

Symbolic deformation techniques for polynomial system solving

Lecture 1

BY GRÉGOIRE LECERF

Université de Versailles & CNRS
France

<http://www.math.uvsq.fr/~lecerf>

Complexity of Numerical Computation, 2009

General Introduction to algebraic solvers

$$f_1(x_1, \dots, x_n) = \dots = f_s(x_1, \dots, x_n) = 0, \quad g(x_1, \dots, x_n) \neq 0$$

Motivation

- Cornerstone for all operations arising in computational algebraic geometry and differential algebra.
- Several applications in the industry: signal theory, robotics (motion planning), cryptography,...
- At the present time no quasi-optimal algorithm is known for the general case.
- Still a very active research area: several methods, symbolic and numeric, offer different advantages and drawbacks according to the system to be solved.
- Deciding which is the best method on a given system is a difficult theoretical and practical problem.

Known families of algorithms

- First techniques and heuristics go back to the very early ages of mathematics. The first general method seems to be due to KRONECKER (1882).
- General symbolic algorithmic descriptions really started in the sixties:
 - **standard bases**: constructive elimination was used by HIRONAKA in his seminal works in desingularization;
 - **Gröbner bases**: popularized via BUCHBERGER's algorithm.
- Latter, older symbolic techniques have been studied and improved for computations: **resultants**, **triangular decompositions**, **MACAULAY's matrices**, **F4&5** (by FAUGÈRE), etc.
- Numerical techniques (**subdivisions**, **Newton**, **homotopy continuation**, etc) have been designed independently until the 90's.
- Nowadays mixed numerical and symbolic techniques offer good performances. Complexity analysis has been carefully done in several cases.

Sample of general references

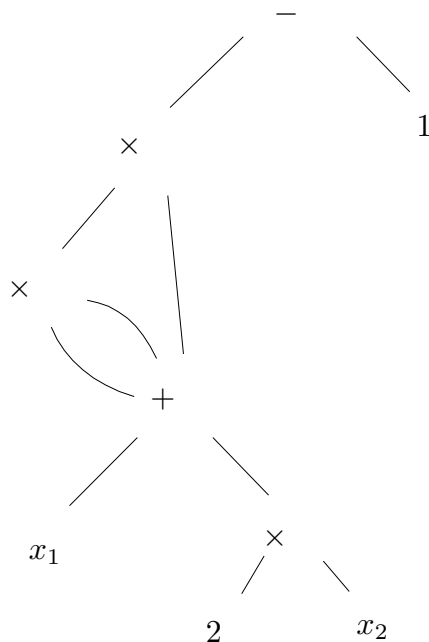
- BECKER and WEISPFENNING, Gröbner bases. A computational approach to commutative algebra, Springer, 1993.
- GREUEL, PFISTER, BACHMANN, and LOSSEN, A **Singular** Introduction to Commutative Algebra, Springer, 2007.
- COX, LITTLE, and O'SHEA, Ideals, varieties, and algorithms. An introduction to computational algebraic geometry and commutative algebra, Springer, 1997.
- COX, LITTLE, and O'SHEA, Using algebraic geometry, Springer, 2005.
- VON ZUR GATHEN, and GERHARD, Modern computer algebra, Cambridge University Press, 2003.
- SCHENK, Computational algebraic geometry, Cambridge University Press, 2003 – examples with Macaulay 2.

- SOMMESE, and WAMPLER, The Numerical Solution of Systems of Polynomials: Arising in Engineering And Science, Word Scientific Publishing, 2005.
- BLUM, CUCKER, SHUB, and SMALE, Complexity and real computation, Springer, 1997.
- DEDIEU, Points fixes, zéros et la méthode de Newton, Springer, 2006.
- ...

