

# Nonlinear high-gain observers

Daniele Carnevale

Dipartimento di Ing. Civile ed Ing. Informatica (DICII),  
University of Rome "Tor Vergata"

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PhD school of Bertinoro, SIDRA 2008,.

## The linear case: reminiscences...

When the system  $P(A, B, C, D)$  is linear and time-invariant (LTI, in continuous or discrete time) a Luenberger-type observer can be designed to obtain global exponential converging estimate  $\hat{x}$  of the plant state  $x$ .

The problem of estimating the state at time  $t$  is equivalent to estimate the initial condition  $x(0)$  ( $t_0 = 0$ ) given that  $x(t) = e^{At}x(0) + \int_0^t e^{A(t-\tau)}Bu(\tau)d\tau$ . The classical Luenberger observer can be designed implementing a LTI which consists into a **copy** of the plant  $P$  and a **linear correction** term as

$$\begin{cases} \dot{\hat{x}} = A\hat{x} + Bu + L(y - \hat{y}), \\ \hat{y} = C\hat{x} + Du. \end{cases} \quad (1)$$

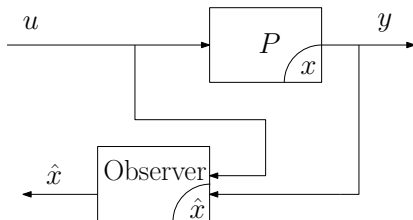


Figure: The observer scheme.

# The linear case: reminiscences...

## Theorem (Observer for LTI systems)

Let  $(A, B, C, D)$  and  $u(t)$  be known for all  $t \geq 0$  and assume that the system is **detectable**, i.e.

$$(\text{detectability}) \quad \text{rank} \left( \begin{bmatrix} C \\ A - \lambda_i I \end{bmatrix} \right) = n, \quad \forall \lambda_i \in \sigma\{A\} \cap \mathbb{C}_{bad}, \quad (2)$$

where  $n = \dim(x)$ ,  $\mathbb{C}_{bad} \triangleq \{s \in \mathbb{C} : \text{Re}(s) \geq 0\}$  if  $t \in \mathbb{R}$  or  $\mathbb{C}_{bad} \triangleq \{s \in \mathbb{C} : |s| \geq 1\}$  if  $t \in \mathbb{Z}$ .

Then there exists a **correction matrix**  $L$  such that  $A - LC$  can be rendered **Hurwitz** if  $t \in \mathbb{R}$  or **Shur** if  $t \in \mathbb{Z}$ , yielding

$$\Downarrow$$

$$\lim_{t \rightarrow \infty} \|x(t) - \hat{x}(t)\| \leq \lim_{t \rightarrow \infty} c_0 \|x(0) - \hat{x}(0)\| e^{-\gamma t} = 0, \quad (3)$$

for some  $c_0 > 0$  and  $\gamma > 0$ , i.e. the origin  $e = x - \hat{x} = 0$  of the estimation error system is globally exponentially stable.

# The linear case: reminiscences...

## LTI systems: proof .

The continuous/discrete time (we use in this case the operator  $\Delta$ ) dynamics of the estimation error  $e(t)$  are described by

$$\begin{aligned}\Delta e &= \Delta x - \Delta \hat{x} = A\hat{x} + Bu - (A\hat{x} + Bu + L(y - \hat{y})) \\ &= A(x - \hat{x}) + LC(x - \hat{x}) = (A - LC)e.\end{aligned}\tag{4}$$

Then, it is a linear autonomous system whose time evolution can be evaluated analytically in continuous and discrete time (within the square brackets) as

$$e(t) = e^{(A-LC)t}x_0, \quad [e(t) = (A - LC)^t x_0].$$

Assume without lack of generality that the matrix  $A - LC$  has all distinct eigenvalues and reduce to the continuous time case. To clearly retrieve the bound in (3), perform the change of co-ordinates  $z(t) = Te(t)$  with the invertible matrix  $T$  that has as rows the left eigenvectors of the matrix  $A - LC$ . Then  $\dot{z}(t) = \Lambda z(t)$  with  $\Lambda = \text{diag}\{\gamma_i\} = T(A - LC)T^{-1}$  and  $\gamma_i \in \sigma\{A - LC\}$  for  $i = 1 \dots n$  and

$$\begin{aligned}\|e(t)\| &= \|T^{-1}z(t)\| = \|T^{-1}e^{\Lambda t}z_0\| = \|T^{-1}e^{\Lambda t}Te_0\| \\ &\leq \|T^{-1}\| \|T\| \|e^{\Lambda t}\| \|e_0\| \leq \sqrt{\frac{\lambda_{\max}(T'T)}{\lambda_{\min}(T'T)}} e^{-\gamma_{\min} t} \|e_0\|.\end{aligned}\tag{5}$$

# The linear case: reminiscences...

## Remark (Observability)

**Observability** implies **detectability**, where

$$\text{(observability)} \quad \text{rank} \left( \begin{bmatrix} C \\ CA \\ CA^2 \\ \vdots \\ CA^{n-1} \end{bmatrix} \right) = n \Leftrightarrow \text{rank} \left( \begin{bmatrix} C \\ A - \lambda_i I \end{bmatrix} \right) = n, \forall \lambda_i \in \sigma\{A\} \quad (6)$$

Furthermore, if the system  $P$  is **observable**, the parameter  $\lambda$  in (3) can be arbitrarily chosen picking wisely  $L$  and even more, all the eigenvalues of the estimation error dynamic matrix  $A - LC$  can be freely assigned ( $\exists! L$ ).

## Remark (Discrete time: Finite time estimation error convergence)

If  $t \in \mathbb{Z}$  and the system is **observable** or even less it is **finite-time detectable**, i.e.

$$\text{(finite-time detectability)} \quad \text{rank} \left( \begin{bmatrix} C \\ A - \lambda_i I \end{bmatrix} \right) = n, \forall \lambda_i \in \sigma\{A\} : \lambda_i \neq 0, \quad (7)$$

then there exists  $L$  such that  $\sigma\{A - LC\} = \{0\}$  yielding  $e(t) = 0$  for all  $t \geq n$  and any  $e_0$ .

# Observability Canonical Form

Consider the system

$$\begin{cases} \dot{x} &= f(x, u), \\ y &= h(x, u), \end{cases} \quad (8)$$

with  $x \in \mathbb{R}^n$  and  $u \in \mathbb{R}^m$  and  $y \in \mathbb{R}$ , with  $f(\cdot)$  and  $h(\cdot)$  sufficiently smooth. *High-gain observers* investigated by **Gauthier and Kupca** are strongly related to a specific global diffeomorphism  $\Phi : \mathbb{R}^n \rightarrow \mathbb{R}^n$ ,  $z = \Phi(x)$  such that the system (8) is rewritten into the **Gauthier-Kupca's Observability Canonical Form**

$$\begin{cases} \dot{z}_1 &= \tilde{f}_1(z_1, z_2, u), \\ \dot{z}_2 &= \tilde{f}_2(z_1, z_2, z_3, u), \\ &\vdots \\ \dot{z}_{n-1} &= \tilde{f}_{n-1}(z_1, z_2, \dots, z_{n-1}, z_n, u), \\ \dot{z}_n &= \tilde{f}_n(z_1, z_2, \dots, z_{n-1}, z_n, u), \\ y &= \tilde{h}(z_1, u), \end{cases} \quad (9)$$

(note the *Brunovsky-like + lower-triangular* structure) where

$$\frac{\partial \tilde{h}}{\partial z_1} \neq 0, \quad \frac{\partial \tilde{f}_i}{\partial z_{i+1}} \neq 0, \quad \forall i \in \{1, 2, \dots, n-1\}, z \in \mathbb{R}^n, u \in \mathbb{R}^m. \quad (10)$$

# Observability Canonical Form: necessary conditions

Let  $f(0, 0) = 0$ ,  $h(0, 0) = 0$  and define recursively

$$\varphi_1(x, u) := h(x, u), \quad \varphi_i(x, u) := \frac{\partial \varphi_{i-1}}{\partial x} f(x, u), \quad (11)$$

for  $i = 1, 2, \dots, n$  and the incremental  $i$ -vector-valued functions

$$\Phi_i(x, u) := \begin{bmatrix} \varphi_1(x, u) \\ \vdots \\ \varphi_i(x, u) \end{bmatrix}. \quad (12)$$

Let  $K_i(x, u)$  be the null subspace of  $\partial \Phi_i / \partial x$  evaluated at  $(x, u)$ , i.e.

$$K_i(x, u) = \ker \left[ \frac{\partial \Phi_i}{\partial x} \right]_{(x, u)}, \quad (13)$$

and note that the map  $D_i(u) : x \rightarrow K_i(x, u)$  is a distribution on  $\mathbb{R}^n$ , the collection of which is called the **canonical flag** ( $u$  is the “wind” that changes the manifold)

## Canonical flag: uniformity

The **canonical flag**  $D_i(u)$  is said to be **uniform** if for all  $i = 1, 2, \dots, n$  and all  $x \in \mathbb{R}^n$  it holds

(regularity):  $\dim(K_i(x, u)) = n - i$  for all  $u \in \mathbb{R}^m$ ;

(u-independency):  $K_i(x, u)$  is independent of  $u$  (same subspace).

