Hybrid Analog-Digital Solution of Nonlinear Partial Differential Equations

<u>Yipeng Huang,</u> Ning Guo, Kyle Mandli, Mingoo Seok, Yannis Tsividis, Simha Sethumadhavan

Columbia University

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The Best of the 20th Century: Editors Name Top 10 Algorithms Compiled by Barry Cipra

Most mentioned in

Society for Industrial and Applied Mathematics The Princeton Companion to Applied Mathematics Compiled by Nick Higham

Newton methods

2016

Matrix factorizations (e.g., LU decomposition)

Eigenvalue algorithms (e.g., QR algorithm) Monte Carlo method

Fast Fourier transform

Krylov subspace iteration methods (e.g., conjugate gradients)

Simplex method for linear programming

Others: Fortran compiler, Quicksort, integer relation detection, fast multipole

Others: JPEG, PageRank, Kalman filter

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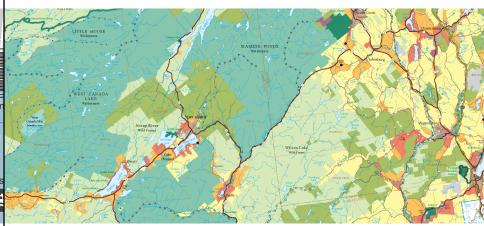
Discipline	Nonlinear PDEs	Cause of nonlinear behavior
Applied physics	Plasma & fluids	Multiphysics
Applied mathematics	Nonlinear waves	Dispersive effects
Chemical engineering	Combustion models	Multiphysics
Civil engineering	Solid mechanics	Nonlinear spring forces
Electrical engineering	Circuit simulation	Nonlinear components
Operations research	Convex optimization	Nonlinear objectives & constraints
Mechanical engineering	Optimal control	Nonlinear Euler-Lagrange equations



Simple map

Few turns

Nonlinear



Check map often

Need to start close

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Motivation for hybrid analog-digital architecture

Both analog and digital needed for target workload

diversity

iviotivation for hybrid analog digital aformotato				
	Ability to solve	Solution	Technique	
	nonlinear	accuracy &	diversity	Problem sizes

precision

problems

Analog

Digital

Outline

Motivation:

Analog avoids digital pitfalls in nonlinear problems

Architecture:

Hybrid analog-digital system combines both for speed & precision How to map a PDE problem to a prototype analog accelerator

Evaluation:

- 100× faster for approximate solution
- 5.7× faster and 11.6× less energy when analog helps GPU

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Motivation:

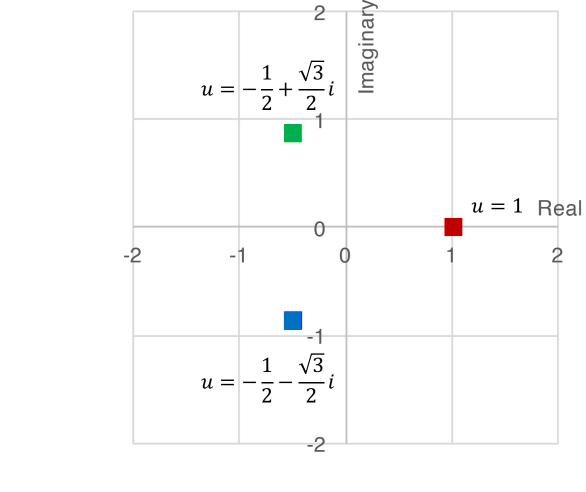
Analog avoids <u>digital pitfalls in nonlinear problems</u>

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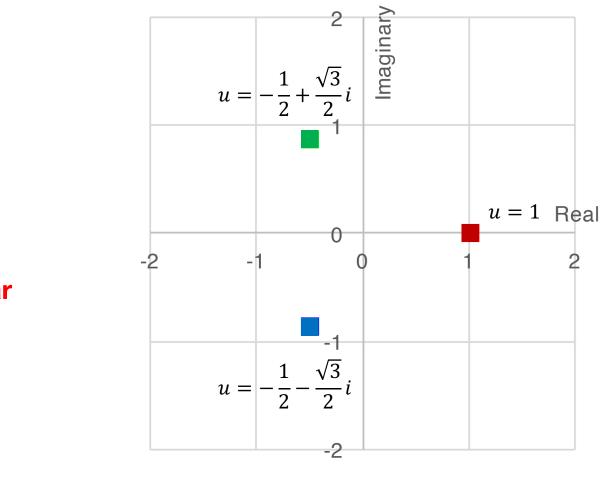
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Solve for *u*: $f(u) = u^3 - 1 = 0$