Introduction to the Kronecker solver

Representation of multivariate polynomials

- **Dense representation**: store all the monomials up to a certain degree.
Used in Gröbner bases, triangular decompositions.
 $f(x_1, x_2) = 8x_2^3 + 12x_1x_2^2 + 6x_1^2x_2 + x_1^3 + 0x_2^2 + 0x_1x_2 + 0x_1^2 + 0x_2 + 0x_1 - 1$
- **Sparse representation**: store only the non-zero monomials.
 $f(x_1, x_2) = 8x_2^3 + 12x_1x_2^2 + 6x_1^2x_2 + x_1^3 - 1$
- **Functional representation**: store a function for evaluating the polynomial at any given point.
Used in most of the numerical solvers and the **Kronecker solver**.
 $f(x_1, x_2) = (x_1 + 2x_2)^3 - 1 =$



Directed acyclic graph (DAG)

Impact of the representation on the complexity

Example 1. Solve a linear system made of symbolic coefficients:

$$\begin{pmatrix} a_{1,1} & \dots & a_{n,1} \\ \vdots & \ddots & \vdots \\ a_{n,1} & \dots & a_{n,n} \end{pmatrix} \begin{pmatrix} x_1 \\ \vdots \\ x_n \end{pmatrix} = \begin{pmatrix} b_1 \\ \vdots \\ b_n \end{pmatrix}.$$

Dense and sparse representation: $\det(a_{i,j})$ has $n!$ monomials of degree n .

Functional representation: $\det(a_{i,j})$ can be evaluated with $\mathcal{O}(n^4)$ operations by Berkowitz' algorithm.

Example 2. Decide if two univariate polynomials with symbolic coefficients have a common root:

$$f_1(x) = a_0 + a_1 x + \dots + a_n x^n, \quad f_2(x) = b_0 + b_1 x + \dots + b_n x^n.$$

Dense and sparse representation: Resultant (f_1, f_2) is a polynomial in the $2(n+1)$ coefficients of size that grows exponentially with n .

Functional representation: Resultant (f_1, f_2) can be evaluated in $\mathcal{O}(n^4)$ as the determinant of the Sylvester matrix.

Example 3. Polynomial system in $2n$ variables with n random equations of degree d .

Dense and sparse representation: **eliminant polynomials** in n variables and degree d^n , hence a size that grows with d^{n^2} for fixed d and n goes to infinity.

Functional representation: such eliminant polynomials can be evaluated with $d^{\mathcal{O}(n)}$ operations (e.g. via the Kronecker algorithm).

Paradigm. **Polynomials produced by an elimination procedure have nice evaluation properties.**

Prerequisite

\mathbb{K} : any field with algebraic closure $\bar{\mathbb{K}}$.

$\mathbb{K}[x_1, \dots, x_n]$: polynomial ring over \mathbb{K} with n variables.

$\mathcal{I} \subseteq \mathbb{K}[x_1, \dots, x_n]$: ideal.

Zariski topology

Definition 4. The **affine variety** $\mathcal{V}(\mathcal{I})$ defined by \mathcal{I} :

$$\mathcal{V}(\mathcal{I}) = \{(a_1, \dots, a_n) \in \bar{\mathbb{K}}^n \mid \forall f \in \mathcal{I}, f(a_1, \dots, a_n) = 0\}.$$

Proposition 5. $\mathcal{V}(\mathcal{I}_1) \cap \mathcal{V}(\mathcal{I}_2) = \mathcal{V}(\mathcal{I}_1 + \mathcal{I}_2)$, $\mathcal{V}(\mathcal{I}_1) \cup \mathcal{V}(\mathcal{I}_2) = \mathcal{V}(\mathcal{I}_1 \cap \mathcal{I}_2)$.

Definition 6. **Zariski topology** of $\bar{\mathbb{K}}^n$: affine varieties are the closed set.

Definition 7. The **vanishing ideal** $\mathcal{I}(\mathcal{E})$ of a subset $\mathcal{E} \subseteq \bar{\mathbb{K}}^n$:

$$\mathcal{I}(\mathcal{E}) = \{f \in \mathbb{K}[x_1, \dots, x_n] \mid \forall (a_1, \dots, a_n) \in \mathcal{E}, f(a_1, \dots, a_n) = 0\}.$$

Proposition 8. (Nullstellensatz) $\mathcal{I}(\mathcal{V}(\mathcal{J})) = \sqrt{\mathcal{J}} := \{f \mid \exists n, f^n \in \mathcal{J}\}$.

