

Observers for non-linear systems

Manipulation Lab talk

Siddhartha Srinivasa

The Robotics Institute
Carnegie Mellon University

Outline

General framework

An example

Non-linear systems

Some differential geometry

Review of linear observability

Observability rank condition

Linear observers

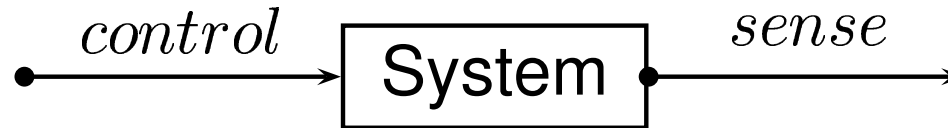
Observer design : Lie-algebraic method

Conclusions

Things I did not do

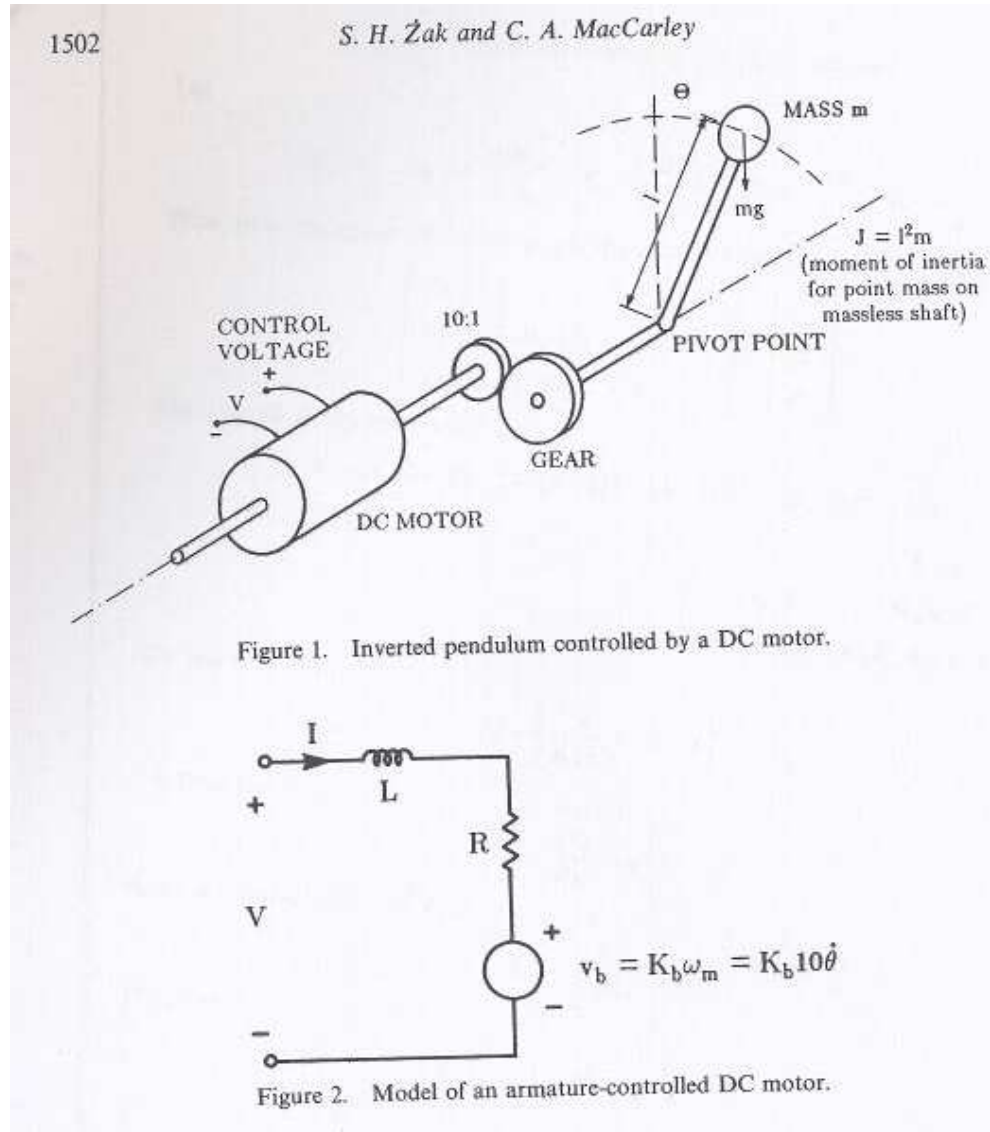
References

General framework



- Identify forces and torques
- Equations of motion, constraint equations
- Pick suitable state variables
- Write the equations (implicit) in state-space form (explicit)
- Analyze the state-space equations for system behaviour

