

General Linear Second Order Equation

$$\left\{ \begin{array}{l} \underbrace{a(x)u_{xx}(x)}_{\text{diffusion}} + \underbrace{b(x)u_x(x)}_{\text{advection}} + \underbrace{c(x)u(x)}_{\text{growth/decay}} = \underbrace{f(x)}_{\text{source}} \quad x \in]0, 1[\\ u(0) = \alpha \\ u(1) = \beta \end{array} \right\}$$

Approximation:

$$a_i \frac{u_{i-1} - 2u_i + u_{i+1}}{h^2} + b_i \frac{u_{i+1} - u_{i-1}}{2h} + c_i u_i = f_i$$

where $a_i = a(x_i)$, $b_i = b(x_i)$, $c_i = c(x_i)$.

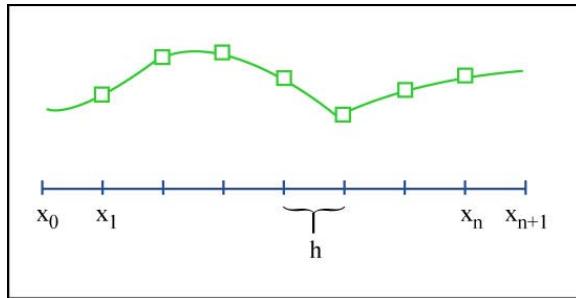


Image by MIT OpenCourseWare.

Linear system: $A \cdot \vec{u} = \vec{f}$

$$A = \frac{1}{h^2} \begin{bmatrix} h^2 c_1 - 2a_1 & a_1 + \frac{hb_1}{2} & & & \\ a_2 - \frac{hb_2}{2} & h^2 c_2 - 2a_2 & a_2 + \frac{hb_2}{2} & & \\ & \ddots & \ddots & \ddots & \\ & & a_{n-1} - \frac{hb_{n-1}}{2} & h^2 c_{n-1} - 2a_{n-1} & a_{n-1} + \frac{hb_{n-1}}{2} \\ & & & a_n - \frac{hb_n}{2} & h^2 c_n - 2a_n \end{bmatrix}$$

$$\vec{f} = \begin{bmatrix} f_1 - \left(\frac{a_1}{h^2} - \frac{b_1}{2h}\right)\alpha \\ f_2 \\ \vdots \\ f_{n-1} \\ f_n - \left(\frac{a_n}{h^2} + \frac{b_n}{2h}\right)\beta \end{bmatrix}$$

Potential Problems:

- A non-symmetric
 - If $|a(x)| \ll |b(x)|$, instabilities possible due to central differences.
- Often better approximations possible.

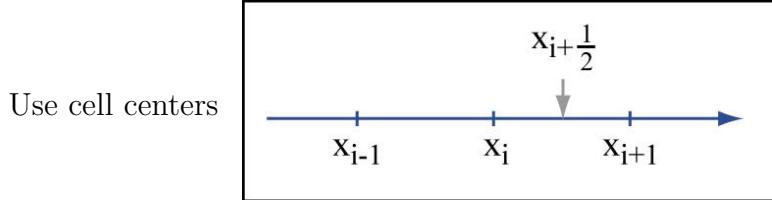
Ex.: Heat equation in rod with variable conductivity

$$(\kappa(x)u_x)_x = f(x) \quad (*)$$

$$\Leftrightarrow \kappa(x)u_{xx} + \kappa_x(x)u_x = f(x) \quad (**)$$

Can discretize $(**)$ as before. Suboptimal results.

Better: discretize $(*)$ directly (in line with physics)



$$\kappa(x_{i+\frac{1}{2}})u_x(x_{i+\frac{1}{2}}) \approx \kappa_{i+\frac{1}{2}} \cdot \frac{u_{i+1} - u_i}{h} \quad \text{Image by MIT OpenCourseWare.}$$

$$\begin{aligned} \Rightarrow (\kappa u_x)_x(x_i) &\approx \frac{1}{h} \left(\kappa_{i+\frac{1}{2}} \cdot \frac{u_{i+1} - u_i}{h} - \kappa_{i-\frac{1}{2}} \cdot \frac{u_i - u_{i-1}}{h} \right) \\ &= \frac{1}{h} (\kappa_{i-\frac{1}{2}} u_{i-1} - (\kappa_{i-\frac{1}{2}} + \kappa_{i+\frac{1}{2}}) u_i + \kappa_{i+\frac{1}{2}} u_{i+1}) \end{aligned}$$

$$A = \frac{1}{h^2} \begin{bmatrix} -(\kappa_{\frac{1}{2}} + \kappa_{\frac{3}{2}}) & \kappa_{\frac{3}{2}} & & & \\ \kappa_{\frac{3}{2}} & -(\kappa_{\frac{3}{2}} + \kappa_{\frac{5}{2}}) & \kappa_{\frac{5}{2}} & & \\ & \ddots & \ddots & \ddots & \\ & & \kappa_{n-\frac{3}{2}} & -(\kappa_{n-\frac{3}{2}} + \kappa_{n-\frac{1}{2}}) & \kappa_{n-\frac{1}{2}} \\ & & & \kappa_{n-\frac{3}{2}} & -(\kappa_{n-\frac{1}{2}} + \kappa_{n+\frac{1}{2}}) \end{bmatrix}$$

Symmetric matrix, $-A$ positive definite.

