

# Nonlinear Event-triggered Control and Self-triggered Control for Linear Systems

Fairouz Zobiri, Nacim Meslem, Brigitte Bidégaray-Fesquet

Univ. Grenoble Alpes, Laboratoire Jean Kuntzmann and GIPSA-lab, Grenoble, France



# Recap

Recall that in the case of a linear system

$$\dot{x}(t) = Ax(t) + Bu(t),$$

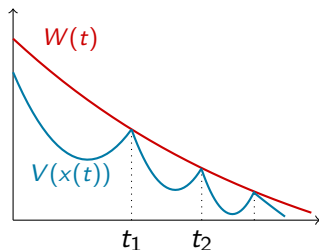
$u$  is the event-triggered control law

$$\begin{aligned} u(t_k) &= -Kx(t_k), & t = t_k, & k \in \mathbb{N} \\ u(t) &= u(t_k), & t \in [t_k, t_{k+1}). \end{aligned}$$

The time instants  $t_k$  are defined as

$$t_k = \{t > t_{k-1} \mid V(x(t)) \geq W(t)\}.$$

In the linear case:  
 $V(x(t)) = x(t)^T P x(t)$ , and  
 $W(t) = W_k e^{-\alpha(t-t_k)}$ , or a  
constant threshold.



# Nonlinear Case

In the case of the nonlinear system of the form

$$\dot{x}(t) = f(x, u).$$

- No standard form for the Lyapunov function exists,
- finding a Lyapunov function can be an arduous task,
- event-triggered control algorithm cannot be described in details.

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# Contraction Analysis!

# Contraction Analysis Overview

Consider the system

$$\dot{x} = f(x). \quad (1)$$

Consider two neighboring trajectories.  $\delta x$  is the virtual displacement between them. A contraction region is defined as a region where

$$\frac{1}{2} \delta x^T \left( \frac{\partial f^T}{\partial x} + \frac{\partial f}{\partial x} \right) \delta x \leq -\beta \delta x^T \delta x.$$

A trajectory that starts in a contraction region remains there, and the system is exponentially stable.

**Not always the case!**

# Contraction Analysis Overview

Operate the following coordinate change

$$\delta z = \Theta \delta x.$$

Where  $\Theta(x)$  is a square matrix. In the new coordinate system

$$\frac{d}{dt} \delta z = \left( \dot{\Theta} + \Theta \frac{\partial f}{\partial x} \right) \Theta^{-1} \delta z = F \delta z$$

A contraction region is then defined as

$$\delta x^T \left( \frac{\partial f^T}{\partial x} M + \dot{M} + M \frac{\partial f}{\partial x} \right) \delta x \leq -\beta_m \delta x^T M \delta x.$$

where  $\beta_m > 0$  and  $M(x) = \Theta^T \Theta$  is a positive definite square matrix.

# Nonlinear Event-Triggered Control

Consider the system

$$\dot{x} = f(x) + g(x)u,$$

where  $u$  is an event-triggered control law, and  $x_r$  is a reference trajectory that can be generated by

$$\dot{x}_r = f(x_r) + g(x_r)u_r, \quad (2)$$

where  $u_r$  is a continuous-time control law.

Let  $\delta x$  be the virtual displacement between the two trajectories

$$\delta x = x - x_r.$$

If the two trajectories are close enough, the virtual velocity is approximated by

$$\delta \dot{x} \approx A(x)\delta x + g(x)\delta u, \quad A(x) = \frac{\partial f}{\partial x}. \quad (3)$$

where  $\delta u = -K(x)\delta x$ .

# Nonlinear Event-Triggered Control

The generalized Jacobian is  $F = \left( \dot{\Theta} + \Theta(A(x) - Kg(x)) \right) \Theta^{-1}$ .