### Proposition

*System (8) is globally diffeomorphic to a system in **Gauthier-Kupca's observability canonical form** only if its canonical flag is uniform.*



# Canonical flag: uniformity

## Proposition

*System (8) is globally diffeomorphic to a system in **Gauthier-Kupca's observability canonical form** only if its canonical flag is uniform.*

**Sketch of the proof:** If a system is already in the observability canonical form then

$$y = \tilde{h}(z_1, u) (= h(x, u) = \varphi_1(x, u))$$

yielding (as  $\varphi$  was evaluated with respect to (8) with  $(h, f)$ , now  $\tilde{\varphi}$  is evaluated with the system in the observability canonical form, i.e. with respect to  $(\tilde{h}, \tilde{f})$ )

$$\tilde{\varphi}_1(z_1, u) \rightarrow \tilde{\varphi}_i(z_1, \dots, z_i, u),$$

and by assumption (obs. canonical form)

$$\frac{\partial \tilde{\varphi}_i}{\partial z_i} \neq 0, \forall z_1, z_2, \dots, z_i, u.$$

$\Downarrow$

$$K_i(z, u) = \text{span} \begin{bmatrix} 0 \\ I_{n-i} \end{bmatrix}, \forall i = 1, \dots, n,$$

then the canonical flag (of systems in canonical observability form) is **uniform**.

This property is left unchanged by a diffeomorphism.  $\square$

# Observability Canonical Form

## Remark

The **uniform** (necessary) condition is also *sufficient* for the existence of a **local** diffeomorphism to transform (8) into (9)

# Observability Canonical Form: sufficient conditions

## Proposition

Consider (8) and the map  $\Phi : \mathbb{R}^n \rightarrow \mathbb{R}^n$ ,  $z = \Phi(x)$  as

$$\Phi(x) := \begin{bmatrix} \varphi_1(x, 0) \\ \varphi_2(x, 0) \\ \vdots \\ \varphi_n(x, 0) \end{bmatrix},$$

and suppose that

- i) the canonical flag of (8) is **uniform**;
- ii)  $\Phi(\cdot)$  is a global diffeomorphism.

Then, system (8) is globally diffeomorphic, via  $\Phi(x)$ , to a system in Gauthier-Kupca's observability canonical form.

**Proof:** By Assumption

$$\dim \left( \ker \left[ \frac{\partial \Phi_i}{\partial x} \right]_{(x,u)} \right) = n - i, \forall u \in \mathbb{R}^m.$$

Let  $T : \mathbb{R}^n \rightarrow \mathbb{R}^n$ ,  $T(z) = x$ , i.e.  $T(\Phi(x)) = x$ .

# Observability Canonical Form: sufficient conditions - proof

Since by definition  $\Phi(x) := \Phi_n(x, u)$ , then  $\Phi_n(x, 0) = z = \Phi_n(T(z), 0)$  whose partial derivatives with respect to  $z$  yield

$$\left( \left[ \frac{\partial \Phi_n}{\partial x} \right]_{\substack{x = T(z) \\ u = 0}} \right) \frac{\partial T}{\partial z} = I, \forall z \in \mathbb{R}^n.$$

This implies that the left-side matrix in the above equality is such that for all  $j > i$  it holds

$$\left( \left[ \frac{\partial \Phi_i}{\partial x} \right]_{\substack{x = T(z) \\ u = 0}} \right) \frac{\partial T}{\partial z_j} = 0, \forall z \in \mathbb{R}^n, \quad (14)$$

$$\Downarrow \quad (15)$$

$$\frac{\partial T}{\partial z_j} \in \ker \left( \left[ \frac{\partial \Phi_i}{\partial x} \right]_{\substack{x = T(z) \\ u = 0}} \right)$$

$$\Downarrow (\text{u-independency of } K_i)$$

$$\frac{\partial T}{\partial z_j} \in \ker \left( \left[ \frac{\partial \Phi_i}{\partial x} \right]_{\substack{x = T(z) \\ u = \mathbf{u}}} \right), \forall j > i, z, u. \quad (16)$$

# Observability Canonical Form: sufficient conditions - proof

Exploit the change of co-ordinates  $z = \Phi(x)$  on (8), then

$$\begin{cases} \dot{z} &= \tilde{f}(z, u), \\ y &= \tilde{h}(z, u), \end{cases}, \quad (17)$$

where

$$\tilde{h}(z, u) = h(T(z), u) \text{ (prove that } \tilde{h}(z_1, u) = \tilde{\varphi}_1(z_1, u)),$$

$$\tilde{f}(z, u) = \frac{\partial \Phi(x)}{\partial x} f(x, u) = \left( \left[ \frac{\partial \Phi_n}{\partial x} \right]_{x=T(z)} \right) f(T(z), u) = \begin{cases} \tilde{f}_1(z_1, z_2, u), \\ \tilde{f}_2(z_1, z_2, z_3, u), \\ \vdots \\ \tilde{f}_{n-1}(z_1, \dots, z_n, u), \\ \tilde{f}_n(z_1, \dots, z_n, u), \end{cases}$$

Define now

$$\tilde{\varphi}_1(z, u) = \tilde{h}(z, u), \quad \tilde{\varphi}_i(z, u) := \frac{\partial \tilde{\varphi}_{i-1}}{\partial z} \tilde{f}(z, u), \quad \forall i = 1, \dots, n,$$

and note that by selection of  $\varphi_i(\cdot)$  it holds

$$\tilde{\varphi}_1(z, u) = \varphi_1(T(z), u), \quad \tilde{\varphi}_i(z, u) = \varphi_i(T(z), u),$$

yielding...

# Observability Canonical Form: sufficient conditions - proof

...yielding

$$\tilde{\Phi}_i(x, u) := \begin{bmatrix} \tilde{\varphi}_1(z, u) \\ \tilde{\varphi}_2(z, u) \\ \vdots \\ \tilde{\varphi}_n(z, u) \end{bmatrix} = \Phi_i(T(z), u).$$

Equation (15) with  $i = 1$  yields

$$\left( \left[ \frac{\partial \Phi_1}{\partial x} \right]_{\substack{x = T(z) \\ u = 0}} \right) \frac{\partial T}{\partial z_j} = 0$$

for all  $j > 1$ , i.e.  $\tilde{\varphi}_1(z, u)$  depends only by  $z_1$  then

$$\frac{\partial \tilde{\varphi}_1}{\partial z} = \left[ \frac{\partial \tilde{\varphi}_1}{\partial z_1}, 0, \dots, 0 \right],$$

and by uniformity we have also

$$\frac{\partial \tilde{h}}{\partial z_1} = \frac{\partial \tilde{\varphi}_1}{\partial z_1} \neq 0.$$

# Observability Canonical Form: sufficient conditions - proof

By the definition of  $\tilde{\varphi}_i$  and what has been highlighted before, then

$$\tilde{\varphi}_2(z, u) = \frac{\partial \tilde{h}}{\partial z_1} \tilde{f}_1(z, u).$$

Reiterating (15) for  $i = 2$  and  $j > 2$  then

$$\left( \left[ \frac{\partial \Phi_2}{\partial x} \right]_{\substack{x = T(z) \\ u = 0}} \right) \frac{\partial T}{\partial z_j} = 0,$$

hence  $\tilde{\varphi}_2(z, x)$  depends only on  $z_1$  and  $z_2$ , which implies that

$$\frac{\partial \tilde{f}_1}{\partial z_j} = 0, \forall j > 2,$$

and also  $\tilde{f}_1(z, u)$  depends only on  $z_1$  and  $z_2$ . Furthermore

$$\frac{\partial \tilde{\varphi}_2(z, u)}{\partial z} = \left( \star, \frac{\partial}{\partial z_2} \left( \frac{\partial \tilde{h}(z, u)}{\partial z_1} \tilde{f}_1(z, u) \right), 0, \dots, 0 \right) = \left( \star, \frac{\partial \tilde{h}(z, u)}{\partial z_1} \frac{\partial \tilde{f}_1(z, u)}{\partial z_2}, 0, \dots, 0 \right)$$

# Observability Canonical Form: sufficient conditions - proof

...and by uniformity assumption

$$\frac{\partial \tilde{f}_1(z, u)}{\partial z_2} \neq 0, \forall z_1, z_2 \text{ and } u.$$

Iterating the same procedure the result follows, i.e. the change of co-ordinates  $z = \Phi(x)$  (equivalently  $x = T(z)$ ...but  $T$  could be very difficult to find!) transforms (8) into

$$\left\{ \begin{array}{lcl} \dot{z}_1 & = & \tilde{f}_1(z_1, z_2, u), \\ \dot{z}_2 & = & \tilde{f}_2(z_1, z_2, z_3, u), \\ & \vdots & \\ \dot{z}_{n-1} & = & \tilde{f}_{n-1}(z_1, z_2, \dots, z_{n-1}, z_n, u), \\ \dot{z}_n & = & \tilde{f}_n(z_1, z_2, \dots, z_{n-1}, z_n, u), \\ y & = & \tilde{h}(z_1, u). \end{array} \right. \quad (18)$$

□



# The change of co-ordinate in case of input-affine systems

Consider the input-affine system described by

$$\begin{cases} \dot{x} &= f(x) + g(x)u, \\ y &= h(x), \end{cases} \quad (19)$$

where the functions  $\varphi_i(x, u)$  are given by (the output  $y$  and its derivatives up to the  $n - 1$  order with  $u(t) \equiv 0$ )

$$\varphi_1(x, u) = h(x),$$

$$\varphi_2(x, u) = \frac{\partial h}{\partial x}(f(x) + g(x)u) = L_f h(x) + L_g h(x)u,$$

$$\varphi_3(x, u) = L_f^2 h(x) + (L_g L_f h(x) + L_f L_g h(x))u + L_g^2 h(x)u^2,$$

$$\vdots$$

that by  $u$  - *independency* can be rewritten picking  $u = 0$  as

$$\Phi_n(x, 0) = \begin{bmatrix} h(x) \\ L_f h(x) \\ L_f^2 h(x) \\ \vdots \\ L_f^{n-1} h(x) \end{bmatrix} := \Phi(x). \quad (20)$$

