## Approximate Factorization of Complex Multivariate Polynomials

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Joint work with Shuhong Gao, John May, Zhengfeng Yang, and Lihong Zhi

May and Yang received the ACM SIGSAM's ISSAC 2004 Distinguished
Student Author Award for this work

Factorization of noisy polynomials over the complex numbers [my '98 "Challenges"]

$$
81 x^{4}+16 y^{4}-648 z^{4}+72 x^{2} y^{2}-648 x^{2}-288 y^{2}+1296=0
$$



$$
\left(9 x^{2}+4 y^{2}+18 \sqrt{2} z^{2}-36\right)\left(9 x^{2}+4 y^{2}-18 \sqrt{2} z^{2}-36\right)=0
$$

$$
\begin{aligned}
81 x^{4}+16 y^{4}-648.003 z^{4}+ & 72 x^{2} y^{2}+.002 x^{2} z^{2}+.001 y^{2} z^{2} \\
& -648 x^{2}-288 y^{2}-.007 z^{2}+1296
\end{aligned}
$$

## Conclusion on my exact algorithm [JSC 1(1)'85]

"D. Izraelevitz at Massachusetts Institute of Technology has already implemented a version of algorithm 1 using complex floating point arithmetic. Early experiments indicate that the linear systems computed in step $(L)$ tend to be numerically ill-conditioned. How to overcome this numerical problem is an important question which we will investigate."

## The Approximate Factorization Problem [LATIN '94]

 Given $f \in \mathbb{C}[x, y]$ irreducible, find $\tilde{f} \in \mathbb{C}[x, y]$ s.t. $\operatorname{deg} \tilde{f} \leq \operatorname{deg} f$, $\tilde{f}$ factors, and $\|f-\tilde{f}\|$ is minimal.
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We use 2-norm, and multi-degree: $\operatorname{mdeg} f=\left(\operatorname{deg}_{x} f, \operatorname{deg}_{y} f\right)$

Degree bound is important:
$(1+\delta x) f$ is reducible but for $\delta<\varepsilon /\|f\|$,

$$
\|(1+\delta x) f-f\|=\|\delta x f\|=\delta\|f\|<\varepsilon
$$

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- Several algorithms and heuristics to find a nearby factorizable $\hat{f}$ if $f$ is "nearly factorizable" [Corless et al. '01 \& '02, Galligo and Rupprecht '01, Galligo and Watt '97, Huang et al. '00, Sasaki '01,...]


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- There are lower bounds for $\min \|f-\tilde{f}\|$ ("irreducibility radius") [Kaltofen and May ISSAC 2003]


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- A new practical algorithm to compute approximate multivariate GCDs
- A practical algorithm to find the factorization of a nearby factorizable polynomial given any $f$
especially "noisy" $f$ :
Given $f=f_{1} f_{2}+f_{\text {noise }}$,
we find $\bar{f}_{1}, \bar{f}_{2}$ s.t. $\left\|f_{1} f_{2}-\bar{f}_{1} \bar{f}_{2}\right\| \approx\left\|f_{\text {noise }}\right\|$
even for large noise: $\left\|f_{\text {noise }}\right\| /\|f\| \geq 10^{-3}$

Maple Demonstration

## Ruppert's Theorem

$f \in \mathbb{K}[x, y], \operatorname{mdeg} f=(m, n)$
$\mathbb{K}$ is a field, algebraically closed, and characteristic 0
Theorem. $f$ is reducible $\Longleftrightarrow \exists g, h \in \mathbb{K}[x, y]$, non-zero,

$$
\frac{\partial}{\partial y} \frac{g}{f}-\frac{\partial}{\partial x} \frac{h}{f}=0
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\operatorname{mdeg} g \leq(m-2, n), \operatorname{mdeg} h \leq(m, n-1)
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PDE $\rightsquigarrow$ linear system in the coefficients of $g$ and $h$

