer based on Busawon's high gain observer using an appropriate time depended function, which can be chosen to make each estimated state converge faster to its real value. The proof is given to prove the stability of the proposed observer using Lyapunov function approach. The fermentation process in stirred tank bioreactor is used for the simulation. Two cases have been done with the original Busawon's observer and the modified observer. The effectiveness of the proposed method is shown through the simulation results applied to bioreactor system.

II. High gain observer structure

For general nonlinear system, a high gain observer is used to handle part of the nonlinearity of the system by choosing a sufficiently large value of a given design parameter. This part briefly summaries the high gain observer for a class of nonlinear systems in a special canonical observable form, which is studied by Busawon et al.[5]

Consider single-output system as follows:

$$\dot{z} = F(s,z)\,z + G(u,s,z) \quad (1)$$

$$y = Cz \quad (2)$$

where

$$F(s,z) = \begin{bmatrix} 0 & f_1(s,z) & 0 & \cdots & 0 \\ 0 & 0 & f_2(s,z) & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & f_{n-1}(s,z) \\ 0 & 0 & 0 & \cdots & 0 \end{bmatrix} \quad (3)$$

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Hak Kyeong Kim, Sang Bong Kim: Room 414, Dept. of Mechanical Eng., College of Eng., Building 9, Pukyong National University, San 100, YongDong-Dong, Nam-Ku, Pusan 608-739, Korea. (hakkyong@simmani.com, kimsb@pknu.ac.kr)

Tan Tien Nguyen: Dept. of Mechanical Engineering, Hochiminh City University of Technology, 268, Lythuongkiet Street, Dist. 10. Hochiminh City, Vietnam.(E-mail:tiennt@yahoo.com)

$$G(u,s,z)=\begin{bmatrix} g_1(u,s,z_1) \\ g_2(u,s,z_1,z_2) \\ \vdots \\ g_{n-1}(u,s,z_1,z_2,\cdots,z_{n-1}) \\ g_n(u,s,z) \end{bmatrix} \quad (4)$$

$$C=\begin{bmatrix}1 & 0 & \cdots & 0\end{bmatrix} \quad (5)$$

$z=(z_1,z_2,...,z_n)\in R^n$, $u\in R^m$, $y\in R$ and s is a known function, f_i are class C^1 that the first derivatives are continuous with respect to their arguments.

Let $N(s,\xi,t)$ be observability matrix for system Eqs. (1)-(5) as follows

$$N(s,\xi,t)=diag\big[1, f_1(s,\xi), f_1(s,\xi)f_2(s,\xi), \\ \text{L}, f_1(s,x)f_2(s,x)\text{L} f_{n-1}(s,x)\big] \quad (6)$$

Consider the following algebraic Lyapunov equation

$$\frac{dS_\lambda}{dt}=\lambda S_\lambda + A^T S_\lambda + S_\lambda A - C^T C = 0 \quad (7)$$

where S_λ is the symmetric positive definite matrix, λ is a positive number and matrix A is of the form:

$$A=\begin{bmatrix} 0 & 1 & \cdots & 0 \\ \vdots & \ddots & \ddots & \vdots \\ 0 & 0 & \cdots & 1 \\ 0 & 0 & \cdots & 0 \end{bmatrix} \quad (8)$$

We assume the followings:

A1) There exists a subset $U\subset L^\infty(R^+,R^m)$ and two compact sets $K_1\subset K_2$ such that every trajectory $z(t)$ associated to any $u\in U$ and issued from K_1 to K_2.

A2) $s(t)$ is known and bounded in class C^1 and $\dot{s}(t)$ is also bounded.

A3) $\exists\alpha_1>0, \forall u\in R^m, \forall z\in R^n, \forall t\ge 0: |f_i(s(t),z)|>\alpha_1$

A4) $\exists\alpha_2>0, \forall u\in R^m, \forall z\in R^n, \forall t\ge 0: |g_i(u,s(t),z)|>\alpha_2$ for $i=1,\cdots,n$.

A5) $\exists\beta,\gamma\ge 0; \forall u\in R^m, \forall z\in R^n; \forall t\ge 0$

$$\left\|\frac{\partial f_j(s(t),z)}{\partial z}\right\|\le\beta,\quad \left\|\frac{\partial g_i(u(t),s(t),z)}{\partial z}\right\|\le\gamma$$

for $j=1,\cdots,n\text{-}1$ and $i=1,\cdots,n$.