# The change of co-ordinate in case of input-affine systems

If the canonical flag of (19) is **uniform** and  $\Phi(x)$  is a **global diffeomorphism**, the system is transformable via  $\Phi(x)$  into a *uniform observability canonical form*

$$\begin{cases} \dot{z} &= \tilde{f}(z) + \tilde{g}(z)u, \\ y &= \tilde{h}(z), \end{cases} \quad (21)$$

where

$$\tilde{f}(z) = \left( \frac{\partial \Phi(x)}{\partial x} f(x) \right)_{x=\Phi^{-1}(z):=T(z)}, \quad (22)$$

$$\tilde{g}(z) = \left( \frac{\partial \Phi(x)}{\partial x} g(x) \right)_{x=\Phi^{-1}(z)}, \quad (23)$$

$$\tilde{h}(z) = h(\Phi^{-1}(x)). \quad (24)$$

Since  $\varphi_1(x) = h(x)$  and  $z = \Phi(x)$ , then  $z_1 = h(x) = y$  yielding  $\tilde{h}(z) = z_1$ .  
Moreover,

$$z_2 = \varphi_2(x) = \left( \frac{dy(t)}{dt} \right)_{\substack{x = \Phi^{-1}(z), \\ u = 0}} = \left( \frac{\partial \varphi_1(x, u)}{\partial x} (f(x) + g(x)u) \right)_{\substack{x = \Phi^{-1}(z), \\ u = 0}},$$

=  $z_1$ .....then....

# The change of co-ordinate in case of input-affine systems

If the canonical flag of (19) is **uniform** and  $\Phi(x)$  is a **global diffeomorphism**, the system is transformable via  $\Phi(x)$  into a *uniform observability canonical form*

$$\begin{cases} \dot{z} &= \tilde{f}(z) + \tilde{g}(z)u, \\ y &= \tilde{h}(z), \end{cases} \quad (25)$$

where

$$\tilde{f}(z) = \begin{bmatrix} z_2 \\ z_3 \\ \vdots \\ z_n \\ \tilde{f}_n(z_1, z_2, \dots, z_n) \end{bmatrix} \quad (26)$$

is a **chain of  $n - 1$  integrators** and knowing the fact that  $\tilde{f}_i(z) + \tilde{g}_i(z)u$  depends only on  $(z_1, z_2, \dots, z_i, z_{i+1})$  then

$$\tilde{g}(z) = \begin{bmatrix} \tilde{g}_1(z_1, z_2) \\ \tilde{g}_2(z_1, z_2, z_3) \\ \vdots \\ \tilde{g}_{n-1}(z_1, z_2, \dots, z_n) \\ \tilde{g}_n(z_1, z_2, \dots, z_n) \end{bmatrix} \quad (27)$$

# The change of co-ordinate in case of input-affine systems

It is possible to show that  $g_i$  does not depend on  $z_{i+1}$ . In fact,

$$\tilde{\varphi}_1(z, u) = z_1, \quad (28)$$

$$\tilde{\varphi}_2(z, u) = z_2 + \tilde{g}_1(z_1, z_2)u, \quad (29)$$

whose Jacobian is

$$\begin{bmatrix} \frac{\partial \tilde{\varphi}_1(z, u)}{\partial z} \\ \frac{\partial \tilde{\varphi}_2(z, u)}{\partial z} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & \dots & 0 \\ \frac{\partial \tilde{g}_1(z, u)}{\partial z_1} u & \left(1 + \frac{\partial \tilde{g}_1(z_1, z_2)}{\partial z_2} u\right) & 0 & \dots & 0 \end{bmatrix}$$

yielding, by **uniformity** (that is no changed by the diffeomorphism  $\Phi$ ) condition for all  $(z_1, z_2)$ , that  $\frac{\partial \tilde{g}_1}{\partial z_2} = 0$ . This holds also for  $\tilde{g}_i$  with  $i > 4$ .

# The change of co-ordinate in case of input-affine systems

The **uniform observability canonical form** of **input-affine** systems is

$$\left\{ \begin{array}{l} \dot{x} = f(x) + g(x)u, \\ y = h(x), \end{array} \quad z = \Phi(x) \right\} \Rightarrow \left\{ \begin{array}{l} \dot{z}_1 = z_2 + \tilde{g}_1(z_1)u, \\ \dot{z}_2 = z_3 + \tilde{g}_2(z_1, z_2)u, \\ \vdots \\ \dot{z}_{n-1} = z_n + \tilde{g}_{n-1}(z_1, \dots, z_n)u, \\ \dot{z}_n = \tilde{f}_n(z_1, \dots, z_n, u) + \tilde{g}_n(z_1, \dots, z_n)u, \\ y = z_1. \end{array} \right. \quad (30)$$

# High-gain global asymptotic observer: framework

Let

$$\mathbf{z}_i = [z_1, z_2, \dots, z_i]',$$

and rewrite the observer canonical form concisely (with some abuse of notation, they should be  $\tilde{f}(\cdot)$  and  $\tilde{g}(\cdot)$ ) as

$$\left\{ \begin{array}{ll} \dot{z}_1 &= f_1(\mathbf{z}_1, z_2, u), \\ \dot{z}_2 &= f_2(\mathbf{z}_2, z_3, u), \\ &\vdots \\ \dot{z}_{n-1} &= f_{n-1}(\mathbf{z}_{n-1}, z_n, u), \\ \dot{z}_n &= f_n(\mathbf{z}_n, u), \\ y &= h(z_1, u). \end{array} \right. \quad (31)$$

# High-gain global asymptotic observer: framework

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$$\mathbf{z}_i = [z_1, z_2, \dots, z_i]',$$

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$$\begin{cases} \dot{z}_1 &= f_1(\mathbf{z}_1, z_2, u), \\ \dot{z}_2 &= f_2(\mathbf{z}_2, z_3, u), \\ &\vdots \\ \dot{z}_{n-1} &= f_{n-1}(\mathbf{z}_{n-1}, z_n, u), \\ \dot{z}_n &= f_n(\mathbf{z}_n, u), \\ y &= h(z_1, u). \end{cases} \quad (31)$$

## Assumption (Technical)

- i)  $\|f_i(\mathbf{z}_i, z_{i+1}, u) - f_i(\bar{\mathbf{z}}_i, z_{i+1}, u)\| \leq L\|\mathbf{z}_i - \bar{\mathbf{z}}_i\|$  for some  $L > 0$ , all  $z_i$  and  $\bar{z}_i$  belonging to  $\mathbb{R}^n$  and uniformly in  $z_{i+1}$ ,  $u$  and  $i = 1, \dots, n$  (*Globally Lipschitz*);
- ii) There exists real numbers  $\beta > \alpha > 0$  such that

$$\beta \geq \left\| \frac{\partial h}{\partial z_1} \right\| \geq \alpha, \beta \geq \left\| \frac{\partial f_i}{\partial z_{i+1}} \right\| \geq \alpha, \forall z \in \mathbb{R}^n, u \in \mathbb{R}^m, i = 1, \dots, n-1.$$

# High-gain global asymptotic observer: technical assumptions

## Assumption (Technical)

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- ii) There exists real numbers  $\beta > \alpha > 0$  such that

$$\beta \geq \left| \frac{\partial h}{\partial z_1} \right| \geq \alpha, \beta \geq \left| \frac{\partial f_i}{\partial z_{i+1}} \right| \geq \alpha, \forall \mathbf{z} \in \mathbb{R}^n, u \in \mathbb{R}^m, i = 1, \dots, n-1.$$

## Remark

Assumption i) is automatically satisfied if it is known - a priori - that  $\mathbf{z}(t) \subset \mathcal{Z}$  for all  $t \geq 0$  and  $\mathcal{Z}$  is a compact subset of  $\mathbb{R}^n$ .



# The high-gain observer

The high-gain observer consists in a **copy of the system** (31) plus a **correction term** proportional to the output estimation error  $y(t) - \hat{y}(t)$ , namely

$$\left\{ \begin{array}{lll} \dot{\hat{z}}_1 & = f_1(\hat{\mathbf{z}}_1, \hat{z}_2, u) & + k c_{n-1} (y - \hat{y}), \\ \dot{\hat{z}}_2 & = f_2(\hat{\mathbf{z}}_2, \hat{z}_3, u) & + k^2 c_{n-2} (y - \hat{y}), \\ & \vdots & \vdots \\ \dot{\hat{z}}_{n-1} & = f_{n-1}(\hat{\mathbf{z}}_{n-1}, \hat{z}_n, u) & + k^{n-1} c_1 (y - \hat{y}), \\ \dot{\hat{z}}_n & = f_n(\hat{\mathbf{z}}_n, u) & + k^n c_0 (y - \hat{y}), \\ \hat{y} & = h(\hat{z}_1, u). \end{array} \right. \quad (32)$$

where the observer gain  $k > 0$  and parameters  $(c_{n-1}, \dots, c_0)$  have to be selected.