## Gao's PDE based Factorizer

Change degree bound: $\operatorname{mdeg} g \leq(m-1, n), \operatorname{mdeg} h \leq(m, n-1)$
so that: \# linearly indep. solutions to the $\mathrm{PDE}=$ \# factors of $f$
Require square-freeness: $\operatorname{GCD}\left(f, \frac{\partial f}{\partial x}\right)=1$

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Let

$$
G=\operatorname{Span}_{\mathbb{C}}\{g \mid[g, h] \text { is a solution to the PDE }\} .
$$

Any solution $g \in G$ satisfies $g=\sum_{i=1}^{r} \lambda_{i} \frac{\partial f_{i}}{\partial x} \frac{f}{f_{i}}$ with $\lambda_{i} \in \mathbb{C}$, so

$$
f=f_{1} \cdots f_{r}=\prod_{\lambda \in \mathbb{C}} \operatorname{gcd}\left(f, g-\lambda \frac{\partial f}{\partial x}\right)
$$

( $f_{i}$ the distinct irreducible factors of $f$ )
With high probability $\exists$ distinct $\lambda_{i}$ s.t. $f_{i}=\operatorname{gcd}\left(f, g-\lambda_{i} \frac{\partial f}{\partial x}\right)$

## Gao's PDE based Factorizer

Algorithm
Input: $f \in \mathbb{K}[x, y], \mathbb{K} \subseteq \mathbb{C}$
Output: $f_{1}, \ldots, f_{r} \in \mathbb{C}[x, y]$

1. Find a basis for the linear space $G$, and choose a random element $g \in G$.
2. Compute the polynomial $E_{g}=\prod_{i}\left(z-\lambda_{i}\right)$ via an eigenvalue formulation
If $E_{g}$ not squarefree, choose a new $g$
3. Compute the factors $f_{i}=\operatorname{gcd}\left(f, g-\lambda_{i} \frac{\partial f}{\partial x}\right)$ in $\mathbb{K}\left(\lambda_{i}\right)$.

In exact arithmetic the extention field $\mathbb{K}\left(\lambda_{i}\right)$ is found via univariate factorization.

## Adapting to the Approximate Case

The following must be solved to create an approximate factorizer from Gao's algorithm:

1. Computing approximate GCDs of bivariate polynomials;
2. Determining the numerical dimension of $G$, and computing an approximate solution $g$;
3. Computing a $g$ s.t. the polynomial $E_{g}$ has no clusters of roots.

Determining the Number of Approximate Factors
Let $\operatorname{Rup}(f)$ be the matrix from Gao's algorithm Recall:

$$
\# \text { of factors of } f=\operatorname{Nullity}(\operatorname{Rup}(f))
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$\operatorname{Rup}(f)$ has nullity $r$ if
$\sigma_{m} \geq \ldots \geq \sigma_{r+1} \neq 0$ and $\sigma_{r}=\ldots=\sigma_{1}=0$.

Say $\operatorname{Rup}(f)$ has nullity $r$ with tolerance $\varepsilon$ if:

$$
\sigma_{m} \geq \ldots \geq \sigma_{r+1}>\varepsilon \geq \sigma_{r} \geq \ldots \geq \sigma_{1}
$$

Find a "best" $\varepsilon$ from the largest gap choose $\varepsilon=\sigma_{r}$ s.t. $\sigma_{r+1} / \sigma_{r}$ is maximal

## Determining the Number of Approximate Factors

If $f$ is irreducible
largest gap in the sing. values of $\operatorname{Rup}(f) \rightsquigarrow \#$ of approx. factors

Recall:

$$
G=\operatorname{Span}_{\mathbb{C}}\{g \mid[g, h] \in \operatorname{Nullspace}(\operatorname{Rup}(f))\}
$$

If $r$ is position of the largest gap in the sing. values of $\operatorname{Rup}(f)$, approx. version of $G$ is Span of last $r$ sing. vectors of $\operatorname{Rup}(f)$