A6) $N(s,\xi,t)$ is full rank for all $t\ge 0$ and its time derivative is bounded.

Theorem 1[5]: Assume that the system (1) satisfies Assumptions (A1)-(A6). Then, there exists $\lambda>0$ such that the following equation is an exponential observer for the system 1):

$$\dot{\hat{z}}=F(s,\hat{z})\hat{z}+G(u,s,\hat{z})-N^{-1}(s,\hat{z},t)S_\lambda^{-1}C^T(C\hat{z}-y) \quad (9)$$

III. Modified observer

This section introduces a modified observer based on the above Busawon's high gain observer using an appropriate time depending function $H(t)$, which can be chosen to make each estimated state converge faster to its real value.

$$H(t)=diag\left[1,h_1(t),h_2(t),\cdots,h_{n-1}(t)\right] \quad (10)$$

Now, let $M(s,\xi,t)$ be observability matrix for system Eqs (1)-(5) as follows:

$$M(s,\xi,t)=diag\left[1, f_1(s,\xi), \frac{f_1(s,\xi)f_2(s,\xi)}{h_1(t)}, \cdots, \frac{f_1(s,\xi)f_2(s,\xi)\cdots f_{n-1}(s,\xi)}{h_1(t)h_2(t)\cdots h_{n-2}(t)}\right] \quad (11)$$

We assume the followings:

A7) $H(t)$ is bounded function and rank $(H(t))=n$.

A8) $M(s,\xi,t)$ is full rank for all $t\ge 0$ and its time derivative is bounded.

The proposed modified observer can be cited in the following theorem 2.

Theorem 2: Assume that the system (1) satisfies Assumptions (A1)-(A5) and (A7)-(A8). Then, there exists $\lambda>0$ such that the follow ing equation is an exponential observer for the system (1):

$$\dot{\hat{z}}=F(s,\hat{z})\hat{z}+G(u,s,\hat{z})-H(t)M^{-1}(s,\hat{z},t)S_\lambda^{-1}C^T(C\hat{z}-y) \quad (12)$$

Proof of theorem 2

For the sake of simplicity, note that $F\equiv F(s,z)$, $\hat{F}\equiv F(s,\hat{z})$, $G\equiv G(u,s,z)$, $\hat{G}\equiv G(u,s,\hat{z})$, $H\equiv H(t)$ and $\hat{M}\equiv M(s,\hat{z},t)$.

Define the observer error, $\varepsilon=\hat{z}-z$. Its first derivative yields

$$\dot{\varepsilon}=\dot{\hat{z}}-\dot{z} \\ =(\hat{F}-H\hat{M}^{-1}S_\lambda^{-1}C^TC)\varepsilon+(\hat{F}-F)z+(\hat{G}-G) \quad (13)$$

Now define a new variable

$$\bar{\varepsilon}=\hat{M}\Delta_\lambda\varepsilon \;\rightarrow\; \varepsilon=\Delta_\lambda^{-1}\hat{M}^{-1}\bar{\varepsilon} \quad (14)$$

where

$$\Delta_\lambda=\text{diag}\left[1,\frac{1}{\lambda},\frac{1}{\lambda^2},\cdots,\frac{1}{\lambda^{n-1}}\right] \quad (15)$$

then we have

$$\dot{\bar{\varepsilon}}=\dot{\hat{M}}\Delta_\lambda\varepsilon+\hat{M}\Delta_\lambda\dot{\varepsilon}$$

Using relation shown in Appendix A, we can derive the following

$$\dot{\bar{\varepsilon}}=\dot{\hat{M}}\hat{M}^{-1}\bar{\varepsilon}+\lambda(A-HS_1^{-1}C^TC)\bar{\varepsilon} \\ +\hat{M}\Delta_\lambda(\hat{F}-F)z+\hat{M}\Delta_\lambda(\hat{G}-G) \quad (16)$$

The Lyapunov function is chosen as follows

$$V=\bar{\varepsilon}^TS_1\bar{\varepsilon}=\|\bar{\varepsilon}\|_{S_1}^2\ge 0 \quad (17)$$

