Computation of normal forms for polynomial and maybe Ore matrices

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Hermite Normal Forms

Given nonsingular $\mathbf{A} \in \mathbb{K}[D]^{n \times n}$. Compute U and H:

(i) U unimodular, i.e. invertible in $\mathbb{K}[D]^{n \times n}$

(iii) $\mathbf{U} \cdot \mathbf{A} = \mathbf{H}$

(iii) \mathbf{H} in (row) Hermite form , i.e.

$$\mathbf{H} = \begin{bmatrix} h_{11} & h_{12} & \cdots & \cdots & h_{1n} \\ 0 & h_{22} & h_{23} & & h_{2n} \\ \vdots & & \ddots & \ddots & \vdots \\ \vdots & & & \ddots & h_{n-1,n} \\ 0 & \cdots & \cdots & 0 & h_{nn} \end{bmatrix} \quad \begin{array}{c} h_{ii} \text{monic} \\ \text{deg } h_{ji} < \text{ deg } h_{ii} \end{array}$$

.

Popov Normal Form

Given nonsingular $\mathbf{A} \in \mathbb{K}[D]^{n \times n}$. Compute U and P:

(i) U unimodular,

(iii) $\mathbf{U} \cdot \mathbf{A} = \mathbf{P}$

(iii) P in (row) Popov form , i.e. after possibly permuting rows

$$\mathbf{P} = \begin{bmatrix} p_{11} & p_{12} & p_{13} & \cdots & p_{1n} \\ p_{21} & p_{22} & p_{23} & & p_{2n} \\ \vdots & \vdots & p_{33} & \ddots & \vdots \\ \vdots & \vdots & \ddots & p_{n-1,n} \\ p_{n1} & p_{n,2} & p_{n,3} & \cdots & p_{nn} \end{bmatrix}$$
 lcoeff (**P**) special

More on Normal forms

- Hermite : solving systems of linear equations
- Popov :
 - * convert Transfer function representation to linear system representation in linear systems theory
 - * also called *Polynomial Echelon Form* in Kailath
- Also shifted Popov form : one rescales the row degrees
- Also two sided Smith and Jacobson Forms (Mark's talk)

Example: Conversion to first order

Higher order system of linear differential equations

$$\begin{array}{rll} y_1''(t)+(t+2)y_1(t)&+&t^2y_2''(t)+y_2(t)&+&y_3'(t)+y_3(t)&=&0\\ y_1''(t)-3y_1(t)&+&2t^2y_2''(t)+y_2'(t)+y_2(t)&+&y_3'''(t)-y_3''(t)+2t^2y_3(t)&=&0\\ y_1'(t)+y_1(t)&+&y_2''(t)+2ty_2'(t)-y_2(t)&+&y_3'''(t)&=&0. \end{array}$$

Example: Conversion to first order

Higher order system of linear differential equations

Represent system in operator form

$$\begin{bmatrix} D^2 + (t+2) & t^2 D^2 + 1 & D+1 \\ D^2 - 3 & 2t D^2 + D + 1 & D^5 - D^3 + 2t^2 \\ D+1 & D^2 + 2t D + 1 & D^4 \end{bmatrix} \cdot \begin{bmatrix} y_1(t) \\ y_2(t) \\ y_3(t) \end{bmatrix} = \mathbf{0}.$$

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(row) Lcoeff =
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 (col) Lcoeff = $\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$

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Change to new higher order system

Represent system in operator form

$$\begin{bmatrix} D^2 + (t+2) & t^2 D^2 + 1 & D+1 \\ D+3 & D^3 + D+1 & D^3 - 2t^2 \\ D+1 & D^2 + 2tD + 1 & D^4 \end{bmatrix} \cdot \begin{bmatrix} y_1(t) \\ y_2(t) \\ y_3(t) \end{bmatrix} = \mathbf{0}.$$

Hence can rewrite as

$$y_1''(t) = -(t+2)y_1(t) - t^2y_2''(t) - y_2(t) - y_3'(t) - y_3(t)$$

$$y_2'''(t) = -y_1'(t) - 3y_1(t) - 2y_2'(t) + y_2(t) - y_3'''(t) + 2t^2y_3(t)$$

$$y_3''''(t) = -y_1'(t) - y_1(t) - y_2''(t) - 2ty_2'(t) - y_2(t)$$

Hermite and Popov are connected:

Monomials on vectors $\mathbb{K}^{1 \times n}[z]$:

$$z^{\alpha}e_{j} = [0, \dots, 0, z^{\alpha}, 0, \dots, 0]$$

Ordering on monomials of $\mathbb{K}^{1 \times n}[z]$:

• Position over Term (POT):

$$z^{\alpha}e_i < z^{\beta}e_j \quad \Longleftrightarrow \quad i < j \text{ or } i = j \text{ and } \alpha < \beta$$

If *M* submodule of $\mathbb{K}^{1 \times n}[z]$ then can speak of Gröbner bases.