## Approximate Factorization

Input: $f \in \mathbb{C}[x, y]$ abs. irreducible, approx. square-free Output: $f_{1}, \ldots, f_{r}$ approx. factors of $f$, and $c$

1. Compute the SVD of $\operatorname{Rup}(f)$, determine $r$, its approximate nullity, and choose $g=\sum a_{i} g_{i}$, a random linear combination of the last $r$ right singular vectors
2. compute $E_{g}$ and its roots via an eigenvalue computation
3. For each $\lambda_{i}$ compute the approximate GCD $f_{i}=\operatorname{gcd}\left(f, g-\lambda_{i} f\right)$ and find an optimal scaling: $\min _{c}\left\|f-c \prod_{i=1}^{r} f_{i}\right\|$

## Approx. GCD: Generalized Sylvester Matrix

A pair $g, h \in \mathbb{K}[x, y]$ has GCD of degree at least $k$ iff
$\exists$ non-zero solutions $u, v \in \mathbb{K}[x, y]$ to:

$$
\frac{g}{h}=\frac{v}{u}, \operatorname{tdeg}(u) \leq \operatorname{tdeg}(h)-k, \operatorname{tdeg}(v) \leq \operatorname{tdeg}(g)-k
$$

or

$$
u g-v h=0, \operatorname{tdeg}(u) \leq \operatorname{tdeg}(h)-k, \operatorname{tdeg}(v) \leq \operatorname{tdeg}(g)-k
$$

Equation gives a linear system in the coefficients of $u$ and $v$
Denote the matrix of the system $\operatorname{Syl}_{k}(g, h)$

## Computing the Approximate GCD

Input: $g$ and $h$ relatively prime
Output: $d \notin \mathbb{K}$, approx. GCD of $g$ and $h$

1. Find $p$ from the largest gap in the singular values of $\mathrm{Syl}_{1}(g, h)$
2. Find $k \in \mathbb{Z}$ which solves $\min _{k}\left|p-\binom{k+2}{2}\right|$
3. Find $[\mathbf{u}, \mathbf{v}]$, the right singular vector corresponding to smallest singular value of $\operatorname{Syl}_{k}(g, h)$ [compute with an iterative method]
4. Find a $d$ to minimize $\|h-d u\|_{2}^{2}+\|g-d v\|_{2}^{2}$, using least squares ("Approximate division")

Also possible to add iterative improvement á la Zeng\&Dayton'04

## Notes on the Repeated Factor Case

We say $f$ is approximately square-free if:
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Compute the approximate quotient $\bar{f}$ of $f$ and $\operatorname{gcd}\left(f, \frac{\partial f}{\partial x}\right)$ and factor the approximately square-free kernel $\bar{f}$

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Determine multiplicity of approximate factors $f_{i}$ by comparing the degrees of the approximate GCDs:

$$
\operatorname{gcd}\left(f_{i}, \partial^{k} f / \partial x^{k}\right)
$$

Table of Benchmarks

| Example | $\operatorname{tdeg}\left(f_{i}\right)$ | $\frac{\sigma_{r+1}}{\sigma_{r}}$ | $\frac{\sigma_{r}}{\\|R(f)\\|_{2}}$ | coeff. <br> error | backward <br> error | time(sec) |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Nagasaka'02 | 2,3 | 11 | $10^{-3}$ | $10^{-2}$ | $1.08 \mathrm{e}-2$ | 14.631 |
| Kaltofen'00 | 2,2 | $10^{9}$ | $10^{-10}$ | $10^{-4}$ | $1.02 \mathrm{e}-9$ | 13.009 |
| Sasaki'01 | 5,5 | $10^{9}$ | $10^{-10}$ | $10^{-13}$ | $8.30 \mathrm{e}-10$ | 5.258 |
| Sasaki'01 | 10,10 | $10^{5}$ | $10^{-6}$ | $10^{-7}$ | $1.05 \mathrm{e}-6$ | 85.96 |
| Corless et al'01 | 7,8 | $10^{7}$ | $10^{-8}$ | $10^{-9}$ | $1.41 \mathrm{e}-8$ | 19.628 |
| Corless et al'02 | $3,3,3$ | $10^{8}$ | $10^{-10}$ | 0 | $1.29 \mathrm{e}-9$ | 9.234 |
| Zeng'04 | $(5)^{3}, 3,(2)^{4}$ | $10^{7}$ | $10^{-9}$ | $10^{-10}$ | $2.09 \mathrm{e}-7$ | 73.52 |