Using Eqs. (14)-(16) and the relation in Appendix B, the first derivative of Lyapunov function can be written as

$$\dot{V}=2\bar{\varepsilon}^TS_1\dot{\bar{\varepsilon}} \\ =2\bar{\varepsilon}^TS_1\dot{\hat{M}}\hat{M}^{-1}\bar{\varepsilon}-\lambda V$$

$$-\lambda\bar{\varepsilon}^T C^T C\bar{\varepsilon} - 2\lambda\bar{\varepsilon}^T S_1(H-I)S_1^{-1}C^T C\bar{\varepsilon}$$
$$+2\bar{\varepsilon}^T S_1\hat{M}\Delta_\lambda(\hat{F}-F)z + 2\bar{\varepsilon}^T S_1\hat{M}\Delta_\lambda(\hat{G}-G)$$
$$\dot{V} \le -\lambda V + 2\left\|\dot{\hat{M}}\hat{M}^{-1}\right\|\|S_1\bar{\varepsilon}\|\|\bar{\varepsilon}\|$$
$$-\lambda\|C\bar{\varepsilon}\|^2 - 2\lambda\|S_1\bar{\varepsilon}\|\|\bar{\varepsilon}\|\left\|(H-I)S_1^{-1}C^T C\right\|$$
$$+2\|S_1\bar{\varepsilon}\|\|\hat{M}\|\left\|\Delta_\lambda(\hat{F}-F)z\right\| + 2\|S_1\bar{\varepsilon}\|\|\hat{M}\|\left\|\Delta_\lambda(\hat{G}-G)\right\| \quad (18)$$

Using Assumption (A5), the boundedness of the state and the triangular structure of G and f_i, with some positive constants γ_1, γ_2, we obtain[5]

$$\left\|\Delta_\lambda(\hat{F}-F)z\right\| \le \gamma_1\|\Delta_\lambda\varepsilon\| = \gamma_1\left\|\hat{M}^{-1}\bar{\varepsilon}\right\| \le \gamma_1\left\|\hat{M}^{-1}\right\|\|\bar{\varepsilon}\|$$
$$\left\|\Delta_\lambda(\hat{G}-G)\right\| \le \gamma_2\|\Delta_\lambda\varepsilon\| = \gamma_2\left\|\hat{M}^{-1}\bar{\varepsilon}\right\| \le \gamma_2\left\|\hat{M}^{-1}\right\|\|\bar{\varepsilon}\|$$

Define $\eta_1 \equiv \left\|\dot{\hat{M}}\hat{M}^{-1}\right\|$, $\eta_2 \equiv \left\|(H-I)S_1^{-1}C^T C\right\|$,

$$\|S_1\bar{\varepsilon}\|\|\bar{\varepsilon}\| \equiv \sigma V = \sigma\bar{\varepsilon}^T S_1\bar{\varepsilon}, \quad \rho \equiv 2\eta_1 + 2_1\gamma_1 + 2\gamma_2$$

Then we can rewrite (18) as follows

$$\dot{V} \le -\lambda V + 2\eta_1\|S_1\bar{\varepsilon}\|\|\bar{\varepsilon}\| + 2\gamma_1\|S_1\bar{\varepsilon}\|\|\bar{\varepsilon}\|$$
$$+2\gamma_2\|S_1\bar{\varepsilon}\|\|\bar{\varepsilon}\| - 2\lambda\|S_1\bar{\varepsilon}\|\|\bar{\varepsilon}\|\eta_2$$
$$\dot{V} \le -[\lambda(1+2\eta_2\sigma) - \rho\sigma]V \quad (19)$$

If λ is chosen so as to satisfy $\lambda \ge (\rho\sigma)/(1+2\eta_2\sigma)$, $\dot{V}$ achieves negative. Hence, $\bar{\varepsilon} \to 0$, $\varepsilon = \Delta_\lambda^{-1}\hat{M}^{-1}\bar{\varepsilon} \to 0$ when $t \to \infty$. ■

When the matrix $H(t)$ in (10) is chosen as an identity matrix, the proposed observer is the high-gain nonlinear observer which has been studied in the works of Busawon et al.[5]. The first element of $H(t)$ is 1 corresponding to the measured state of system. Another element of $H(t)$ can be chosen under the Assumption (A7) to make the estimated state converge faster to its real value.

