ISSN No: 2348-4845
International Journal & Magazine of Engineering, Technology, Management and Research
A Peer Reviewed Open Access International Journal

Observer Synthesis for Nonlinear of Switched Dynamical Systems Application to Bioreactor

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Abstract:

Switched systems constitute a subclass of hybrid systems, which are systems where both continuous and discrete event dynamics are tangled together. In this work, we construct an observer for nonlinear systems under rather generaltechnical assumptions that some functions are globally Lipschitz. This observer works either for autonomous systems or for nonlinear systems that are observable for any input. A tentative application to biological systems is described.

Index Terms:
Switching systems, High gain observer, Hybrid dynamical system.

1.INTRODUCTION:

During the two last decades, Hybrid Dynamical Systems (HDSs) have been greatly investigated. These systems have the property to tangle discrete and continuous dynamics. They allow modeling a large class of systems arising in a great variety of fields of interest, such as electronics, physics, chemistry, etc. Many works regard the stability, controllability and observability of HDSs.Further works related to observation of HDSs can be found in .An interesting class of HDSs is that of Switched Dynamical Systems (SDSs) that are HDSs with no jumps in the state. In particular, Linear Switched Dynamical Systems (LSDSs) constitute a well studied class of dynamical systems.They are characterized by some switching time instants, when the equations describing the continuous dynamics change. It is common to assume that the number of switching's in any finite time interval is finite, viz. no Zero phenomena occur.

While for LSDSs some results on observability properties and observer design can be found in the literature, nonlinear SDSs suffer from a lack of available results. In the present paper, the study is focused on the observabilityproperties of the class of nonlinear SDSs for which each subsystem admits a linearization, modulo an output injection, . Moreover, starting from an observer synthesis technique for LSDSs, the observer design is generalized to the considered class of nonlinear SDS.

Some know facts about linear switched dynamical systems:

In this section the following class of LSDS is considered Consider single-output analytic equation

$$\Sigma:\begin{cases}\dot{x} = f(x)\\ y = h(x)\end{cases}$$

in which $x \in R^n$, and moreover there is a "physical subset" $\Omega \in R^n$ under consideration, on which we are interested in the observation problem. In most practical cases, Ω will be an open connected relatively compact subset of R^n, and in the ideal cases, n will be positively-invariant under the dynamics ($\sum$). We assume that ($\sum$) is observable on Ω, i.e., the data of the output $y\,(t)$ on any finite time interval $[t_0 t_i]\,, t_i > t_0$ completely determines the initial state $x(t_r)$. (At least for trajectories $x(t)$, such that $x(t) \in \Omega$ for any $t \in [t_0, t_1]$) The fact that ($\sum$) is observable is equivalent to the requirement that the set of functions, called the observation space of ($\sum$), $\Theta(\Sigma) = \{h, L_f h, \cdots, L_f^i h, \cdots i \geq 0\}$ separates the points on Ω, i.e., $\forall x_1, x_2 \in \Omega, \exists i,$

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International Journal & Magazine of Engineering, Technology, Management and Research
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s.t. $L_f^i h(x_1) \neq L_f^i h(x_2)$ (*L* denotes the Lie derivative operator). This is due to the formula $(t) = \sum_{k=0}^{+\infty} L_f^k h(x_0)\, t^k / k!$.

It is easily seen that when (e) is observable, the map is almost everywhere regular .Our main assumptions will be as follows. Our main assumptions will be as follows. ***HI***: F_Σ is a diffeomorphism from $\boldsymbol{\Omega}$ onto $F_\Sigma(\boldsymbol{\Omega})$ [as soon as there **is** no ambiguity we refer to $\boldsymbol{\Omega}$ instead of $F_\Sigma(\boldsymbol{\Omega})$. From this assumption it follows that, on $\boldsymbol{\Omega}$, in the global coordinate system defined by $F_\Sigma(\sum)$ can be written as the following.

H2: φ can be extended from $\boldsymbol{\Omega}$ to all of R^n by a C^∞ function, globally Lipschitzian on R^n (w.r.t. any norm).Definition *1:* When Assumptions H1 and H2 hold, we say that $(\sum)$ is uniformly observable ***on*** $\boldsymbol{\Omega}$, or $(\sum')$ is uniformly Uniform observability clearly means that the initial state can be observable *on* R^n.