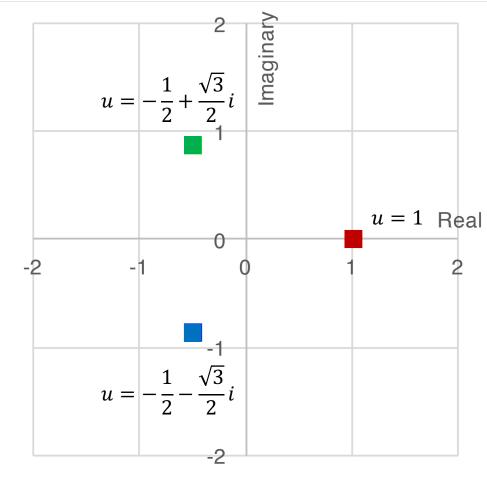
Solve for u: $f(u) = u^3 - 1 = 0$ nonlinear

Solve for *u*:
$$f(u) = u^3 - 1 = 0$$

Using Newton's method: $u_{next} = u_{curr} - \frac{f(u_{curr})}{f'(u_{curr})}$

With some initial guess
$$u_0$$

Returns one of three final solutions



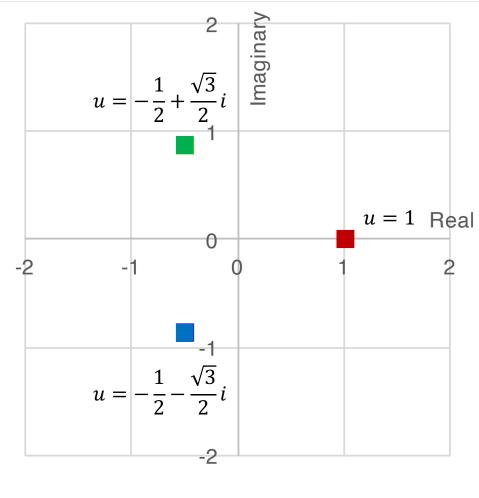
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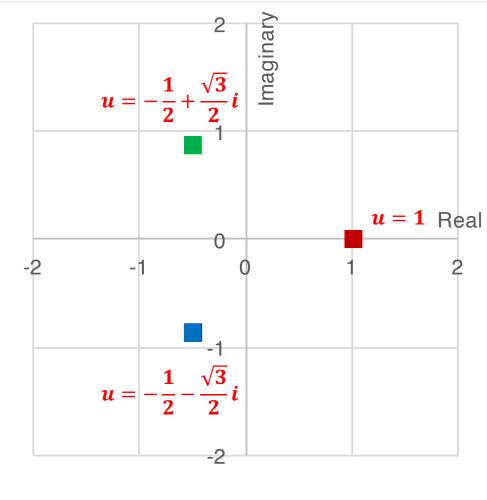
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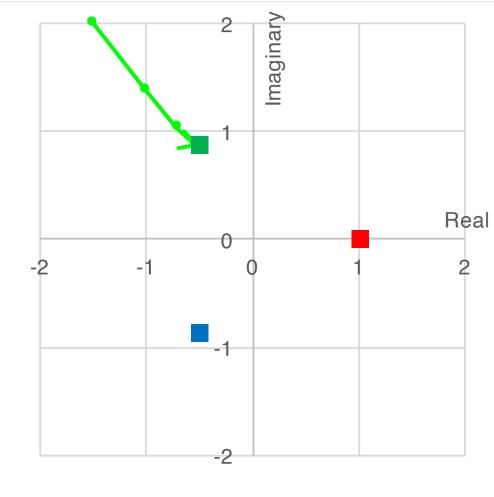
Using Newton's method:

$$u_{next} = u_{curr} - \frac{u_{curr}^3 - 1}{3u_{curr}^2}$$

With initial guess: $u_0 = -1.5 + 2i$

Returns final solution:

$$u_{final} = -\frac{1}{2} + \frac{\sqrt{3}}{2}i$$



Solve for *u*: $f(u) = u^3 - 1 = 0$

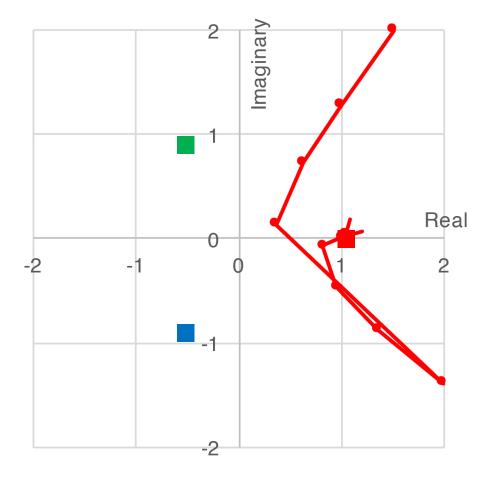
Using Newton's method:

$$u_{next} = u_{curr} - \frac{u_{curr}^3 - 1}{3u_{curr}^2}$$

With initial guess: $u_0 = 1.5 + 2i$

Returns final solution:

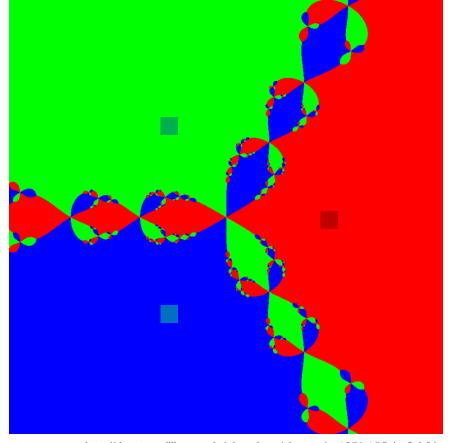
$$u_{final} = 1$$



Plot of final solution vs. initial guess for Newton's method

Three colors indicate which of the three roots the initial guesses go to

Like hiking in wilderness, important to start close to destination ...or else easy to get lost



http://dept.cs.williams.edu/~heeringa/classes/cs135/s15/labs/lab3/

Solve for *u*: $f(u) = u^3 - 1 = 0$

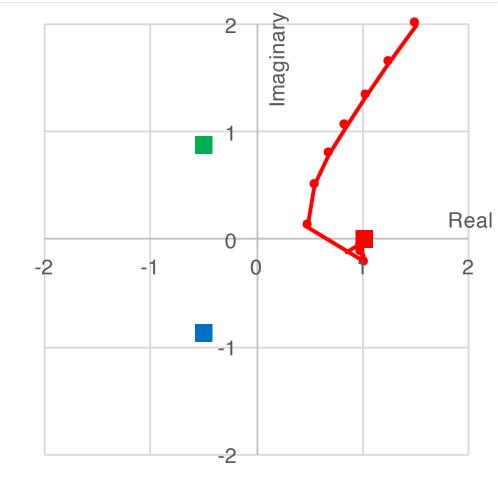
Using **damped** Newton's method:

$$u_{next} = u_{curr} - \frac{1}{2} \frac{u_{curr}^3 - 1}{3u_{curr}^2}$$

With initial guess: $u_0 = 1.5 + 2i$

Returns final solution:

$$u_{final} = 1$$



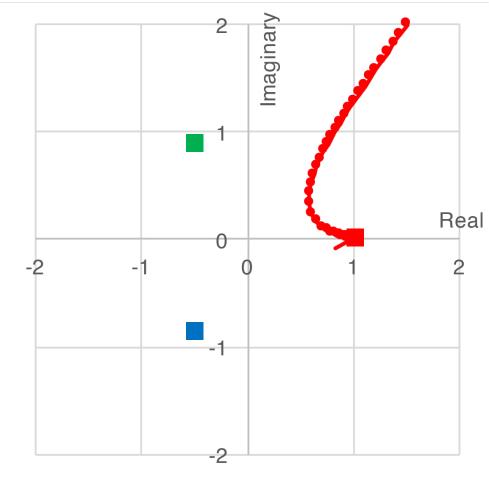
Solve for *u*: $f(u) = u^3 - 1 = 0$

Using **damped** Newton's method:

$$u_{next} = u_{curr} - \frac{1}{8} \frac{u_{curr}^3 - 1}{3u_{curr}^2}$$

With initial guess: $u_0 = 1.5 + 2i$

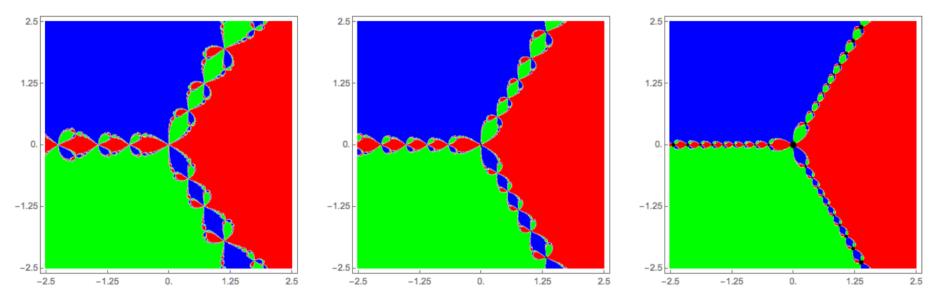
 $u_{final} = 1$



Like hiking in wilderness, better to check map often Don't go too far between checking map, or else easy to get lost

With smaller damping parameter, plot becomes more contiguous...

