

Some Questions:

$\vec{n}^T \vec{A}_v \vec{n}$ looks like what?

Let's begin by looking @ the normal dot product with the flux \vec{f}_c

$$\vec{n} \cdot \vec{f}_c(\vec{g}) = \left\{ \begin{array}{l} \rho n_x + \rho v n_y \\ (\rho v^2 + p) n_x + \rho v n_y \\ \rho v n_x + (\rho v^2 + p) n_y \\ (\rho E + \rho J) n_x + (\rho v E + \rho v) n_y \end{array} \right\} \Rightarrow \vec{n} \cdot \vec{f}_c(\vec{g}) \text{ is } \left[\begin{array}{c} \{E\}, \{F\} \\ \{n_x\}, \{n_y\} \end{array} \right]$$

? Now becomes what does

$\vec{n}^T \vec{A}_v \nabla \vec{g}$ look like?

$$\begin{bmatrix} n_x, n_y \end{bmatrix} \begin{bmatrix} [G_{11}] & [G_{12}] \\ [G_{21}] & [G_{22}] \end{bmatrix} \begin{bmatrix} L \frac{\partial \vec{g}}{\partial x} \\ L \frac{\partial \vec{g}}{\partial y} \end{bmatrix}^T = \begin{bmatrix} n_x, n_y \end{bmatrix} \left\{ \begin{array}{l} [G_{11}] \frac{\partial E}{\partial x} + [G_{12}] \frac{\partial F}{\partial x} \\ [G_{21}] \frac{\partial E}{\partial y} + [G_{22}] \frac{\partial F}{\partial y} \end{array} \right\}$$

= $n_x E_v + n_y F_v$ - as expected. Thus we'll do
asymmetry few except:

$$\begin{bmatrix} \frac{\partial E}{\partial x}, \frac{\partial F}{\partial y} \end{bmatrix} \begin{bmatrix} [G_{11}] & [G_{12}] \\ [G_{21}] & [G_{22}] \end{bmatrix} \begin{bmatrix} n_x \\ n_y \end{bmatrix} = \begin{bmatrix} \frac{\partial E}{\partial x} \\ \frac{\partial F}{\partial y} \end{bmatrix}$$

$$\begin{bmatrix} \frac{\partial E}{\partial x}, \frac{\partial F}{\partial y} \end{bmatrix} \left\{ \begin{array}{l} [G_{11}] n_x + [G_{12}] n_y \\ [G_{21}] n_x + [G_{22}] n_y \end{array} \right\} = \begin{bmatrix} [G_{11}] \left\{ \frac{\partial E}{\partial x} \right\} n_x + [G_{12}] \left\{ \frac{\partial F}{\partial y} \right\} n_y \\ [G_{21}] \left\{ \frac{\partial E}{\partial y} \right\} n_x + [G_{22}] \left\{ \frac{\partial F}{\partial y} \right\} n_y \end{bmatrix}$$

This not the same as my original derivation or Kosako's Version. I think the it should be written as $\nabla \vec{g}^T [\vec{A}_v]^T \vec{n}$ then it will come out.

Thus if the source term is in fact $\nabla \phi^T A \vec{n}$ then the equation to be solved for the auxiliary variables is given by

$$\int_{\Omega_e} \phi^+ \delta_n^+ d\Omega = -\frac{1}{2} \int_{\partial\Omega_e^f} \phi^+ (\vec{n}^T A \vec{v}^T \vec{n})^+ \cdot (\vec{q}^F - \vec{q}^+) dS$$

where $\partial\Omega_e^f$ is the sum over all faces on the element essentially the rhs is face based.

$\delta_n = \sum S_{nj} \phi_j$ then we do the volume integral

$$M_{ij}^+ = \int_{\Omega_e} \phi_i^+ \phi_j^+ d\Omega$$

The surface integral will gives a RHS,

$$\sum_{\partial\Omega_e^f} -\frac{1}{2} \int_{\partial\Omega_e^f} \phi_i^+ (\vec{n}^T A \vec{v}^T \vec{n})^+ \cdot (\vec{q}^F - \vec{q}^+) dS$$

So for the element +

$$M_{ij} = \int_{\Omega_e} \phi_i^+ \phi_j^+ d\Omega$$

Remark:

- 1) The $S_n = S_{nx} + S_{ny}$ per field we do it normally where the MIT paper does not.