## Theorem (Global asymptotic high-gain observer)

*Consider the system (31) and the observer (32). Let the technical assumption hold and select the vector parameters  $(c_{n-1}, \dots, c_0)$  such that the polynomial  $p(s) = s^n + c_{n-1}s^{n-1} + \dots + c_0$  is Hurwitz.*

*Then, there exists a “sufficiently high” value of  $k$  (high-gain) such that the origin of the estimation error  $e = \hat{z} - z$  system is uniformly **globally asymptotically** (exponentially) stable.*

# The high-gain observer dynamics (proof of the main result)

**Proof:** the mean value theorem yields

$$\begin{aligned} f_i(\hat{\mathbf{z}}_i, \hat{z}_{i+1}, u) - f_i(\mathbf{z}_i, z_{i+1}, u) &+ f_i(\mathbf{z}_i, \hat{z}_{i+1}, u) - f_i(\mathbf{z}_i, z_{i+1}, u) = \\ f_i(\hat{\mathbf{z}}_i, \hat{z}_{i+1}, u) - f_i(\mathbf{z}_i, \hat{z}_{i+1}, u) &+ f_i(\mathbf{z}_i, \hat{z}_{i+1}, u) - f_i(\mathbf{z}_i, z_{i+1}, u) = \\ F_i(\mathbf{z}_i(t), \hat{\mathbf{z}}_i(t), \hat{z}_{i+1}(t), u(t)) &+ \frac{\partial f_i}{\partial z_{i+1}}(\mathbf{z}_i(t), \delta_i(t), u(t)) e_{i+1}, \end{aligned}$$

where  $\delta_i(t) \in [\hat{z}_{i+1}(t), z_{i+1}(t)]$  (swap their order if necessary), similarly

$$y(t) - \hat{y}(t) = y(t) - h(\hat{z}_1(t), u(t)) = \frac{\partial h}{\partial z_1}(\delta_0(t), u(t)) e_1,$$

with  $\delta_0(t) \in [\hat{z}_1(t), z_1(t)]$  (swap their order if necessary). Define

$$g_{i+1}(t) := \frac{\partial f_i}{\partial z_{i+1}}(\mathbf{z}_i(t), \delta_i(t), u(t)), \quad i \geq 0, \quad \text{and} \quad g_1(t) := \frac{\partial h}{\partial z_1}(\delta_0(t), u(t)),$$

then, since  $e_i = \hat{z}_i - z_i$ , it holds

$$\dot{e}_i(t) = g_{i+1}(t) e_{i+1} - k^i c_{n-i} g_1(t) e_1 + F_i(\mathbf{z}_i(t), \hat{\mathbf{z}}_i(t), \hat{z}_{i+1}(t), u(t))$$

# The high-gain observer dynamics (proof of the main result...)

The estimation error system is

$$\begin{bmatrix} \dot{e}_1 \\ \dot{e}_2 \\ \vdots \\ \dot{e}_{n-1} \\ \dot{e}_n \end{bmatrix} = \begin{bmatrix} -k c_{n-1} g_1(t) & g_2(t) & 0 & \dots & 0 & 0 \\ -k^2 c_{n-2} g_1(t) & 0 & g_3(t) & \dots & 0 & 0 \\ \vdots & \vdots & \dots & \dots & \ddots & \vdots \\ -k^{n-1} c_1 g_1(t) & 0 & 0 & \dots & 0 & g_n(t) \\ -k^n c_0 g_1(t) & 0 & 0 & \dots & 0 & 0 \end{bmatrix} \begin{bmatrix} e_1 \\ e_2 \\ \vdots \\ e_{n-1} \\ e_n \end{bmatrix} + \begin{bmatrix} F_1(\cdot) \\ F_2(\cdot) \\ \vdots \\ F_{n-1}(\cdot) \\ F_n(\cdot) \end{bmatrix} \quad (33)$$

Consider now the **scaled** estimation error defined as

$$\tilde{e}_i = \frac{e_i}{k^i}, \quad i = 1, 2, \dots, n, \quad (34)$$

yielding

$$\begin{aligned} \dot{\tilde{e}}_i &= k^{-i} \dot{e}_i = k^{-i} \left( g_{i+1}(t) e_{i+1} + c_{n-i} g_1(t) k^i e_1 + F_i(\cdot) \right) \\ &= g_{i+1}(t) k^{-i} e_{i+1} + c_{n-i} g_1(t) e_1 + k^{-i} F_i(\cdot) \\ &= g_{i+1}(t) k \tilde{e}_{i+1} + c_{n-i} g_1(t) k \tilde{e}_1 + k^{-i} F_i(\cdot). \end{aligned}$$

# The high-gain observer dynamics (proof of the main result...)

The scaled estimation error system is

$$\begin{aligned}
 \begin{bmatrix} \dot{\tilde{e}}_1 \\ \dot{\tilde{e}}_2 \\ \vdots \\ \dot{\tilde{e}}_{n-1} \\ \dot{\tilde{e}}_n \end{bmatrix} &= \textcolor{red}{k} \begin{bmatrix} -c_{n-1}g_1(t) & g_2(t) & 0 & \dots & 0 & 0 \\ -c_{n-2}g_1(t) & 0 & g_3(t) & \dots & 0 & 0 \\ \vdots & \vdots & \dots & \dots & \ddots & \vdots \\ -c_1g_1(t) & 0 & 0 & \dots & 0 & g_n(t) \\ -c_0g_1(t) & 0 & 0 & \dots & 0 & 0 \end{bmatrix} \begin{bmatrix} \tilde{e}_1 \\ \tilde{e}_2 \\ \vdots \\ \tilde{e}_{n-1} \\ \tilde{e}_n \end{bmatrix} + \begin{bmatrix} \textcolor{red}{k}^{-1}F_1(\cdot) \\ \textcolor{red}{k}^{-2}F_2(\cdot) \\ \vdots \\ \textcolor{red}{k}^{-n+1}F_{n-1}(\cdot) \\ \textcolor{red}{k}^{-n}F_n(\cdot) \end{bmatrix} \\
 &= \underbrace{\textcolor{red}{k}A(t)\tilde{e}}_{\text{linear in } e \text{ (time-varying)}} + \underbrace{\tilde{F}_{\textcolor{red}{k}}(z(t), \hat{z}(t), u(t))}_{\text{nonlinear in } e = \hat{z} - z \text{ (time-varying)}}. \quad (35)
 \end{aligned}$$

The globally Lipschitz Assumption  $i$ ) on  $f_i$  is such that

$\|F_i(\cdot)\| \leq L\|\hat{\mathbf{z}}_i(t) - \mathbf{z}_i(t)\|$ , then

$$\|F_i(\cdot)\| \leq L\|\mathbf{e}_i\| = L\sqrt{e_1^2 + e_2^2 + \dots + e_i^2} = L\sqrt{\textcolor{red}{k}^2\tilde{e}_1^2 + \textcolor{red}{k}^4\tilde{e}_2^2 + \dots + \textcolor{red}{k}^{2i}\tilde{e}_i^2}.$$

Furthermore, if  $k \geq 1$ , the following holds

$$\|\textcolor{red}{k}^{-i}F_i(\cdot)\| = L\sqrt{\frac{\textcolor{red}{k}^2\tilde{e}_1^2 + \textcolor{red}{k}^4\tilde{e}_2^2 + \dots + \textcolor{red}{k}^{2i}\tilde{e}_i^2}{\textcolor{red}{k}^{2i}}} \underbrace{\leq}_{k \geq 1} L\|\tilde{\mathbf{e}}_i\| \underbrace{\leq}_{i \leq n} L\|\tilde{\mathbf{e}}\|.$$

The proof continues relying on the next lemma...

# The high-gain observer dynamics (proof of the main result...)

## Lemma

Consider a time-varying matrix of the form

$$A(t) = \begin{bmatrix} 0 & g_2(t) & 0 & \dots & 0 & 0 \\ 0 & 0 & g_3(t) & \dots & 0 & 0 \\ \vdots & \vdots & \dots & \dots & \ddots & \vdots \\ 0 & 0 & 0 & \dots & 0 & g_n(t) \\ 0 & 0 & 0 & \dots & 0 & 0 \end{bmatrix} - \begin{bmatrix} c_{n-1} \\ c_{n-2} \\ \vdots \\ c_1 \\ c_0 \end{bmatrix} [g_1(t), 0, 0, \dots, 0, 0], \quad (36)$$

and suppose there exists real numbers <sup>a</sup>  $\beta > \alpha > 0$  such that

$$\beta \geq g_i(t) \geq \alpha, \quad \forall t \geq 0 \text{ and } i = 1, 2, \dots, n. \quad (37)$$

Then, there exist a set of real numbers  $c_0, c_1, \dots, c_{n-1}, \lambda > 0$  and a symmetric positive definite **constant** matrix  $S \in \mathbb{R}^{n \times n}$ , with  $\lambda$  and  $S$  only depending on  $\alpha, \beta$ , and the parameters  $c_i$  such that

$$A'(t)S + SA(t) \leq -\lambda I. \quad (38)$$

<sup>a</sup>In our proof, they are exactly the ones in the Technical Assumption whereas  $A(t)$  is the one defined in (35).

# The high-gain observer dynamics (proof of the main result...)

Consider the candidate Lyapunov function  $V(\tilde{e}) = \tilde{e}' S \tilde{e}$ , then

$$\begin{aligned} \dot{V}(\tilde{e}(t)) &= k \tilde{e}'(t) (A'(t)S + SA(t)) \tilde{e}(t) + 2\tilde{e}'(t)S\tilde{F}_k(t) \\ &\leq -k\lambda \|\tilde{e}(t)\|^2 + 2\|S\| L \underbrace{\sqrt{n}}_{\text{n components of } \tilde{F}_k} \|\tilde{e}(t)\|^2 = -(k\lambda - 2\|S\|L\sqrt{n}) \|\tilde{e}(t)\|^2, \end{aligned} \quad (39)$$

and defining

$$k^* := \frac{2\|S\|L\sqrt{n}}{\lambda},$$

if  $k$  is sufficiently **high**, i.e.  $k > k^*$  (and  $k > 1$ ), then<sup>1</sup>

$$\dot{V}(\tilde{e}(t)) \leq -\frac{c_k}{\lambda_S} V(\tilde{e}(t)) \quad (40)$$

where  $\bar{\lambda}_S$  is the largest eigenvalue of  $S$ ,  $c_k := (k\lambda - 2\|S\|L\sqrt{n}) > 0$  yielding

$$\lim_{t \rightarrow \infty} \tilde{e}(t) = 0 \Rightarrow \lim_{t \rightarrow \infty} e(t) = 0$$

---

<sup>1</sup> $S$  and  $L$  do not depend on  $k$ .

