

Numerical Accuracy Stuff: Tools. . . and Prerequisites

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Numerical Accuracy Stuff: Tools... and Prerequisites

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Blind use of tools = Hazard



Motivations

- Blind use of tools = Hazard
- FPA is an error-prone subject
- Many many recent tools ... but free space towards panacea

Prerequisites

- Floating point arithmetic for dummies
- Errors and measures
- Accuracy vs. Precision: the rule of thumb
- Motto: Don't forget the problem and its data!

Tools

- What tool for which question?
- Tools: some well-known oldies
- Tools: some works in progress

Sources of errors in numerical computing

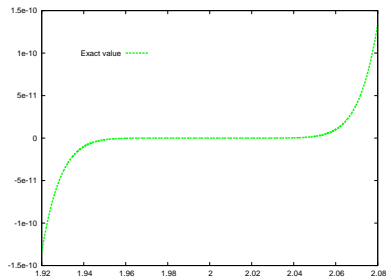
- Mathematical model
- Truncation errors
- Data uncertainties
- Rounding errors

Rounding errors may totally corrupt a FP computation

- Floating-point arithmetic **approximates** real one
- **Accumulation** of billions of floating point operations
 - May compensate. . .
 - but very few are enough to ruin effort
- **Intrinsic difficulty** to accurately solve the problem
 - Data dependency, condition

Example: Schoolbook level

Evaluation of univariate polynomials with **exact** floating point coefficients

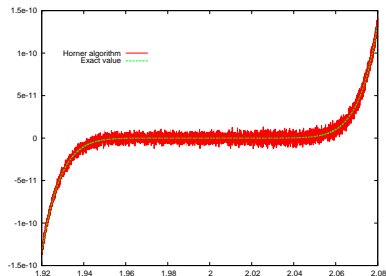


$p(x) = (x - 2)^9$ around $x = 2$ in IEEE binary64

● expanded form

Example: Schoolbook level

Evaluation of univariate polynomials with **exact** floating point coefficients



$p(x) = (x - 2)^9$ around $x = 2$ in IEEE binary64

● expanded form

● developed polynomial + Horner algorithm

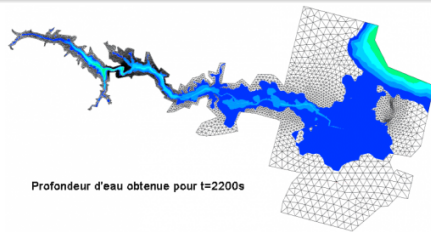
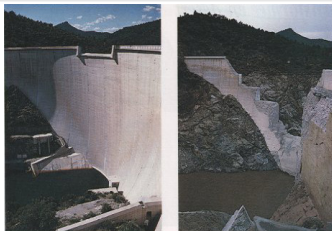
Interesting example!

- Problem? No problem: exact data!
- One problem + one algorithm + one precision
but different accuracy for different data
- Algorithms:
 - the **rich** vs. the **poor**
 - the good vs. the ugly: summation

Example: Industrial case

OpenTelemac2D simulation of Malpasset dam break (1959)

- A five year old dam break: 433 dead people and huge damage
- Triangular mesh: 26000 elements and 53000 nodes
- Water flow simulation → 35min. after break, 2sec. time step

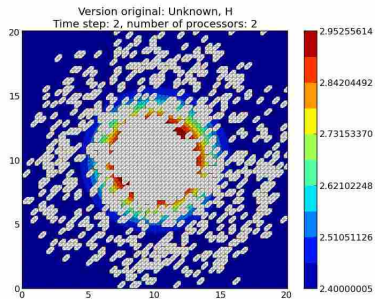
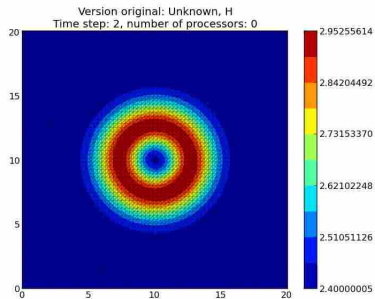


Reproducible simulation? Accurate simulation?

