

# Applications of common factor computation in signal processing

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# Issue: exact properties are lost under noise

data                      a set of polynomials

exact property        existence of a common factor

distance problem:

*how far is the data from having the property?*

# Approximate GCD computation . . .

given polynomials  $p^1, \dots, p^N$  and a natural number  $d$

$$\begin{array}{ll} \text{minimize} & \text{over } \hat{p}^1, \dots, \hat{p}^N \quad \sum_{i=1}^N \|p^i - \hat{p}^i\|_2^2 \\ \text{subject to} & \deg(\gcd(\hat{p}^1, \dots, \hat{p}^N)) \geq d \end{array}$$

$\gcd(\hat{p}^1, \dots, \hat{p}^N)$  — greatest common divisor of  $\hat{p}^1, \dots, \hat{p}^N$

... has applications in signal processing

Blind FIR system identification

Distance to uncontrollability

Common dynamics estimation

## Problem formulation (exact data)

**given:** output observations  $y^1, \dots, y^N$  of FIR system

(generated by unknown inputs  $u^1, \dots, u^N$ )

**find:** the impulse response  $h$  of the FIR system

# Result: it is a GCD problem

if

- ▶ at least  $N = 2$  responses  $y^1, \dots, y^N$  are given
- ▶  $u^1, \dots, u^N$  have finite support, and
- ▶  $\gcd(u^1(z), \dots, u^N(z)) = 1$

then

$$h(z) = \alpha \gcd(y^1(z), \dots, y^N(z))$$

$\alpha$  — unknown scaling factor

# Problem formulation (noisy data)

assumption:

$$y_d^i = \bar{y}^i + \tilde{y}^i, \quad \text{for } i = 1, \dots, N$$

$\tilde{y}$  — zero mean, white, Gaussian noise

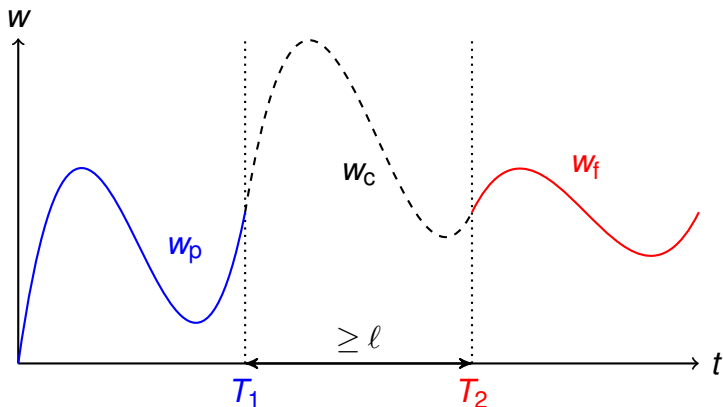
maximum-likelihood estimator:

$$\text{minimize} \quad \sum_{i=1}^N \|y_d^i - \hat{y}^i\|_2^2$$

$$\text{subject to} \quad \hat{y}^i = \hat{h} \star \hat{u}^i, \quad \text{for } i = 1, \dots, N$$

↪ approximate common factor computation

Controllability property, defined in terms of the system's trajectories  $w = \begin{bmatrix} u \\ y \end{bmatrix}$



for all  $w_p, w_f \in \mathcal{B}$ , there is  $w_c$ , such that  $w_p \wedge w_c \wedge w_f \in \mathcal{B}$   
 (" $\wedge$ " denotes "concatenation" of trajectories)



# Linear time-invariant systems

polynomial representation ( $\sigma$  — unit shift)

$$\mathcal{B}_{i/o}(p, q) := \left\{ \begin{bmatrix} u \\ y \end{bmatrix} \mid p(\sigma)y = q(\sigma)u \right\}$$

fact:  $\mathcal{B}_{i/o}(p, q)$  is controllable iff  $(p, q)$  are co-prime

distance between systems

$$\text{dist}(\mathcal{B}_{i/o}(p, q), \mathcal{B}_{i/o}(\hat{p}, \hat{q})) := \left\| \begin{bmatrix} q \\ p \end{bmatrix} - \begin{bmatrix} \hat{q} \\ \hat{p} \end{bmatrix} \right\|_2$$

# Distance to uncontrollability problem

given  $\mathcal{B}_{i/o}(p, q)$ , find the uncontrollability radius

$$\text{dist}_{\text{unctr}}(\mathcal{B}) := \min_{\hat{\mathcal{B}} \in \overline{\mathcal{L}_{\text{ctrb}}}} \text{dist}(\mathcal{B}, \hat{\mathcal{B}})$$

$\overline{\mathcal{L}_{\text{ctrb}}}$  — set of uncontrollable LTI systems

$\rightsquigarrow$  approximate common factor computation with  $d = 1$

# Model-based common dynamics estimation

given systems  $\mathcal{B}_1, \dots, \mathcal{B}_N$ , find their "common dynamics"

$$\mathcal{B} := \mathcal{B}_1 \cap \dots \cap \mathcal{B}_N$$

kernel representation  $\mathcal{B}_i = \{ y \mid R^i(\sigma)y = 0 \}$

fact

$$R(z) = \text{gcd} (R^1(z), \dots, R^N(z))$$

# Data-driven common dynamics estimation

given data  $y_1 \in \mathcal{B}_1, \dots, y_N \in \mathcal{B}_N$

find the common dynamics  $\mathcal{B} := \mathcal{B}_1 \cap \dots \cap \mathcal{B}_N$

model-based approach:  $(y_1, \dots, y_N) \mapsto (R^1, \dots, R^N) \mapsto \mathcal{B}$

data-driven approach:  $(y_1, \dots, y_N) \mapsto \mathcal{B}$

# Subspace common dynamics estimation

assume that  $\text{rank}(\text{hankel}(y^i))$  is maximal

then  $\mathcal{B}_i = \text{span}(\text{hankel}(y^i))$

finding  $\mathcal{B}$  is a common subspace computation problem