

Computational Fluid Dynamics: Lecture 4 (ME EN 6720)

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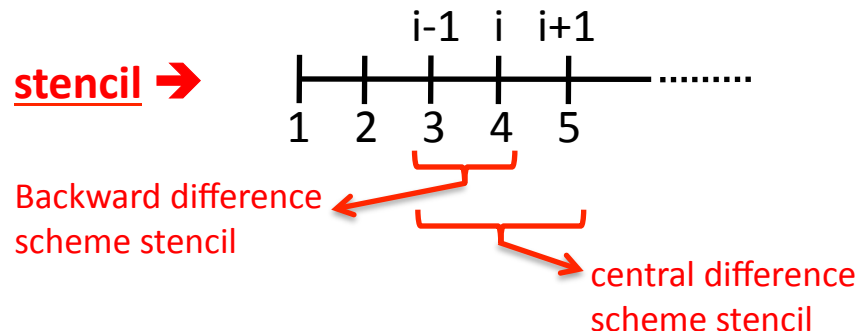
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Finite difference approximations from polynomials

Other ways to develop finite difference approximations (besides Taylor Series)

- **curve fitting** through points:

- We can fit a polynomial of degree $n-1$ (where n is our stencil size)



- Example: fitting a 1st order polynomial (stencil with $n=2$)

- The equation for a line in point-slope form is:

$$(y - y_1) = m(x - x_1) \quad \text{where } m = \frac{y_1 - y_2}{x_1 - x_2}$$

- For our two points we have:

$$\left. \begin{aligned} (x_1, y_1) &= (x_i, u_i) \\ (x_2, y_2) &= (x_{i-1}, u_{i-1}) \end{aligned} \right\} \quad \text{where } m = \frac{u_i - u_{i-1}}{x_i - x_{i-1}}$$

Finite difference approximations from polynomials

-Inserting these into our equation of a line:

$$(y - u_i) = \frac{u_i - u_{i-1}}{x_i - x_{i-1}}(x - x_i)$$

-We want $\frac{\partial u}{\partial x}$ (or in this case $\frac{\partial y}{\partial x}$) \rightarrow taking 1st derivative of the above equation

$$\frac{\partial y}{\partial x} = \frac{u_i - u_{i-1}}{x_i - x_{i-1}}, \quad x_i - x_{i-1} = \Delta x_i, \quad \Rightarrow \boxed{\frac{\partial u}{\partial x} = \frac{u_i - u_{i-1}}{\Delta x_i}} \quad \text{Our backwards difference scheme}$$

-We could also do this with a stencil of 3 ($i-1, i, i+1$) and fit a 2nd order polynomial (parabola) to the points

-This is a little more difficult algebraically (3 coefficients, 3 points, 3 equations) and for our 1st derivative we can obtain

$$\frac{\partial u}{\partial x} = \frac{u_{i+1}(\Delta x_i)^2 - u_{i-1}(\Delta x_{i+1})^2 + u_i[(\Delta x_{i+1})^2 - (\Delta x_i)^2]}{\Delta x_{i+1}\Delta x_i(\Delta x_{i+1} + \Delta x_i)}$$

-Note, we haven't assumed uniform grid spacing ($\Delta x_i = \Delta x_{i-1} = \Delta x_{i+1}$) if we do \rightarrow

$$\boxed{\frac{\partial u}{\partial x} = \frac{u_{i+1} - u_{i-1}}{2\Delta x}} \quad \text{Our central difference scheme}$$

Finite difference approximations from linear combinations

Finite difference schemes as linear combinations

- Another (very similar) way to look at this is as follows (ex 1st derivative):

$$\textcircled{*} \quad \frac{\partial u}{\partial x} = \alpha u_i + \beta u_{i-1} + \gamma u_{i+1} \quad (\text{assume 1st derivative is a linear combination of 3 points})$$