Saturation

Definition 9. *Saturation* of \mathcal{I} with respect to $g \in \mathbb{K}[x_1, \dots, x_n]$:

$$\mathcal{I}: g^\infty = \{f \in \mathbb{K}[x_1, \dots, x_n] \mid \exists n, g^n f \in \mathcal{I}\}.$$

Proposition 10. $\mathcal{V}(\mathcal{I}: g^\infty)$ is the Zariski closure of $\mathcal{V}(\mathcal{I}) \setminus \mathcal{V}(g)$.

Example 11. $\mathcal{I} = x_1(x_1^2 + x_2^2 - 1)$, $g = x_1$, $\mathcal{I}: g^\infty = (x_1^2 + x_2^2 - 1)$.

Overview of the Kronecker solver

\mathbb{K} : any field of characteristic 0, or sufficiently large.

f_1, \dots, f_s, g : polynomials in $\mathbb{K}[x_1, \dots, x_n]$.

$$f_1(x_1, \dots, x_n) = \dots = f_s(x_1, \dots, x_n) = 0, \quad g(x_1, \dots, x_n) \neq 0$$

Notations

$$\mathcal{I}_i = (f_1, \dots, f_i): g^\infty, \quad \mathcal{J}_i = \mathcal{I}_i + (x_1, \dots, x_{n-i}), \quad \mathcal{K}_i = \mathcal{I}_i + (x_1, \dots, x_{n-i-1})$$

Assumptions

For simplicity we assume that the system is **regular** and **reduced**:

- $s = n$,
- f_{i+1} is a **nonzerodivisor** modulo \mathcal{I}_i : $f_{i+1} h \in \mathcal{I}_i \Rightarrow h \in \mathcal{I}_i$,
- \mathcal{I}_i is radical: $\mathcal{I}_i = \sqrt{\mathcal{I}_i}$.

Consequences

- $\dim \mathcal{I}_i = n - i$.
- The system admits a finite number of solutions.

Main idea

With sufficiently generic coordinates $\mathcal{V}(\mathcal{J}_i)$ is a **finite set of points**, and $\mathcal{V}(\mathcal{K}_i)$ is a **curve**.

We construct a **symbolic deformation** from

$$\mathcal{J}_i: f_1(x_1, \dots, x_n) = \dots = f_i(x_1, \dots, x_n) = x_1 = \dots = x_{n-i} = 0, \quad g(x_1, \dots, x_n) \neq 0,$$

to

$$\mathcal{J}_{i+1}: f_1(x_1, \dots, x_n) = \dots = f_{i+1}(x_1, \dots, x_n) = x_1 = \dots = x_{n-i-1} = 0, \quad g(x_1, \dots, x_n) \neq 0,$$

by following the curve

$$\mathcal{K}_i: f_1(x_1, \dots, x_n) = \dots = f_i(x_1, \dots, x_n) = x_1 = \dots = x_{n-i-1} = 0, \quad g(x_1, \dots, x_n) \neq 0.$$

Representation of the finite solution sets

A zero-dimensional solution set \mathcal{E} can be parametrized in this way:

$$\mathcal{E} = \{(v_1(\alpha), \dots, v_n(\alpha)) \mid q(\alpha) = 0\},$$

with q and the v_i in $\mathbb{K}[T]$.

Definition 12. The data of sufficiently generic coordinates, and of such a representation for \mathcal{J}_i is called a **lifting fiber** for \mathcal{I}_i .