IV. Application to stirred tank bioreactor

4.1 Process model

The system dynamic equations on the substrate and the biomass in bioreactor are given as the following[8]

$$\dot{S} = -k\mu(S)X + (S_{in}-S)D \quad (20)$$

$$\dot{X} = \mu(S)X - XD \quad (21)$$

where

- X : biomass concentration in the reactor
- S : substrate concentration in the reactor
- D : dilution rate
- μ : the specific growth rate
- k : the known yield coefficient
- S_{in} : external inlet substrate concentration

The specific growth rate is known to be a complex function of plant states and several biological parameters. More than 60 expressions have been suggested. One of the well-known model is the Haldane's law as follows

$$\mu(S) = \frac{k_i\mu_m S}{k_s k_i + k_i S + S^2} \quad (22)$$

where

- μ_m : the maximum specific growth rate
- k_s : saturation constant
- k_i : inhibition constant

4.2 Observer design

We consider two cases: 1) measure substrate concentration S and then estimate biomass concentration X using Haldane's specific growth rate and 2) measure biomass concentration X and then estimate the specific growth rate μ without any assumption on its model.

4.2.1 Case 1: Estimation of X from the measurement of S when μ satisfies Haden's law

The system can be rewritten in the following form

$$\begin{bmatrix}\dot{S}\\ \dot{X}\end{bmatrix} = \begin{bmatrix}0 & -k\mu(S)\\ 0 & 0\end{bmatrix}\begin{bmatrix}S\\ X\end{bmatrix} + \begin{bmatrix}D(S_{in}-S)\\ \mu(S)X - DX\end{bmatrix} \quad (23)$$

$$y = \begin{bmatrix}1 & 0\end{bmatrix}\begin{bmatrix}S\\ X\end{bmatrix} \quad (24)$$

Apply the proposed observer (12) with

$$\hat{z} = [\hat{S} \quad \hat{X}]^T$$
$$F(s,\hat{z}) = \begin{bmatrix}0 & f_1(s,\xi)\\ 0 & 0\end{bmatrix} = \begin{bmatrix}0 & -k\mu(\hat{S})\\ 0 & 0\end{bmatrix}$$
$$\mu(\hat{S}) = \frac{k_i\mu_m\hat{S}}{k_s k_i + k_i\hat{S} + \hat{S}^2}$$
$$G(u,s,\hat{z}) = \begin{bmatrix}D(S_{in}-\hat{S})\\ \mu(\hat{S})\hat{X} - D\hat{X}\end{bmatrix}$$
$$H(t) = \begin{bmatrix}1 & 0\\ 0 & h_1(t)\end{bmatrix}$$
$$M^{-1}(s,\hat{z},t) = \begin{bmatrix}1 & 0\\ 0 & \frac{1}{f_1(s,\hat{z})}\end{bmatrix} = \begin{bmatrix}1 & 0\\ 0 & -\frac{1}{k\mu(\hat{S})}\end{bmatrix}$$
$$S^{-1}{}_\lambda = \begin{bmatrix}2\lambda & \lambda^2\\ \lambda^2 & \lambda^3\end{bmatrix}$$
$$C = \begin{bmatrix}1 & 0\end{bmatrix}$$
$$\hat{z} - z = \begin{bmatrix}\hat{S}-S & \hat{X}-X\end{bmatrix}^T$$

The proposed observer is as follows

$$\begin{cases}\dot{\hat{S}} = -k\mu(S)\hat{X} + (S_{in}-\hat{S})D - 2\lambda(\hat{S}-S)\\ \dot{\hat{X}} = \mu(\hat{S})\hat{X} - \hat{X}D + h_1(t)\frac{\lambda^2}{k\mu(\hat{S})}(\hat{S}-S)\end{cases} \quad (25)$$

4.2.2 Case 2: Estimation of μ from the measurement of X without any assumption on the model of μ

In this case, no information on μ is available, we assume instead that μ satisfies $\dot{\mu} = \phi(t)$ with unknown bounded function $\phi(t)$. The system can be rewritten in the following form

$$\begin{bmatrix}\dot{X}\\ \dot{\mu}\end{bmatrix}=\begin{bmatrix}0 & X\\ 0 & 0\end{bmatrix}\begin{bmatrix}X\\ \mu\end{bmatrix}+\begin{bmatrix}-XD\\ \phi\end{bmatrix} \quad (26)$$

$$y=\begin{bmatrix}1 & 0\end{bmatrix}\begin{bmatrix}X\\ \mu\end{bmatrix} \quad (27)$$