The control law is taken as

$$u = \int_{x_r}^x -K(\chi) d\chi.$$

The event-triggering conditions ensure that the trajectory remains inside a region of contraction, and the next sampling instant

$$t_k = \{t > t_{k-1} \mid \delta x^T \left( (A - gK)^T M + \dot{M} + M(A - gK) \right) \delta x \geq 0\}.$$



## Numerical Example

Consider the second order system

$$\begin{aligned}\dot{x}_1 &= x_2 + \sin x_1, \\ \dot{x}_2 &= x_1^2 + u, \\ x_0 &= [1.2 \quad 1]^T.\end{aligned}$$

We take

$$F = \begin{bmatrix} -2 & 1 \\ 1 & -3 \end{bmatrix}, \Theta = \begin{bmatrix} 1 & 0 \\ \cos x_1 + 2 & 1 \end{bmatrix}, M = \begin{bmatrix} (\cos x_1 + 2)^2 + 1 & \cos x_1 + 2 \\ \cos x_1 + 2 & 1 \end{bmatrix}$$

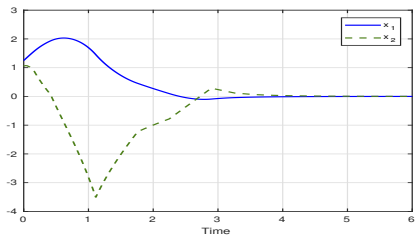
$$K = - \begin{bmatrix} -2x_1 + x_2 \sin x_1 - 2 \cos^2 x_1 - 3 \cos x_1, & -3 - \cos x_1 \end{bmatrix}.$$

And we select for the reference trajectory

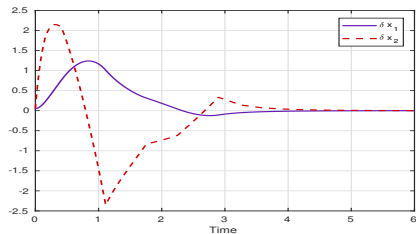
$$u_r = -x_1^2 - (x_2 + \sin x_1) \cos x_1 - k_1 x_1 - k_2 (x_2 + \sin x_1),$$

where  $k_1 = 6$ ,  $k_2 = 5$  and  $x_{r0} = [1.25 \quad 1.05]^T$ .

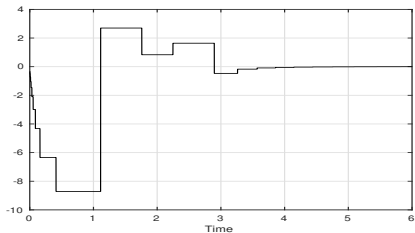
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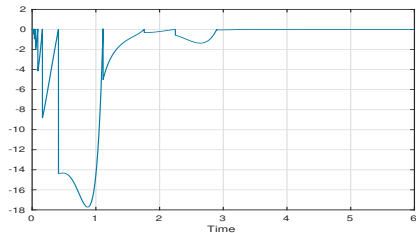
(a) States of the system



(b) Virtual displacement



(c) Control signal



(d) ETC

# Self-Triggered Control

# Self-Triggered Control

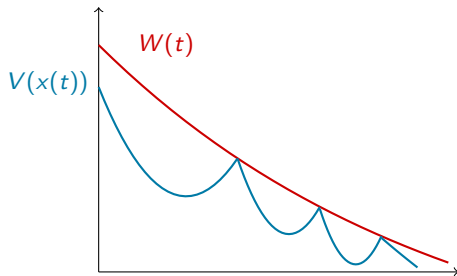
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$$x(t_0) = x_0.$$

$$u(t_k) = -Kx(t_k), \quad t \in [t_k, t_{k+1}).$$

In self-triggered control,  $t_{k+1}$  is computed at  $t_k$ .



# Self-Triggered Control

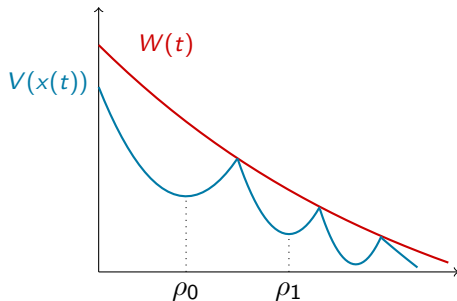
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# Self-Triggered Control

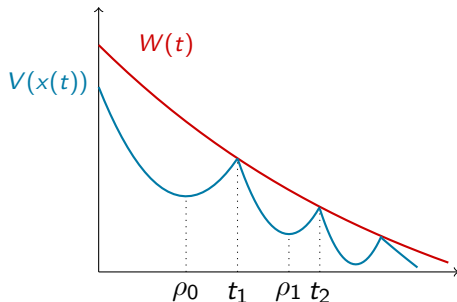
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# Self-Triggered Control

The self-triggered algorithm is divided into two stages

- look for  $\rho_k$ , the minimizer of  $V(x(t))$  on the interval  $[t_k, t_{k+1})$ .
- use  $\rho_k$  as a starting point to solve  $W(t) - V(x(t)) = 0$ .