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POT reduced Gröbner bases for $M \iff M$ in Hermite Form.

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Hermite to Popov via FGLM: PhD thesis J. Middeke (2011)

Computation in Polynomial Domains

Polynomial Matrices

- Fast, deterministic algorithms for Hermite and Popov
- Complexity : $O^{\sim}(n^{\omega}[s])$ where *s* bounded by average
 - : of row and column degrees of A
 - : output size $O(n^2s)$, \implies good complexity.

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- G. Labahn, V. Neiger and W. Zhou, Fast, deterministic computation of determinants and Hermite normal forms of polynomial matrices, To appear in Journal of Complexity
- V. Neiger and Thi Xuan Vu, Computing Canonical Bases of Modules of Univariate Relations, Proceedings of ISSAC'17, (2017).

- Polynomial-time over $\mathbb{Q}[x]$: Kannan 1985.
- $O^{\sim}(n^4d)$: Hafner-McCurley 1991 deterministic
- $O^{\sim}(n^{\omega+1}d)$: Hafner-McCurley (1991), Villard (1996) Storjohann and L. (1996) deterministic
- $O^{\sim}(n^3d^2)$: Mulders and Storjohann (2003) deterministic
- $O^{\sim}(n^3d)$: Gupta and Storjohann (2012) probabilistic
- $O^{\sim}(n^{\omega}d)$: Gupta and Storjohann (2012) probabilistic
- $O^{\sim}(n^{\omega}s)$: L.-Neiger-Zhou deterministic

Techniques

(1) Triangularize

- Finding Diagonals
- Complexity
- (2) Normalize to Hermite Form
- (3) Normalize to (shifted) Popov Form

Given nonsingular A: Partition U and A and reduce via

$$\mathbf{U} \cdot \mathbf{A} = \begin{bmatrix} \mathbf{U}_u \\ \mathbf{U}_d \end{bmatrix} \begin{bmatrix} \mathbf{A}_\ell & \mathbf{A}_r \end{bmatrix} = \begin{bmatrix} \mathbf{B}_1 & * \\ 0 & \mathbf{B}_2 \end{bmatrix}.$$

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Here

(i) U_d a left kernel basis of A_ℓ
(ii) B₁ (= U_u · A_ℓ) is nonsingular and a row basis of A_ℓ.
(iii) B₂ = U_d · A_r,

Recurse on \mathbf{B}_1 and \mathbf{B}_2 to get diagonal elements

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Important to control size (measured by row degrees).

Cannot actually compute all of ${\bf U}$ - it's too big.

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Approach for Hermite

- Triangularize A (fast for all 3 steps)
 - Gives diagonal entries of H which can be large
- Reduce remaining off-diagonal entries (fast)
- Remember: Avoid computing unimodular multiplier U

Size measures : Shifted Degrees

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rdeg
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$$\operatorname{rdeg}_{\vec{s}} \mathbf{p} = \max_{1 \le i \le n} \left[\operatorname{deg} p^{(i)} + s_i \right] = \operatorname{rdeg} \mathbf{p} \cdot x^{\vec{s}}.$$

- e.g. rdeg
$$\begin{bmatrix} x & x^2 \end{bmatrix} = 2$$
, rdeg $_{[3,1]} \begin{bmatrix} x & x^2 \end{bmatrix} = rdeg \begin{bmatrix} x^4 & x^3 \end{bmatrix} = 4$

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- For any matrix A: $\operatorname{rdeg}_{-\vec{s}} \mathbf{A} \leq 0$ same as $\operatorname{cdeg} \mathbf{A} \leq \vec{s}$

Given $\mathbf{F} \in \mathbb{K}[z]^{m \times n}$, $m \le n$:

A Left Kernel Basis for \mathbf{F} is a $\mathbb{K}[z]$ module basis for

 $\{ \mathbf{p} \in \mathbb{K}[x]^m \mid \mathbf{p} \cdot \mathbf{F} = 0 \}$

Can represent basis as matrix $\mathbf{M} \in \mathbb{K}[z]^{* \times m}$.

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Minimal Kernel Basis if matrix M is row reduced,

Shifted \vec{s} -Minimal Kernel Basis if $\mathbf{M} \cdot \vec{z^{s}}$ is row reduced.

Row Bases

Given $\mathbf{F} \in \mathbb{K}[x]^{m \times n}$ with $m \ge n$.