Apply the proposed observer (12) to the system with

$$\hat{z}=[\hat{X} \quad \hat{\mu}]^T$$

$$F(s,\hat{z})=\begin{bmatrix}0 & f_1(s,\xi)\\ 0 & 0\end{bmatrix}=\begin{bmatrix}0 & \hat{X}\\ 0 & 0\end{bmatrix}$$

$$G(u,s,\hat{z})=\begin{bmatrix}-\hat{X}D\\ \hat{\phi}\end{bmatrix}$$

$$H(t)=\begin{bmatrix}1 & 0\\ 0 & h_1(t)\end{bmatrix}$$

$$M^{-1}(s,\hat{z},t)=\begin{bmatrix}1 & 0\\ 0 & \dfrac{1}{f_1(s,\hat{z})}\end{bmatrix}=\begin{bmatrix}1 & 0\\ 0 & \dfrac{1}{\hat{X}}\end{bmatrix}$$

$$S^{-1}{}_{\lambda}=\begin{bmatrix}2\lambda & \lambda^2\\ \lambda^2 & \lambda^3\end{bmatrix}$$

$$C=\begin{bmatrix}1 & 0\end{bmatrix}$$

$$\varepsilon=\hat{z}-z=\begin{bmatrix}\hat{X}-X & \hat{\mu}-\mu\end{bmatrix}^T$$

which yields

$$\begin{cases}\dot{\hat{X}}=\hat{\mu}\hat{X}-\hat{X}D-2\lambda(\hat{X}-X)\\ \dot{\hat{\mu}}=-h_1(t)\lambda^2\dfrac{\hat{X}-X}{\hat{X}}\end{cases} \quad (28)$$

The time depending function is chosen as

$$h_1(t)=1-e^{-t}+\varepsilon \quad (29)$$

where ε is a small number enough not to give an effect on simulation result. This function is stable and converges to unit when $t\rightarrow\infty$. Hence it satisfies Assumption (A7).

V. Simulation results

To verify the effectiveness of the proposed observer, simulations have been done with Busawon's observer and the proposed modified observer. The observers are used to estimate system states in the controlled system which has been done in our previous work[1].

The numerical values used for this simulation follow the work of Simutis et al.[7] and are given as Table 1.

Table 1. The numerical values for simulation.

Parameters		Units	Values
Saturation constant	k_s	g/l	0.1
Maximum specific growth rate	μ_m	$1/h$	0.3
Yield coefficient	k		2.0
Inhibition constant	k_i	g/l	50.0
Influent substrate concentration	S_{in}	g/l	20.0

In Busawon observer, $H(t)=diag([1,1])$ and in the proposed modified observer, $H(t)=diag[1,1-e^{-t}+\varepsilon]$. The noise of zero mean and standard deviation of 5% is used in this simulation.

The first simulation is done with estimation of X from the measurement of S when μ satisfies Halden's law. Parameter λ is chosen as 6. Simulation results are given in Figs. 1-6. Fig. 1 shows reference substrate concentration S_{ref}, output substrate concentration S and estimated substrate concentra-tion $\hat{S}$ by proposed method and Busawon method when reference substrate S_{ref} is assumed to be changed as a step type with the constant influent substrate concentration. Because we measure S, the values of $\hat{S}$ can be estimated using Busawon's and the proposed observer's results are not far from those real values and can be seen form Fig. 3. Fig. 2 shows output biomass concentration X and those estimated values $\hat{X}$ using both observers. The proposed observer estimates output substrate X faster than Busawon's observer as shown in Fig. 4. The errors of estimation are given in Figs. 5 and 6. Both figures show that the proposed observer has better performance comparing to Busawon's observer. When the time is large enough, both observers are identical because we choose $h_1(t)=1-e^{-t}+\varepsilon$ which converges to unit when $t\rightarrow\infty$.

The second simulation is done with estimation of μ from the measurement of X without any assumption on the model of μ. Parameter λ is chosen as 2. Simulation results are given in Figs. 7-9. Fig. 7 shows the biomass concentrations and their errors are given in Fig. 9. The specific growth rates of the controlled process are given in Fig. 8 and their errors are given in Fig. 10. The bigger value of λ is chosen, the faster the estimation value converges to its real value. Of course, there is the bigger estimation error. From these figures, we can conclude that the proposed observer has a better performance comparing to the original Busawon's observer.

