Relaxing order basis computation

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Context

Let $\mathbb{K}$ be a field, $F = \sum_{i \geqslant 0} F_i x^i \in \mathbb{K}[[x]]^{m \times n}$ a matrix of power series, σ a positive integer and (F, σ) be the $\mathbb{K}[x]$-module defined by the set of $v \in \mathbb{K}[x]^{1 \times m}$ such that $vF \equiv 0 \bmod x^\sigma$.

Definition of Order basis: $P \in \mathbb{K}[x]^{m \times m}$ is a (left) $(\sigma, \vec{s})$-order basis of F if the rows of P form a $\vec{s}$-row reduced basis of (F, σ) (see [1]).

Order basis are used in: column reduction [2]; minimal nullspace basis [3]; block Wiedemann algorithm [4]; ...

Two existing algorithms

Input: $F \in \mathbb{K}[[x]]^{m \times n}$, $\sigma \in \mathbb{N}^*$ and $\vec{s} \in \mathbb{Z}^m$
Output: $P \in \mathbb{K}[x]^{m \times m}$ a $(\sigma, \vec{s})$-order basis of F and
$\vec{u} \in \mathbb{Z}^m$ the shifted $\vec{s}$-row degree of P.

To simplify the presentation, let us assume w.l.o.g. that:

1. the procedure $\mathsf{Basis}(F, \vec{s})$ handles the $(1, \vec{s})$-order basis case
2. $n = O(m)$ and the shift $\vec{s}$ is balanced, as in [2]

M-Basis

Naive algorithm, iterative on the order σ, which costs $O(m^\omega \sigma^2)$ op. in $\mathbb{K}$.

- ✗ Quadratic complexity in the precision σ
- ✓ Easy to stop at any intermediate step
- ✓ Minimal knowledge on F, only coefficients $F_0, \dots, F_k$ at step k

Algorithm 1: $\mathsf{M\text{-}Basis}(F, \sigma, \vec{s})$

$P, \vec{u} := \mathsf{Basis}(F \bmod x,\ \vec{s}\,)$
for $k = 1$ ***to*** $\sigma - 1$ **do**
  $F' := x^{-k} P \cdot F \bmod x^{k+1}$
  $P_k, \vec{u} := \mathsf{Basis}(F',\ \vec{u}\,)$
  $P := P_k \cdot P$
return $P, \vec{u}$

PM-Basis

Recursive variant using a divide and conquer strategy on the order σ which costs $O(m^\omega \mathsf{M}(\sigma) \log(\sigma)) = \tilde{O}(m^\omega \sigma)$ operations in $\mathbb{K}$.

- ✓ Quasi-linear complexity in the precision σ
- ✗ Not convenient for early termination
- ✗ Often requires to know coefficients of F in advance

Algorithm 2: $\mathsf{PM\text{-}Basis}(F,\ \sigma,\ \vec{s})$

1: **if** $\sigma = 1$ **then**
2:   **return** $\mathsf{Basis}(F \bmod x,\ \vec{s})$
3: **else**
4:   $P_l, \vec{u}_l := \mathsf{PM\text{-}Basis}(F,\ \sigma/2,\ \vec{s})$
5:   $F' := (x^{-\sigma/2} P_l \cdot F) \bmod x^{\sigma/2}$
6:   $P_h, \vec{u}_h := \mathsf{PM\text{-}Basis}(F',\ \sigma/2,\ \vec{u}_l)$
7:   **return** $P_h \cdot P_l, \vec{u}_h$

Our contribution

1. Give an algorithm for order basis with the following properties:
   - ✓ **Quasi-optimality**: it takes a quasi-linear time in the precision σ;
   - ✓ **Early termination**: easy to stop at any intermediate step;
   - ✓ **Relaxed algorithm**: minimal knowledge on the input F at each step.
2. Use 1 to improve the complexity of block Wiedemann approach.

Fast iterative algorithm

Iterative-PM-Basis

Iterative version of PM-Basis that regroups computations step by step

- ✓ Quasi-linear complexity in the precision σ
- ✓ Convenient for early termination
- ✗ Often requires to know coefficients of F in advance

