

Lec. 7 (04/21/2020)

Construction of Lyapunov Functions : (How to engineer)

Three methods
well-known in literature

Method # 1

(Variable Gradient Method)

Method # 2

(Krasovskii Method)

Method # 3

SOS
(Sum-of-squares
method)

Method #1 : Variable Gradient Method :

To construct $V(\underline{x})$ for $\dot{\underline{x}} = \underline{f}(\underline{x})$

$$\text{Let } \underline{g}(\underline{x}) := \nabla_{\underline{x}} V \equiv \frac{\partial V}{\partial \underline{x}}$$

$$\begin{aligned} \text{we know: } \dot{V} &= \left\langle \frac{\partial V}{\partial \underline{x}}, \underline{f} \right\rangle \\ &= \left\langle \underline{g}, \underline{f} \right\rangle \end{aligned}$$

Idea: Instead of engineering V (scalar valued \underline{f})
let us instead engineer \underline{g} (vector valued \underline{f})

Claim: If $\underline{g}(\underline{x})$ is gradient of a scalar f
then its Jacobian $\left[\frac{\partial \underline{g}}{\partial \underline{x}} \right]$ is a symmetric matrix.
 $\Leftrightarrow \frac{\partial g_i}{\partial x_j} = \frac{\partial g_j}{\partial x_i} \quad \forall i, j = 1, \dots, n$

Why? If $\underline{g} = \nabla_{\underline{x}} V$, then $\left[\frac{\partial \underline{g}}{\partial \underline{x}} \right] = \text{Hess}(V) \Rightarrow \text{Symmetric}.$

Construct \underline{g} such that ① $\left[\frac{\partial \underline{g}}{\partial \underline{x}} \right]$ is symmetric.

② $\langle \underline{g}, \underline{f} \rangle < 0$.

Then,
$$V(\underline{x}) = \int_0^{\underline{x}} \langle \underline{g}(\underline{y}), d\underline{y} \rangle$$

Integral taken over any path joining $\underline{0}$ to \underline{x}

(line integral of gradient vector field is independent of the path)

For example, if we take integral along the co-ordinate axes, then

$$V(\underline{x}) = \int_0^{x_1} g_1(y_1, 0, \dots, 0) dy_1 + \int_0^{x_2} g_2(x_1, y_2, 0, \dots, 0) dy_2 \\ + \dots + \int_0^{x_n} g_n(x_1, x_2, \dots, x_{n-1}, y_n) dy_n$$

By leaving some parameters in $\underline{g}(\underline{x})$ undetermined, try to choose the parameters such that $V(\underline{x})$ becomes positive def. function.

Example:

$$\dot{x}_1 = x_2$$

$$\dot{x}_2 = -h(x_1) - ax_2$$

spl. case of this
→ pendulum

→ HW 2, p 2

$$a = 1$$

$$h(x_1) = x_1 - x_1^3$$

$a > 0$, $h(\cdot)$ is locally Lipschitz

$$h(0) = 0.$$

$$\boxed{y h(y) > 0} \quad \forall \{y \neq 0 \mid -b < y < c\}$$

$$b, c > 0.$$

we want ①
$$\boxed{\frac{\partial g_1}{\partial x_2} = \frac{\partial g_2}{\partial x_1}}$$

$$\textcircled{2} \quad \dot{V} = \langle \underline{g}, \underline{f} \rangle$$

$$= g_1(\underline{x})x_2 - g_2(\underline{x})(h(x_1) + a(x_2))$$

$$< 0 \quad \forall \underline{x} \neq \underline{0}.$$

$$\textcircled{3} \quad V(\underline{x}) = \int_0^{\underline{x}} \langle \underline{g}(\underline{y}), d\underline{y} \rangle > 0 \quad \forall \underline{x} \neq \underline{0}.$$

Try: $g(\underline{x}) = \begin{pmatrix} \alpha(\underline{x}) x_1 + \beta(\underline{x}) x_2 \\ \gamma(\underline{x}) x_1 + \delta(\underline{x}) x_2 \end{pmatrix} = \begin{pmatrix} g_1(x_1, x_2) \\ g_2(x_1, x_2) \end{pmatrix}$

$$\frac{\partial g_1}{\partial x_2} = \frac{\partial g_2}{\partial x_1}$$

Where $\alpha(\cdot)$, $\beta(\cdot)$, $\gamma(\cdot)$, $\delta(\cdot)$ are to be determined.