- 2). The S_n is face based L_P . Thus in the loop over the faces we would need to do this on L_P .

Viscous fluxes for N.S. Equations, (Surface).

We have previously derived terms for Euler and Volume viscous flux.

This leaves us with the following integral.

$$-\int_{\partial V_L} \llbracket \phi \rrbracket^T \{ [A_V] \cdot \vec{\nabla} \phi \} ds - \int_{\partial V_L} \llbracket \vec{\phi} \rrbracket^T \{ \bar{[A_V]}^T \vec{\nabla} \phi \} ds$$

The above is designed such that its transpose is the same then consider transposing it.

$$\textcircled{1} \text{ Becomes } \int_{\partial V_L} \llbracket \vec{\phi} \rrbracket^T \{ [A_V]^T \vec{\nabla} \phi \} ds - \int_{\partial V_L} \llbracket \phi \rrbracket^T \{ [A_V] \vec{\nabla} \phi \} ds$$

Thus $\textcircled{1} = \textcircled{2}^*$, $\textcircled{2} = \textcircled{1}^*$ giving a symmetric viscous

operator.

This has implementation implications because our symmetry term has to be correct.

The integral 1 is easily written as

$$-\int_{\partial V_L} \phi^+ \{ E v_n + F v_y \} ds = \textcircled{1}$$

a bit trickier.

$$[A_V]^T = \begin{bmatrix} G_{11}^T & G_{21}^T \\ G_{12}^T & G_{22}^T \end{bmatrix},$$

thus this gives the following

$$-\int_{\partial V_L} (g^+ - g^-) \left\{ \left(G_{11}^T \frac{\partial \phi}{\partial x} + G_{21}^T \frac{\partial \phi}{\partial y}, G_{12}^T \frac{\partial \phi}{\partial x}, G_{22}^T \frac{\partial \phi}{\partial y} \right) \cdot (n_x, n_y) \right\} ds$$

Then the penalty piece is written out as.

$\int \mu \{ G_{11} + G_{22} \} \phi_i^+ (\vec{g}^+ - \vec{g}^-) ds$ thus giving the entire surface integral as.

$$-\int_{\partial\Omega} \phi_i^+ \{ E_v n_x + F_v n_y \} - (\vec{g}^+ - \vec{g}^-) \left\{ \left[G_{11}^T \frac{\partial \phi_i}{\partial x} + G_{21}^T \frac{\partial \phi_i}{\partial y} \right] n_x + \left[G_{12}^T \frac{\partial \phi_i}{\partial x} + G_{22}^T \frac{\partial \phi_i}{\partial y} \right] n_y \right\},$$

$$+ \mu \{ G_{11} + G_{22} \} (\vec{g}^+ - \vec{g}^-) \cdot \phi_i^+ ds$$

with

$$G_{11} = \frac{\partial E_v}{\partial g_x}$$

$$G_{12} = \frac{\partial E_v}{\partial g_y}$$

$$G_{21} = \frac{\partial F_v}{\partial g_x}$$

$$G_{22} = \frac{\partial F_v}{\partial g_y}$$

Remark in Symmetric term $\frac{\partial \phi_i}{\partial x}, \frac{\partial \phi_i}{\partial y}$ are scalar multipliers

matrices thus terms like

$[G_{11}^T \frac{\partial \phi_i}{\partial x} + G_{21}^T \frac{\partial \phi_i}{\partial y}]$ we use Matrices and they

operate on $4 \times 1 (\vec{g}^L - \vec{g}^R)$ to give 4×1 vector for Residual.

Linearization of Viscous Residuals:

$$R_v = \int_{\Omega_K} \frac{\partial \phi_i}{\partial x} \vec{E}_v + \frac{\partial \phi_i}{\partial y} \vec{F}_v d\Omega_K$$

$$\frac{\partial R_v}{\partial \vec{g}} = \int_{\Omega_K} \frac{\partial \phi_i}{\partial x} \frac{\partial \vec{E}_v}{\partial \vec{g}} + \frac{\partial \phi_i}{\partial y} \frac{\partial \vec{F}_v}{\partial \vec{g}} d\Omega_K$$

We are left to derive 2 terms: $\frac{\partial \vec{E}_v}{\partial \vec{g}}$, $\frac{\partial \vec{F}_v}{\partial \vec{g}}$