Algorithm 3: $\mathsf{Iterative\text{-}PM\text{-}Basis}(F, \sigma, \vec{s})$

1: $P_0, \vec{u} := \mathsf{Basis}(F \bmod x,\ \vec{s})$
2: $P := [P_0]$ **and** $S := [0, \dots, 0, F]$ with $\lceil \log_2(\sigma) \rceil$ zeros
3: **for** $k = 1$ ***to*** $\sigma - 1$ **do**
4:   $\ell := \nu_2(k)$ and $\ell' := \begin{cases} \lceil \log_2(\sigma) \rceil & \text{if } k = 2^\ell \\ \nu_2(k - 2^\ell) & \text{otherwise} \end{cases}$
5:   Merge first $\ell + 1$ elements of P by multiplication — product tree step 7
6:   $S[\ell + 1] := (x^{-2^\ell} P[1] \cdot S[\ell' + 1]) \bmod x^{2^\ell}$ — middle product step 5
7:   $P_k, \vec{u} := \mathsf{Basis}(S[\ell + 1] \bmod x,\ \vec{u}\,)$ — recursive leafs step 2
8:   Insert P_k at the beginning of P
9: **return** $\prod_i P[i]$

Relaxing the order basis algorithm

Problem:
At step $k = 2^\ell$, Iterative-PM-Basis requires $S[\lceil \log_2(\sigma) \rceil + 1] \bmod x^{2^{\ell+1}}$, that is $F \bmod x^{2^{\ell+1}}$, to perform the middle product of step 6. However, we only need the middle product modulo x at step k, and therefore $F \bmod x^{1+2^\ell}$. The other coefficients of the middle product will be used in the next steps.

Solution:
Compute the middle products gradually with the additional constraint of not using any coefficient of the input before necessary, *i.e.* using a **relaxed** algorithm.

Definition of relaxed (or on-line) algorithm:
When computing the coefficient in x^k of the output, a *relaxed* algorithm can read at most the coefficients in $1, \dots, x^k$ of the input.

Relaxed middle product

Two methods for a relaxed middle product algorithm:

1. Compute a full $2n \times n$ product using a relaxed multiplication algorithm on polynomial of matrices ([5])
2. Compute just the middle product as in Figure 1 to gain asymptotically a factor 2 compared to method 1.

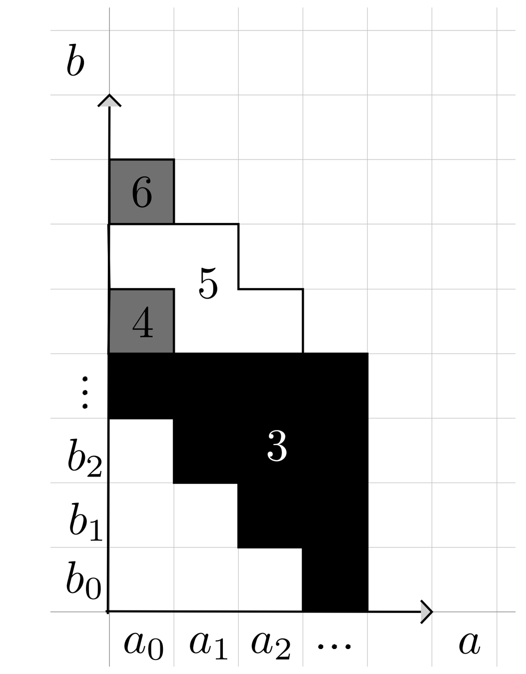

Figure 1: Relaxed middle product

Relaxed-PM-Basis

Using this relaxed middle product within Iterative-PM-Basis, we obtain a new order basis algorithm relaxed w.r.t. F, which costs $O(k^\omega \mathsf{M}(\sigma) \log^2(\sigma))$.

- ✓ Quasi-linear complexity in the precision σ (with an extra $\log_2(\sigma)$)
- ✓ Convenient for early termination
- ✓ Requires minimal knowledge on F

Application to block Wiedemann algorithm

Let $A \in \mathrm{GL}_N(\mathbb{K})$ with $O(N)$ non-zero elements and $S = \sum_{i \in \mathbb{N}} U A^i V x^i$ for random $U, V^T \in \mathbb{K}^{n \times N}$. The block Wiedemann approach uses a $(\sigma, \vec{s})$-order basis of $F = [S^T \mid I_n]^T \in \mathbb{K}[[x]]^{2n \times n}$ to solve sparse linear systems $Ay = b$.

Current approach:
Computing S at precision σ costs $O(n^{\omega - 1} N \sigma)$ operations in $\mathbb{K}$, which is dominant since $n \ll N$. An *a priori* bound δ on the order σ is hard to find or may be loose. To circumvent this the paper [6] proposes a stopping criteria which has to be integrated into an iterative algorithm.

Benefits of our approach:

1. Iterative-PM-Basis provides the first iterative algorithm with quasi-linear time complexity that can use stopping criteria from [6].
2. Relaxed-PM-Basis improves the complexity of 1 on average by a constant factor because less coefficients of S need to be computed.

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