# The high-gain observer dynamics (proof of the main result...)

## Remark (Peaking phenomenon)

The differential inequality (40) together with the selected Lyapunov function,  $V(\tilde{e}) = \tilde{e}' S \tilde{e}$ , yield

$$V(\tilde{e}(t)) \leq V(\tilde{e}(0)) e^{-\frac{c_k}{\bar{\lambda}_S} t}.$$

Since for any  $x \in \mathbb{R}^n$  it holds  $\underline{\lambda}_S \|x\|^2 \leq x' S x = V(x) \leq \bar{\lambda}_S \|x\|^2$  where  $(\underline{\lambda}_S, \bar{\lambda}_S)$  are the smaller and the largest eigenvalues of  $S$ , respectively, then

$$\|\tilde{e}(t)\|^2 \leq \frac{1}{\bar{\lambda}_S} V(\tilde{e}(t)) \leq \frac{\bar{\lambda}_S}{\underline{\lambda}_S} \|\tilde{e}(0)\|^2 e^{-\frac{c_k}{\bar{\lambda}_S} t},$$

which is an appealing bound for the **scaled** estimation error  $\tilde{e}(t)$ ... nevertheless

$$\|e(t)\| = \left\| \begin{bmatrix} k & 0 & \dots & 0 \\ 0 & k^2 & \dots & 0 \\ \vdots & \dots & \ddots & 0 \\ 0 & 0 & \dots & k^n \end{bmatrix} \tilde{e}(t) \right\| \leq \underbrace{k^n}_{k > 1} \|\tilde{e}(t)\| \leq k^n \|e(0)\| \sqrt{\frac{\bar{\lambda}_S}{\underline{\lambda}_S}} e^{-\frac{c_k}{2\bar{\lambda}_S} t}. \quad (41)$$

The higher the  $k$  is, the faster  $\|e(t)\|$  converges to zero...but the transient amplitude of  $e(t)$  increases polynomially in  $k$  as well! **[Peaking phenomenon]**

# The high-gain observer dynamics (proof of the lemma...)

We now prove Lemma 1 used in the proof of Theorem 1. As first, note that

$$g_i(t) = \alpha\delta_i(t) + (1 - \delta_i(t))\beta = \beta - (\beta - \alpha)\delta_i(t),$$

for some functions  $\delta_i(t) \in [0, 1]$ . The matrix  $A(t)$  in (36) can be rewritten as

$$A(t) = \begin{bmatrix} -c_{n-1}g_1(t) & g_2(t) & 0 & \dots & 0 & 0 \\ -c_{n-2}g_1(t) & 0 & g_3(t) & \dots & 0 & 0 \\ \vdots & \vdots & \dots & \dots & \ddots & \vdots \\ -c_1g_1(t) & 0 & 0 & \dots & 0 & g_n(t) \\ -c_0g_1(t) & 0 & 0 & \dots & 0 & 0 \end{bmatrix} =$$

$$\beta \left( \begin{bmatrix} -c_{n-1} & 1 & 0 & \dots & 0 & 0 \\ -c_{n-2} & 0 & 1 & \dots & 0 & 0 \\ \vdots & \vdots & \dots & \dots & \ddots & \vdots \\ -c_1 & 0 & 0 & \dots & 0 & 1 \\ -c_0 & 0 & 0 & \dots & 0 & 0 \end{bmatrix} - \gamma \begin{bmatrix} -c_{n-1}\delta_1(t) & \delta_2(t) & 0 & \dots & 0 & 0 \\ -c_{n-2}\delta_1(t) & 0 & \delta_3(t) & \dots & 0 & 0 \\ \vdots & \vdots & \dots & \dots & \ddots & \vdots \\ -c_1\delta_1(t) & 0 & 0 & \dots & 0 & \delta_n(t) \\ -c_0\delta_1(t) & 0 & 0 & \dots & 0 & 0 \end{bmatrix} \right)$$

Then, defining  $A_c$  and  $\Delta_i(t)$  accordingly to the above equation,  $A(t)$  is rewritten as

$$A(t) = \beta (A_c - \gamma \Delta_c(t)), \quad \text{where } \gamma := \frac{\beta - \alpha}{\beta}, \quad 1 > \gamma > 0 \quad (\text{since } \beta > \alpha > 0).$$



# The high-gain observer dynamics (proof of the lemma...)

Given the special (companion form - observer) structure of  $A_c$ , then it is possible to select the parameters  $c_i$  ( $i = 1, 2, \dots, n$ ) such that the characteristic polynomial of  $A_c$ ,  $p_{A_c}(s) = s^n + c_{n-1}s^{n-1} + \dots + c_1s + c_0$ , is Hurwitz.

Then, there exists a matrix  $S = S' \succ 0$  such that

$$A'_c S + S A_c = -hI,$$

for a desired  $h > 0$  ( $c_i(h)$ ). This choice yields, for any  $x \in \mathbb{R}^n$ ,

$$\begin{aligned} x' (A'(t)S + S A(t)) x &= \beta x' (A'_c S + S A'_c - \gamma (\Delta'_c(t)S + S \Delta_c(t))) x, \\ &\leq \beta (-h\|x\|^2 + \gamma |x' (\Delta'_c(t)S + S \Delta_c(t)) x|) \\ &\leq \beta \left( -h\|x\|^2 + \gamma \max_{i=1,\dots,n} \{\delta_i(t)\} |x' (A'_c S + S A_c) x| \right) \\ &\leq \beta h \left( -1 + \gamma \max_{i=1,\dots,n} \{\delta_i(t)\} \right) \|x\|^2 \\ &\leq -\beta h(1 - \gamma) \|x\|^2 \underbrace{=}_{\lambda := \beta h(1 - \gamma) > 0} -\lambda \|x\|^2, \end{aligned}$$

that complete the proof of the Lemma.  $\square$

## Example: the Van der Pol oscillator

The Van der Pol oscillator is described by

$$\ddot{y}(t) = \mu(1 - y^2(t))\dot{y}(t) - y(t),$$

with  $\mu > 0$  represents a nonlinear damping coefficient. The system is already written in the observer canonical form<sup>2</sup> ( $z = I x$ ), in fact, let  $x_1 = y$  and  $x_2 = \dot{y} = \dot{x}_1$ , then

$$\begin{cases} \dot{x}_1 &= x_2, \\ \dot{x}_2 &= -x_1 + \mu(1 - x_1^2)x_2, \\ y &= x_1, \end{cases} \quad (42)$$

Can we implement the high-gain observer just introduced?

---

<sup>2</sup>This is always the case when the system differential equations are written with respect to the output.

## Example: the Van der Pol oscillator

The Van der Pol oscillator is described by

$$\ddot{y}(t) = \mu(1 - y^2(t))\dot{y}(t) - y(t),$$

with  $\mu > 0$  represents a nonlinear damping coefficient. The system is already written in the observer canonical form<sup>3</sup> ( $z = I x$ ), in fact, let  $z_1 = y$  and  $z_2 = \dot{y} = \dot{z}_1$ , then

$$\begin{cases} \dot{z}_1 &= z_2, \\ \dot{z}_2 &= -z_1 - \mu(1 - z_1^2)z_2, \\ y &= z_1, \end{cases} \quad (43)$$

☹️: The Technical assumption *i*) is not satisfied with respect to  $f_2(\cdot)$ , in fact  $f_2(z)$  is not **globally** Lipschitz (whereas  $f_1(z_1) = z_1$  is Lipschitz, and *ii*) is satisfied for any  $0 < \alpha < 1$  and  $\beta \geq 1$ ).

😊: the state of a Van der Pol oscillator remains bounded.

---

<sup>3</sup>This is always the case when the system differential equations are written with respect to the output.

## Example: the Van der Pol oscillator

The high-gain observer for the oscillator is

$$\begin{cases} \dot{\hat{z}}_1 &= \hat{z}_2 & + k c_1 (y - \hat{y}), \\ \dot{\hat{z}}_2 &= -\hat{z}_1 + \mu(1 - \hat{z}_1^2)\hat{z}_2 & + k^2 c_0 (y - \hat{y}), \\ \hat{y} &= \hat{z}_1. \end{cases} \quad (44)$$

The polynomial  $p_c(s) = s^2 + c_1 s + c_0$  is Hurwitz iff (Cartesio's law)  $c_1 > 0$  and  $c_0 > 0$ . We assume now to know the set  $\mathcal{D}$  where the attractive limit cycle belongs to. Then, we can evaluate  $L$  such that, for all  $z \in \mathcal{D}$  it holds

$$\|\hat{z}_1 + \mu(1 - \hat{z}_1^2)\hat{z}_2 - (-z_1 + \mu(1 - z_1^2)z_2)\| \leq L \|\hat{z} - z\| = L\|e\|.$$

We pick  $c_0 = 2$ ,  $c_1 = 1$  and different  $k \in \{1, 10, 100\}$  (the  $k^*$  has not been evaluated numerically....laziness...).