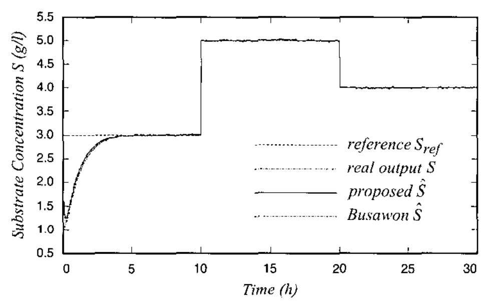

Fig. 1. Substrate concentrations: reference, estimations and output during the step change of biomass substrate concentration.

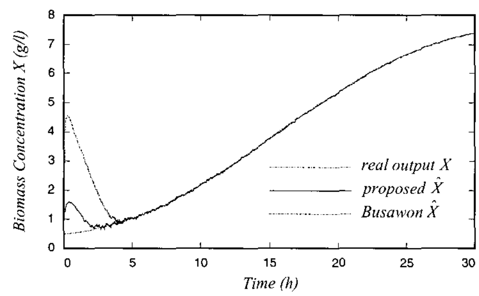

Fig. 2. Biomass concentrations: estimations and output during the step change of biomass substrate concentration.

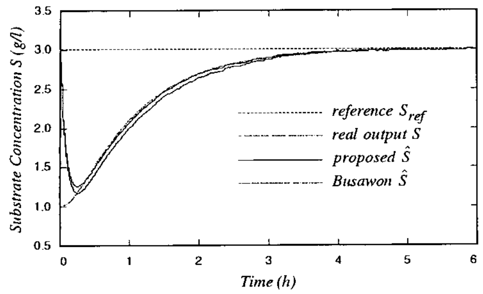

Fig. 3. Substrate concentrations: reference, estimations and output during the step change of biomass substrate concentration.

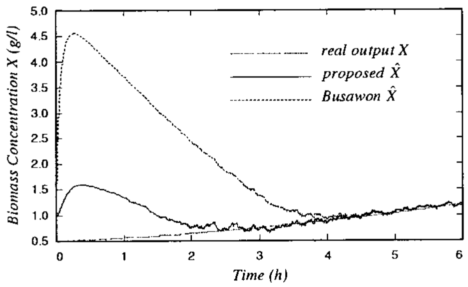

Fig. 4. Biomass concentrations: estimations and output during the step change of biomass substrate concentration.

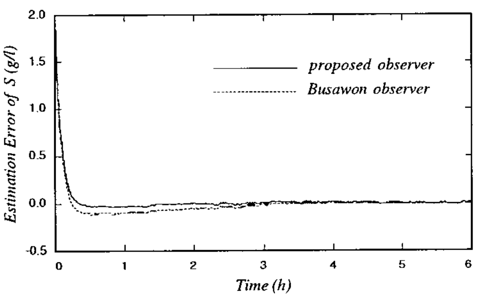

Fig. 5. Errors of estimated substrate concentration.

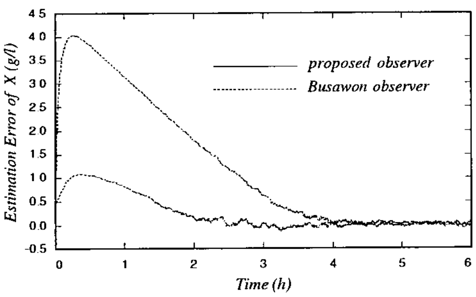

Fig. 6. Errors of estimated biomass concentration.

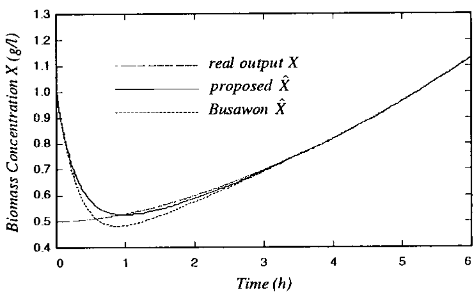

Fig. 7. Biomass concentration.