From symmetry requirement:

$$\beta(\underline{x}) + \frac{\partial \alpha}{\partial x_2} x_1 + \frac{\partial \beta}{\partial x_2} x_2 = \gamma(\underline{x}) + \frac{\partial \gamma}{\partial x_1} x_1 + \frac{\partial \delta}{\partial x_1} x_2$$

From \dot{V} :

$$\begin{aligned} \dot{V}(\underline{x}) = & \underline{\alpha(\underline{x}) x_1 x_2} + \beta(\underline{x}) x_2^2 - \underline{\alpha \gamma(\underline{x}) x_1 x_2} \\ & - \alpha \delta(\underline{x}) x_2^2 - \underline{\delta(\underline{x}) x_2 h(x_1)} - \gamma(\underline{x}) x_1 h(x_1) \end{aligned}$$

Let us cancel the cross terms:

To cancel the cross terms:

$$\boxed{\alpha(\underline{x})x_1 - a\delta(\underline{x})x_1 - \delta(\underline{x})h(x_1) = 0}$$

$$\Rightarrow \dot{V} = -[a\delta(\underline{x}) - \beta(\underline{x})]x_2^2 - \delta(\underline{x})x_1h(x_1)$$

To simplify further, fix $\beta(\underline{x}) = \beta$, $\delta(\underline{x}) = \delta$,
 $\delta(\underline{x}) = \delta$
constants:

$$\alpha(\underline{x}) = a\delta + \frac{\delta h(x_1)}{x_1} \Rightarrow \underbrace{\alpha(\underline{x}) \equiv \alpha(x_1)}$$

fnc. of x_1 alone

$$\Rightarrow \boxed{\frac{\partial \alpha}{\partial x_2} = 0}$$

Then, simplify the symmetry requirement condition:

$$\beta + \cancel{\frac{\partial \alpha}{\partial x_2} x_1} + \cancel{\frac{\partial \beta}{\partial x_2} x_2} = \cancel{\delta(\underline{x})} + \cancel{\frac{\partial \delta}{\partial x_1} x_1} + \cancel{\frac{\partial \delta}{\partial x_1} x_2}$$

$$\Rightarrow \beta + 0 + 0 = \gamma + 0 + 0 \Rightarrow \boxed{\beta = \gamma}$$

Therefore, $g(\underline{x}) = \left[\frac{a\gamma x_1 + \delta h(x_1) + \gamma x_2}{\delta x_1 + \delta x_2} \right]$

Now, $V(\underline{x}) = \int_0^{x_1} g_1(y_1, 0) dy_1 + \int_0^{x_2} g_2(x_1, y_2) dy_2$

$$= \int_0^{x_1} (a\gamma y_1 + \delta h(y_1)) dy_1 + \int_0^{x_2} (\delta x_1 + \delta y_2) dy_2$$

$$= \frac{1}{2} \underline{x}^T P \underline{x} + \delta \int_0^{x_1} h(y) dy, \text{ where } P := \begin{bmatrix} a\gamma & \gamma \\ \gamma & \gamma \end{bmatrix}$$

For $V(\cdot)$ to be positive definite, we need:

$$a\gamma > 0, \quad a\delta\gamma - \gamma^2 > 0 \Leftrightarrow \underline{\gamma(a\delta - \gamma) > 0}$$

Choose $\gamma > 0 \Rightarrow \boxed{a\delta > \gamma > 0}$.

\therefore Choosing $\delta > 0$, $0 < \gamma < a\delta$, ensures

$V(\underline{x})$ is a pos. def. function.

and \dot{V} is a neg. def. function.