- we can examine the Taylor series approximation for each term:

$$u_{i+1} = u_i + \left(\frac{\partial u}{\partial x} \right)_i \Delta x + \left(\frac{\partial^2 u}{\partial x^2} \right)_i \frac{(\Delta x)^2}{2!} + \left(\frac{\partial^3 u}{\partial x^3} \right)_i \frac{(\Delta x)^3}{3!} + O(\Delta x^4)$$

$$u_i = u_i$$

$$u_{i-1} = u_i - \left(\frac{\partial u}{\partial x} \right)_i \Delta x + \left(\frac{\partial^2 u}{\partial x^2} \right)_i \frac{(\Delta x)^2}{2!} - \left(\frac{\partial^3 u}{\partial x^3} \right)_i \frac{(\Delta x)^3}{3!} + O(\Delta x^4)$$

- substituting these into $\textcircled{*}$

$$\begin{aligned} \frac{\partial u}{\partial x} = & \alpha u_i + \beta \left[u_i - \left(\frac{\partial u}{\partial x} \right)_i \Delta x + \left(\frac{\partial^2 u}{\partial x^2} \right)_i \frac{(\Delta x)^2}{2!} - \left(\frac{\partial^3 u}{\partial x^3} \right)_i \frac{(\Delta x)^3}{3!} + O(\Delta x^4) \right] + \\ & \gamma \left[u_i + \left(\frac{\partial u}{\partial x} \right)_i \Delta x + \left(\frac{\partial^2 u}{\partial x^2} \right)_i \frac{(\Delta x)^2}{2!} + \left(\frac{\partial^3 u}{\partial x^3} \right)_i \frac{(\Delta x)^3}{3!} + O(\Delta x^4) \right] \end{aligned}$$

- we can sub α, β, γ into our original linear combination to obtain our 2nd order centered difference for the 2nd derivative

Finite difference approximations from linear combinations

-grouping terms:

$$0 = u_i(\alpha + \beta + \gamma) + \left(\frac{\partial u}{\partial x}\right)_i(-1 - \Delta x\beta + \Delta x\gamma) + \left(\frac{\partial^2 u}{\partial x^2}\right)_i \frac{(\Delta x)^2}{2!}(\beta + \gamma) + \left(\frac{\partial^3 u}{\partial x^3}\right)_i \frac{(\Delta x)^3}{3!}(-\beta + \gamma) + O(\Delta x^4)$$

-now equating coefficients:

$$\begin{aligned} \alpha + \beta + \gamma &= 0 \quad \leftarrow \text{should go away} \\ \text{what we want} \rightarrow \Delta x(\gamma - \beta) &= 1 \\ \beta + \gamma &= 0 \quad \leftarrow \text{should go away} \end{aligned}$$

Our leading order error term (truncation) is $= \frac{\Delta x^3}{3!}(-\beta + \gamma)$

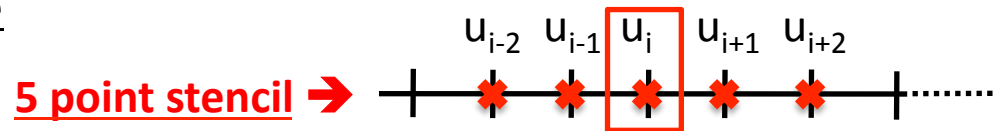
-using our coefficients we get:

$$\begin{aligned} \alpha &= 0, \quad \beta = 1/2\Delta x, \quad \gamma = -1/2\Delta x \\ \Rightarrow \frac{\partial u}{\partial x} &= \frac{u_{i+1} - u_{i-1}}{2\Delta x} \quad \text{our CDS} \end{aligned}$$

Higher-order finite difference approximations

How can we get higher-order of accuracy from finite difference schemes?