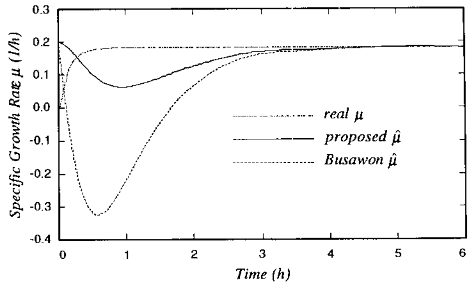

Fig. 8. Specific growth rates: real value, estimated values with proposed and Busawon's observer.

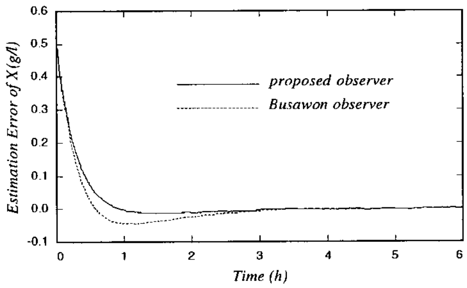

Fig. 9 Errors of estimated biomass concentration.

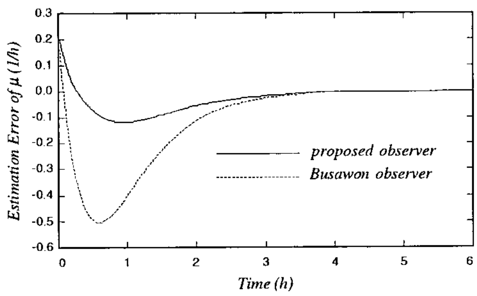

Fig. 10. Errors of estimated specific growth rate.

VI. Conclusion

A modified nonlinear observer based on Busawon's observer is introduced. By using appropriate time depending bounded function, the modified observer shows faster convergence to its real value than Busawon's observer. The proof of the stability of the modified observer using Lyapunov function approach is given. The modified observer is applied for estimating output substrate concentration and biomass concentration of a continuous baker's yeast cultivating process in stirred tank bioreactor. In the case of using no model of specific growth rate, we can also use the proposed observer to estimate the specific growth rate using only measuring the biomass concentration. The effectiveness of the modified observer is shown through the simulation. The simulation results show that the proposed observer has good performance with smaller error and faster estimation than Busawon's observer.

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Appendix A

$$\hat{M}\Delta_\lambda(\hat{F}-H\hat{M}^{-1}S_\lambda^{-1}C^TC)\Delta_\lambda^{-1}\hat{M}^{-1}$$
$$=\Delta_\lambda\hat{M}\hat{F}\Delta_\lambda^{-1}\hat{M}^{-1}-\Delta_\lambda\hat{M}H\hat{M}^{-1}S_\lambda^{-1}C^TC\Delta_\lambda^{-1}\hat{M}^{-1}$$
$$=\Delta_\lambda\hat{M}\hat{F}\hat{M}^{-1}\Delta_\lambda^{-1}-\Delta_\lambda\hat{M}H\hat{M}^{-1}S_\lambda^{-1}C^TC\Delta_\lambda^{-1}\hat{M}^{-1}$$
$$=\Delta_\lambda HA\Delta_\lambda^{-1}-\lambda\Delta_\lambda\hat{M}\hat{M}^{-1}H\Delta_\lambda^{-1}S_1^{-1}\Delta_\lambda^{-1}C^TC$$
$$=\lambda A-\lambda\Delta_\lambda H\Delta_\lambda^{-1}S_1^{-1}\Delta_\lambda^{-1}C^TC$$
$$=\lambda(A-H\Delta_\lambda\Delta_\lambda^{-1}S_1^{-1}C^TC)=\lambda(A-HS_1^{-1}C^TC)$$

where

$$\hat{M}\hat{F}\hat{M}^{-1}=HA$$
$$C^TC\Delta_\lambda^{-1}\hat{M}^{-1}=C^TC$$
$$S_\lambda^{-1}=\lambda\Delta_\lambda^{-1}S_1^{-1}\Delta_\lambda^{-1}$$
$$\Delta_\lambda HA\Delta_\lambda^{-1}=\lambda HA=\lambda A$$