For example, taking $\gamma = ka\delta$, for some $0 < k < 1$,
gives $V(\underline{x}) = \frac{\delta}{2} \underline{x}^T \begin{bmatrix} ka^2 & ka \\ ka & 1 \end{bmatrix} \underline{x} + \delta \int_0^{x_1} h(y) dy$

as a Lyapunov function over domain

$$\mathcal{X} := \{ \underline{x} \in \mathbb{R}^2 \mid -b < x_1 < c \}$$

Method # 2 : Krasovskii's Method :

Theorem : Let $\underline{x}^* = \underline{0}$ be a fixed point for $\dot{\underline{x}} = \underline{f}(\underline{x})$. If \exists $\underline{P} > 0$ ($\Leftrightarrow \underline{x}^T \underline{P} \underline{x} > 0 \forall \underline{x} \neq \underline{0}$)

such that

$$\left[\frac{\partial \underline{f}}{\partial \underline{x}} \right]^T \underline{P} + \underline{P} \left[\frac{\partial \underline{f}}{\partial \underline{x}} \right] < 0$$

constant matrix

($= -Q$ where $Q > 0$)

$$\forall \underline{x} \in \mathcal{D} \subseteq \mathbb{R}^n$$

then $\underline{x}^* = \underline{0}$ is A.S. with $V(\underline{x}) = \underline{f}(\underline{x})^T \underline{P} \underline{f}(\underline{x})$

- If in addition, $\mathcal{D} \equiv \mathbb{R}^n$, and $V(\underline{x})$ is radially unbounded, then $\underline{x}^* = \underline{0}$ is GAS.

Proof : (Sketch) $V(\underline{x}) = \underline{f(\underline{x})}^T \mathcal{P} \underline{f(\underline{x})}$

$$V(\underline{x}) = 0 \text{ iff } \underline{f(\underline{x})} = \underline{0} \Leftrightarrow \underline{x}^* = \underline{0}$$

$$V(\cdot) > 0 \text{ for } \underline{x} \neq \underline{0}$$

$$\dot{V} = \langle \nabla V, \underline{f} \rangle$$

$$= 2 \underline{f(\underline{x})}^T \underbrace{\left\{ \left(\frac{\partial \underline{f}}{\partial \underline{x}} \right)^T \mathcal{P} + \mathcal{P} \left(\frac{\partial \underline{f}}{\partial \underline{x}} \right) \right\}}_{\Sigma_f} \underline{f(\underline{x})}$$

$$\text{then } \dot{V} < 0 \quad \forall \underline{x} : \underline{f(\underline{x})} = \underline{0} \Leftrightarrow \underline{x} = \underline{x}^*$$

Example:

($P = ??$)

(Try $P = I$)

$$\left. \begin{aligned} \dot{x}_1 &= -7x_1 + 4x_2 \\ \dot{x}_2 &= x_1 - x_2 - x_2^5 \end{aligned} \right\} V(\underline{x}) = \underline{f}^T \cancel{P} \underline{f}$$

\downarrow
 I

$$= \underline{f}^T \underline{f}$$

$$= (-7x_1 + 4x_2)^2 + (x_1 - x_2 - x_2^5)^2 \geq 0$$

Radially
unbounded.

Jacobian:

$$\frac{\partial \underline{f}}{\partial \underline{x}} = \begin{bmatrix} \frac{\partial f_1}{\partial x_1} & \frac{\partial f_1}{\partial x_2} \\ \frac{\partial f_2}{\partial x_1} & \frac{\partial f_2}{\partial x_2} \end{bmatrix}$$

$$= \begin{bmatrix} -7 & 4 \\ 1 & (-1 - 5x_2^4) \end{bmatrix}$$

$$\left[\frac{\partial f}{\partial \underline{x}} \right]^T \cancel{P}^T I + \cancel{P}^T I \left[\frac{\partial f}{\partial \underline{x}} \right]$$

$$= \begin{bmatrix} -\underline{\underline{7}} & \underline{\underline{4}} \\ \underline{\underline{1}} & \underline{\underline{(-1-5x_2^4)}} \end{bmatrix}^T + \begin{bmatrix} -7 & 4 \\ 1 & (-1-5x_2^4) \end{bmatrix}$$

$$= - \begin{bmatrix} \textcircled{14} & -5 \\ -5 & 2(1+5x_2^4) \end{bmatrix} \begin{matrix} \leftarrow \det(\cdot) \\ \boxed{14} > 0 \\ = 3 + 140x_2^4 > 0 \end{matrix}$$