...at the cost of more digital computation time



José M. Gutiérrez, "Numerical Properties of Different Root-Finding Algorithms Obtained for Approximating Continuous Newton's Method," Algorithms 2015

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Analog avoids digital pitfalls in nonlinear problems

Architecture:

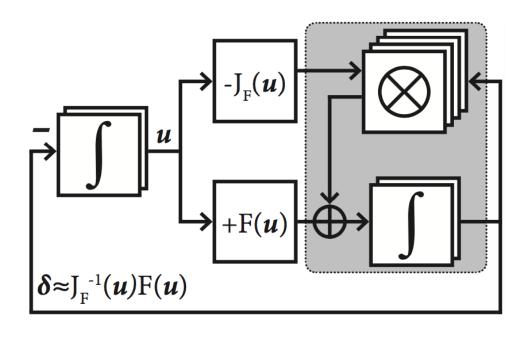
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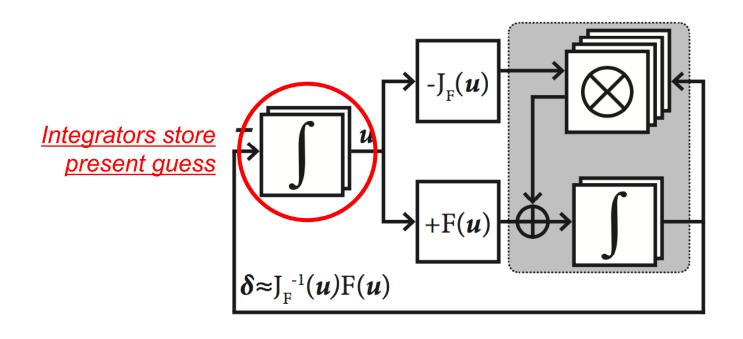
Evaluation:

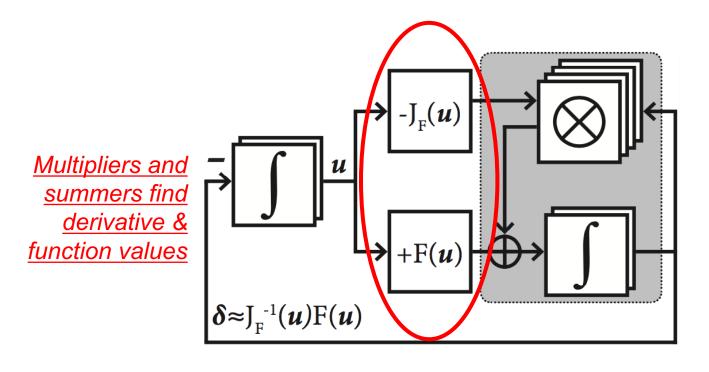
- 100× faster for approximate solution
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Push damped Newton's method to limit, get continuous Newton's method

Take (nearly) infinitely many (nearly) infinitesimal steps Like continuously checking map while hiking in wilderness

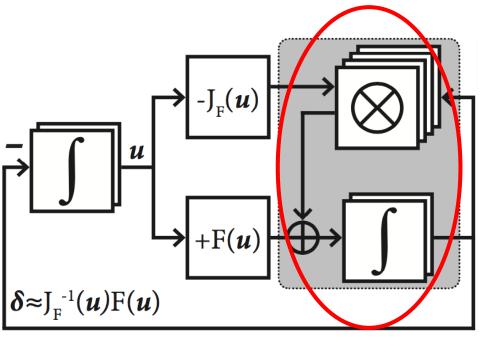






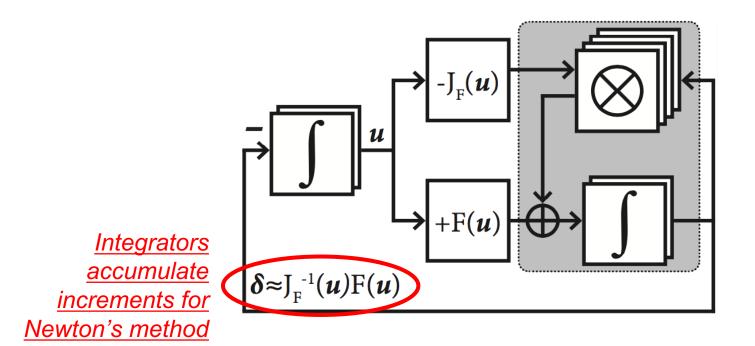
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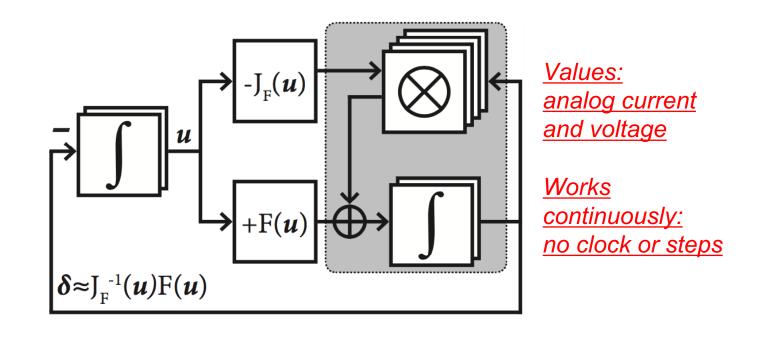
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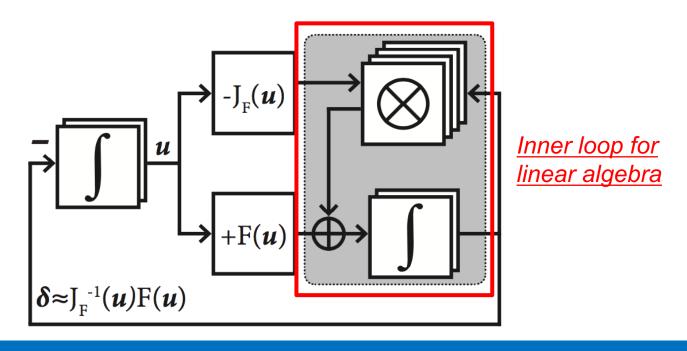


Negative feedback solves linear algebra problem

Huang et al., ISCA 2016

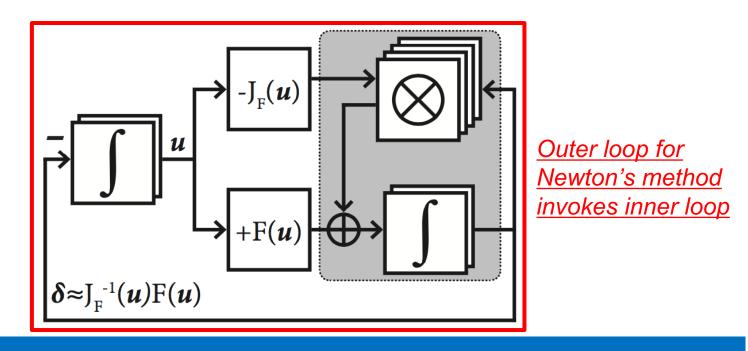






Takeaway 1 of 4: how to do more work in analog?

Create analog inner loops by nesting circuits with different convergence rates



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Create analog inner loops by nesting circuits with different convergence rates

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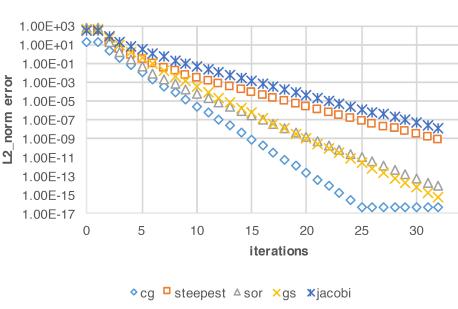
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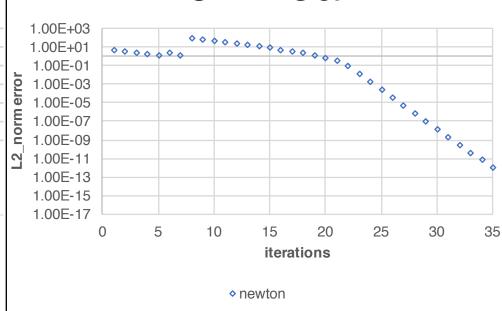
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First few digits of solution cheap

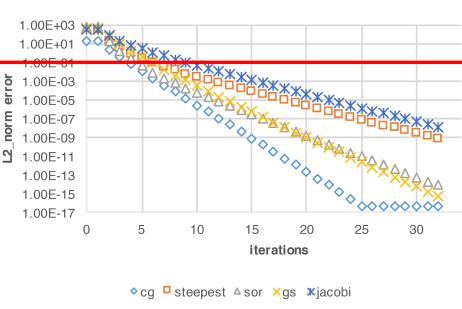
Last few digits of solution expensive

Nonlinear



Rough guess solution expensive

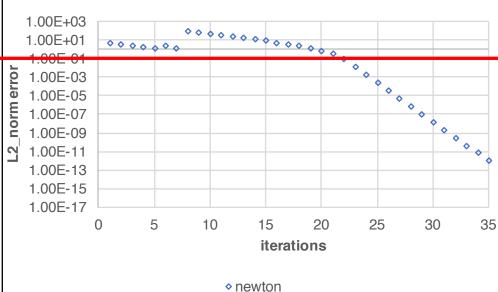
Refined solution from guess cheap



First few digits of solution cheap

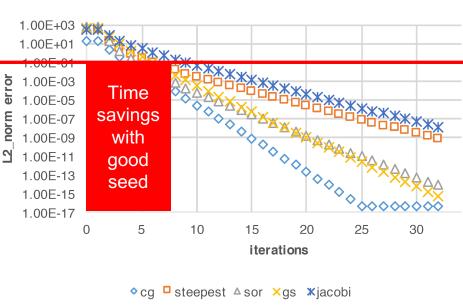
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Nonlinear



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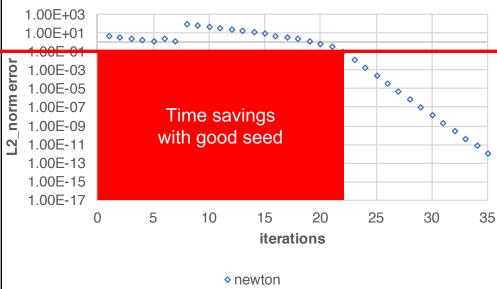
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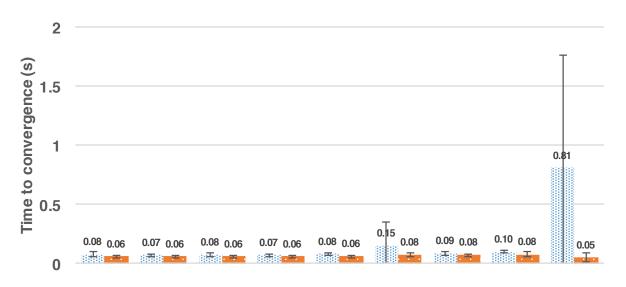
Nonlinear



Rough guess solution expensive

Refined solution from guess cheap

Solve time for digital and seeded digital solver



More nonlinear →

■ baseline digital solver ■ analog seeded digital solver

Takeaway 2 of 4: how to increase solution accuracy? Cheap analog approximation → good digital initial guess

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Digital: lots of methods and code for breaking down PDEs We want to keep existing code while using accelerator

Analog: can only solve ordinary differential equations... ...and algorithms phrased as ODEs, such as continuous Newton's

Takeaway 3 of 4: how to minimize reprogramming?

Retarget kernels in existing digital code to accelerate in analog

$$\frac{\partial \mathbf{u}}{\partial t} + (\mathbf{u} \cdot \nabla)\mathbf{u} - \frac{1}{\text{Re}}\nabla^2\mathbf{u} = \text{RHS}$$

$$\begin{cases} \frac{\partial u}{\partial t} + u\frac{\partial u}{\partial x} + v\frac{\partial u}{\partial y} - \frac{1}{\text{Re}}(\frac{\partial^2 u}{\partial x^2} + \frac{\partial^2 u}{\partial y^2}) = \text{RHS}_0 \\ \frac{\partial v}{\partial t} + u\frac{\partial v}{\partial x} + v\frac{\partial v}{\partial y} - \frac{1}{\text{Re}}(\frac{\partial^2 v}{\partial x^2} + \frac{\partial^2 v}{\partial y^2}) = \text{RHS}_1 \end{cases}$$

Core nonlinear part of the Navier-Stokes equations for fluid dynamics u and v are velocity of fluid in x- and y- dimensions, respectively

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Why nonlinear: because derivatives of u and v have u and v as coefficients

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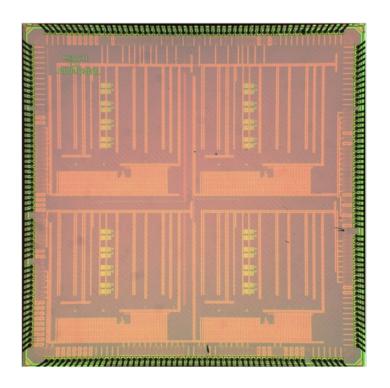
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Why nonlinear: because derivatives of u and v have u and v as coefficients how nonlinear the PDE is depends on choice of Re, Reynolds number

To solve this PDE, do space discretization and time stepping results in system of nonlinear algebraic equations, which we solve in analog

Prototype analog accelerator for nonlinear systems of equations

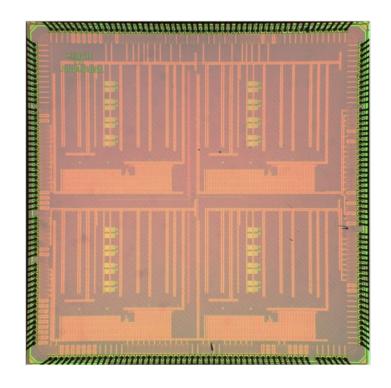
Tiled programmable analog accelerator Enhanced calibration for all analog units



Prototype analog accelerator for nonlinear systems of equations

Tiled programmable analog accelerator Enhanced calibration for all analog units

Analog in/out for multi-chip operation
Sparse global connectivity b/w tiles for PDEs;
Dense local connectivity b/w function units for variety of nonlinear functions, derivatives

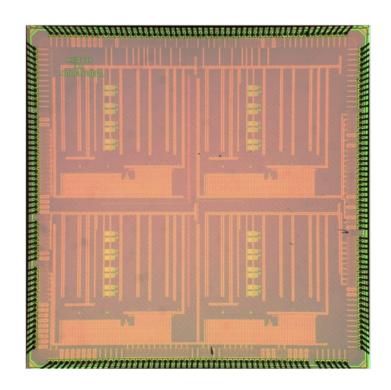


Prototype analog accelerator for nonlinear systems of equations

Tiled programmable analog accelerator Enhanced calibration for all analog units

Analog in/out for multi-chip operation Sparse global connectivity b/w tiles for PDEs; Dense local connectivity b/w function units for variety of nonlinear functions, derivatives

Solve 2D Burgers' equation with 2 chips x-velocity field in one chip y-velocity field in the other



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Analog avoids digital pitfalls in nonlinear problems

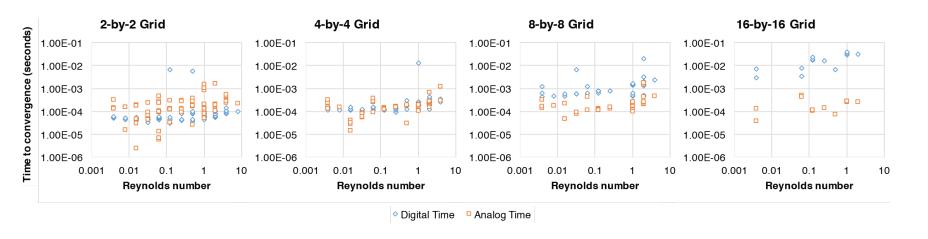
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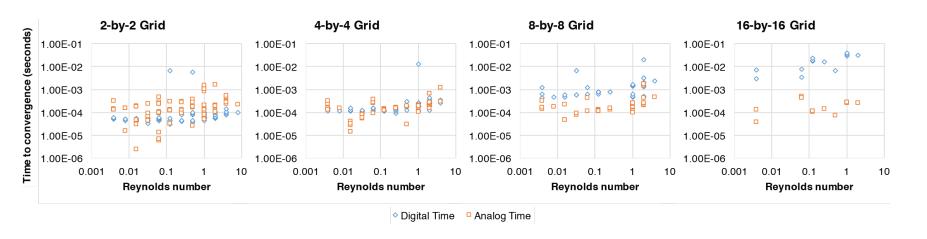
Performance simulation of scaled-up analog accelerators



Analog accelerator performance vs. digital for larger problem sizes

Plot of solution time to same accuracy vs. how nonlinear problem is

Performance simulation of scaled-up analog accelerators



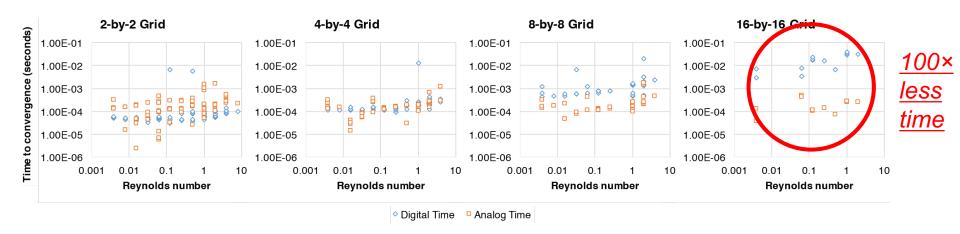
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Analog: solution time for 2-by-2 grid validated using prototype chip

Digital: solution time from damped Newton's method solver

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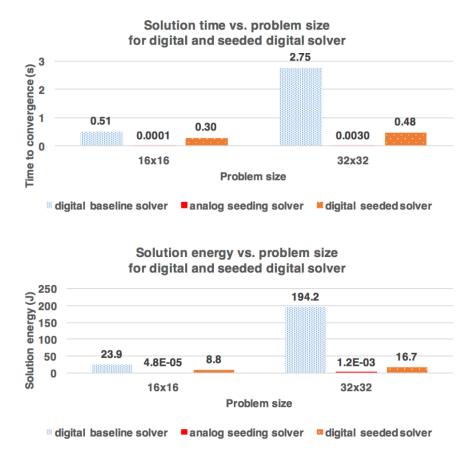
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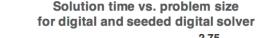
Plot of solution time & energy vs. problem size 32×32 2D problem has 2048 variables at play

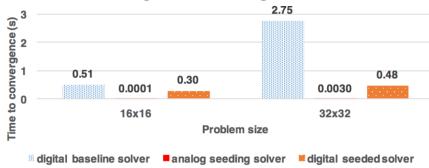


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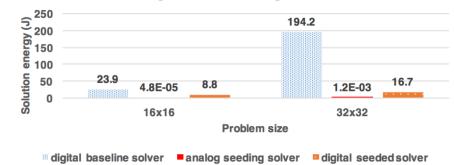
Comparing:

GPU alone to high precision
Analog approximation
GPU with analog approx. to high precision





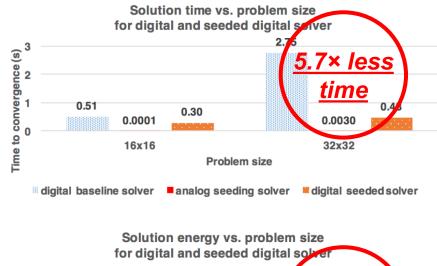
Solution energy vs. problem size for digital and seeded digital solver

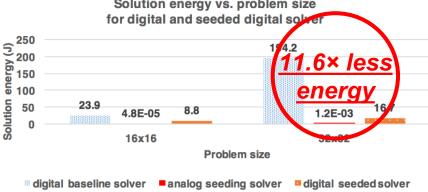


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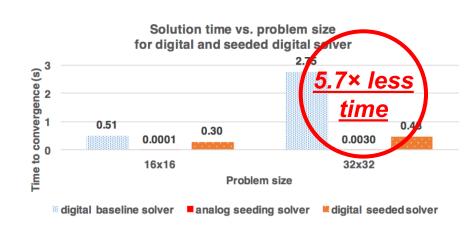
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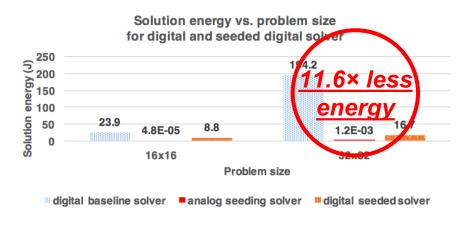
Comparing:

GPU alone to high precision Analog approximation GPU with analog approx. to high precision

Time and energy saved here is significant

PDE solver workloads repeatedly call these innermost loops as dominant kernel

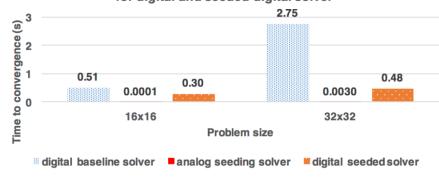




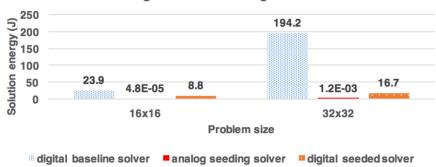
Scaling out beyond analog size constraint? 16-by-16 chip uses 350mm2, 400mW

Takeaway 4 of 4:
how to increase problem size?
Extremely low power analog can scale
out and stack differently than digital

Solution time vs. problem size for digital and seeded digital solver



Solution energy vs. problem size for digital and seeded digital solver



Nonlinear is analog killer app!

Nonlinear is analog killer app! Why it works:

Cheap analog approximation \rightarrow good digital initial guess

Retarget kernels in existing digital code to accelerate in analog

Extremely low power analog can scale out and stack differently than digital

How to do more work in analog?	Create analog inner loops by nesting circuits with different convergence

How to increase

How to minimize

reprogramming?

How to increase

problem size?

solution accuracy?