Great for linear solvers \rightarrow CG (conjugate gradient method).

2D/3D

$$\nabla \cdot (\kappa \nabla u) = f$$

||

$$2D: (\kappa(x)u_x)_x + (\kappa(x)u_y)_y \longleftarrow 2 \times 1D$$

Errors, Consistency, Stability

Presentation for Poisson equation, but results transfer to any linear finite difference scheme for linear PDE.

$$u''(x) = f(x) \rightsquigarrow A \cdot U = F$$

↑
vector of approximate function values U_i

true solution values: $\hat{U} = \begin{bmatrix} u(x_1) \\ \vdots \\ u(x_n) \end{bmatrix}$

Local Truncation Error (LTE)

Plug true solution $u(x)$ into FD scheme:

$$\begin{aligned} \tau_i &= \frac{1}{h^2}(u(x_{i-1}) - 2u(x_i) + u(x_{i+1})) - f(x_i) \\ &= u''(x_i) + \frac{1}{12}u'''(x_i)h^2 + O(h^4) - f(x_i) \\ &= \frac{1}{12}u'''(x_i)h^2 + O(h^4) \end{aligned}$$

$$\tau = \begin{bmatrix} \tau_1 \\ \vdots \\ \tau_n \end{bmatrix} = A \cdot \hat{U} - F$$

$$\Rightarrow A\hat{U} = F + \tau$$

Global Truncation Error (GTE)

Error vector: $E : U - \hat{U}$

$$\left. \begin{array}{l} AU = F \\ A\hat{U} = F + \tau \end{array} \right\} \Rightarrow AE = -\tau \text{ and } E = 0 \text{ at boundaries}$$

$$\text{Discretization of } \left\{ \begin{array}{l} -e''(x) = -\tau(x) \quad]0, 1[\\ e(0) = 0 = e(1) \end{array} \right\}$$

$$T(x) \approx \frac{1}{12}u'''(x)h^2$$

$$\Rightarrow e(x) \approx -\frac{1}{12}u''(x)h^2 + \frac{1}{12}h^2(u''(0) + x(u''(1) - u''(0)))$$

Message: Global error order = local error order if method stable.

Stability

$$\begin{aligned} \text{Mesh size } h : A^h \cdot E^h &= -\tau^h \\ \Rightarrow E^h &= -(A^h)^{-1} \cdot \tau^h \\ \Rightarrow \|E^h\| &= \|(A^h)^{-1} \cdot \tau^h\| \leq \|(A^h)^{-1}\| \cdot \underbrace{\|\tau^h\|}_{O(h^2)(\text{LTE})} \end{aligned}$$

Stability: $\|(A^h)^{-1}\| \leq C \quad \forall h < h_0$
Inverse FD operators uniformly bounded.

$$\Rightarrow \|E^h\| \leq C \cdot \|\tau^h\| \quad \forall h < h_0.$$

Consistency

$\|\tau^h\| \rightarrow 0$ as $h \rightarrow 0$
LTE goes to 0 with mesh size

Convergence

$\|E^h\| \rightarrow 0$ as $h \rightarrow 0$
GTE goes to 0 with mesh size

Lax Equivalence Theorem

consistency + stability \iff convergence

Proof: (only “ \implies ” here)

$$\|E^h\| \leq \|(A^h)^{-1}\| \cdot \|\tau^h\| \leq C \cdot \|\tau^h\| \xrightarrow{\substack{\uparrow \\ \text{stability}}} 0 \text{ as } h \rightarrow 0$$

\uparrow
consistency

Also: $O(h^P)$ LTE + stability $\implies O(h^P)$ GTE

Stability for Poisson Equation

Consider 2-norm

$$\|U\|_2 = (\sum_i U_i^2)^{\frac{1}{2}}$$

$\|A\|_2 = \rho(A) = \max_p |\lambda_p|$ largest eigenvalue

$$\Rightarrow \|A^{-1}\|_2 = \rho(A^{-1}) = \max_p |\lambda_p^{-1}| = (\min_p |\lambda_p|)^{-1}$$

Stable, if eigenvalues of A^h bounded away from 0 as $h \rightarrow 0$

In general, difficult to show.

But for Poisson equation with Dirichlet boundary conditions, it is known that

$$\lambda_p = \frac{2}{h^2}(\cos(p\pi h) - 1)$$

$$\Rightarrow \lambda_1 = \frac{2}{h^2}(-\frac{1}{2}\pi^2 h^2 + O(h^4)) = -\pi^2 + O(h^2) \quad \text{Stable } \checkmark$$

$$\text{Hence: } \|E^h\|_2 \leq \|(A^h)^{-1}\|_2 \cdot \|\tau^h\|_2 \approx \frac{1}{\pi^2} \|\tau^h\|_2.$$

MIT OpenCourseWare
<http://ocw.mit.edu>

18.336 Numerical Methods for Partial Differential Equations
Spring 2009

For information about citing these materials or our Terms of Use, visit: <http://ocw.mit.edu/terms>.