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# Techniques for the automatic debugging of scientific floating-point programs

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#### Outline of the talk

1. Motivation and objective of the project

2. Locating numerical anomalies

3. Conclusion and perspective

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#### Motivation and objective

- The field of large-scale scientific applications has been growing rapidly
  - in cycles used



in complexity of software

→ both these make finding bugs harder (especially for non experts)

#### Objectives of the project

- reduce difficulty of debugging
- automatic techniques for detecting and suggesting remedies for roundoff and other numerical exception problems (anomalies)

#### Motivation and objective

Techniques for detecting suspected anomalies vary :

- 1. in the costs of their application,
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Goal ~> automate debugging now done by hand

- intelligent and automatic tool
  - locate automatically suspected anomalies
  - with or without source code
  - at runtime or statically
- help developers whose expertise does not extend to numerical error-analysis
  - shorten debugging time and improve their productivity

#### What are the usual source of anomalies?

- Common source of anomalies :
  - rounding error accumulations
  - conditional branches involving floating-point comparisons
    - e.g. NaN leading to a convergence misbehavior
  - vagaries of programming languages
    - Fortran : conversion of constants in full double precision accuracy (unlike C)

double	precision	c1	0.1d0	~~>	0.100000000000000555
double	precision	c2	0.1	$\sim \rightarrow$	0.10000000149011611938

- under/overflows
- cancellation, benign or catastrophic
- resolution of ill-conditioned problems, ...

#### Hardware problems : misbehavior of floating-point programs

## Example of avoidable numerical anomalies

Given *n*, evaluate the definite integral using Simpson's rule, with  $h = \frac{b-a}{2\cdot n}$ 

$$\int_{a}^{b} f(x) \cdot dx = \frac{h}{3} \Big[ f(a) + 4 \cdot f(a+h) + 2 \cdot f(a+2 \cdot h) + \dots + 4 \cdot f(a+(2 \cdot n-1) \cdot h) + f(b) \Big].$$

- Implementation with a conditional branch
  - terminate the loop when  $a+k \cdot h \ge b$
  - may result in an extra iteration, if a+k · h is slightly less than b due to roundoff error

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```
unsigned int n = 10000;
double a = 0, b = 1, h = (b-a)/(2.*n);
double x = a;
double r = f(xk); // r ≈ f(a)
while(1){
xk = xk + h;
r = r + 4.* f(xk); // r ≈ r + 4.f(a + k.n)
xk = xk + h;
if (xk + EPSILON >= b)
break;
r = r + 2.* f(xk); // r ≈ r + 2.f(a + k.n)
}
r = r + f(xk); // r ≈ r + f(b)
r = (h/3.) * r;
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- **Example of fix** :  $a + k \cdot h + \varepsilon \ge b$ 
  - how to determine ε semi-automatically?

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#### Another fix : make loop variable integer

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#### How to detect these usual anomalies?

- Detection can be done by static or dynamic analysis
- When suspected, these usual anomalies may be detected by :
  - altering rounding mode of floating-point arithmetic hardware
    - → may not be available on every architectures (e.g. GPU)
  - extending precision of floating-point computation
    - ---- may increase runtime significantly (use of software implementation)
  - modifying comparisons by adding an unobvious tolerance
  - using interval arithmetic
    - → produces a certificate, but runtime cost increases significantly
    - → intervals may grow too wide to be useful
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#### How to quickly detect usual anomalies using dynamic analysis?