The ***Statement*** of the Result

$$\dot{\hat{x}} = F'(\hat{x}) - S_\infty^{-1} C'(C\hat{x} - y) \qquad \hat{x} \in R^n$$

Assumption 1: for each time instant $t \in [0, \infty)$, the function value $\sigma(t)$ is known.

Assumption 2: the switching function σ has a minimal dwell time τ_{min} .

Assumption 3: each subsystem is observable

2.ESTIMATORS AND OBSERVERS:

A problem arises in which the internal states of many systems cannot be directly observed, and therefore state feedback is not possible. What we can do is try to design a separate system, known as an observer or an estimator that attempts to duplicate the values of the state vector of the plant, except in a way that is observable for use in state feedback. Some literature calls these components "observers", although they do not strictly observe the state directly. Instead, these devices use mathematical relations to try and determine an estimate of the state. Therefore, we will use the term "estimator", although the terms may be used interchangeably.

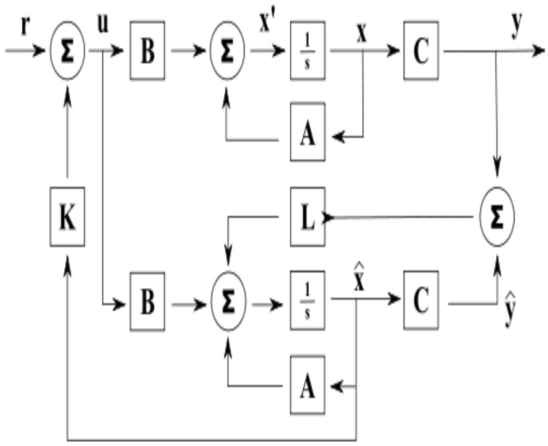
3.CREATING AN ESTIMATOR:

Notice that we know the A, B, C, and D matrices of our plant, so we can use these exact values in our estimator. We know the input to the system, we know the output of the system, and we have the system matrices of the system. What we do not know, necessarily, are the initial conditions of the plant. What the estimator tries to do is make the estimated state vector approach the actual state vector quickly, and then mirror the actual state vector. We do this using the following system for an observer:

$$\hat{x}' = A\hat{x} + Bu + L(y - \hat{y})$$

$$\hat{y} = C\hat{x} + Du$$

L is a matrix that we define that will help drive the error to zero, and therefore drive the estimate to the actual value of the state. We do this by taking the difference between the plant output and the estimator output.



In order to make the estimator state approach the plant state, we need to define a new additional state vector called state error signal $e_x(t)$. We define this error signal as:

$$e_x(t) = x - \hat{x}$$

and it's derivative:

$$e_x'(t) = x' - \hat{x}'$$

We can show that the error signal will satisfy the following relationship:

$$e_x'(t) = Ax + Bu - (A\hat{x} + Bu + L(y - \hat{y}))$$

$$e_x'(t) = A(x - \hat{x}) - L(Cx - C\hat{x})$$

$$e_x'(t) = (A - LC)e_x(t)$$

We know that if the eigenvalues of the matrix *(A + LC)* all have negative real parts that:

ISSN No: 2348-4845
International Journal & Magazine of Engineering, Technology, Management and Research
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$$e_x(t) = e^{(A+LC)}e_x(t_0) \longrightarrow 0$$

when $t \to \infty$.

This $e_x(\infty) = 0$ means that the difference between the state of the plant $x(t)$ and the estimated state of the observer $\hat{x}(t)$ tends to fade as time approaches infinity.

4. SEPARATION PRINCIPLE:

We have two equations:

$$e_x[k+1] = (A - LC)e_x[k]$$

$$x[k+1] = (A - BK)x[k] + BK \cdot e_x[k]$$

We can combine them into a single system of equations to represent the entire system:

$$\begin{bmatrix} e_x[k+1] \\ x[k+1] \end{bmatrix} = \begin{bmatrix} A - LC & 0 \\ +BK & A - BK \end{bmatrix} \begin{bmatrix} e_x[k] \\ x[k] \end{bmatrix}$$

We can find the characteristic equation easily using the separation principle. We take the Z-Transform of this digital system, and take the determinant of the coefficient matrix to find the characteristic equation. The characteristic equation of the whole system is:

(remember the well known $(zI - A)^{-1}$)

$$\begin{vmatrix} zI - A + LC & 0 \\ -BK & zI - A + BK \end{vmatrix} = |zI - A + LC||zI - A + BK|$$

Notice that the determinant of the large matrix can be broken down into the product of two smaller determinants. The first determinant is clearly the characteristic equation of the estimator, and the second is clearly the characteristic equation of the plant. Notice also that we can design the L and K matrices independently of one another.It is worth mentioning that if the order of the system is n, this characteristic equation (full-order state observer plus original system) becomes of order 2n and so has twice the number of roots of the original system.