Remark 13. Also known as **witness sets** in the numerical algorithms works by SOMMESE *et al.*

Representation of the solution curves

A solution curve \mathcal{C} can be parametrized in this way:

$$\mathcal{C} = \overline{\left\{ \left(\frac{w_1(\alpha, \beta)}{q'(\alpha, \beta)}, \dots, \frac{w_n(\alpha, \beta)}{q'(\alpha, \beta)} \right) \mid q(\alpha, \beta) = 0, q'(\alpha, \beta) \neq 0 \right\}},$$

where q and the w_i are in $\mathbb{K}[t, T]$, $q' = \frac{\partial q}{\partial T}$.

With sufficiently generic coordinates we have: $\deg_t q$ and $\deg_t w_i \leq \deg_T q$.

Definition 14. *The data of sufficiently generic coordinates, and of such a representation for \mathcal{K}_i is called a **lifting curve** for \mathcal{I}_i .*

Overview of the algorithm

1. Perform a random affine change of the variables.
 - this makes \mathcal{J}_i have a finite set of solutions that are all regular.
2. Initialize the process with the solution set of $\mathcal{J}_0 = (x_1, \dots, x_n)$.

From the finite solution set of \mathcal{J}_i compute the one of \mathcal{J}_{i+1} as follows:

- a) **Lifting step**: compute a representation of the curve \mathcal{K}_i .
 - b) **Intersection step**: compute a representation of the finite set of points of $\mathcal{K}_i + (f_{i+1})$, that is the intersection of the latter curve with the hypersurface defined by f_{i+1} .
 - c) **Cleaning step**: deduce $\mathcal{J}_{i+1} = (\mathcal{K}_i + (f_{i+1})) : g^\infty$, by removing from the previous set the points in the hypersurface $g = 0$.
3. Rewrite the solutions of \mathcal{J}_n in terms of the original variables.

Example 15. (with no inequation). $\mathcal{J}_0 = (x_1, \dots, x_n)$, the only solution is 0.

1. First step, $i = 0$.
 - a) lifting: we obtain $\mathcal{K}_0 = (x_1, \dots, x_{n-1})$ that defines a line.
 - b) intersection: $\mathcal{K}_0 + (f_1) = (f_1) + (x_1, \dots, x_{n-1})$ defines the solutions of $f_1(0, \dots, 0, x_n) = 0$.
2. Second step, $i = 1$.
 - a) lifting: $\mathcal{K}_1 = (f_1) + (x_1, \dots, x_{n-2})$ corresponds to the curve defined by $f_1(0, \dots, 0, x_{n-1}, x_n) = 0$.
 - b) intersection: $\mathcal{K}_1 + (f_2) = (f_1, f_2) + (x_1, \dots, x_{n-2})$ corresponds to the intersection of the two plane curves $f_1(0, \dots, 0, x_{n-1}, x_n) = 0$ and $f_2(0, \dots, 0, x_{n-1}, x_n) = 0$.
3. Third step, $i = 2$.
 - a) lifting: $\mathcal{K}_2 = (f_1, f_2) + (x_1, \dots, x_{n-3})$ corresponds to the curve defined by $f_1(0, \dots, 0, x_{n-2}, x_{n-1}, x_n) = f_2(0, \dots, 0, x_{n-2}, x_{n-1}, x_n) = 0$.
 - b) intersection: $\mathcal{K}_2 + (f_3) = (f_1, f_2, f_3) + (x_1, \dots, x_{n-3})$ corresponds to the intersection of the latter curve with $f_3(0, \dots, 0, x_{n-2}, x_{n-1}, x_n) = 0$.
4. ...

Examples

Example 16. Graphical example with **Axel** (MOURRAIN et al., <http://axel.inria.fr>).