#### Isolating failure-inducing code fragment

- Does the anomaly (bug) really depend on the whole input code ?
- First step in processing any bug : simplification
  - eliminating all the details in the original code that are not relevant
    - $\rightsquigarrow$  isolate the difference that causes the bug (failure)
  - often people spend a lot of time isolating failure-inducing code fragment
- Usually carried out by hand
  - long and tedious + may miss some relevant simplification
  - need to automate this process

#### Framework flowchart



#### Framework flowchart



# Transformations using CIL (C Intermediate Language)

- CIL<sup>1</sup> : high-level representation of C programs
  - analysis and source-to-source transformation of C programs

int main( void )
float a; float b;
float c;
a = b + c; //
return 0; }



CIL : Intermediate Language and Tools for Analysis and Transformation of C Programs. Proc. of Conference on Compiler Construction, 2002

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#### Currently implemented transformations

- ► FloatToDouble : float ⇒ double,
- ▶ RoundingMode : RN ⇒ {RU,RD,RZ},
- ▶ DoubleToDD : double ⇒ double-double,
- ► FlipFunction : implementation1 ⇒ implementation2.

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- $\stackrel{\longrightarrow}{\longrightarrow} \mbox{if the input is still inaccurate, increase} \label{eq:constraint} the granularity of the splitting$

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Future improvement : consider the efficiency (performance) of changes ?

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#### More realistic example (D.H. Bailey)

Calculate the arc length of the function g defined as

$$g(x) = x + \sum_{0 \le k \le 5} 2^{-k} \sin(2^k \cdot x), \quad \text{over } (0, \pi).$$

Summing for  $x_k \in (0, \pi)$  divided into *n* subintervals

$$\sqrt{h^2+(g(x_k+h)-g(h))^2},$$

with  $h = \pi/n$  and  $x_k = k \cdot h$ . If n = 1000000, we have

result = 5.795776322412856 (all double-double)  $\rightarrow 20x$  slower = 5.795776322413031 (all double)

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- = 5.795776322413031 (all double)
- = 5.795776322412856 (only the summand is in double-double)

→ almost the same speed

• only 1 change is necessary  $\rightsquigarrow$  found in  $\approx$  30 sec.

# Bug in dgges subroutine of LAPACK

#### LAPACK bug report<sup>3</sup>

I have the following problem with dgges. For version 3.1.1 and sooner, I get a reasonable result, for version 3.2 and 3.2.1, I get info=n+2.

- The only difference between LAPACK 3.1.1 and 3.2.x
  - some calls to dlarfg replaced by dlarfp
- First step : simplification
  - which call(s) to dlarfp made the program fail?

<sup>3.</sup> See http://icl.cs.utk.edu/lapack-forum/viewtopic.php?f=2&t=1783 for details.

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- The only difference between LAPACK 3.1.1 and 3.2.x
  - some calls to dlarfg replaced by dlarfp
- First step : simplification
  - which call(s) to dlarfp made the program fail?
- Automation with delta-debugging
  - 25610 calls to dlarfp = 25610 possible changes
  - ▶ all changes but 1 did not matter → found in about 1m. 50 sec.
    - → much easier to find which line of code was the source of this bug

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#### NaN/Inf checking and some infinite loop isolation

- Problem : NaN/Inf occurring in floating-point programs may be the source of some infinite loops
- How to detect where NaN/Inf occur during the run of the program ?
  - by testing the result of each floating-point operations
  - by testing overflow/invalid flag (only works if created by programs, not input)
    - → need an exception handler

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How to detect where NaN/Inf occur during the run of the program?

- by testing the result of each floating-point operations
- by testing overflow/invalid flag (only works if created by programs, not input)
  - → need an exception handler
- Just try to show loop termination or detect loop non-termination

#### Conclusion and perspective

- Goal ~→ automatic debugging of scientific floating-point programs
- Framework for the automatic isolation of numerical anomalies
  - transformation / instrumentation using CIL
  - effective changes found using Delta-Debugging

#### Current and future work

- implementation of other transformations (FloatToFF, ...)
- apply to database bugs of LAPACK
- NaN/Inf checking for isolating some infinite loops (loop non-termination)
- modifying comparisons that go astray by adding an unobvious tolerance
- isolation of floating-point constants that are not converted in full precision
- identification of hardware features that could facilitate "debugging process" while not impacting normal floating-point performance

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