- Any application of dynamical system is solved by luenberger observer and high gain observer
- An M-file program is written in MATLAB for steady state and transient analysis by using Lipschitz theorem.
- Grobner's formulae are applied for real values estimation (for improving stability range).
- By considering white (or Gaussian) noise for state estimation.

5.M.FILE PROGRAM :

```
% in this M-file we simulate the high-gain observer
with updated gain and

% time
clear all
close all
clc

                         %%%parameter of the observer
a1=1;
alpha=.9;                              %a1*alpha<=1;
a2=0.1;
a3=0.1;

                    %%%%%%Parameter of the Euler integration

dt=.001;                                % pas d'integration
tf=40;                                     % Final time
NbP=tf/dt;                   % Number of integration step
Nbtk=1;                               % Estimation counter
Tpast=0;
 global sin;
sin=.3;
            % Biological parameter for the bioreactor
                                     %%%%% Noise Parameter
StandDev = 0.05;     % Standard deviation of
measurement noise
umax=.3;                            % Input maximal value
                          %%%%%%%%%% initialization

t=zeros (1,NbP+1);
xo=zeros(2,NbP+1);
x=zeros (2,NbP+1);
zo=zeros(2,NbP+1);
z=zeros(2,NbP+1);
u=zeros(1,NbP);
LL=zeros(1,NbP);
c =zeros(1,NbP);

                       %%%%%% Initialization of the state
x(:,1)=[.15 ;0.003];
z(:,1)=[.15 ; x(1,1)*x(2,1)/(x(1,1)-x(2,1))];

                         %% Initialization of the observer

xo(:,1)=[.15 ; 0.003 ];                  % Observer state
zo(:,1)=[.15 ; 0.08 ];
M(1)=5;                              % High-gain parameter
L(1)=1;                              % High-gain parameter

 %%normal form
```

ISSN No: 2348-4845
International Journal & Magazine of Engineering, Technology, Management and Research
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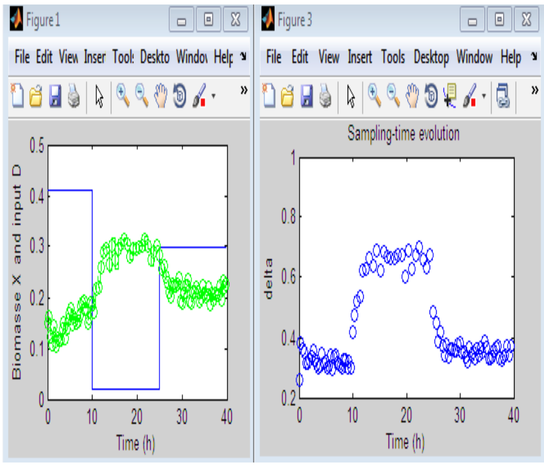
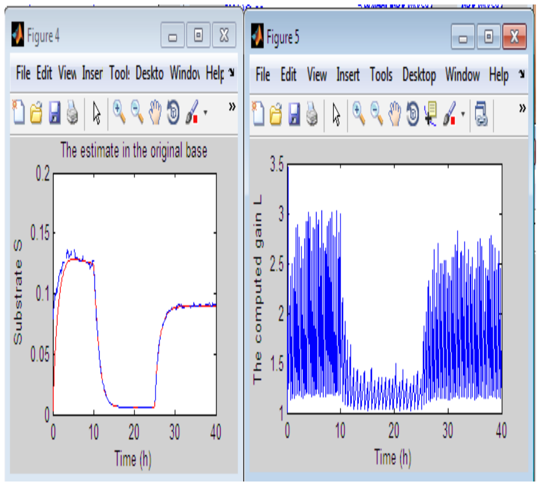
```
A=[0 1   0  0];
C=[1 0];
[k1, k2]=solve ('k1/2 - (k1^2 + 4*k2)^(1/2)/2=-1','k1/2 + (k1^2 + 4*k2)^(1/2)/2=-1');
 K=[k1 0;k2 0];
                                % Data of the grid which compute the max of the Lipschitz constant
x2min = 0.001;
x2max = 0.05;
x1min = 0.01;
x1max = 0.3;
                                % Initialization of the variables
t(1)=0;
q=1;
tt(1)=0;
y(1)=x(1,1);
yob (1)=z(1,1);
for k=1:NbP
 t(k+1)=k*dt;
                                % The controled input sequence
 If t (k)<=10
      u(k)=0.41;
   elseif (t(k)-10)>=0
      if t(k)<=25
      u(k)=0.02;
      elseif (t(k)-25)>=0
         if t(k)<=35
            u(k)=0.3;
        else
         u(k)=.3;
         end
     end
   end
 end

figure (4)
plot(t,z(2,:),'r',t,zo(2,:),'--')   % The estimate in the original base
xlabel('Time (h)')
ylabel(' Substrate S')
title('The estimate in the original base')
figure(5)
plot(t(1:end-1),LL)
xlabel('Time (h)')
ylabel('The computed gain L')
```

