

EEN-E2001 Computational Fluid Dynamics Lecture 1: Partial Differential Equations and Finite Difference Method

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CFD simulation and PDE solution includes at least the following aspects covered on the course

- 1) **Physics** identification. System length and timescales.
- 2) Mathematical equations and physics interpretation boundary/initial conditions.
- 3) Objectives, feasibility, and time-constraints.
- 4) Numerical method and modeling assumptions.
- 5) Geometry and mesh generation.
- 6) **Computing** i.e. running simulation.
- 7) Visualization and post-processing.

8) **Validation and verification, reference data**. Reporting, analysis and discussion of the results. Are the results sane?

Background

CFD at Aalto/ENG

Computational fluid dynamics team at Aalto University/ENG, Finland

- Prof. V.Vuorinen + Prof. O.Kaario + 20 researchers
- 15 supervised PhD's, 100+ journal papers
- Hydrogen, e-fuels, reactive multiphase flow, heat transfer, gas-/hydrodynamics
- OpenFOAM, StarCCM+, STAR-CD, LES/DNS/RANS/DES, DLBFoam

Wind power efficiency in landscapes Healthy

Healthy indoor air/vertical farming Energy conversion to H2/burners



COVID-19: a rather unexpected, new context to CFD



Simulation: V.Vuorinen Visualization: M.Gadalla

Partial differential equations

Convection and diffusion as transport mechanisms

In fluid dynamics, we are interested in understanding how different variables – e.g. velocity/concentration/temperature - change in space (x,y,z) and time (t). Unknown functions below could be typically velocity and concentration fields. Transport mechanisms: convection (velocity) and diffusion (molecular)



Ordinary differential equations (ODEs) describe commonly time dependency of physical system. No space coordinate dependency.

ODE for y=y(t)=? (e.g. radioactivity decay/Newton's cooling law)

$$\frac{dy}{dt} = -\lambda y(t)$$

Initial condition $v(t=0) = y_o$

Analytical solution

$$y(t) = y_o e^{-\lambda t}$$

First of all, to resolve space-dependent functions, we need enough many grid points i.e. high enough resolution.



Partial differential equations (PDEs) describe <u>space-time dependency</u> of a physical system.

Convection-diffusion (CD) eqn is the key PDE of fluid dynamics.

CD-eqn is a general conservation law (mass, momentum, energy,..)



Smoke cloud moving in air can be accurately modeled by solving Navier-Stokes equation and CD-eqn for smoke concentration

 $\frac{\vec{u} = \vec{u}(x, y, z, t)}{c = c(x, y, z, t)} \left[\frac{\partial c}{\partial t} + \vec{u} \cdot \nabla c = \alpha \nabla^2 c \right]$



For a PDE problem to be well posed, it is necessary to have boundary and initial conditions.

E.g. convection-diffusion equation (1d)

$$\frac{\partial c}{\partial t} + u \frac{\partial c}{\partial x} = \alpha \frac{\partial^2 c}{\partial x^2}$$

Initial condition

$$c(x,t=0)=c_o(x)$$

Boundary conditions. For example: fixed values,

$$c(x=0)=c_1 \ c(x=L)=c_2$$

Convection equation (1d)

Analytical solution: shape maintained and function travels/shifts at velocity u

CD2/FD (central difference, 2nd order, finite difference): **numerical dispersion** is additionally noted at later times E.g. concentration cloud moves due to wind.

$$\frac{\partial c}{\partial t} + u \frac{\partial c}{\partial x} = 0$$



Convection-diffusion equation (1d)

Solutions travel at velocity u while amplitude decreases

$$\frac{\partial c}{\partial t} + u \frac{\partial c}{\partial x} = \alpha \frac{\partial^2 c}{\partial x^2}$$

c=e.g. temperature, concentration α=diffusivity [m²/s]



Diffusion equation i.e. heat equation (1d)

Solution amplitude decreases and the diffusion spreads the function E.g. heat conducts from more hot towards cooler parts



c=e.g. temperature, concentration α =diffusivity [m²/s]



Wave equation (1d)

Waves start traveling in opposite directions with velocities $\pm\,u$ E.g. sound waves in air



c=wave amplitude u=wave speed (e.g. speed of sound)



Example: solution of the convection equation by pen and paper

A smoke cloud concentration c(x,t) is transported by wind along the x-direction. The initial condition c(x,t=0) = g(x) and the wind velocity u>0 and t=time.

$$\frac{\partial c}{\partial t} + u \frac{\partial c}{\partial x} = 0$$

We observe that the solution is c=g(x-ut) because if we substitute this expression to the convection eqn above then it fulfills the equation.

Proof:

1) Define a new variable z=x-ut

2) By chain rule of derivation applied on c=g(x-ut):

(i) $c_t = c_z z_t = -u c_z$ and (ii) $c_x = c_z z_x = c_z$

3) **Thus:** $c_t + uc_x = -uc_z + uc_z = 0$

Conclusion: the solution has the same shape as the initial condition and it is just "shifting" in positive x-direction at velocity u (as we saw earlier).