Example 17. Naive implementation with **Mathemagix** (VAN DER HOEVEN, LECERF, MOURRAIN, RUATTA, *et al.* <http://www.mathemagix.org>) – currently used graphical interface is **GNU TeXmacS** (VAN DER HOEVEN *et al.*, <http://www.texmacs.org>).

```
Mmx] include "gregorix/kronecker_naive.mmx";
```

```
Mmx] n:= 3;
```

```
f == [ x1^2 + x2^2 + x3^2 - 2,
        x1^2 + x2^2 - 1,
        x1 - x2 + 3 * x3 ];
```

```
x == [x1, x2, x3];
```

```
y == [x1, x2 - 2 * x3, x3];
```

```
f == replace (f, x, y)
```

$$\left[(x_2 - 2x_3)^2 + x_1^2 + x_3^2 - 2, (x_2 - 2x_3)^2 + x_1^2 - 1, x_1 - x_2 + 5x_3 \right]$$

```
Mmx] T == polynomial (rational 0, 1);
```

```
q == monic_part evaluate (replace (f[0], [x1,x2],
                                   [0:>Symbolic,0]),
```

```
                                   [x3], [T], polynomial);
```

```
v == [T];
```

```
Mmx] $lifting_fiber (x, q, v) // for f1(0,0,x3)= 0
```

$$\begin{array}{lcl} x_1 & = & 0 \\ x^2 - \frac{2}{5} = 0, & x_2 & = 0 \\ x_3 & = & x \end{array}$$

```
Mmx] K1 == lift_curve (f[0,1], x, q, v);
```

```
q == car K1; w == car cdr K1;
```

```
Mmx] $lifting_curve (x, q, w) // for f1(0,x2,x3)= 0
```

$$\begin{array}{lcl} x_1 & = & 0 \\ x_2 & = & x \\ y^2 - \frac{4}{5}xy + \frac{1}{5}x^2 - \frac{2}{5} = 0, & x_3 & = \frac{\frac{4}{5}xy - \frac{2}{5}x^2 + \frac{4}{5}}{2y - \frac{4}{5}x} \end{array}$$

```
Mmx] J2 == intersect (f[1], x, q, w);
```

```
q == car J2; v == car cdr J2;
```

```
Mmx] $lifting_fiber (x, q, v) // for f1(0,x2,x3)= f2(0,x2,x3)= 0
```

$$\begin{array}{lcl} x_1 & = & 0 \\ x^4 - 10x^2 + 9 = 0, & x_2 & = x \\ x_3 & = & \frac{-1}{12}x^3 + \frac{13}{12}x \end{array}$$

```
Mmx] K2 == lift_curve (f[0,2], x, q, v);
```

```
q == car K2; w == car cdr K2;
```

```
Mmx] $lifting_curve (x, q, w)
```

```
// for f1(x1,x2,x3)= f2(x1,x2,x3)= 0
```

$$\begin{array}{lcl} x_1 & = & x \\ y^4 + (2x^2 - 10)y^2 + x^4 + 6x^2 + 9 = 0, & x_2 & = \frac{(-4x^2 + 20)y^2 - 4x^4 - 24x^2 - 36}{4y^3 + (4x^2 - 20)y} \\ x_3 & = & \frac{8y^2 - 8x^2 - 24}{4y^3 + (4x^2 - 20)y} \end{array}$$

```

Mmx] J3 == intersect (f[2], x, q, w);
      q == car J3; v == car cdr J3;
Mmx] $lifting_fiber (x, q, v) // for f1= f2= f3= 0

```

$$\begin{aligned}
x1 &= x \\
x^4 - x^2 + 16 = 0, \quad x2 &= \frac{5}{12}x^3 - \frac{13}{12}x \\
x3 &= \frac{1}{12}x^3 - \frac{5}{12}x
\end{aligned}$$

Feature summary

- Take advantage of the evaluation properties of the system.
- Handle easily $g \neq 0$.
- Cost depends on a geometric degree.
- Use dense polynomials in two variables only – fast arithmetic available.
- High probability of success.

L : evaluation cost of the system.

d : maximum of the total degree of the f_i .

δ : maximum number of solutions of the intermediate systems \mathcal{J}_i .

D : final number of solutions.

Theorem 18. [[GIUSTI, LECERF, SALVY, 2001](#)] *The Kronecker solver takes*

$$n(nL + n^4)(d\delta)^2 \log(d\delta)^{\mathcal{O}(1)}$$

operations in \mathbb{K} .