The initial condition of the observer is set equal to  $\hat{z}_0 = (0, 0)$  whereas  $z_0 = (1, 1)$ .

# Example: the Van der Pol oscillator

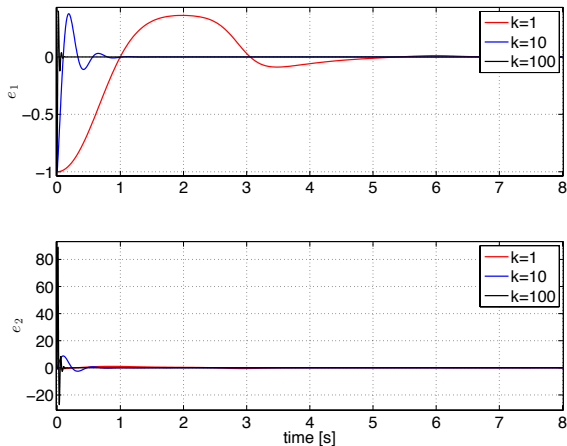


Figure: High gain observer for the Van der Pol oscillator: estimation errors for different  $k$ .

# Example: the Van der Pol oscillator

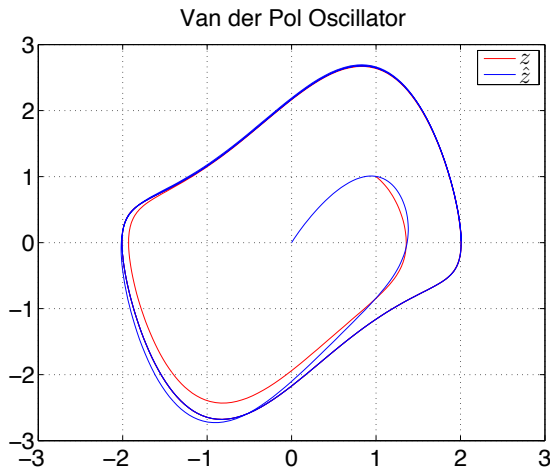


Figure: High gain observer for the Van der Pol oscillator: phase plot with  $k = 1$ .

# Example: the Van der Pol oscillator

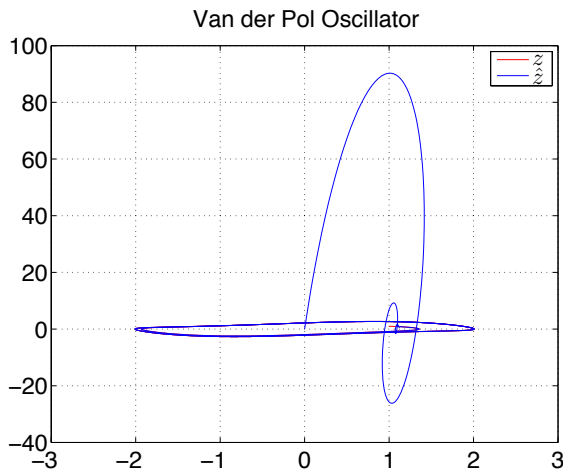


Figure: High gain observer for the Van der Pol oscillator: phase plot with  $k = 100$ .

## Example: the Van der Pol oscillator

What does it happen if the parameter  $\mu$  is not known exactly?

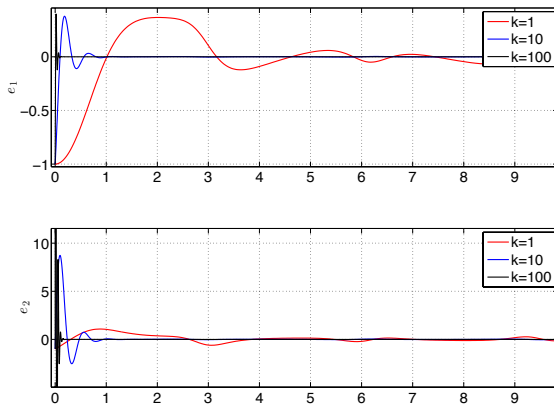


Figure: High gain observer for the Van der Pol oscillator with  $\bar{\mu} = 0.8\mu$  and different values of  $k$  (note the peaking phenomenon visible for  $k = 100$ ).



## Example: the Van der Pol oscillator

A constant estimate  $\bar{\mu}$  is considered and the observer is

$$\begin{cases} \dot{\hat{z}}_1 &= \hat{z}_2 & + k c_1 (y - \hat{y}), \\ \dot{\hat{z}}_2 &= -\hat{z}_1 + \bar{\mu}(1 - \hat{z}_1^2)\hat{z}_2 & + k^2 c_0 (y - \hat{y}), \\ \hat{y} &= \hat{z}_1. \end{cases} \quad (45)$$

The scaled estimation error dynamics are described by

$$\begin{bmatrix} \dot{\tilde{e}}_1 \\ \dot{\tilde{e}}_2 \end{bmatrix} = k \begin{bmatrix} -c_1 g_1(t) & g_2(t) \\ -c_0 g_1(t) & 0 \end{bmatrix} \begin{bmatrix} \tilde{e}_1 \\ \tilde{e}_2 \end{bmatrix} + \begin{bmatrix} k^{-1} F_1(\cdot) \\ k^{-2} F_2(\cdot) \end{bmatrix}, \quad (46)$$

where  $g_1(t) = g_2(t) = 1$ ,  $F_1(\cdot) = 0$  and

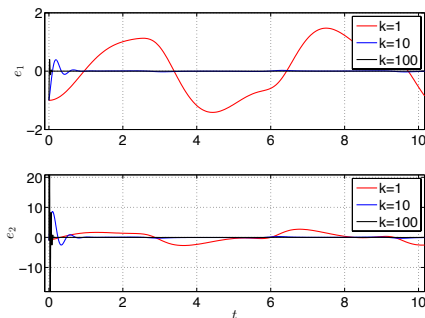
$$\begin{aligned} F_2(\cdot) &= -e_1 + \bar{\mu}(1 - \hat{z}_1^2)\hat{z}_2 - \mu(1 - \hat{z}_1^2)\hat{z}_2 = -e_1 + \mu(e_2 - \hat{z}_1^2\hat{z}_2 + z_1^2 z_2), \\ &= \underbrace{-e_1 + \mu(e_2 - \hat{z}_1^2\hat{z}_2 + z_1^2 z_2)}_{=0 \text{ if } e=0} + \underbrace{(\bar{\mu} - \mu)(1 - \hat{z}_1^2)\hat{z}_2}_{\text{can be } \neq 0 \text{ when } e=0}. \end{aligned} \quad (47)$$

There is a *non-vanishing perturbation term* that ruins asymptotic convergence. Nevertheless, the gain  $k$  gives certain degree of robustness to un-modeled dynamics reducing the perturbation term.

# Hi: the Van der Pol oscillator

...take it (very) easy....

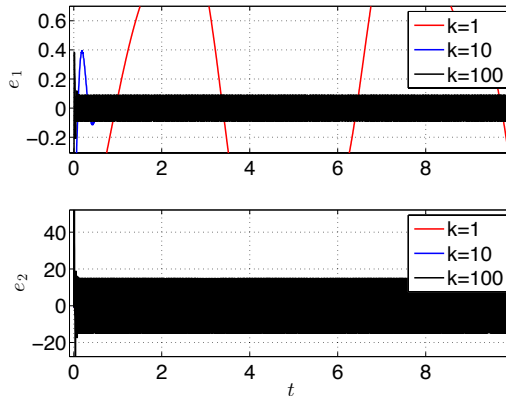
$$\begin{cases} \dot{\hat{z}}_1 &= \hat{z}_2 & + k c_1 (y - \hat{y}), \\ \dot{\hat{z}}_2 &= & + k^2 c_0 (y - \hat{y}), \\ \hat{y} &= \hat{z}_1. \end{cases} \quad (48)$$



**Figure:** The High gain observer for the Van der Pol oscillator in (48) for different values of  $k$ .

## Example: the Van der Pol oscillator

...wait, not too easy...



**Figure:** The High gain observer for the Van der Pol oscillator in (48) for different values of  $k$  in case of **measurement noise**  $d = 0.2 \sin(2\pi 50 t)$ .

## Example: the Van der Pol oscillator

Highlighting the main features of the high-gain observer:

- 😊: very easy to implement when the model is written with differential equation involving the measurable output  $y$
- 😊: robust to un-modeled dynamics
- 😊: easy to tune.
- 😞: finding the nonlinear map  $\Phi(\cdot)$  often requires complicated calculation
- 😞: it suffers of **peaking phenomenon** and it is sensitive to measurement noise (related to “high” gains).
- 😞: the globally Lipschitz assumption  $i)$  is very restrictive (as well as  $ii)$ ).

**Discretization:** the discretized version (Euler...) can be implemented but in this case the sampling and quantization introduce un-modeled dynamics (good...) and noise (ouch!).

# A nonlinear separation principle: introduction

Consider a system in the observability canonical form rewritten as

$$\begin{cases} \dot{z} &= f(z, u), \\ y &= h(z, u), \end{cases} \quad (49)$$

with  $f(0, 0) = h(0, 0) = 0$  and assume there exists a **feedback law**  $u = \alpha(z)$  such that the equilibrium  $z = 0$  ( $\Rightarrow \alpha(0) = 0$ ) of the closed-loop system

$$\dot{z} = f(z, \alpha(z))$$

is **GAS** (Globally Asymptotically Stable). Outlines of the proof:

- A saturated control  $u = \sigma_\gamma(\alpha(z))$  with the estimate  $\hat{z}$  is considered in place of  $u = \alpha(z)$  (only semi-global stability is achieved).
- It is shown that, independently by the selection of the observer gain  $k$ , the state of the closed-loop system remains bounded for a bounded time  $T$  no matter the estimation error is.
- The observer gain  $k$  is selected such that within a time  $T$  the estimation error is smaller than a desired value  $\varepsilon$ .
- It is shown that  $|z(t)|$  goes to zero since the estimation error goes to zero.