6.SIMULATION RESULTS:





7.GABOR FUNCTIONS:

```
% Compute two Gabor functions often also
% called Gabor atoms, or also gaborettes.
t=-10:0.001:10;
b1=0;
a1=1;
 b2=6;
a2=1./1.9;
g1=real(exp((-((t-b1)).^2)).*(exp(i.*((2).*pi).*((t-b1)))));
g2=real(exp((-((t-b2)).^2)).*(exp(i.*((4).*pi).*((t-b2)))));
 plot(t,g1,'b',t,g2,'b');
axis([-10 10 -2.05 2.05]);
title('Two Gabor functions');
```

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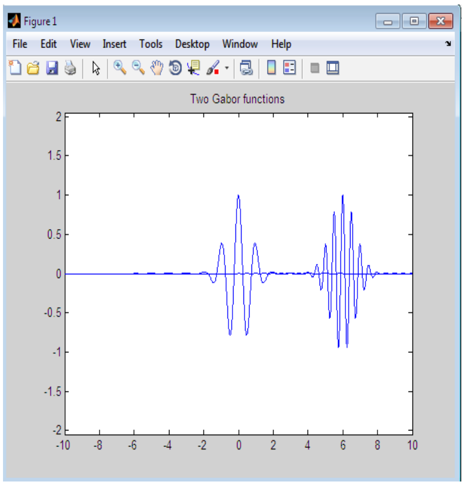
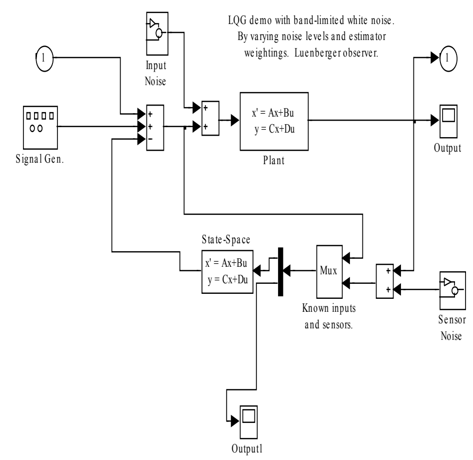
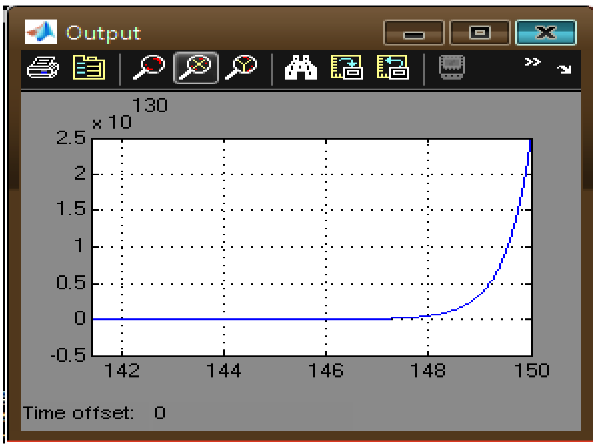


8.LUENBERGER OBSERVER





9. CONCLUSION:

In this paper the problem of observer synthesis has been studied for some class of switched systems. A Luenbergerlike observer for SDS has been extended to a class of nonlinear system linearizable with output injection.

Moreover, a high gain observer design has been proposed for classof hybrid systems, which can be transformed to a triangular form by a diffeomorphism. An application to an electronic oscillator, whose equations are singularly perturbed, has beenpresented.Further studies should focus on modeling a class of singularly perturbed system with modeled by SDS, such asBelousov–Zhabotinsky system, or systems with fast actuators, and include a thorough study on the impact of switching estimation for those classes of systems.

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