Appendix B

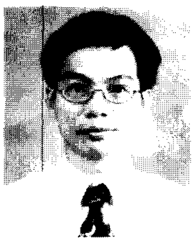
$$2\bar{\varepsilon}^TS_1\dot{\hat{M}}\hat{M}^{-1}\bar{\varepsilon}+2\lambda\bar{\varepsilon}^TS_1(A-HS_1^{-1}C^TC)\bar{\varepsilon}$$
$$=2\bar{\varepsilon}^TS_1\dot{\hat{M}}\hat{M}^{-1}\bar{\varepsilon}+\lambda\bar{\varepsilon}^T(2S_1A-2S_1HS_1^{-1}C^TC)\bar{\varepsilon}$$
$$=2\bar{\varepsilon}^TS_1\dot{\hat{M}}\hat{M}^{-1}\bar{\varepsilon}+\lambda\bar{\varepsilon}^T(2S_1A)\bar{\varepsilon}-\lambda\bar{\varepsilon}^T(2S_1HS_1^{-1}C^TC)\bar{\varepsilon}$$
$$=2\bar{\varepsilon}^TS_1\dot{\hat{M}}\hat{M}^{-1}\bar{\varepsilon}+\lambda\bar{\varepsilon}^T(-S_1+C^TC)\bar{\varepsilon}$$
$$-\lambda\bar{\varepsilon}^T(2S_1HS_1^{-1}C^TC)\bar{\varepsilon}$$
$$=2\bar{\varepsilon}^TS_1\dot{\hat{M}}\hat{M}^{-1}\bar{\varepsilon}+\lambda\bar{\varepsilon}^T(-S_1+C^TC-2S_1HS_1^{-1}C^TC)\bar{\varepsilon}$$
$$=2\bar{\varepsilon}^TS_1\dot{\hat{M}}\hat{M}^{-1}\bar{\varepsilon}$$
$$-\lambda\bar{\varepsilon}^TS_1\bar{\varepsilon}+\lambda\bar{\varepsilon}^T(-C^TC+2C^TC-2S_1HS_1^{-1}C^TC)\bar{\varepsilon}$$
$$=2\bar{\varepsilon}^TS_1\hat{M}\hat{M}^{-1}\bar{\varepsilon}-\lambda V$$
$$-\lambda\bar{\varepsilon}^TC^TC\bar{\varepsilon}-2\lambda\bar{\varepsilon}^T(S_1HS_1^{-1}-I)C^TC\bar{\varepsilon}$$
$$=2\bar{\varepsilon}^TS_1\hat{M}\hat{M}^{-1}\bar{\varepsilon}-\lambda V$$
$$-\lambda\bar{\varepsilon}^TC^TC\bar{\varepsilon}-2\lambda\bar{\varepsilon}^TS_1(H-I)S_1^{-1}C^TC\bar{\varepsilon}$$

where

$$\bar{\varepsilon}^T(2S_1A)\bar{\varepsilon}=\bar{\varepsilon}^T(-S_1+C^TC)\bar{\varepsilon}$$

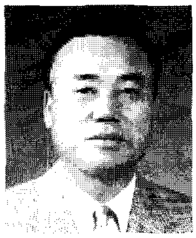
Hak Kyeong Kim

He was born in Korea on November 11, 1958. He received the B.S. and M.S. degrees at Dept. of Mechanical Engineering from Pusan National University, Korea in 1983 and 1985. He received Ph.D degree at the Dept. of Mechatronics Engineering, Pukyong National University, Pusan, Korea in February, 2002. His fields of interest are Identification, Biomechanical Control, Environmental Monitoring, and Image Processing Control.



Tan Tien Nguyen

He was born in Vietnam on June 29, 1968. He received the B.S. at the Dept. of Mechanical Engineering, Hochiminh City University of Technology, Vietnam in 1990. He received M.S. degree and Ph.D degree at the Dept. of Mechanical Engineering, Pukyong National University, Pusan, Korea in August, 1998 and in August, 2001. He is a Professor of the Dept. of Mechanical Engineering, Hochiminh City University of Technology, Vietnam. His fields of interest are Robust Control, Nonlinear Control and Welding Automation Process Control.



Sang Bong Kim

He was born in Korea on August 6, 1955. He received the B.S. and M.S. degrees from National Fisheries University of Pusan, Korea in 1978 and 1980. He received PhD. degree in Tokyo Institute of Technology, Japan in 1988. After then, he is a Professor of the Dept. of Mechanical Engineering, Pukyong National University, Pusan, Korea. His research has been on Robust Control, Biomechanical Control, and Mobile Robot Control.