Recall $\vec{E}_v = \vec{E}_v(\vec{g}, \vec{\nabla} \vec{g})$, $\vec{F}_v = \vec{F}_v(\vec{g}, \vec{\nabla} \vec{g})$

$$1). \frac{\partial \vec{E}_v}{\partial \vec{g}} = \frac{\partial \vec{E}_v}{\partial (g_N)} \cdot \frac{\partial (g_N)}{\partial \vec{g}} + \frac{\partial \vec{E}_v}{\partial (g_Y)} \cdot \frac{\partial (g_Y)}{\partial \vec{g}} + \frac{\partial \vec{E}_v}{\partial \vec{g}} \cdot \frac{\partial \vec{g}}{\partial \vec{g}}$$

$$\frac{\partial \vec{E}_v}{\partial \vec{g}} = [G_{11}] \left[\frac{\partial \phi_j}{\partial x} \right] + [G_{12}] \left[\frac{\partial \phi_j}{\partial y} \right] + \left[\frac{\partial \vec{E}_v}{\partial \vec{g}} \right] [\phi_j]$$

$\frac{\partial \vec{E}_v}{\partial \vec{g}}$ has yet to be derived.

$$2) \frac{\partial \vec{F}_v}{\partial \vec{g}} = \frac{\partial \vec{F}_v}{\partial (g_N)} \cdot \frac{\partial (g_N)}{\partial \vec{g}} + \frac{\partial \vec{F}_v}{\partial (g_Y)} \cdot \frac{\partial (g_Y)}{\partial \vec{g}} + \frac{\partial \vec{F}_v}{\partial \vec{g}} \cdot \frac{\partial \vec{g}}{\partial \vec{g}}$$

$$= [G_{21}] \left[\frac{\partial \phi_j}{\partial x} \right] + [G_{22}] \left[\frac{\partial \phi_j}{\partial y} \right] + \left[\frac{\partial \vec{F}_v}{\partial \vec{g}} \right] [\phi_j]$$

$\frac{\partial \vec{F}_v}{\partial \vec{g}}$ - has yet to be derived.

Derivation of $\frac{\partial \vec{E}_v}{\partial \vec{g}}$, $\frac{\partial \vec{F}_v}{\partial \vec{g}}$

Consider

$$Ev = \begin{bmatrix} 0 \\ \mu \frac{\max}{\text{Reax}} \left\{ \frac{4}{3} \frac{\partial u}{\partial x} - \frac{2}{3} \frac{\partial v}{\partial y} \right\} \\ \mu \frac{\max}{\text{Reax}} \left\{ \frac{\partial v}{\partial x} + \frac{\partial u}{\partial y} \right\} \\ \mu \frac{\max}{\text{Reax}} \left[\frac{8}{Pr} \frac{\partial e}{\partial x} + U \left\{ \frac{4}{3} \frac{\partial u}{\partial x} - \frac{2}{3} \frac{\partial v}{\partial y} \right\} + V \left\{ \frac{\partial u}{\partial y} + \frac{\partial v}{\partial x} \right\} \right] \end{bmatrix}$$

Recall $\mu = \mu(\vec{g})$ thus

$$\frac{\partial Ev}{\partial g} = \begin{bmatrix} 0 \\ \frac{\partial \mu}{\partial g} \frac{\max}{\text{Reax}} \left\{ \frac{4}{3} \frac{\partial u}{\partial x} - \frac{2}{3} \frac{\partial v}{\partial y} \right\} + \mu \frac{\max}{\text{Reax}} \left\{ \frac{4}{3} \frac{\partial}{\partial g} \left(\frac{\partial u}{\partial x} \right) - \frac{2}{3} \frac{\partial}{\partial g} \left(\frac{\partial v}{\partial y} \right) \right\} \\ \frac{\partial \mu}{\partial g} \frac{\max}{\text{Reax}} \left\{ \frac{\partial v}{\partial x} + \frac{\partial u}{\partial y} \right\} + \mu \frac{\max}{\text{Reax}} \left\{ \frac{\partial}{\partial g} \left(\frac{\partial v}{\partial x} \right) + \frac{\partial}{\partial g} \left(\frac{\partial u}{\partial y} \right) \right\} \\ \frac{\partial \mu}{\partial g} \frac{\max}{\text{Reax}} \left[\frac{8}{Pr} \frac{\partial e}{\partial x} + U \left\{ \frac{4}{3} \frac{\partial u}{\partial x} - \frac{2}{3} \frac{\partial v}{\partial y} \right\} + V \left\{ \frac{\partial u}{\partial y} + \frac{\partial v}{\partial x} \right\} \right] + \mu \frac{\max}{\text{Reax}} \left[\frac{8}{Pr} \frac{\partial}{\partial g} \left(\frac{\partial e}{\partial x} \right) + \frac{\partial u}{\partial g} \left\{ \frac{4}{3} \frac{\partial u}{\partial x} - \frac{2}{3} \frac{\partial v}{\partial y} \right\} + U \left\{ \frac{4}{3} \frac{\partial}{\partial g} \left(\frac{\partial u}{\partial x} \right) - \frac{2}{3} \frac{\partial}{\partial g} \left(\frac{\partial v}{\partial y} \right) \right\} + \frac{\partial v}{\partial g} \left\{ \frac{\partial u}{\partial x} + \frac{\partial v}{\partial y} \right\} + V \left\{ \frac{\partial}{\partial g} \left(\frac{\partial v}{\partial x} \right) + \frac{\partial}{\partial g} \left(\frac{\partial u}{\partial y} \right) \right\} \right] \end{bmatrix}$$

Thus we need

$$\frac{\partial u}{\partial g} \left(\frac{\partial u}{\partial x} \right) = \frac{\partial}{\partial g} \left(\frac{\partial u}{\partial g} \cdot \frac{\partial \bar{g}}{\partial x} \right) = \frac{\partial^2 u}{\partial g^2} \cdot \frac{\partial \bar{g}}{\partial x}, \quad \frac{\partial}{\partial g} \left(\frac{\partial v}{\partial y} \right) = \frac{\partial^2 v}{\partial g^2} \cdot \frac{\partial \bar{g}}{\partial y}$$

$$\frac{\partial}{\partial g} \left(\frac{\partial v}{\partial x} \right) = \frac{\partial}{\partial g} \left(\frac{\partial v}{\partial g} \cdot \frac{\partial \bar{g}}{\partial x} \right) = \frac{\partial^2 v}{\partial g^2} \cdot \frac{\partial \bar{g}}{\partial x}, \quad \frac{\partial}{\partial g} \left(\frac{\partial u}{\partial y} \right) = \frac{\partial^2 u}{\partial g^2} \cdot \frac{\partial \bar{g}}{\partial y}$$

$$\frac{\partial}{\partial g} \left(\frac{\partial e}{\partial x} \right) = \frac{\partial^2 e}{\partial g^2} \cdot \frac{\partial \bar{g}}{\partial x}, \quad \frac{\partial}{\partial g} \left(\frac{\partial e}{\partial y} \right) = \frac{\partial^2 e}{\partial g^2} \cdot \frac{\partial \bar{g}}{\partial y}$$

This further leads to needs for 3rd order derivatives
 but there are matrices operating on vectors thus
 we will write them as such. To avoid doing
 matrix multiplication in the code. By hand we will
 derive the matrices in terms of vectors like $\frac{du}{d\bar{g}}$ etc.

$$\frac{\partial^2 U}{\partial \theta^2} = \begin{bmatrix} -\left(L \frac{\partial v}{\partial \theta} \frac{1}{\rho} - \frac{v}{\rho^2} \frac{\partial \theta}{\partial \theta}\right) & \frac{1}{\rho} \cdot \frac{v}{\rho} - \frac{v}{\rho^2} = +\frac{\partial v}{\rho^2} - \frac{1}{\rho^2}, 0, 0 \\ -\frac{1}{\rho^2} \frac{\partial p}{\partial \theta} & \\ 0 & \\ 0 & \end{bmatrix}$$

$$\Rightarrow \frac{\partial}{\partial \theta} \left(\frac{\partial v}{\partial \theta} \frac{\partial \theta}{\partial \theta} \right) = \begin{bmatrix} -L \frac{\partial v}{\partial \theta} \frac{1}{\rho} - \frac{v}{\rho^2} \frac{\partial \theta}{\partial \theta} \cdot \left\{ \frac{\partial \theta}{\partial \theta} \right\} \\ -\frac{1}{\rho} \frac{\partial p}{\partial \theta} \cdot \left\{ \frac{\partial \theta}{\partial \theta} \right\} \\ 0 \\ 0 \end{bmatrix}$$

