

# On the decay rate for degenerate gradient flows subject to persistent excitation

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# Degenerate gradient flows

$$\dot{x}(t) = -c(t)c(t)^\top x(t), \quad x \in \mathbb{R}^n, c : [0, +\infty) \rightarrow \mathbb{R}^n. \quad (\text{DGF})$$

These systems appear in algorithms for, e.g.,

1. Gradient descent with incomplete knowledge of the gradient
2. Identification and model reference adaptive control
3. Consensus in multi-agent systems

## Objectives

- (a) Guarantee convergence and stability of (DGF) at the origin
- (b) extract information on the decay rate (in case of exponential convergence).

# Motivation: Adaptive filters

## Problem

$z(t) = h^\top c(t)$  scalar output system, estimate parameter  $h \in \mathbb{R}^n$ , knowing input  $c : [0, +\infty) \rightarrow \mathbb{R}^n$  and output  $z : [0, +\infty) \rightarrow \mathbb{R}$ .

Let  $\hat{h} : [0, +\infty) \rightarrow \mathbb{R}^n$  estimate of  $h$  so that

$$\frac{d}{dt} \hat{h}(t) = (z(t) - \hat{z}(t))c(t), \quad \hat{z}(t) := \hat{h}(t)^\top c(t).$$

Error vector  $x(t) = h - \hat{h}(t)$  satisfies (DGF):

$$\dot{x}(t) = -(z(t) - \hat{z}(t))c(t) = -(x(t)^\top c(t))c(t)$$

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Convergence to 0 of (DGF)  $\iff$  Quality of the estimator  $\hat{h}$

Obvious fact:  $c : [0, +\infty) \rightarrow \mathbb{R}^n$  must "visit regularly" all directions!!  
 $\Rightarrow$  Need for such condition to have convergence.

# Persistent excitation

We say that  $c$  verifies the *persistent excitation* condition if

$$\exists a, b, T > 0, \quad \forall t \geq 0, \quad a \text{Id}_n \leq \int_t^{t+T} c(s)c(s)^\top ds \leq b \text{Id}_n. \quad (\text{PE})$$

**Theorem (cf., Anderson, Narendra, et al. 80s)**

Signal  $c$  verifies (PE) *if and only if* (DGF) is uniformly globally exponentially stable at 0, i.e.,

$$\exists C, \alpha > 0, \quad \|x(t)\| \leq Ce^{-\alpha(t-s)}\|x(s)\|, \quad \forall t > s \geq 0,$$

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- (PE) says that  $c$  “visits all directions of  $\mathbb{R}^n$  during a time window”.
- Upper bound  $b$  is *essential*: (cf. Barabanov *et al.* 2005), if  $b = +\infty$  it can happen that

$$x(t) \longrightarrow \bar{x} \neq 0 \quad \text{as } t \rightarrow +\infty$$

## Decay rate

Under (PE), system  $\dot{x} = -cc^\top x$  is *globally exponentially stable*:

$$\|x(t)\| \leq Ce^{-\alpha t} \|x(0)\|, \quad \forall t \geq 0, \quad (\text{GES})$$

with  $C, \alpha$  only depending on  $a, b, T$ .

*Decay rate* for a signal  $c$  verifying (DGF)

$$R(c) := \sup\{\alpha > 0 \mid (\text{GES}) \text{ holds}\} = - \limsup_{t \rightarrow +\infty} \frac{\log \|\Phi_c(t, 0)\|}{t},$$

$\Phi_c(t, 0)$  = fundamental matrix of (DGF) from 0 to  $t$ .

### Definition

The *worst decay rate* is

$$R(a, b, T, n) := \inf\{R(c) \mid c \text{ satisfies (PE) with parameters } a, b, T\}.$$

$\rightsquigarrow$  Yields *guaranteed* convergence rate for ANY signal  $c$  verifying (DGF).



# Main result

Many lower bounds for  $R(a, b, T, n)$  exist in the literature, of the type:

**Theorem (cf., Andersson and Krishnaprasad (2002))**

*There exists  $C_1 > 0$  such that*

$$R(a, b, T, n) \geq \frac{C_1 a}{(1 + nb^2)T}, \quad \forall T > 0, a < b, n \in \mathbb{N}.$$

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## Theorem (C.-Mason-Prandi)

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↪ We recover the result by Barabanov *et al.* (2005) if  $b = +\infty$ .