A *Row Basis* for **F** is a $\mathbb{K}[x]$ module basis for

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Again

(i) Represent row basis as full rank matrix $\mathbf{T} \in \mathbb{K}[x]^{r \times n}$.

(ii) Can find unimodular matrix U with $\mathbf{U} \cdot \mathbf{F} = \begin{bmatrix} \mathbf{T} \\ \mathbf{0} \end{bmatrix}$.

Costs

 $\mathbf{F} \in \mathbb{K} [x]^{n \times n}, \quad \vec{s} \in \mathbb{Z}^m \text{ bounds row degrees}, \quad \sum \vec{s} \le \xi$

Theorem: (Zhou,L,Storjohann) ISSAC (2012)

š-Minimal left kernel basis computation costs $O^{\sim}(m^{\omega}s)$.

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Theorem: (Zhou, L (ISSAC 2013)

Row basis computation costs $O^{\sim}(m^{\omega}s)$.

Note: depends on fast Nullspace bases computation.

Complexity

 $\mathbf{F} \in \mathbb{K}[x]^{n \times m}, \quad \vec{s} \in \mathbb{Z}^n \text{ bounds row degrees}, \quad \sum \vec{s} \le \xi$

Theorem

For **M** a \vec{s} -minimal kernel basis of **F**: $\sum \text{rdeg}_{\vec{s}} \mathbf{M} \leq \sum \vec{s}$

Theorem (i) $\mathbf{A} \in \mathbb{K} [x]^{n \times m}$, $m \le n$, $\vec{s} \in \mathbb{Z}^n$ bounding row degrees of \mathbf{A} (ii) $\mathbf{B} \in \mathbb{K} [x]^{k \times n}$ with $k \in O(n)$, $\sum \operatorname{rdeg}_{\vec{s}} \mathbf{B} \le \sum \vec{s} \in O(\xi)$ Multiply \mathbf{B} and \mathbf{A} : $O^{\sim}(m^2 n^{\omega - 2} s) \subset O^{\sim}(n^{\omega} s)$, $s = \xi/n$.

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Theorem

 $\mathbf{A} \in \mathbb{K}[x]^{n \times n}$. Diagonals costs $O^{\sim}(n^{\omega} \lceil s \rceil)$ where $s = \frac{\sum \operatorname{cdeg} \mathbf{A}}{n}$.

Determinants

Diagonals not enough - need to worry about unimodular part.

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For det U = det [$U_{\ell} U_r$] we do:

1 det U = det U mod
$$z$$
 = det U = det $[U_{\ell}, U_r]$

$$\mathbf{2} \ \mathbf{V} = \mathbf{U}^{-1} = \begin{bmatrix} \mathbf{V}_u \\ \mathbf{V}_d \end{bmatrix}$$

3 U_r and V_u determined in column bases computation

• Find U_{ℓ}^* such that $U^* = [U_{\ell}^*, U_r]$ is unimodular

5 Let
$$V_u = \mathbf{V}_u \mod z$$
. Then det $\mathbf{U} = \frac{\det U^*}{\det V_u U_{\ell^*}}$

Rest : Reduction of Off-diagonals

Know : $\vec{\delta}$ diagonal degrees of **H**. Set $\mu = \max(\vec{\delta})$

 $\mathbf{A} \cdot \mathbf{x}^{\vec{\mu} - \vec{\delta}} \xrightarrow{\text{reduce}} \mathbf{R} \cdot \mathbf{x}^{\vec{\mu} - \vec{\delta}} \xrightarrow{\text{normalize}} \mathbf{H} = \ \mathbf{lc}_{-\vec{\delta}}(\mathbf{R})^{-1} \cdot \mathbf{R}$

where **R** is any $-\vec{\delta}$ -row reduced form of **A**.

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Answer : Partial linearization of Storjohann (2007): $A \rightarrow \mathcal{L}(A)$

Smooths shifts, keeps properties of A while enlarging a bit.

Consider H with diagonal degrees (2, 37, 7, 18).

$$\mathbf{H} = \begin{bmatrix} (2) & [36] & [6] & [17] \\ & (37) & [6] & [17] \\ & & (7) & [17] \\ & & & (18) \end{bmatrix},$$

[d]: degree at most d and (d): monic , degree exactly d.