If $\mathbb{K} = \mathbb{Q}$, the resolution is done modulo a “suitable” prime number p . Then the solutions over \mathbb{Q} are lifted with $(nL + n^4)\eta D \log(\eta D)^{\mathcal{O}(1)}$ bit operations, where η is the bit-size of the integers of the output.

Example 19. Random equations of degree 2, with coefficients of bit-size 2.

$\delta = 2^n$ (Bézout), $\eta \sim 2^n$ (arithmetic Bézout)

Cost of the resolution modulo p : $4^n n^{\mathcal{O}(1)}$ operations mod p .

Bit-cost of the lifting of the integers: $4^n n^{\mathcal{O}(1)}$.

Size of the output: at least $\theta(n4^n)$ (arithmetic Bézout).

Quasi optimality!

Goals of the present lectures

Rest of this lecture

- Brief history of the Kronecker solver

Lecture 2

- Incremental solving
- Computational dimension theory
- Computational degree theory

Lecture 3

- Representation of the solution sets
- Complete presentation of the Kronecker solver
- Overview of the possible extensions

Historical digression

- We could discard the lifting step by using a functional representation of \mathcal{I}_i as follows: $(f_1, \dots, f_i): g^\infty =$

$$(q(x_1, \dots, x_r, T), x_{r+1} - v_{r+1}(x_1, \dots, x_r, T), \dots, x_n - v_n(x_1, \dots, x_r, T)), \quad (1)$$

in $\mathbb{K}(x_1, \dots, x_r)[x_{r+1}, \dots, x_n]$, with $r = n - i$.

- This was the way the Kronecker solver started to be designed, but it leads to a much higher cost.
- Then the **Newton operator** was introduced to compress the representation in (1):
 1. Specialize (1) at a random value $x_1 = a_1, \dots, x_r = a_r$.
 2. Use a variant of the Newton iterator to get a good functional representation of (1), with size bounded in terms of L and $\deg q$ only.
- Using such a functional representation in all the intermediate steps of the solver has the following advantages:
 - easier mathematical description,
 - better control of the probabilities,
 - possibility to have deterministic algorithms for a non-uniform complexity model;

but the following drawbacks:

- memory management for the functional representation,
 - non-optimized algorithms for polynomials,
 - the deterministic non-uniform model is not tractable into practice.
- Moving from this original version of the solver to the one presented here appealed to the **deforestation paradigm**: elimination of useless temporary data structures.
- The Kronecker algorithm already presented is deforested: functional data structures are only used for the input polynomials.

Brief history of the Kronecker solver

- [Homage to KRONECKER](#) (1882) method, but far more sophisticated.
- GIUSTI, HEINTZ, MORAIS, PARDO: first symbolic algorithms exploiting functional representation at the beginning of the 90s: dimension, Noether position, Nullstellensatz.
- The [non-deforested version of the Kronecker solver](#) first appeared in works by GIUSTI, HÄGELE, HEINTZ, MONTAÑA, MORAIS, MORGENSTERN, PARDO, 1993, 1995, 1997, 1998: incremental solving, symbolic Newton operator, polynomial time.
- Simplifications and first extensions: Ph.D theses of MORAIS (1997) and HÄGELE (1998).
- Functional data structures implementation: CASTAÑO, LLOVET, MARTÍNEZ (1996), HÄGELE (1998), BRUNO, HEINTZ, MATERA, WACHENCHAUZER (2002).
- Practical computation of the dimension, and [deforestation paradigm](#): GIUSTI, HÄGELE, MARCHAND, LECERF, SALVY (2000).
- Practical [deforested version of the Kronecker](#) solver: GIUSTI, LECERF, SALVY (2001). Implementation in Magma. LECERF's Ph.D thesis (2001).
- Better probability and space analyses: MATERA (1999), HEINTZ, MATERA, WAISSBEIN (2001).
- Extension for computing the Chow form: JERONIMO, KRICK, SABIA, SOMBRA (2001, 2004).