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| Random $\left(f_{i} \in \mathbb{Z}\right)$ | 9,7 | 486 | $10^{-4}$ | $10^{-4}$ | $2.14 \mathrm{e}-4$ | 43.823 |
| $"$ | $6,6,10$ | $10^{3}$ | $10^{-6}$ | $10^{-5}$ | $2.47 \mathrm{e}-4$ | 539.67 |
| $"$ | $4,4,4,4,4$ | 273 | $10^{-6}$ | $10^{-5}$ | $1.31 \mathrm{e}-3$ | 3098. |
| $"$ | $3,3,3$ | 1.70 | $10^{-3}$ | $10^{-1}$ | $7.93 \mathrm{e}-1$ | 29.25 |
| $"$ | 18,18 | $10^{4}$ | $10^{-7}$ | $10^{-6}$ | $3.75 \mathrm{e}-6$ | 3173. |
| $"$ | $12,7,5$ | 8.34 | $10^{-4}$ | $10^{-3}$ | $8.42 \mathrm{e}-3$ | 4370. |
| Not Sqr Free | $5,(5)^{2}$ | $10^{3}$ | $10^{-5}$ | $10^{-5}$ | $6.98 \mathrm{e}-5$ | 34.28 |
| 3 variables | 5,5 | $10^{4}$ | $10^{-5}$ | $10^{-5}$ | $1.72 \mathrm{e}-5$ | 332.99 |
| $f_{i} \in \mathbb{C}$ | 6,6 | $10^{6}$ | $10^{-8}$ | $10^{-7}$ | $2.97 \mathrm{e}-7$ | 30.034 |

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More than two variables: direct approach

- PDEs can be generalized to many variables

$$
\begin{gathered}
\frac{\partial}{\partial y_{i}} \frac{g}{f}-\frac{\partial}{\partial x} \frac{h_{i}}{f}=0, \forall 1 \leq i \leq k \\
\operatorname{deg} g \leq \operatorname{deg} f, \quad \operatorname{deg} h_{i} \leq \operatorname{deg} f, \forall 1 \leq i \leq k \\
\operatorname{deg}_{x} g \leq\left(\operatorname{deg}_{x} f\right)-1, \quad \operatorname{deg}_{y_{i}} h_{i} \leq\left(\operatorname{deg}_{y_{i}} f\right)-1, \forall 1 \leq i \leq k
\end{gathered}
$$

## More than two variables: interpolation

- Our multivariate implementation together with Wen-shin Lee's numerical sparse interpolation code quickly factors polynomials arising in engineering Stewart-Gough platforms

Polynomials were 3 variables, factor multiplicities up to 5 , coefficient error $10^{-16}$, and were provided to us by Jan Verschelde

## Stewart Platform Example



## Drexler's 1992 nano Stewart platform

## Current Investigations

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- More generally, use blackbox matrix SVD algorithms
$\operatorname{Rup}(f) \cdot \mathbf{v}$ costs 4 polynomial multiplications
Should make very large problems possible
- Also need sparse interpolation for "very noisy" inputs to handle sparse multivariate problems


## Code + Benchmarks at:

http://www.mmrc.iss.ac.cn/~lzhi/Research/appfac.html Or

http://www.kaltofen.us (click on "Software")