# Preliminaries

By the inverse Lyapunov theorem, if  $u = \alpha(z)$  renders the origin of (49) GAS, then there exist a smooth function  $W(z)$ , class  $\mathcal{K}_\infty$  functions  $\bar{\alpha}(\cdot)$ ,  $\underline{\alpha}(\cdot)$  and  $w(\cdot)$  such that

$$\underline{\alpha}(|z|) \leq W(z) \leq \bar{\alpha}(|z|), \quad \frac{\partial W}{\partial z} f(z, \alpha(z)) \leq -w(|z|), \quad \forall z \in \mathbb{R}^n.$$

Let the Technical Assumption *i*) and *ii*) hold (they will be removed) and the high-gain observer rewritten in a more general form as

$$\dot{\hat{z}} = \underbrace{f(\hat{z}, u)}_{\text{copy of the plant}} + \underbrace{G(y - h(\hat{z}, u))}_{\text{output-injection}}. \quad (50)$$

**Remark (From state feedback  $u = \alpha(z)$  to output feedback  $u = \alpha(\hat{z})$ )**

In the linear case the **separation principle** holds, then it is possible to design the observer and the control law independently and let  $u = \alpha(\hat{z})$ .

In the nonlinear case the stability analysis of the closed loop system with  $u = \alpha(\hat{z})$  have to be performed taking into account the estimation error dynamics.

In the latter case, in fact, exponential convergent estimates could even lead to finite escape time.

# Saturation and peaking phenonemon

Note that the estimation error  $e$  is related to  $\tilde{e}$  by

$$e = \hat{z} - z = \text{diag}\{k, k^2, \dots, k^n\} \tilde{e} = D_k \tilde{e},$$

yielding

$$\dot{z} = f(z, \alpha(\hat{z})) = f(z, \alpha(z + D_k \tilde{e})). \quad (51)$$

For large  $k$ , the estimation error  $e = D_k \tilde{e}$  exhibits transients with large amplitude values. To cope with the issues induced by the peaking phenomenon, the input  $u$  is “saturated” as

$$u = \sigma_\gamma(\alpha(\hat{z})),$$

where  $\sigma_\gamma(s) = s$  for all  $s : |s| \leq \gamma$  and is bounded elsewhere such that  $\sigma_\gamma(s) \leq 2\gamma$ . Then, **global** stability is lost (in general) and only **semi-global** stability is guaranteed.

On the other way around, it will be proven that the input saturation guarantees certain degree of decoupling between the observer design (selection of the parameter  $k$ ) and the output feedback law.

# The closed-loop analysis

Consider the system in closed loop with the observer, i.e.

$$\dot{z} = f(z, \sigma_\gamma(\alpha(\hat{z}))) = f(z, \sigma_\gamma(\alpha(z + D_k \tilde{e}))) = F(z) + H(z, \tilde{e}), \quad (52)$$

$$\dot{\hat{z}} = f(\hat{z}, \sigma_\gamma(\alpha(\hat{z}))) + G(h(z, \sigma_\gamma(\alpha(\hat{z}))) - h(\hat{z}, \sigma_\gamma(\alpha(\hat{z})))), \quad (53)$$

where  $F(z) = f(z, \alpha(z))$ ,  $H(z, \tilde{e}) = f(z, \sigma_\gamma(\alpha(z + D_k \tilde{e}))) - f(z, \alpha(z))$ .

Select  $R > 0$  such that  $(z(0), \tilde{e}(0)) \in \mathcal{A} := \mathcal{B}_R \times \mathcal{B}_R$  (then  $\hat{z}(0) = 0$ ), where  $\mathcal{B}_R := \{x \in \mathbb{R}^n : |x| \leq R\}$ , and

$$\Omega_c := \{z \in \mathbb{R}^n : W(z) \leq c\} \supset \mathcal{B}_R, \quad \Omega_{c+1} \supset \Omega_c \supset \mathcal{B}_R.$$

To leave unchanged the original control law within the set  $\Omega_{c+1}$ , pick

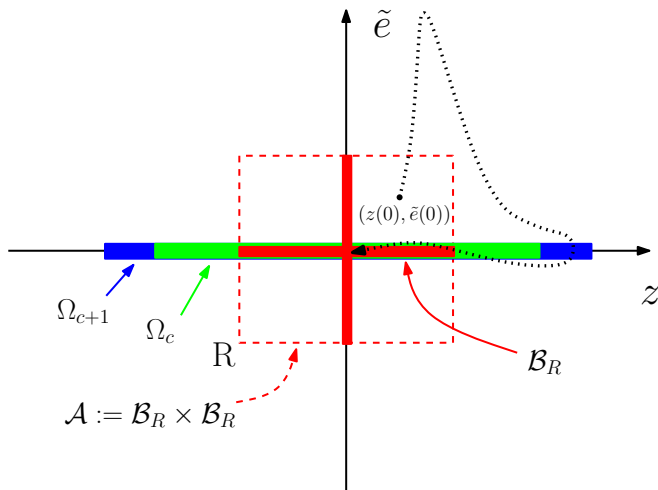
$$\gamma = \max_{z \in \Omega_{c+1}} \{\alpha(z)\} + 1.$$

Then there exist positive numbers  $M_0$ ,  $M_1$ ,  $\delta$  and  $M_2$  depending on  $R$  (the set  $\Omega_c$  and  $\Omega_{c+1}$  depend on  $R$ ) such that

$$\underbrace{\|H(z, \tilde{e})\| \leq M_0}_{\forall z \in \Omega_{c+1}, \tilde{e} \in \mathbb{R}^n}, \quad \underbrace{\|H(z, \tilde{e})\| \leq M_1 \|D_k \tilde{e}\|}_{\forall z \in \Omega_{c+1}}, \quad \underbrace{\left\| \frac{\partial W}{\partial z} \right\| \leq M_2}_{\forall z \in \Omega_{c+1}}.$$



# The closed-loop analysis: picture of the extended state space



**Figure:** The extended state space when  $\dim(z) = \dim(\tilde{e}) = 1$ . The set  $\mathcal{B}_R$  in this case is simply a segment.

## The closed-loop analysis: the saturation benefits

Due to the saturated input, regardless the values of  $\tilde{e}(t)$ , as long as  $z(t) \in \Omega_{c+1}$ , it holds

$$\dot{W}(z(t)) = \frac{\partial W}{\partial z} (F(z) + H(z, \tilde{e})) \leq -w(|z|) + \frac{\partial W}{\partial z} M_0 \leq -w(|z|) + M_2 M_0,$$

Denoting with  $M = M_2 M_0$ , the above inequality yields

$$\dot{W}(z(t)) \leq M \Rightarrow W(z(t)) \leq W(z(0)) + M t \Rightarrow z(t) \in \Omega_{c+1} \forall t \in [0, 1/M), \quad (54)$$

that is obtained by imposing  $W(T) = c + 1 = W(0) + MT = c + MT$ . Note that the time  $T = 1/M$  at which  $z(t)$  might leave (a worst case analysis has been performed) the set  $\Omega_{c+1}$  does not depend on  $k$  but on  $R$ .



The  $z(t)$ , thanks to the function  $\sigma_\gamma(\cdot)$  selected, remains bounded (within the set  $\Omega_{c+1}$ ) at least a time  $T$ .

## The closed-loop analysis: the estimation error convergence

We recall that

$$V(\tilde{e}) = \tilde{e}' S \tilde{e}, \quad \dot{V}(\tilde{e}(t)) \leq -c_k V(\tilde{e}(t)), \text{ with } c_k := k \lambda - 2\|S\|\sqrt{n}.$$

yielding

$$\|\tilde{e}(t)\|^2 \leq \frac{1}{\underline{\lambda}_S} V(\tilde{e}(t)) \leq \frac{\bar{\lambda}_S}{\underline{\lambda}_S} \|\tilde{e}(0)\|^2 e^{-c_k t},$$

where  $\underline{\lambda}_S \|\tilde{e}\|^2 \leq \tilde{e}' S \tilde{e} = V(x) \leq \bar{\lambda}_S \|\tilde{e}\|^2$ , and  $(\underline{\lambda}_S, \bar{\lambda}_S)$  are the smaller and the largest eigenvalues of  $S$ , respectively. Then

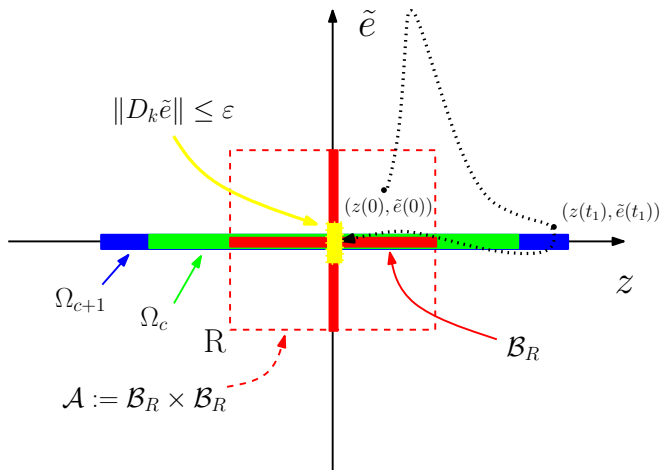
$$\|\tilde{e}(t)\| \leq \sqrt{\frac{\bar{\lambda}_S}{\underline{\lambda}_S}} \|\tilde{e}(0)\| e^{-\frac{c_k}{2} t},$$

and with the suggested selection  $\hat{z}(0) = 0$  and  $k \geq 1$  yields

$$\|D_k \tilde{e}(t)\| \leq k^n \sqrt{\frac{\bar{\lambda}_S}{\underline{\lambda}_S}} R e^{-\frac{c_k}{2} t}. \quad (55)$$

It is now clear that, due to the convergence properties of the exponential which depends on  $k$ , it is possible to select a sufficiently high value  $k^*$  such that if  $k \geq k^*$  then  $\|D_k \tilde{e}(t)\| \leq \varepsilon$  for any desired  $\varepsilon > 0$  before  $z(t)$  leaves the set  $\Omega_{c+1}$ , i.e. for  $t < T = 1/M$ .