An example



An example

- Inverted pendulum with DC motor control
- DC motor armature controlled
- motor inertia « pendulum inertia

For the motor

$$V = Li + Ri + V_b$$

$$V_b = K_b(10\dot{\theta})$$

$$T_m = K_m i$$

For the pendulum

$$T_p = 10T_m$$

$$T_p = -l^2 m \ddot{\theta} + l m g \sin(\theta)$$

An example

Choose state variables

$$x_1 = \theta \quad x_2 = \dot{\theta} \quad x_3 = i$$

State space form

$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \\ \dot{x}_3 \end{bmatrix} = \begin{bmatrix} x_2 \\ \frac{g}{l} \sin(x_1) + \frac{10K_m}{l^2 m} x_3 \\ -\frac{10K_b}{l} x_2 - \frac{R}{l} x_3 \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ \frac{1}{L} \end{bmatrix} u$$

Non-linear systems

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

$$y = h(x)$$

$$\dot{x} = f(x) + \sum_{i=1}^m u_i g_i(x)$$

x	system state in a state-space manifold $M \subseteq \mathbb{R}^n$
f, g_i	smooth vector fields on M
f	drift vector field
g_1, g_2, \dots, g_m	input vector fields
u_1, u_2, \dots, u_m	scalar controls
h	output map