- we can increase the accuracy of standard finite difference schemes by expanding the stencil size



- if we do a Taylor series expansion for each term, combine and cancel we can derive an estimate for the 1st derivative:

$$\left. \frac{\partial u}{\partial x} \right|_i = \frac{-u_{i+2} + 8u_{i+1} - 8u_{i-1} + u_{i-2}}{2\Delta x} + \mathbf{O}(\Delta x^4)$$

- and in a similar fashion we can develop an estimate for the 2nd derivative

$$\left. \frac{\partial^2 u}{\partial x^2} \right|_i = \frac{-u_{i+2} + 16u_{i+1} - 30u_i + 16u_{i-1} - u_{i-2}}{12\Delta x^2} + \mathbf{O}(\Delta x^4)$$

Higher-order finite difference approximations: Padé schemes

- Increasing our stencil width is not always desirable
- One answer**: introduce $\frac{\partial u}{\partial x}$ estimates on the LHS when we do our linear combination:

$$\left. \frac{\partial u}{\partial x} \right|_i + \lambda \left. \frac{\partial u}{\partial x} \right|_{i-1} + \zeta \left. \frac{\partial u}{\partial x} \right|_{i+1} = \alpha u_i + \beta u_{i-1} + \gamma u_{i+1}$$

- our Taylor series for each term is:

$$u_{i+1} = u_i + \left(\frac{\partial u}{\partial x} \right)_i \Delta x + \left(\frac{\partial^2 u}{\partial x^2} \right)_i \frac{(\Delta x)^2}{2!} + \left(\frac{\partial^3 u}{\partial x^3} \right)_i \frac{(\Delta x)^3}{3!} + \left(\frac{\partial^4 u}{\partial x^4} \right)_i \frac{(\Delta x)^4}{4!} + \left(\frac{\partial^5 u}{\partial x^5} \right)_i \frac{(\Delta x)^5}{5!} + O(\Delta x^6)$$

$$u_i = u_i$$

$$u_{i-1} = u_i - \left(\frac{\partial u}{\partial x} \right)_i \Delta x + \left(\frac{\partial^2 u}{\partial x^2} \right)_i \frac{(\Delta x)^2}{2!} - \left(\frac{\partial^3 u}{\partial x^3} \right)_i \frac{(\Delta x)^3}{3!} + \left(\frac{\partial^4 u}{\partial x^4} \right)_i \frac{(\Delta x)^4}{4!} - \left(\frac{\partial^5 u}{\partial x^5} \right)_i \frac{(\Delta x)^5}{5!} + O(\Delta x^6)$$

$$\left. \frac{\partial u}{\partial x} \right|_{i+1} = \left(\frac{\partial u}{\partial x} \right)_i + \left(\frac{\partial^2 u}{\partial x^2} \right)_i \Delta x + \left(\frac{\partial^3 u}{\partial x^3} \right)_i \frac{(\Delta x)^2}{2!} + \left(\frac{\partial^4 u}{\partial x^4} \right)_i \frac{(\Delta x)^3}{3!} + \left(\frac{\partial^5 u}{\partial x^5} \right)_i \frac{(\Delta x)^4}{4!} + O(\Delta x^5)$$

$$\left. \frac{\partial u}{\partial x} \right|_{i-1} = \left(\frac{\partial u}{\partial x} \right)_i - \left(\frac{\partial^2 u}{\partial x^2} \right)_i \Delta x + \left(\frac{\partial^3 u}{\partial x^3} \right)_i \frac{(\Delta x)^2}{2!} - \left(\frac{\partial^4 u}{\partial x^4} \right)_i \frac{(\Delta x)^3}{3!} + \left(\frac{\partial^5 u}{\partial x^5} \right)_i \frac{(\Delta x)^4}{4!} + O(\Delta x^5)$$

Higher-order finite difference approximations: Padé schemes

- substituting these in and collecting terms:

$$\begin{aligned} & \frac{\partial u}{\partial x} \Big|_i (1 + \lambda + \zeta) + \Delta x \frac{\partial^2 u}{\partial x^2} \Big|_i (-\lambda + \zeta) + \frac{(\Delta x)^2}{2!} \frac{\partial^3 u}{\partial x^3} \Big|_i (\lambda + \zeta) + \frac{(\Delta x)^3}{3!} \frac{\partial^4 u}{\partial x^4} \Big|_i (-\lambda + \zeta) + \frac{(\Delta x)^4}{4!} \frac{\partial^5 u}{\partial x^5} \Big|_i (\lambda + \zeta) + O(\Delta x^5) = \\ & u_i (\alpha + \beta + \gamma) + \Delta x \frac{\partial u}{\partial x} \Big|_i (-\beta + \gamma) + \frac{(\Delta x)^2}{2!} \frac{\partial^2 u}{\partial x^2} \Big|_i (\beta + \gamma) + \frac{(\Delta x)^3}{3!} \frac{\partial^3 u}{\partial x^3} \Big|_i (-\beta + \gamma) + \\ & \frac{(\Delta x)^4}{4!} \frac{\partial^4 u}{\partial x^4} \Big|_i (\beta + \gamma) + \frac{(\Delta x)^5}{5!} \frac{\partial^5 u}{\partial x^5} \Big|_i (-\beta + \gamma) + O(\Delta x^6) \end{aligned}$$