 $\delta = 1 + \lfloor (2 + 37 + 7 + 18)/4 \rfloor = 17$. Construct by "expanding columns":

$$\widetilde{\mathbf{H}} = \begin{bmatrix} (2) & [16] & [16] & [2] & [6] & [16] & 0 \\ & [16] & [16] & (3) & [6] & [16] & [0] \\ & & & (7) & [16] & [0] \\ & & & & [16] & (1) \end{bmatrix}.$$

H and $\widetilde{\mathbf{H}}$ are related by $\mathbf{H} = \widetilde{\mathbf{H}} \cdot \mathcal{E}_{\vec{\delta}}$ where

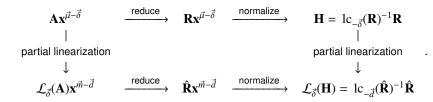
$$\boldsymbol{\mathcal{E}}_{\vec{o}} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & x^{17} & 0 & 0 \\ 0 & x^{34} & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & x^{17} \end{bmatrix}$$

Insert elementary rows in $\widetilde{\mathbf{H}}$ by

$$\mathcal{L}_{\vec{\delta}}(\mathbf{H}) = \begin{bmatrix} (2) & [16] & [16] & [2] & [6] & [16] & [0] \\ x^{17} & -1 & & & \\ & x^{17} & -1 & & \\ & [16] & [16] & (3) & [6] & [16] & [0] \\ & & & (7) & [16] & [0] \\ & & & x^{17} & -1 \\ & & & & [16] & (1) \end{bmatrix}$$

Column degrees $\vec{d} = (2, 17, 17, 3, 7, 17, 1)$ - maximum 17.

Main property kept : shifted row reduction.



Theorem

Let $\mathbf{A} \in \mathbb{K}[x]^{n \times n}$ nonsingular with $\vec{\delta}$ the degrees of the diagonal entries of the Hermite form.

Then the Hermite form is computed using $O^{\sim}(n^{\omega}d)$ field operations.

Repeat : partial linearization (this time with rows) :

(i) Enlarge : $\mathbf{A} \rightarrow \mathcal{L}^{c}(\mathbf{A})$

- size of $\mathcal{L}^{c}(\mathbf{A})$ at most twice size of \mathbf{A}
- degree $\mathcal{L}^{c}(\mathbf{A})$ at most average of \mathbf{A}
- (ii) Compute Hermite form of $\mathcal{L}^{c}(\mathbf{A})$
- (iii) **H** is found in upper left corner of Hermite form of $\mathcal{L}^{c}(\mathbf{A})$

Theorem

 $\mathbf{A} \in \mathbb{K}[x]^{n \times n}$ nonsingular. Hermite form computed: $O^{\sim}(n^{\omega}[s])$.

• M. Giesbrecht and M. Sub Kim, (2013) Domain $\mathbf{A} \in \mathcal{F}(t)[D_t]^{n \times n}$

- Hermite: Polynomial \mathcal{F} operations in n, deg_D A, and deg_t A (also polynomial in the coefficient bit-length when $\mathcal{F} = Q$).
- M. Barkatou, C. El Bacha, E. Pflügell, G.L. (2013)
 - Two-sided block Popov form for $\mathbf{A} \in \mathcal{F}[[t]][D_t]^{n \times n}$
- B. Beckermann, H. Cheng and G.L, (2006)
 - Fraction-free row reduction Ore matrices
 Order bases for Ore matrices
- M. Khochtali and A. Storjohann, (ISSAC 2017)
 - Fraction-free Popov for Ore matrices

- To the organizers for the invitation
- To the audience for listening

Proof. If cost : g(n) then recurrence relation: (with $s = \frac{\xi}{n}$) $g(n) \in O^{\sim}(n^{\omega}\lceil s\rceil) + g(\lceil n/2\rceil) + g(\lfloor n/2\rfloor)$

Proof.

If cost : g(n) then recurrence relation: (with $s = \frac{\xi}{n}$)

$$g(n) \in O^{\sim}(n^{\omega}\lceil s\rceil) + g(\lceil n/2\rceil) + g(\lfloor n/2\rfloor)$$

$$\in O^{\sim}(n^{\omega-1}\xi + n^{\omega}) + g(\lceil n/2\rceil) + g(\lfloor n/2\rfloor)$$

Proof.

If cost : g(n) then recurrence relation: (with $s = \frac{\xi}{n}$)

$$\begin{split} g(n) &\in O^{\sim}(n^{\omega}\lceil s\rceil) + g(\lceil n/2\rceil) + g(\lfloor n/2\rfloor) \\ &\in O^{\sim}(n^{\omega-1}\xi + n^{\omega}) + g(\lceil n/2\rceil) + g(\lfloor n/2\rfloor) \\ &\in O^{\sim}(n^{\omega-1}\xi + n^{\omega}) + 2g(\lceil n/2\rceil) \\ &\in O^{\sim}(n^{\omega-1}\xi + n^{\omega}) = O^{\sim}(n^{\omega}\lceil s\rceil). \end{split}$$