Review of linear observability

A SISO system

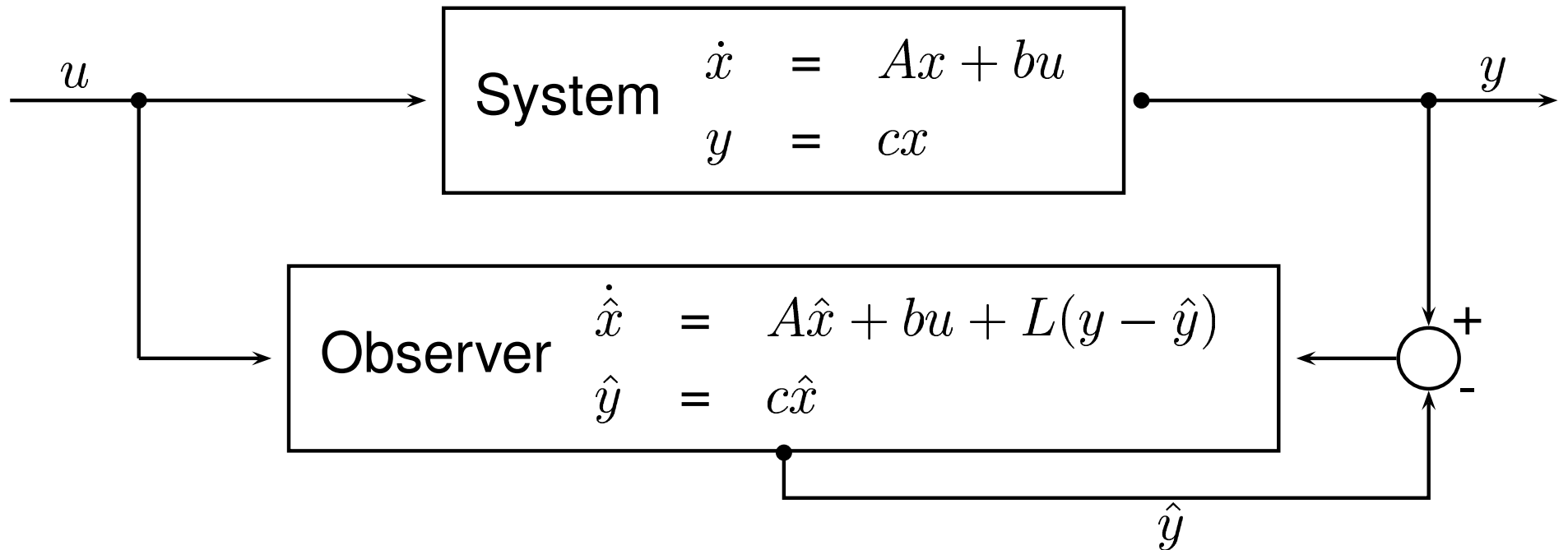
$$\dot{x} = Ax + bu$$

$$y = cx$$

Kalman Rank Condition for observability

$$\text{rank} \begin{pmatrix} c \\ cA \\ cA^2 \\ \vdots \\ cA^{n-1} \end{pmatrix} = n$$

Linear observers



The error dynamics is given by :

$$\dot{e} = (A - LC)e$$

Eigenvalues of $(A-LC)$ arbitrarily placed by a proper choice of L .

A first pass : output injection

Consider the nonlinear system

$$\begin{aligned}\dot{x} &= f(x) & x &\in \mathbb{R}^n \\ y &= h(x) & y &\in \mathbb{R}^p\end{aligned}$$

Create an observer with linear output injection

$$\begin{aligned}\dot{\hat{x}} &= f(\hat{x}) + L(y - \hat{y}) \\ \hat{y} &= h(\hat{x})\end{aligned}$$

where $L \in \mathbb{R}^{n \times p}$ is the observer gain matrix we have control over

A first pass : error dynamics

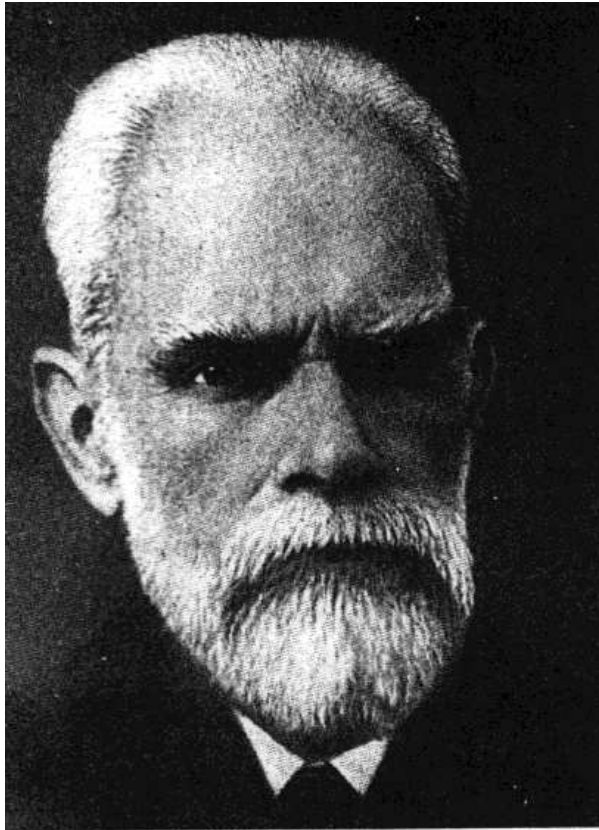
$$\begin{aligned}\dot{e} &= (\dot{x} - \dot{\hat{x}}) \\ &= f(x) - [f(\hat{x}) + L(y - \hat{y})]\end{aligned}$$

Error dynamics is nonlinear and stability is unclear. But ...

The stability of a linearized system about its fixed point implies the *local* stability of the corresponding nonlinear system about that fixed point

Why? I don't have a good answer, but here are some pictures of Lyapunov

The many moods of Aleksandr Mikhailovich Lyapunov



*Александр Михайлович
ЛЯПУНОВ*

angry



happy

A first pass : linearizing error

Linearizing the error dynamics about the fixed point $e = 0$

$$\dot{e} = f(x) - [f(\hat{x}) + L(h(x) - h(\hat{x}))]$$

$$\hat{x} = (x - e)$$

$$\dot{e} = f(x) - [f(x - e) + L(h(x) - h(x - e))]$$

$$f(x - e) = f(x) - e \frac{\partial f}{\partial x}$$

$$h(x - e) = h(x) - e \frac{\partial h}{\partial x}$$

$$\dot{e} = \left(\frac{\partial f}{\partial x} + L \frac{\partial h}{\partial x} \right) e$$

A first pass : conclusion

$$\dot{e} = \left(\frac{\partial f}{\partial x} + L \frac{\partial h}{\partial x} \right) e$$

The linearization is a function of the true state x which is

- not a fixed quantity
- unknown to us ... its what we're trying to estimate!