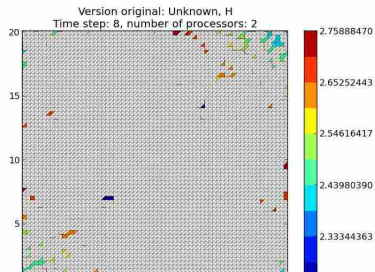
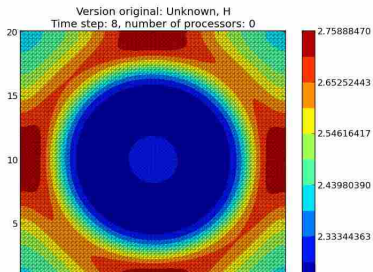
	velocity U	velocity V	depth H
The sequential run	0.4029747E-02	0.7570773E-02	0.3500122E-01
one 64 procs run	0.4935279E-02	0.3422730E-02	0.2748817E-01
one 128 procs run	0.4512116E-02	0.7545233E-02	0.1327634E-01

Bitwise reproducibility failure: gouttedo test case

time step = 2



time step = 8

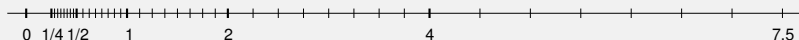


- 1 Context and motivations
- 2 Prerequisite
 - FPA for dummies
 - Errors and Measures
 - Accuracy vs. Precision: The Rule of Thumb
- 3 Tools
 - Old Folks
 - Interval arithmetic
 - CADNA, verrou
 - Recent Tools
 - Herbgrind
 - FP Bench
- 4 Conclusion
- 5 References

IEEE-754 floating point arithmetic (1985, 2008))

Discretisation (toy system) and precision

- Normal floating point: $x = (-1)^s \cdot m \cdot 2^e = \pm \underbrace{1.x_1x_2 \dots x_{p-1}}_{p \text{ bits of mantissa}} \times 2^e$
- Precision: $2^{\mathbf{u}} = 1^+ - 1 = 2^{-p}$



Rounding, correct rounding and unit roundoff

- $\circ(x) = x$ for $x \in \mathbb{F}$, else $\circ(x) = x(1 + e)$ with $|e| \leq \mathbf{u}/2$ (or \mathbf{u})
- Correct rounding: **best accuracy** for $+$, $-$, \times , $/$, $\sqrt{}$



- IEEE-754
 - binary32: $\mathbf{u} \approx 5 \cdot 10^{-8}$, $p = 24$, $e \in \{-126 \dots 127\}$
 - binary64: $\mathbf{u} \approx 10^{-16}$, $p = 53$, $e \in \{-1022 \dots 1023\}$

Counter intuitive FPA

- Add is not associative •
 - Absorption: • $(1 + u) + u \neq 1 + (u + u)$ •
 - Catastrophic cancellation: $(1 + u) - 1 = 0$ •
 - Order matters: • $(1 - 1) + u = u$ •
 - Exact subtraction $x - y$ for $1/2 \leq x/y \leq 2$ • (Sterbenz)
 - Error Free Transformations (EFT) for $+$, \times :
 - add: $x + y = s + e$,
 - sub: $x \times y = p + e$,
- everybody being *computable* FP values •

Automatic Rounding Error Stuff is difficult

Track large errors?

- Small local errors may have large global effect
 - catastrophic cancellation = 1 accurate add + 1 exact sub
- Large local errors may have no global effect
 - error cancellations: $r = (x + y) + z$ for x, y, z resp. computed by $1/u + 1, -(1/u + 1)$, u yields exact $r = u$
- Expression error depends on argument values
 - $(x + y) + z$ is accurate except for catastrophic cancellation values

Motto: don't forget the problem and its data!

Practical limitations: scaling and modularity effects

- Tuning n FP operations between 2 precisions = 2^n cases
- $f(t) + z$ with accurate $f(t) = x + y$ is accurate except for catastrophic cancellation values

Errors

- Forward error: $x - \hat{x}$, in the result space
- Backward error: $d - \hat{d}$, in the data space, for identified \hat{d} such that $f(\hat{d}) = \hat{f}(d)$
- Absolute vs. Relative error
- Maximum vs. Average error
- Error measures: ULPs [1], bits, significant digits [4], no dimension value, interval
- Error bounds: proven vs. estimated vs. measured

Accuracy vs. Precision: The Rule of Thumb (RoT)