We refer to the two stages as the minimization stage and the root-finding stage.

Finding  $\rho_k$  first offers many advantages

- it gives us an idea about the length of the interval  $[t_k, t_{k+1})$ ,
- it is close to  $t_{k+1}$ , allows us to use a locally convergent root-finding algorithm for fast convergence

## Minimization Stage

$$\dot{x}(t) = (A - BK)x(t) + BK e_k(t), \quad e_k(t) = x(t) - x_k(t).$$

Re-write the system's dynamics as

$$\begin{aligned} \dot{\xi}(t) &= \begin{bmatrix} A - BK & BK \\ A - BK & BK \end{bmatrix} \xi(t), \quad \xi(t) = \begin{bmatrix} x(t) & e_k(t) \end{bmatrix}^T, \\ \xi(t_0) &= \begin{bmatrix} x_0 & 0_n^T \end{bmatrix}^T =: \xi_0, \end{aligned} \quad (4)$$

We minimize the function  $V(\xi(t)) = \xi(t)^T \mathcal{P} \xi(t)$ , where

$$\mathcal{P} = \begin{bmatrix} P & 0 \\ 0 & 0 \end{bmatrix}$$

The minimization algorithm is a modified Newton algorithm, that takes  $t_k$  as the initial guess, modifies the search direction whenever it is not a direction of descent and performs a line search to scale the step size.



## Root-finding Stage

The root-finding algorithm is a hybrid Newton-bisection algorithm.

The root is located within an interval of length  $\kappa(\rho_k - t_k)$ ,  $\kappa > 1$ .

A Newton step is taken first, if the new iterate is outside of the interval or too close to the borders, the Newton iterate is rejected and a bisection step is taken instead.

## Numerical Example

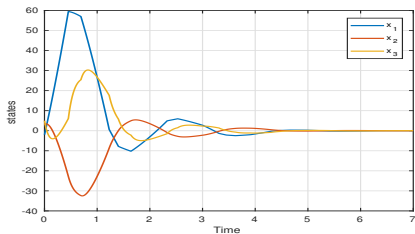
$$\dot{x}(t) = \begin{bmatrix} 1 & 1 & 0 \\ -2 & 0 & 4 \\ 5 & 4 & -7 \end{bmatrix} x(t) + \begin{bmatrix} -1 \\ 0 \\ 1 \end{bmatrix} u(t),$$

with initial state  $x_0 = [-2 \ 3 \ 5]^T$ . Let  $K = [ \ 8.38 \ 26.36 \ 10.38 ]$ , and

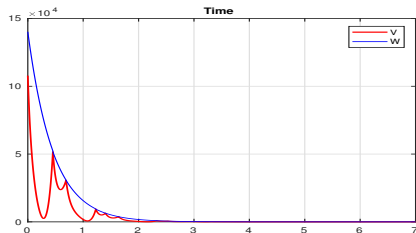
$$V(x(t)) = x(t)^T \begin{bmatrix} 275.7 & 1025.5 & 577.9 \\ 1025.5 & 3840.1 & 2173.5 \\ 577.9 & 2173.5 & 1234.1 \end{bmatrix} x(t), \quad (5)$$

$$W(t_0) = 1.3 V(x_0), \quad \alpha = 2.18.$$

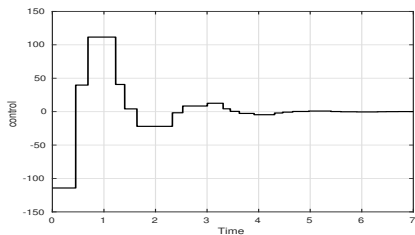
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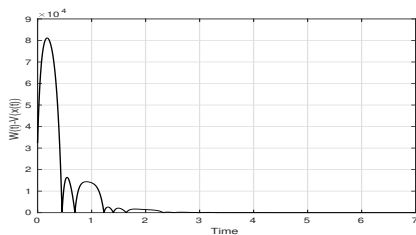
(a) States



(b) PLF and threshold



(c) Self-triggered control



(d) The difference  $W(t) - V(x(t))$