# The closed-loop analysis: the estimation error convergence



**Figure:** The set in yellow is such that  $\|D_k \tilde{e}\| \leq \varepsilon$  and there exists a sufficiently high value  $k^*$  such that if  $k \geq k^*$  then  $\|D_k \tilde{e}(t)\| \leq \varepsilon$  for all  $t \geq t_1$  with  $t_1 < T$ .

# The closed-loop analysis: finite time convergence

Let now  $\varepsilon \leq \delta$ , then the previous inequality

$$\dot{W}(z(t)) \leq -w(|z(t)|) + M_2 M_1 \delta$$

certainly holds true if  $t \leq T$ . Consider the “annular” compact set

$$\Omega_{c+1}^d := \{z \in \mathbb{R}^n : d \leq W(z) \leq c+1\},$$

with  $d \ll c$  and define its “inner radius”  $r$  as

$$r := \min_{z \in \Omega_{c+1}^d} \{\|z\|\}.$$

Since  $w(\cdot) \in \mathcal{K}_\infty$ , then  $w(\|z\|) \geq w(r)$  for all  $z \in \Omega_{c+1}^d$ . This yields the existence of a **sufficiently small values of  $\delta$**  such that

$$M_2 M_1 \delta \leq \frac{1}{2} w(r) \Rightarrow \dot{W}(z(t)) \leq -\frac{1}{2} w(r).$$

Hence  $z(t)$  not only **does not leave** the set  $\Omega_{c+1}$ , but it **enters in finite time** the set  $\Omega_d$ . We have proved so far that if  $(z(0), \tilde{e}(0)) \in \mathcal{A}$ , saturating opportunely the input and selecting a sufficiently high value of  $k$ , then  $\tilde{e}(t)$  decays to zero and  $z(t)$  remains bounded.

## The closed-loop analysis: $\omega$ –limit set

To conclude, the previous analysis highlight the existence of an  $\omega$ –limit set and since  $\tilde{e}(t)$  converges to zero and the restriction of the closed-loop system to  $\tilde{e} = 0$  is

$$\dot{z} = f(z, \sigma_\gamma(\alpha(z))) = f(z, \alpha(z)),$$

in which  $z = 0$  is GAS, then the  $\omega$ –limit set is constituted just by the origin of the extended state space  $(z, \tilde{e}) = (0, 0)$ .

# A separation principle

## A separation principle

Consider the system (49) and assume that there exists a feedback law  $u = \alpha(z)$  that renders the origin  $z = 0$  GAS. Furthermore, let the Technical Assumptions hold so that the high-gain observer of the form (32) can be considered. Then, there exists a saturation function  $\sigma_\gamma(\cdot)$  and a sufficiently large value of  $k$  such that the origin of the extended system

$$\dot{z} = f(z, \sigma_\gamma(\alpha(\hat{z}))), \quad (56)$$

$$\dot{\hat{z}} = f(\hat{z}, \sigma_\gamma(\alpha(\hat{z}))) + G(h(z, \sigma_\gamma(\alpha(\hat{z}))) - h(\hat{z}, \sigma_\gamma(\alpha(\hat{z})))), \quad (57)$$

is semi-globally (with respect to  $z(0)$ ) asymptotically stable.

## Remark

The requirement on the Technical Assumptions can be relaxed. In fact, it has been proven that, independently of  $\tilde{e}(t)$ , the saturated control  $u = \sigma_\gamma(\alpha(z))$  yield  $z(t) \in \Omega_{c+1}$  for at least  $t \leq T = 1/M$ . Then, evaluating  $\alpha$  and  $\beta$  of the Technical Assumption over the set  $\Omega_{c+1}$ , allows to completely define the high-gain observer.

## Observers: A different point of view...

Consider the continuous time nonlinear system described by

$$\dot{x} = f(x, u), \quad (58)$$

$$y = h(x, u), \quad (59)$$

where  $x(t) \in \mathbb{R}^n$  is the state variable,  $u(t) \in \mathbb{R}^m$  denotes the input and  $y(t) \in \mathbb{R}^p$  is the output of the system.

The input  $u$  is **piece-wise constant**, as produced by a sample-and-hold device, with sampling time  $T$ .



## Observers: A different point of view...

Define as  $y_k$  the sampled value of the output such as  $y_i := y(t_i)$ , with  $t_{i+1} - t_i = T$ , for all  $i \geq 0$ . Similarly define the sampled input  $u_i := u(t_i)$ .

Let  $Y_i^q \in \mathbb{R}^{qp}$  and  $U_i^q \in \mathbb{R}^{qm}$  be defined as

$$Y_i^q = \begin{bmatrix} y_{i-N+1} \\ \vdots \\ y_{i-N+q} \end{bmatrix}, \quad U_i^q = \begin{bmatrix} u_{i-N+1} \\ \vdots \\ u_{i-N+q} \end{bmatrix}.$$

Moreover, define  $H(x_{i-N+1}, U_i^N) : \mathbb{R}^{n \times Nm} \mapsto \mathbb{R}^{Np}$  as

$$H(x_{i-N+1}, U_i^N) \triangleq \begin{bmatrix} h(x_{i-N+1}, u_{i-N+1}) \\ h(F_T(x_{i-N+1}, U_i^1), u_{i-N+2}) \\ \vdots \\ h(F_{(N-1)T}(x_{i-N+1}, U_i^{N-1}), u_i) \end{bmatrix}, \quad (60)$$

with  $Y_i^N = H(x_{i-N+1}, U_i^N)$ , where  $F_{qT}$  is such that  $x_{i-N+1+q} = F_{qT}(x_{i-N+1}, U_i^q)$ .

**Note that in general the analytical expression of  $F$  is unknown.**

## Observers: A different point of view...minimization!

The estimation problem can be reformulated as follows.

**Estimation problem:** Find the value  $\hat{x}_{i-N+1}$  such that

$$Y_i^N - H(\hat{x}_{i-N+1}, U_i^N) = 0, \quad (61)$$

holds, and select a suitable  $N$  (assuming that it exists<sup>4</sup>) such that if (61) holds, then  $\hat{x}_k = x_k$  for all  $k \geq i - N + 1$ .  $\square$

The problem of estimation can be recast into a multi-parametric minimization problem for  $V_i(Y_i^N - H(\hat{x}_{i-N+1}, U_i^N))$ , with a positive definite  $V : \mathbb{R}^N \rightarrow \mathbb{R}_{\geq 0}$  such that  $V_i$  is zero iff  $\hat{x}_{i-N+1} = x_{i-N+1}$ .

The map  $F_{qT}(\cdot)$  is not known in general, but it can be numerically evaluated integrating the system vector field between sampling times.

Typically  $N \geq 2n$  works fine, but a larger  $N$  should be considered when the measurements are affected by noise.

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<sup>4</sup>Then the system is defined **N-observable**

## Considerations

- There are available a great number of techniques for multi-parametric minimization problems (line search, Gradient-like, Newton-like, Monte Carlo methods ecc...)
- The computational cost of the selected method should be carefully considered since it has to run on-line (and generically has to converge, or at least give a “better approximation” with respect to the previous one within a time  $T$ ...)
- Gradient and Newton algorithms can not be used in general since the map  $F_{qT}(\cdot)$  is not known (so its explicit dependence by  $x_{i-N+1}$  is unknown) and approximation methods have to be considered.
- Generally the “course of dimensionality” affects this (brutal force) approach.

...nevertheless, it is quite effective in a number of applications.

This observer could be exploited to define a “good” initial condition for your more sophisticated observer (a local, semi-global,...).

...

The goal is:

find  $\hat{x}$  such that  $\hat{x} = \operatorname{argmin} V_i(x)$ .

Gradient algorithm:

$$\dot{\hat{x}}(t) = -\gamma \frac{\partial V_i(\hat{x}(t))}{\partial \hat{x}(t)}, \quad \hat{x}(k+1) = \hat{x}(k) - \gamma \frac{\partial V_i(\hat{x}(k))}{\partial \hat{x}(k)},$$

If  $V_i$  is **strictly quasi-convex** the convergence toward the **unique minimum** is **global** (it may be slow especially around the minimum and in discrete time the chattering phenomenon is likely to happen).

Newton algorithm:

$$\hat{x}(k+1) = \hat{x}(k) - \left( \frac{\partial^2 V_i(\hat{x}(k))}{\partial^2 \hat{x}(k)} \right)^{-1} \frac{\partial V(\hat{x}(k))}{\partial \hat{x}(k)},$$

The global convergence is not guaranteed in general. However, under some technical assumptions (see for example the Kantorovich's Theorem), (locally) the algorithm **converges quadratically**. When the Jacobian of  $V_i$  is not square, the Penn-Rose pseudo-inverse has to be considered.