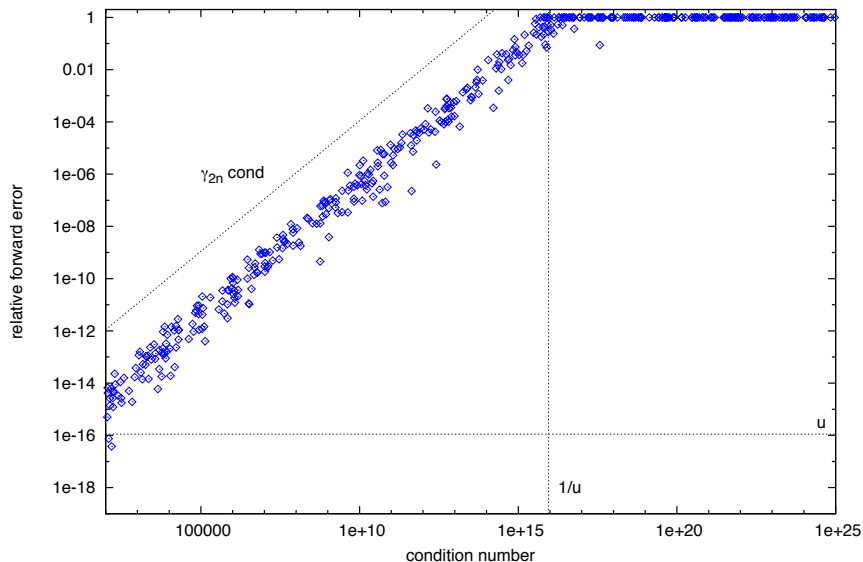
RoT: Accuracy \lesssim Condition Number $\times \mathbf{u}$

- Forward error \lesssim condition \times backward error
- Backward stable in precision \mathbf{u} : relative backward error $\approx \mathbf{u}$

Condition number

- $\lim_{\delta \rightarrow 0} \sup_{|\Delta x| \leq \delta} \frac{|\Delta y|}{|y|} / \frac{|\Delta x|}{|x|}$,
with $y + \Delta y = f(x + \Delta x)$ and $y = f(x)$.
- Differentiable f : $\frac{|x| |f'(x)|}{|f(x)|}$, $\frac{|x| |J(x)|}{|f(x)|}$
- Motto: depends both on problem f and data x
- Example for summation:
 - $\text{cond}(\sum_n x_i) = \sum_n |x_i| / |\sum_n x_i|$
 - arbitrarily larger than $1/\mathbf{u}$ when catastrophic cancellation in $\sum_n x_i$

Accuracy \lesssim Condition number $\times u$



How to verify or validate the accuracy of a FP computation?

- Verify vs. validate
- [M] Backward error analysis, probabilistic analysis, ad-hoc rounding error analysis
- [T] Interval arithmetic, stochastic arithmetic, sensitivity analysis, static analysis (+arithmetic models) , dynamic analysis (+bounds, +references), formal proof assistants

How to identify the error sources?

- [M] Numerical analysis vs. Rounding error analysis
- [M/T] Algorithm/Program instructions vs. Input data range
- [T] Shadow computation: random, stochastic, higher precision, EFT, “exact”, AD

How to improve the accuracy of a FP computation?

- From accurate *enough* to **correctly rounded** for a given **precision**
- [T] More hardware precision, extended precision libraries
- [M/T] More accurate algorithms: expression order, other expression, EFT
 - Hand-made vs. Automatic rewriting tools

Tools: Cost, Efficiency and Tuning

- Cost: reasonable computing **time overheads for running** solutions
- Efficiency: sharp vs. overestimated bound, false positive ratio, non robust optimization
- Tuning: rewrite with a minimal precision for a given accuracy

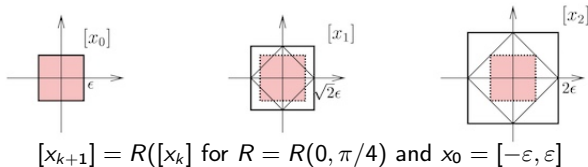
How to recover the numerical reproducibility of parallel FP computation?