Numerical solution using finite difference method

Common space discretization methods needed to solve PDEs

Finite difference: Central scheme (CD2)

$$\frac{\partial c}{\partial x} \approx \frac{c_{i+1} - c_{i-1}}{2\Delta x}$$

Finite volume

$$\frac{\partial c}{\partial x} \approx \frac{\int_{\Delta x} \frac{\partial c}{\partial x} dx}{\Delta x} = \frac{c_{i+1/2} - c_{i-1/2}}{\Delta x}$$

Finite difference: Upwind scheme (u > 0)

$$\frac{\partial c}{\partial x} = \frac{C_i - C_{i-1}}{\Delta x}$$

Finite difference: Downwind scheme (u < 0)

$$\frac{\partial c}{\partial x} = \frac{c_{i+1} - c_i}{\Delta x}$$

Common time discretization methods needed to solve PDEs

Euler method (1st order)



Backward difference (2nd order)

$$\frac{\partial c}{\partial t} \approx \frac{3c_i^{n+1} - 4c_i^n + c_i^{n-1}}{2\Delta t}$$

Finite difference solution of convection-diffusion equation (Explicit Euler method + central difference CD2)



 \rightarrow Can be solved easily by computer (e.g. Week 1 Matlab class).

Discretization formulae come from Taylor series

• For example, where does the central difference formula (CD2) come from?



- A function can be expanded in Taylor series around point \boldsymbol{x}

$$f(x+\Delta x) = f(x) + \frac{\partial f(x)}{\partial x} \Delta x + \frac{1}{2!} \frac{\partial^2 f(x)}{\partial x^2} \Delta x^2 + \frac{1}{3!} \frac{\partial^3 f(x)}{\partial x^3} \Delta x^3 + \dots$$
$$f(x-\Delta x) = f(x) - \frac{\partial f(x)}{\partial x} \Delta x + \frac{1}{2!} \frac{\partial^2 f(x)}{\partial x^2} \Delta x^2 - \frac{1}{3!} \frac{\partial^3 f(x)}{\partial x^3} \Delta x^3 + \dots$$

- We would like to find a numerical, discrete approximation for f'(x) using the values $f(x_i)=f_i$, $f(x_i+\Delta x)=f_{i+1}$ and $f(x_i-\Delta x)=f_{i-1}$
- We see directly that:

$$f(x+\Delta x)-f(x-\Delta x)=2\frac{\partial f(x)}{\partial x}\Delta x+\frac{2}{3!}\frac{\partial^3 f(x)}{\partial x^3}\Delta x^3+O(\Delta x^5)$$
$$\frac{f(x+\Delta x)-f(x-\Delta x)}{2\Delta x}+O(\Delta x^2)\approx\frac{\partial f(x)}{\partial x}, \text{ where } O(\Delta x^2) \text{ is the leading error term.}$$

- The CD2 scheme above is said to be "second order" because the leading order term in the error is a polynomial of degree 2 i.e. $O(\Delta x^2)$
- Taking more points would allow to construct more accurate higher degree discretization schemes which would pose less numerical dispersion/diffusion.

Differential operators

Gradient and divergence

Gradient is a vector operator:

$$\nabla = \vec{i} \frac{\partial}{\partial x} + \vec{j} \frac{\partial}{\partial y} + \vec{k} \frac{\partial}{\partial z}$$

Gradient of a scalar function is a vector:

$$\nabla \phi = \vec{i} \frac{\partial \phi}{\partial x} + \vec{j} \frac{\partial \phi}{\partial y} + \vec{k} \frac{\partial \phi}{\partial z}$$

Divergence of a vector is the scalar product of gradient with vector which is a scalar:

$$\nabla \cdot \boldsymbol{u} = \frac{\partial u_1}{\partial x} + \frac{\partial u_2}{\partial y} + \frac{\partial u_3}{\partial z}$$

Divergence of a gradient is the scalar operator i.e. the Laplacian operator:

$$\nabla \cdot \nabla = \Delta = \frac{\partial^2}{\partial x^2} + \frac{\partial^2}{\partial y^2} + \frac{\partial^2}{\partial z^2}$$

In CD-equation, convection and diffusion terms contain divergence

Convection term:

 $\nabla \cdot (\boldsymbol{u} \phi) = \phi \nabla \cdot \boldsymbol{u} + \boldsymbol{u} \cdot \nabla \phi$

Note:
1 st derivatives

Diffusion term (const. diffusivity):

$$\nabla \cdot (\nu \nabla \phi) = \nu \nabla \cdot \nabla \phi = \nu \frac{\partial^2 \phi}{\partial x^2} + \nu \frac{\partial^2 \phi}{\partial y^2} + \nu \frac{\partial^2 \phi}{\partial z^2}$$

Note: 2nd derivatives

Tensors

Used short-hand notation for multiplying vectors uu

If we define u as 3 by 1 vector then how can we multiply two vectors?

The used short-hand is here understood as matrix product $u = u u^{T}$



In the present notation *uu* defines a 3 by 3 matrix also called a "tensor"



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Divergence of vector and tensor

Divergence of a vector is a scalar:



Divergence of a tensor is a vector:



Thus: we can think that taking divergence reduces the dimensionality of the object.

- divergence of 3 by 3 tensor gives a 3 by 1 vector
- divergence of 3 by 1 vector gives a scalar (think: "1 by 1" matrix)

Einstein summation convention and index notation

Einstein summation convention: if index appears twice, sum over the index

Divergence of vector:

$$\nabla \cdot \boldsymbol{u} = \frac{\partial u_i}{\partial x_i} = \sum_{i=1}^3 \frac{\partial u_i}{\partial x_i}$$

Divergence of tensor:

$$\nabla \cdot \boldsymbol{u} \boldsymbol{u} = \frac{\partial u_i u_j}{\partial x_j} = u_j \frac{\partial u_i}{\partial x_j} + u_i \frac{\partial u_j}{\partial x_j}$$

Divergence of gradient of scalar:





In incompressible flows the latter term is zero:



