Numerical Simulation and Scientific Computing I

Lecture 4: Finite Difference Method, Finite Precision Floating Point Arithmetics



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Quiz

- Q1: Does C++ abstraction (classes, operator overloads, ...)
 lead to run time overhead?
- Q2: How many choices are there to approximate a first derivative on a FDM grid?
- Q3: How big is the memory footprint of a 3D finite difference grid with uniform resolution of 1024 along each dimension?
- Q4: Assume someone provides you a solution uh to a specific linear equation system arising from applying the FDM to a problem, what could you do to check if it is indeed a solution?
- Q5: Assume additionally know the analytical solution u to the problem from Q4, how could you quantify the difference between the solution u and uh?

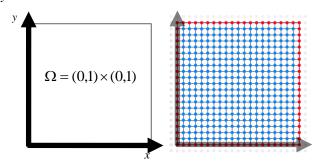
Outline

- Errors
- Vector and matrix norms
- Truncation error FD
- Boundary conditions FD
- Finite precision FP

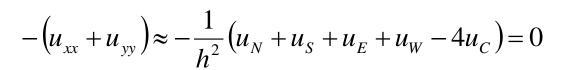
Finite Difference Summary

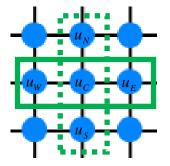
• Starting point
$$-(u_{xx} + u_{yy}) = 0$$
 in $\Omega = (0,1) \times (0,1) + Dirichlet BCs$

- Domain discretization
 - N points per dimension
 - ~N² unknowns



Approximation of (second) derivatives using FD





- Construction of linear equation system
 - A_h has size ~ (N² x N²)

$$A_h \cdot u_h = b_h$$

	,													
	+4	-1	0	-1	0	0	0	0	0		u_6		$\left[\begin{array}{c} u_1 + u_5 \end{array}\right]$	
	-1	+4	-1	0	-1	0	0	0	0		u_7		u_2	
	0	-1	+4	0	0	-1	0	0	0		u_8		$u_3 + u_9$	
1	-1	0	0	+4	-1	0	-1	0	0		u_{11}	1	u_{10}	
$\frac{1}{h^2}$	0	-1	0	-1	+4	-1	0	-1	0		u_{12}	$=\frac{1}{h^2}$	0	
n	0	0	-1	0	-1	+4	0	0	-1		u_{13}	n	u_{14}	
	0	0	0	-1	0	0	+4	-1	0		u_{16}		$u_{15} + u_{21}$	
	0	0	0	0	-1	0	-1	+4	-1	l	u_{17}		u_{22}	
	0	0	0	0	0	-1	0	-1	+4		$\lfloor u_{18} \rfloor$		$\left\lfloor u_{19} + u_{23} \right\rfloor$	
					$\widetilde{A_h}$						x_h		b_h	

Errors

• Discretized problem
$$-\frac{1}{h^2}(u_N + u_S + u_E + u_W - 4u_C) = 0$$
 $A_h u_h - b_h = 0$

$$A_h u_h - b_h = \underline{0}$$

- Total error
 - Difference between known solution and approximate solution of discretized problem

$$u - \hat{u}_h = e_{\text{total}}$$

Discretization/truncation error

$$u - u_h = e_{\text{disc.}}$$

- Difference between known solution and exact solution to discretized problem
- To improve: numerical scheme, resolution
- Algebraic error

$$u_h - \hat{u}_h = e_{\text{algeb}}$$

- Difference between exact and approximate solution of discretized problem
- To improve: solution method, precision/order of finite arithmetic
- Residual

$$A_h \hat{u}_h - b_h = \mathbf{r}_h$$

- Deviation of RHS for approximate solution of discretized problem
- Always available

Residual $A_h \hat{u}_h - b_h = \mathbf{r}_h$

- Relation to algebraic error
 - Interpretation: Residual is the perturbation of the RHS to make the approximate solution fit the discretized problem exactly

$$A_{h}\hat{u}_{h} = \hat{b}_{h}$$

$$A_{h}(u_{h} + \Delta u_{h}) = (b_{h} + \Delta b_{h})$$

$$\underbrace{A_{h}u_{h}}_{b_{h}} + A_{h}\underbrace{\Delta u_{h}}_{e_{\text{algeb.}}} = b_{h} + \underbrace{\Delta b_{h}}_{r_{h}}$$

$$A_h e_{\text{algeb.}} = r_h$$

$$e_{\text{algeb.}} = A_h^{-1} r_h$$

Condition number of A

$$||A_{h}|| \cdot ||e_{\text{algeb.}}|| \ge ||A_{h}e_{\text{algeb.}}|| = ||r_{h}||$$

$$||e_{\text{algeb.}}|| = ||A_{h}^{-1}r_{h}|| \le ||A_{h}^{-1}|| \cdot ||r_{h}||$$

$$\frac{\|e_{\text{algeb.}}\|}{\|u_h\|} \le \kappa(A) \frac{\|r_h\|}{\|b_h\|} = \|A_h^{-1}\| \|A_h\| \frac{\|r_h\|}{\|b_h\|}$$

Vector Norms

- Vector norms
 - positivity
 - homogeneity
 - subadditivity
- Common norms
 - Manhattan norm
 - Euclidean norm
 - Maximum Norm
- "Norm Sphere"

$$||x|| = 1$$

$$||x|| > 0 \quad \forall x \neq 0$$

$$||\alpha x|| = |\alpha| \cdot ||x||$$

$$||x + y|| \le ||x|| + ||y||$$

$$||x||_{1} := \sum_{i=1}^{n} |x_{i}|$$

$$||x||_{2} := \left(\sum_{i=1}^{n} |x_{i}|^{2}\right)^{1/2}$$

$$||x||_{\infty} := \max_{1 \le i \le n} |x_{i}|$$

Matrix Norms

Induced matrix norm

$$||A|| := \max_{x} \frac{||Ax||}{||x||} = \max_{||x||=1} ||Ax||$$

- Matrix norms
 - positivity
 - homogeneity
 - subadditivity
 - sub-multiplicativity
 - consistency

$$||A|| > 0 \quad \forall x \neq 0$$

$$||\alpha A|| = |\alpha| \cdot ||A||$$

$$||A + B|| \le ||A|| + ||B||$$

$$||AB|| \le ||A|| \cdot ||B||$$

$$||Ax|| \le ||A|| \cdot ||x||$$

- Condition number
 - Deformation of how much "norm sphere" is deformed by the matrix

$$\kappa(A) := \frac{\max_{\|x\|=1} \|Ax\|}{\min_{\|x\|=1} \|Ax\|} = \|A^{-1}\| \|A\|$$

Norms Overview

$$||A|| \coloneqq \max_{\|x\|=1} ||Ax||$$

	Vector Norm	Induced Matrix Norm
Manhattan	$\ x\ _1 := \sum_{i=1}^n x_i $	$ A _1 \coloneqq \max_{1 \le j \le n} \sum_{i=1}^n a_{ij} $
Euclidean	$ x _2 := \left(\sum_{i=1}^n x_i ^2\right)^{1/2}$	$\ A\ _2 \coloneqq \sigma_{\max}(A)$
Maximum	$ x _{\infty} := \max_{1 \le i \le n} x_i $	$ A _{\infty} := \max_{1 \le i \le m} \sum_{j=1}^{n} a_{ij} $

Normalizing Norms

- Comparing residual for different resolutions
 - Resolution N, grid spacing h

$$||A_h \hat{u}_h - b_h|| = ||\mathbf{r}_h||$$
$$||x|| := \sqrt{\sum_{i=1}^n |x_i|^2}$$

Increase resolution and compare residual norms

$$\frac{\left\|\mathbf{r}_{h/2}\right\|}{\left\|\mathbf{r}_{h}\right\|} = ?$$

Normalized sequence of norms

- $\|\underline{1}\|_{h_i} = 1$ on domain \mathcal{S}
- Norm for constant function on domain is 1
- Examples

$$||x|| := \max_{z \in \Omega_i} |x_z|$$

$$||x|| := \sqrt{\frac{1}{|\Omega_i|} \sum_{z \in \Omega_i} |x_z|^2}$$

Overview FDM

Continuous Model

Expectations when doubling the resolution?

Finite differences Resolution

$$\|u-u_h\|=\|e_{\mathrm{disc.}}\|$$

Discrete Model

Solver Finite precision/arithmetics

$$||u_h - \hat{u}_h|| = ||e_{\text{algeb.}}||$$

Approximate Solution

Norms

Residual

$$||A_h\hat{u}_h - b_h|| = ||\mathbf{r}_h||$$

Taylor Series Expansion

Approximate "nice" function around a point by its derivatives

$$u(x) = u(x_0) + u'(x_0)(x - x_0) + \frac{u''(x_0)}{2!}(x - x_0)^2 + \frac{u'''(x_0)}{3!}(x - x_0)^3 + \dots + \frac{u^{(n)}(x_0)}{n!}(x - x_0)^n$$

Forward finite difference for first derivative

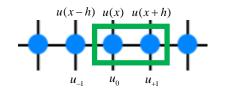
$$\frac{u(x) - u(x_0)}{(x - x_0)} = u'(x_0) + \underbrace{\left(\sum_{n=2}^{\infty} \frac{u^{(n)}(x_0)}{n!} (x - x_0)^n\right)}_{R(\dots)} \cdot \frac{1}{(x - x_0)}$$

setting $x = x_0 + h$ and ξ between x_0 and $x_0 + h$

$$\frac{u(x_0+h)-u(x_0)}{(h)} = u'(x_0) + \underbrace{\frac{u^{(2)}(\xi)}{2!}(h)^2 \cdot \frac{1}{h}}_{R(h^2)}$$

- Remainder term is O(h)
 - Same holds for backward difference

$$\frac{\partial u}{\partial x} = u_{+x} \approx \frac{u_{+1} - u_0}{h}$$



Taylor Series Expansion

• Central difference for second derivative $\frac{\partial u^2}{\partial x^2} = u_{xx} \approx \frac{u_{+1} - 2u_0 + u_{-1}}{h^2}$

$$\frac{\partial u^2}{\partial x^2} = u_{xx} \approx \frac{u_{+1} - 2u_0 + u_{-1}}{h^2}$$

setting
$$x = x_0 + h$$

$$u(x_0 + h) = u(x_0) + u'(x_0)(h) + \frac{u''(x_0)}{2!}(h)^2 + \frac{u'''(x_0)}{3!}(h)^3 + \dots + \frac{u^{(n)}(x_0)}{n!}(h)^n$$
setting $x = x_0 - h$

$$u(x_0 - h) = u(x_0) - u'(x_0)(h) + \frac{u''(x_0)}{2!}(h)^2 - \frac{u'''(x_0)}{3!}(h)^3 + \dots + \frac{u^{(2n)}(x_0)}{2n!}(h)^{2n} - \frac{u^{(2n+1)}(x_0)}{(2n+1)!}(h)^{2n+1}$$

$$u(x_0 + h) + u(x_0 - h) = 2u(x_0) + 2\frac{u''(x_0)}{2!}(h)^2 + 2\left(\sum_{n=2}^{\infty} \frac{u^{(2n)}(x_0)}{(2n)!}(h)^{2n}\right)$$

$$u(x_0 + h) + u(x_0 - h) - 2u(x_0)$$

$$u(x_0 + h) + u(x_0 - h) - 2u(x_0)$$

$$u(x_0 + h) + u(x_0 - h) - 2u(x_0)$$

$$u(x_0 + h) + u(x_0 - h) - 2u(x_0)$$

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$$u(x_0 + h) + u(x_0 - h) - 2u(x_0)$$

$$u(x_0 + h) + u(x_0 - h) - 2u(x_0)$$

Remainder term is O(h²)

Consistency of FDM

Example

$$-\Delta u = -(u_{xx} + u_{yy}) = 0$$
 in $\Omega = (0,1) \times (0,1)$

Using second order central differences

$$\frac{u(x_0+h)+u(x_0-h)-2u(x_0)}{(h)^2}=u''(x_0)+O(h^2)$$

- Test case
 - Find smooth analytic solution
 - Solve discretized problem for h, h/2, h/4, ...
 - Assuming an algeb. error << disc. Error
 - Expected behavior of total error

$$\|u - \hat{u}_h\|_{\infty} \le Ch^2$$

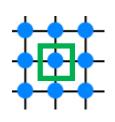
$$\|u - \hat{u}_{h/2}\|_{\infty} \le C \left(\frac{h}{2}\right)^2 = Ch^2 \frac{1}{4}$$

Same holds for residual norm if condition of A_h is "ok"

Boundary Conditions

Interior point

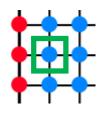
$$-\frac{1}{h^2}(u_N + u_S + u_E + u_W - 4u_C) = 0$$



Dirichlet BC

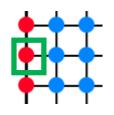
$$u_{w} = g_{1}$$

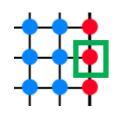
$$-\frac{1}{h^{2}}(u_{N} + u_{S} + u_{E}) - 4u_{C} = \frac{1}{h^{2}}g_{1}$$



- Neumann BC
 - Approximation of first derivative normal to the boundary

$$\frac{\partial u}{\partial n} = \frac{\partial u}{\partial x} = g_2$$





Robin BC

$$\frac{\partial u}{\partial n} + \alpha u = g_3$$

Boundary Conditions

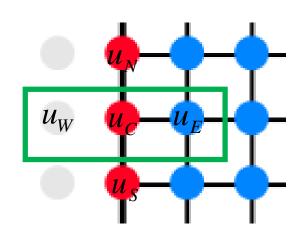
Neumann BC

Central difference (ghost point layer)

$$\frac{\partial u}{\partial n} = \frac{\partial u}{\partial x} = g_2 \approx \frac{u_E - u_W}{2h} \rightarrow u_W = -2hg_2 + u_E$$

$$-\frac{1}{h^2} \left(u_N + u_S + (-2hg_2 + u_E) + u_E - 4u_C \right) = 0$$

$$-\frac{1}{h^2} \left(u_N + u_S + 2u_E - 4u_C \right) = -\frac{2}{h} g_2$$



Boundary Conditions

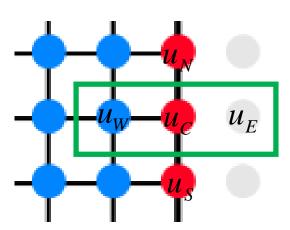
Robin BC

Central difference (ghost point layer)

$$\frac{\partial u}{\partial n} + \alpha u = g_3 \approx \frac{u_E - u_W}{2h} + \alpha u_C \to u_E = 2hg_3 + u_W - 2h\alpha u_C$$

$$-\frac{1}{h^2} (u_N + u_S + (2hg_3 + u_W - 2h\alpha u_C) + u_W - 4u_C) = 0$$

$$-\frac{1}{h^2} (u_N + u_S + 2u_W - (4 + 2h\alpha)u_C) = \frac{2}{h}g_3$$



Consistency of FDM

Example

$$-\Delta u = -(u_{xx} + u_{yy}) = 0$$
 in $\Omega = (0,1) \times (0,1)$

Using second order central differences

$$\frac{u(x_0+h)+u(x_0-h)-2u(x_0)}{(h)^2}=u''(x_0)+O(h^2)$$

Using forward/backward difference for Neumann or Robin BC

$$\frac{u(x_0) + u(x_0 - h)}{(h)^2} = u'(x_0) + O(h)$$

$$\frac{u(x_0 + h) + u(x_0)}{(h)^2} = u'(x_0) + O(h)$$

$$\frac{u(x_0+h)+u(x_0)}{(h)^2} = u'(x_0) + O(h)$$

- Test case
 - Find smooth analytic solution
 - Solve discretized problem for h, h/2, h/4, ...
 - Assuming an algeb. error << disc. Error
 - Expected behavior of total error