- Reproducible *enough* (i.e. modulo validation) vs. bitwise identical
 - At least to debug parallel vs. sequential,
 - also to validate for production step, to certify for legal process
- Reproducible algorithms, libraries vs. hand-made corrections

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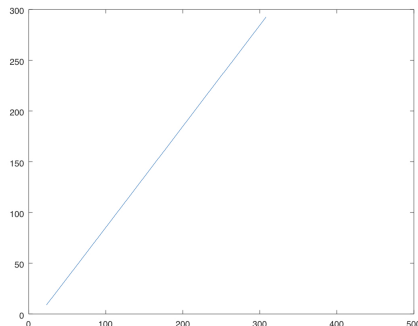
IA at a glance

- Data range or FP arithmetic \rightarrow intervals + interval operation
- A sure (●) but too conservative (●) propagation of absolute errors (●)
- Dependency problem, wrapping effect, variable decorrelation, conservative inclusion of convex set; intervals containing zero
 - $\text{width}([x] - [x]) = 2 \text{ width}([x])$,
 - tight function range: tight *interval* $[F([x])]$
- Best **computing flow driven** convex set?
 - endpoint pair, center+radius, subdivisions, Taylor expansions, affine arithmetic, zonotope, ...



Interval RoT [2]

- $\text{width}(f(X)) \leq \lambda_f(X) \text{width}(X)$, where λ_f : Lipschitz-constant of f .



Interval sum: $\log_{10} \text{width}(s_n)$ vs. $\log_{10} \text{cond}(s_n)$ for $s_n = 1$ [3]

Tools for Interval Arithmetic

IntLab (Rump), MPFI (Revol) and many other

Stochastic Arithmetic (1986, 1995)

- Rounding errors are independent identically distributed (uniform) random variables (●) + (CLT) Gaussian distribution around the exact result (●) of their global effect
- Estimation of the number of significant digits with very few values: $N=3$ samples are enough

Tools: Cadna (UPMC)



- Random IEEE rounding modes, synchronicity + *computing zero* → self validation
- Practical tool at industrial scale: languages, parallelism, support
- New stochastic numeric types + Library + source to source translator
- $\times 15-45$ overhead: costly hardware rounding mode change

Tools: verrou (EDF)

- Parametrized random rounding modes, *asynchronicity*,
- $\times 10-20$ overhead, "no" warning, post-processing tests
- Binary instrumentation (Valgrind), excluded parts (libm)

Many recent tools (2013 →)

Proven bounds for snippets

- Fluctuat (2005, 2013), FPTaylor (2015), Rosa/Daisy (2014,2017), ...
- Abstract model of FPA, forward error: proven (●) but conservative (●)
- Small size targets: 10-20 LOC

Rewriting snippets

- Herbie (2015), Salsa (2015)
- 10 LOC

Detecting *candidate* error causes

- FPDebug (2011), **Herbgrind** (2018)
- Dynamic analysis (Valgrind), shadow computation: MPFR
- False positive, overhead
- Small size targets (●) ... until Herbgrind: 300K LOC (●●●)

- Dynamic analysis, binaries (Valgrind)
- Large programs, different languages, libraries
- Numerical tricks detection: compensation, EFT
- Open platform: front-end to “small sized oriented tools”, ...
- Input range limitations

Steps

- Detecting FP errors: exact shadow computation (MPFR) for every FP assignment
- Collecting **root cause** information
 - selected error dependency chains, symbolic expression, input characteristics

Validation cases

- Gram-Schmidt Orthonormalization, PID controller
- GROMACS: molecular dynamics simulation
 - SPEC FPU, 42K LOC in C + 22K LOC in Fortran
- TRIANGLE: accurate and robust mesh generator

A community infrastructure for cooperation and comparison

- FPCore: description format for FP benchmarks
- Benchmarks: suite drawn for published results
 - 111 benches (v1.1, oct. 2018)
 - FPTaylor (CPU. Utah), Herbie (PLSE, U. Washington) , Rosa (AVA, MPI-SWS, Saarbrücken) , Salsa (LAMPS, UPVD)

Pros & Cons

- FPCore for fair comparison
- Small size cases, numerically safe case (worst 30% cases error = 5-6 bits)
- Others benchmarks: SPEC FPU, Hamming's book,...

- Numerical accuracy stuff: large and old subject, large literature, many tools but free space for human expertise up to the ideal tools
- Our Motto = hard issue to automatic tools
- Herbgrind: a gap in recent developments?
- Corsika: tuning to low precision FP formats \rightarrow full benefit of SIMD speedup e.g. .
 $AVX512 = 16 \times \text{binary32}$

Recent resources

- 30+ tools listed by M. Lam (JMU):
<https://w3.cs.jmu.edu/lam2mo/fpanalysis.html>
- FPBench: <http://fpbench.org>,
<https://github.com/FPBench/FPBench>



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