$\underbrace{\hspace{10em}}_{> 0}$
 $\underbrace{\hspace{10em}}_{< 0}$

$\therefore \underline{x}^* = \underline{0}$ is C.A.S.

Method #3: Sum-of-squares Polynomials / (SOS)

SOS programming / optimization

Lyapunov style Theorems ask to establish

$$\textcircled{1} \quad V(\underline{x}) > 0 \quad \forall \quad \underline{x} \neq \underline{0}$$

$$\textcircled{2} \quad -\dot{V}(\underline{x}) > 0 \quad \forall \quad \underline{x} \neq \underline{0}$$

If LTI then LMI:

$$\underline{\dot{f}}(\underline{x}) = A\underline{x}$$

$$V(\underline{x}) = \underline{x}^T P \underline{x}$$

$$P > 0$$

$$A^T P + P A < 0$$

Idea: Search $V(\underline{x})$ over non-negative polynomials

Polynomial

is a linear combination of monomials:

Monomial

Product of power of variables: $(x^2 y z^3)$

Example:

$$p(x_1, x_2) = \underbrace{x_1^2}_{\text{monomial}} - 2 \underbrace{x_1 x_2^2}_{\text{monomial}} + 2 \underbrace{x_2^4}_{\text{monomial}} + 2 \underbrace{x_1^3 x_2}_{\text{monomial}} - 7 \underbrace{x_2}_{\text{monomial}} + 8$$

polynomial of degree 4

SOS polynomial: A polynomial $p(\underline{x})$ is SOS if \exists other polynomials $g_1(\underline{x}), g_2(\underline{x}), \dots, g_r(\underline{x})$ such that

$$p(\underline{x}) = \sum_{i=1}^r (g_i(\underline{x}))^2$$

Fact: All SOS polynomials are $\geq 0 \forall x \in \mathbb{R}^n$

Converse: Are all ≥ 0 polynomials SOS? (No)

Converse is NOT true:

Counter-example: (Motzkin Polynomial)

$$p(x, y) = x^2 y^4 + x^4 y^2 + 1 - 3x^2 y^2$$

Claim #1: $p \geq 0 \forall (x, y) \in \mathbb{R}^2$.

Proof:

A.M.
Arithmetic
mean

\geq G.M.
Geometric
mean

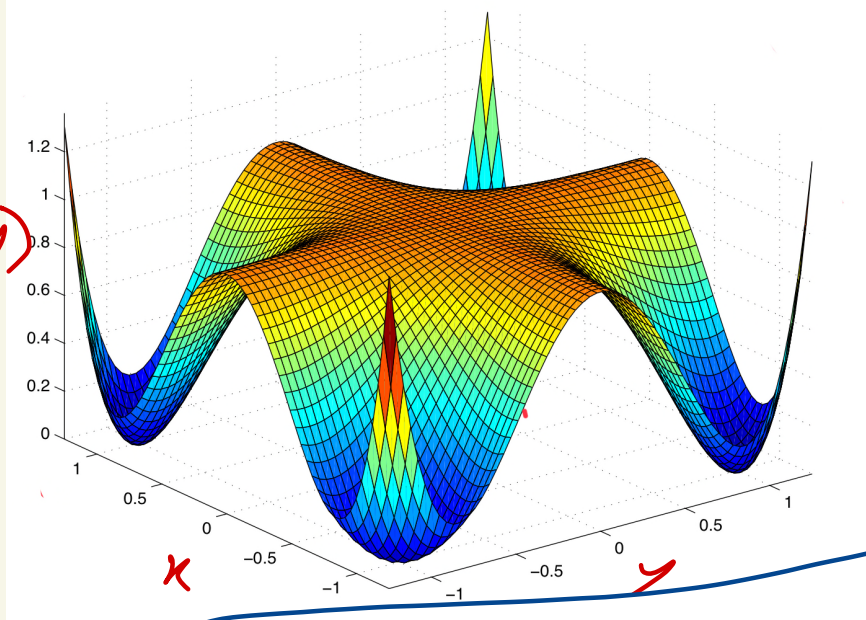
$$\left(\frac{x_1 + x_2 + x_3}{3} \right) \geq (x_1 x_2 x_3)^{1/3}$$