## Application I: $L^2$ -gain for (DGF) systems with linear input

Consider the controlled (DGF) system:

$$\dot{x}(t) = -c(t)c(t)^\top x(t) + u(t), \quad u \in L^2([0, +\infty), \mathbb{R}^n).$$

Let  $\gamma(c)$  be the  $L^2$ -gain of the input/output map  $u \mapsto x$ :

$$\gamma(c) = \sup_{u \in L^2 \setminus \{0\}} \frac{\|x_u\|_2}{\|u\|_2}$$

Rantzer (1999) posed the problem of determining the **worst  $L^2$  gain**:

$$\gamma(a, b, T, n) = \sup\{\gamma(c) \mid c \text{ satisfies (PE)}\}.$$

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### Theorem (C.-Mason-Prandi)

*There exists  $\kappa_0, \kappa_1 > 0$  such that for all  $T > 0$ ,  $a \leq b$ ,  $n \geq 2$ , it holds*

$$\kappa_0 \frac{(1 + b^2)T}{a} \leq \gamma(a, b, T, n) \leq \kappa_1 \frac{(1 + nb^2)T}{a}.$$

# Sketch of the proof

## Idea

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**Polar coordinates:** Letting  $x = r\omega$  for  $r > 0$  and  $\omega \in \mathbb{S}^{n-1}$ , (DGF) reads

$$\begin{cases} \dot{r} &= -(c^\top \omega)^2 r, \\ \dot{\omega} &= -c^\top \omega (c - (c^\top \omega)\omega), \quad (Pol) \end{cases} \quad r_0 = \|x(0)\|, \quad \omega_0 = \frac{x(0)}{\|x(0)\|}.$$



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Connect  $R(a, b, T, n) = \inf R(c)$  with an optimal control problem.

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- (Pol) = Dynamics of  $\omega$  **independent of**  $r$ .
- The dynamics of  $r$  yield:

$$-\log \frac{\|x(T)\|}{\|x(0)\|} = -\log \frac{r(T)}{r(0)} = \int_0^T (c^\top \omega)^2 ds =: J_T(c, \omega_0).$$

## Sketch of the proof II

**Optimal control problem:**

$$\mu(a, b, T, n) := \min J_T(c, \omega_0) = \min \int_0^T (c^\top \omega)^2 ds$$

Here,  $c : [0, T] \rightarrow \mathbb{R}^n$  runs over all signals satisfying

$$a \text{Id}_n \leq \int_0^T c(s)c(s)^\top ds \leq b \text{Id}_n,$$

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**Steps:**

1. Prove that

$$R(a, b, T, n) \leq 2 \frac{\mu(a/2, b/2, T, n)}{T}$$

$\rightsquigarrow$  Show that  $\mu(a/2, b/2, T, n)$  is realized by an optimal control

$c_* : [0, T] \rightarrow \mathbb{R}^n$ , which extends to a  $2T$ -periodic (PE) signal  $c_* : \mathbb{R}_+ \rightarrow \mathbb{R}^n$

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PMP

## More general systems

We obtain the same result for the worst rate of decay for the more general system

$$\dot{x}(t) = -S(t)x(t)$$

where  $S(t) \in \mathbb{R}^{n \times n}$  is such that  $S(t) \geq 0$  and for  $a, b, T > 0$

$$a \text{Id}_n \leq \int_t^{t+T} S(s) ds \leq b \text{Id}_n$$

$\rightsquigarrow$  The family of signals  $S$  is obtained as the convexification of the family  $cc^\top$  where  $c : [0, T] \rightarrow \mathbb{R}^n$  satisfies (PE)

$\rightsquigarrow$  the worst rate of decay is realized by (DGF), e.g.,  $S = cc^\top$

## Open question

For  $a, b, T$  fixed, what dependence on the dimension?

$$\frac{C_1}{n} \leq \lim_{b \rightarrow \infty} R(a, b, T, n) \frac{(1 + b^2)T}{a} \leq C_0.$$

- The technique used in the proof yields also the lower bound

$$R(a, b, T, n) \geq \frac{\mu(a, b, T, n)}{T}.$$

- At the moment we cannot directly access  $\mu(a, b, T, n)$  for  $n \neq 2$ .



Thank you for your attention!



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**Worst Exponential Decay Rate for Degenerate Gradient flows  
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