Also, the linearization is valid only for a small neighbourhood about the fixed point.

Some differential geometry

- $h : \mathbb{R}^n \mapsto \mathbb{R}$ - a smooth function
- $f : \mathbb{R}^n \mapsto \mathbb{R}^n$ - a vector field
- $\langle \cdot, \cdot \rangle$ - the standard dot product on \mathbb{R}^n
- $dh = \nabla h$ - the gradient of h with respect to x

The **Lie derivative** of h w.r.t. f is given by :

$$L_f h = \langle dh, f \rangle = \nabla h \cdot f$$

Also,

$$d(L_f h) = L_f(dh)$$

Example

$$h = x^2 + y + 1$$

$$f = \begin{bmatrix} x \\ xy \end{bmatrix}$$

$$dh = \begin{bmatrix} \frac{\partial h}{\partial x} \\ \frac{\partial h}{\partial y} \end{bmatrix} = \begin{bmatrix} 2x \\ 1 \end{bmatrix}$$

$$L_f h = \langle dh, f \rangle = 2x^2 + xy$$

$$d(L_f h) = \begin{bmatrix} 4x + y \\ x \end{bmatrix}$$

Observability rank condition

The *observation space* O is the linear space of the functions h_1, h_2, \dots, h_p and all repeated Lie derivatives

$$L_{X_1} L_{X_2} \dots L_{X_l} h_j$$

$$j = 1, 2, \dots, k$$

$$l = 1, 2, \dots$$

$$X_i \in [f, g_1, g_2, \dots, g_m]$$

Intuitively, O comprises of the output functions and the magnitude of their derivatives along all possible system trajectories (in infinitesimal time).

Observability rank condition

The *observability codistribution* $dO(x)$ is defined as

$$dO(x) = \text{span}[dH(x) | H \in O]$$

The system is locally observable at state x_0 if

$$\dim[dO(x_0)] = n$$

Must do example...

$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \\ \dot{x}_3 \end{bmatrix} = \begin{bmatrix} x_2 \\ \sin(x_1) + x_3 \\ x_2 + x_3 \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} u$$

$$y = x_1 = h(x)$$

Taking Lie-derivatives

$$dh = [1 \ 0 \ 0]$$

$$L_f h = dh \cdot f = x_2$$

$$d(L_f h) = [0 \ 1 \ 0]$$

$$L_f L_f h = d(L_f h) \cdot f = \sin(x_1) + x_3$$

$$d(L_f L_f h) = [\cos(x_1) \ 0 \ 1]$$

$$O(x) = \begin{bmatrix} dh \\ d(L_f h) \\ d(L_f L_f h) \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ \cos(x_1) & 0 & 1 \end{bmatrix}$$

Observer design : transformation

$$\begin{aligned}\dot{x} &= f(x) & x &\in \mathbb{R}^n \\ y &= h(x) & y &\in \mathbb{R}\end{aligned}$$

We wish to find a smooth one-to-one onto global nonlinear transformation

$$x = T(z)$$

which gives us

$$\begin{aligned}\dot{z} &= Az - g(y) \\ y &= Cz\end{aligned}$$

- Why do we care?
- Isn't that asking for a bit too much?

Why do we care?

Remember, we can measure y .
Create an observer of the form

$$\begin{aligned}\dot{\hat{z}} &= A\hat{z} - g(y) + L(y - \hat{y}) \\ \hat{y} &= C\hat{z}\end{aligned}$$

Error dynamics

$$\begin{aligned}e &= (z - \hat{z}) \\ \dot{e} &= Az - g(y) - [A\hat{z} - g(y) + L(y - \hat{y})] \\ &= (A + LC)e\end{aligned}$$

Error dynamics is exactly like the linear observer!

We can place poles wherever we wish.

Can we really do this?