for all $x_1, x_2, x_3 > 0$

$$\frac{x^2 y^4 + x^4 y^2 + 1}{3} \geq (x^2 y^4 \cdot x^4 y^2 \cdot 1)^{1/3}$$



$p(x,y)$



$$p(x,y) = x^2y^2 + x^4y^2 + 1 - 3x^2y^2$$

Claim #2:

$p(x,y)$ is NOT SOS.

$$\underbrace{(x^2+y^2)^2}_{h^2} p(x,y) = x^2y^2(x^2+y^2+1)(x^2+y^2-2)^2 + (x^2-y^2)^2$$

Hilbert's 17th Problem : (1900, Intl. Congress of Mathematics)

$$p(\underline{x}) \geq 0 \stackrel{??}{\iff} \text{SOS}$$

Artin (1927)

For all polynomials $p(\underline{x}) \geq 0$, there exists polynomial $h(\underline{x})$ such that $h^2 p$ is SOS.

$$\begin{aligned} p &= \frac{g_1^2 + g_2^2 + \dots + g_r^2}{h^2} \\ &= \frac{\text{SOS}}{(\text{poly})^2} = \left(\frac{g_1}{h}\right)^2 + \dots + \left(\frac{g_r}{h}\right)^2 \\ &= \text{SOS of rationals} \end{aligned}$$

Example:

$$p(x, y) = \underline{2x^4 + 2x^3y - x^2y^2 + 5y^4} \text{ is SOS}$$

$$\text{Why: } \{ = \underline{\frac{1}{2} [(2x^2 - 3y^2 + xy)^2 + (y^2 + 3xy)^2]} \}$$

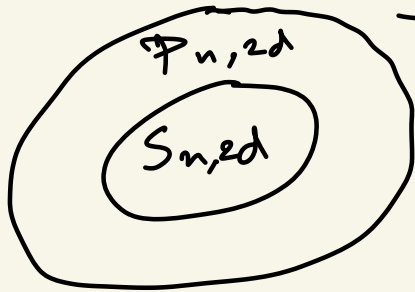
Question:

How to get SOS decomposition (even if it exists)

Definitions:

$\mathcal{P}_{n, 2d}$: All ≥ 0 polynomials in $\underline{x} \in \mathbb{R}^n$ of degree $2d$

$\mathcal{S}_{n, 2d}$: All SOS polynomials in $\underline{x} \in \mathbb{R}^n$ of degree $2d$



Theorem (Hilbert, 1888)

$$P_{n,2d} = S_{n,2d} \quad \text{if and only if}$$

{ either $n = 1$ (univariate polynomials)
or $2d = 2$ (quadratic polynomials)
or $(n, 2d) = (2, 4)$ (bivariate quartic)

Let $[\underline{x}]_d$ be the column of monomials of degree $\leq d$

$$\text{i.e., } [\underline{x}]_d = [1, x_1, x_2, \dots, x_n, x_1^2, x_1 x_2, x_1 x_3, \dots, x_n^d]^T$$

Fact: Any polynomial of degree $\leq 2d$ can be written as

$$p(\underline{x}) = [\underline{x}]_d^T M [\underline{x}]_d, \quad \underline{M} = \underline{M}^T$$

To be continued (next lecture)