$$\|u - \hat{u}_h\|_{\infty} \le Ch$$

$$\|u - \hat{u}_{h/2}\|_{\infty} \le C\frac{h}{2}$$

Finite Precision

$$u_h - \hat{u}_h = e_{\text{algeb.}}$$
 $u - u_h = e_{\text{disc.}}$

- We assumed algebraic error << discretization error
 - Condition number of the problem
 - Solver (e.g., number of iterations)
 - Finite representations and arithmetics used during calculation
- Example
 - III-conditioned system
 - Double precision FP
 - ~16 digits decimal precision
 - Single precision FP
 - ~7digits decimal precision

$$\begin{bmatrix} 0 & -1 \\ 0+\beta & -1 \end{bmatrix} \cdot \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} 1 \\ 1+\beta \end{bmatrix}$$

$$y = -1$$

$$x = \frac{1+\beta-1}{\beta} = 1$$

$$\beta = 1e^{-7} \to \kappa(A) = 2e^{7}$$

$$\beta = 1e^{-15} \to \kappa(A) = 2e^{15}$$

Base 2 Floating Point Representation

- Reasons
 - Hardware implementation
 - Error analysis has tight bounds
 - Extra bit of precision (through normalization)

$$\pm s \cdot 1.dddddddddd \cdot 2^{eeeee}$$

Number of significant decimal digits

$$2^{(binary precision)} = 10^{(decimal precision)}$$

$$\log_{10}(2^{(binary precision)}) = (decimal precision)$$

$$\log_{10}(2^{52+1}) \approx 16$$

$$\log_{10}(2^{23+1}) \approx 7.2$$

$$\log_{10}(2^{10+1}) \approx 3.3$$

Floating Point Representation

s e e e e e d d d d d d d d d d d

- IEEE 754 16bit floating point representation
 - Exponent with 5 digits "e"
 - Significant with 10 digits "d" (precision=10)
 - Sign encoded with 1 digits "s"
 - Base is 2, so digits are bits with state 0 or 1
 - Exponent
 - 00000 = subnormal numbers (for significant>0), otherwise zero
 - 00001 = min, 01111 = bias (=0), 11110 = max
 - 11111 = NaN (for significant>0), otherwise +-infinity

$$\pm s \cdot d.ddddddddd \cdot 2^{eeeee}$$

$$\pm 1 \cdot 2^{00000} \cdot 0.000000000000 = \pm 1 \cdot 2^{0} \cdot \left(0 + \frac{0}{2^{10}}\right) = \pm 0$$

$$\pm 1 \cdot 2^{01111} \cdot 1.000000000000 = \pm 1 \cdot 2^{15-15} \cdot \left(1 + \frac{0}{2^{10}}\right) = \pm 1$$

$$\pm 1 \cdot 2^{11110} \cdot 1.111111111111 = \pm 1 \cdot 2^{30-15} \cdot \left(1 + \frac{2^{10} - 1}{2^{10}}\right) = \pm 65504$$

Quiz

Q1: What are the consequences/differences when using the Maximum norm or Euclidean norm to quantify the residual?

Q2: Which of the discussed matrix norms is the 'cheapest' in terms of computational effort?

Q3: What is the binary representation of "1000" in the IEEE 754 16bit/32bit/64bit FP format?

Q4: What is the difference between BLAS routine 'dgemm' and 'sgemm' / What does the LAPACK routine 'dsysv' do?

Q5: When would you advise to perform a LU decomposition of a matrix instead of a QR decomposition?