Comparative study of nonlinear state-observation techniques

Walcott BL, Corless MJ, Zak SH

International Journal of Control, 1987, Vol. 45, No. 6,
2109-2132

- The derivation is long and complicated
- I don't fully understand it.
- But, I can implement their algorithm

Back to the example

$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \\ \dot{x}_3 \end{bmatrix} = \begin{bmatrix} x_2 \\ \sin(x_1) + x_3 \\ x_2 + x_3 \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} u$$

$$y = x_1 = h(x)$$

The observability matrix is given by

$$O(x) = \begin{bmatrix} dh \\ d(L_f h) \\ d(L_f L_f h) \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ \cos(x_1) & 0 & 1 \end{bmatrix}$$

The Algorithm

- Compute O^{-1}

$$\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ -\cos(t) & 0 & 1 \end{bmatrix}$$

- The *starting vector* $\frac{\partial T}{\partial z_1}$ is the last column of O^{-1}

$$\frac{\partial T}{\partial z_1} = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$$

The Algorithm

- Build the Jacobian matrix of T

$$\frac{\partial T}{\partial z} = \left[\left(ad^0 f, \frac{\partial T}{\partial z_1} \right), \left(ad^1 f, \frac{\partial T}{\partial z_1} \right), \left(ad^2 f, \frac{\partial T}{\partial z_1} \right) \right]$$

$$(ad^1 f, g) = [f, g] = \frac{\partial f}{\partial x} g - \frac{\partial g}{\partial x} f$$

$$(ad^k f, g) = [f, (ad^{k-1} f, g)]$$

$$(ad^0 f, g) = g$$

The Algorithm

- Build the Jacobian matrix of T

$$\frac{\partial T}{\partial z} = \begin{bmatrix} 0 & 0 & 1 \\ 0 & 1 & 1 \\ 1 & 1 & 2 \end{bmatrix}$$

- Solving for T

$$T(0) = 0$$

$$T(z) = \begin{bmatrix} 0 & 0 & 1 \\ 0 & 1 & 1 \\ 1 & 1 & 2 \end{bmatrix} z$$

The Algorithm

- Apply the transformation

$$\dot{z} = \begin{bmatrix} 0 & 0 & 0 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} z + \begin{bmatrix} -\sin(z_3) \\ \sin(z_3) + z_3 \\ z_3 \end{bmatrix}$$

$$y = \begin{bmatrix} 0 & 0 & 1 \end{bmatrix} z = z_3$$

The Algorithm

- The observer

$$\dot{\hat{z}} = \begin{bmatrix} 0 & 0 & 0 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} \hat{z} + \begin{bmatrix} -\sin(y) \\ \sin(y) + y \\ y \end{bmatrix} + \begin{bmatrix} k_1 \\ k_2 \\ k_3 \end{bmatrix} (y - \hat{y})$$

$$\hat{y} = \begin{bmatrix} 0 & 0 & 1 \end{bmatrix} \hat{z}$$

The Algorithm

- Error dynamics

$$e = (z - \hat{z})$$

$$\dot{e} = \begin{bmatrix} 0 & 0 & k_1 \\ 1 & 0 & k_2 \\ 0 & 1 & k_3 \end{bmatrix} e = Ae$$

- Error in original coordinates

$$\dot{e}_{orig} = TAT^{-1}e_{orig}$$

Why was this so easy?

The tricky bit is to go from $\frac{\partial T}{\partial z_1}$ to T . For more complex systems, you will have to integrate n coupled partial differential equations.

Bestle and Zeitz(1983) provide a hack for that.

But I'm not going to go into it.

Conclusions

- Given a nonlinear system, $rank(O(x)) = n$ tells us if the system is observable or not.
- If the system is observable, the Lie-algebraic approach gives a smooth nonlinear transformation T that converts the state space equation into a form that we like.
- Once this is done, we can use good old Luenberger output injection to stabilize the error dynamics.

Things I did not do

- The icky derivations.
- Other kinds of observers : Extended linearization, Thau observer, VSS technique, GHO observer.
- Extended Kalman filters.

References

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4. *Canonical form observer design for non-linear time-variable systems*, D. Bestle and M. Zeitz., Int. J. Control, 38(2):419-431, 1983
5. *Manifolds : Calculus on curved surfaces*, Lyle Noakes, <http://www.maths.uwa.edu.au/~rkealey/mf3/manifolds/manifolds.htm>

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