- if we now equate coefficients:

$$\begin{aligned} 0 &= \alpha + \beta + \gamma \\ 1 + \lambda + \zeta &= \Delta x (-\beta + \gamma) \\ \frac{(\Delta x)^2}{2!} (\lambda + \zeta) &= \frac{(\Delta x)^3}{3!} (-\beta + \gamma) \\ \Delta x (-\lambda + \zeta) &= \frac{(\Delta x)^2}{2} (\beta + \gamma) \\ \frac{(\Delta x)^3}{3!} (-\lambda + \zeta) &= \frac{(\Delta x)^4}{4!} (\beta + \gamma) \end{aligned}$$

Our leading order error term (truncation) is $= \left[\frac{\Delta x^4}{4!} (\lambda + \zeta) - \frac{\Delta x^5}{5!} (-\beta + \gamma) \right] \frac{\partial^5 u}{\partial x^5} \Big|_i$

Higher-order finite difference approximations: Padé schemes

- solving for our coefficients:

$$\alpha = 0, \quad \beta = -\frac{3}{4}\Delta x, \quad \gamma = \frac{3}{4}\Delta x, \quad \lambda = -\frac{1}{4}, \quad \zeta = \frac{1}{4}$$

- so now our scheme is:

$$\left. \frac{\partial u}{\partial x} \right|_{i-1} + 4 \left. \frac{\partial u}{\partial x} \right|_i + \left. \frac{\partial u}{\partial x} \right|_{i+1} = \frac{3}{\Delta x} (u_{i+1} - u_{i-1}) + O(\Delta x^4)$$

- this is usually referred to as a 4th-order compact finite difference scheme or a 4th-order Padé scheme
- another way to derive this is to find the highest order interpolant between three points → Padé schemes can be thought of as fitting splines

finite difference approximations for mixed derivatives

What about mixed partial derivatives?

- mixed derivatives can occur if we transform the equations of motion into different coordinate systems (e.g. spherical coordinates) or map between reference frames

- one option:

$$\frac{\partial^2 u}{\partial x \partial y} = \frac{\partial}{\partial y} \left(\frac{\partial u}{\partial x} \right)$$

- we can use a central difference for $\frac{\partial u}{\partial x}$: $\left. \frac{\partial u}{\partial x} \right|_i = \frac{u_{i+1} - u_{i-1}}{2\Delta x} + \mathbf{O}(\Delta x^2)$

- we now have $\frac{\partial^2 u}{\partial x \partial y} = \frac{\partial}{\partial y} \left(\frac{u_{i+1} - u_{i-1}}{2\Delta x} + \mathbf{O}(\Delta x^2) \right)$

- if we also use central differences in y

$$\frac{\partial^2 u}{\partial x \partial y} = \frac{1}{2\Delta y} \left(\frac{u_{i+1,j+1} - u_{i-1,j+1}}{2\Delta x} - \frac{u_{i+1,j-1} - u_{i-1,j-1}}{2\Delta x} \right) + \mathbf{O}(\Delta x^2) + \mathbf{O}(\Delta y^2)$$

- or $\frac{\partial^2 u}{\partial x \partial y} = \frac{u_{i+1,j+1} - u_{i-1,j+1} - u_{i+1,j-1} + u_{i-1,j-1}}{4\Delta x \Delta y} + \mathbf{O}[\Delta x^2, \Delta y^2]$