Same for $\frac{\partial}{\partial \theta} \left(\frac{\partial v}{\partial \theta} \frac{\partial \theta}{\partial \theta} \right)$ except Replace $\frac{\partial \theta}{\partial \theta}$ w $\frac{\partial \theta}{\partial \theta}$

$$\frac{\partial^2 V}{\partial \theta^2} = \begin{bmatrix} -\left(L \frac{\partial v}{\partial \theta} \frac{1}{\rho} - \frac{v}{\rho^2} \frac{\partial \theta}{\partial \theta}\right) & +\frac{v}{\rho^2} + \frac{v}{\rho^2}, 0, -\frac{1}{\rho^2}, 0 \\ 0 & \\ -\frac{1}{\rho} \frac{\partial p}{\partial \theta} & \\ 0 & \end{bmatrix}$$

$$\Rightarrow \frac{\partial}{\partial \theta} \left(\frac{\partial v}{\partial \theta} \frac{\partial \theta}{\partial \theta} \right) = \left\{ \begin{array}{l} -L \frac{\partial v}{\partial \theta} \frac{1}{\rho} - \frac{v}{\rho^2} \frac{\partial \theta}{\partial \theta} \cdot \left\{ \frac{\partial \theta}{\partial \theta} \right\} \\ 0 \\ -\frac{1}{\rho} \frac{\partial p}{\partial \theta} \cdot \left\{ \frac{\partial \theta}{\partial \theta} \right\} \\ 0 \end{array} \right\}$$

$$\frac{\partial^2 E}{\partial \theta^2} = \left[\begin{array}{l} \frac{1}{\rho} \left[\partial v \left[\frac{\partial v}{\partial \theta} \right] + \partial v \left[\frac{\partial v}{\partial \theta} \right] - \left[\frac{\partial E}{\partial \theta} \right] \right] - \frac{1}{\rho^2} (U^2 + V^2 - E) \frac{\partial p}{\partial \theta} \\ -\left(L \frac{\partial v}{\partial \theta} \right) \frac{1}{\rho} - \frac{v}{\rho^2} \frac{\partial \theta}{\partial \theta} \\ -\left(L \frac{\partial v}{\partial \theta} \right) \frac{1}{\rho} - \frac{v}{\rho^2} \frac{\partial \theta}{\partial \theta} \\ -\frac{1}{\rho^2} \left[\frac{\partial p}{\partial \theta} \right] \end{array} \right] - \frac{U^2}{\rho^2} - \frac{\partial U^2}{\rho^2}$$

gives

$$\frac{\partial}{\partial \xi} \left(\frac{\partial e}{\partial \xi}, \frac{\partial e}{\partial \eta} \right) = \begin{cases} \left[\frac{1}{\rho} \left(\frac{\partial u L}{\partial \xi} + \frac{\partial v}{\partial \eta} - \frac{\partial E}{\partial \xi} \right) - \frac{1}{\rho^2} [v^2 + r^2 E] \right] \cdot \left\{ \frac{\partial \vec{e}}{\partial \xi} \right\} \\ - \left[\frac{1}{\rho} \frac{\partial \vec{e}}{\partial \xi} - \frac{v}{\rho^2} \frac{\partial \vec{p}}{\partial \xi} \right] \cdot \left\{ \frac{\partial \vec{e}}{\partial \eta} \right\} \\ - \left[\frac{1}{\rho} \frac{\partial \vec{e}}{\partial \eta} - \frac{v}{\rho^2} \frac{\partial \vec{p}}{\partial \eta} \right] \cdot \left\{ \frac{\partial \vec{e}}{\partial \eta} \right\} \\ - \frac{1}{\rho} \left[\frac{\partial \vec{p}}{\partial \eta} \right] \cdot \left\{ \frac{\partial \vec{e}}{\partial \eta} \right\} \end{cases}$$

$$F_v = \begin{cases} \frac{\mu_{max}}{R_{ext}} \left\{ \frac{\partial u}{\partial y} + \frac{\partial v}{\partial x} \right\} \\ \frac{\mu_{max}}{R_{ext}} \left\{ \frac{4}{3} \frac{\partial v}{\partial y} - \frac{2}{3} \frac{\partial u}{\partial x} \right\} \\ \frac{\mu_{max}}{R_{ext}} \left[\frac{v}{R} \cdot \frac{\partial e}{\partial y} + u \left(\frac{\partial u}{\partial y} + \frac{\partial v}{\partial x} \right) + v \left(\frac{4}{3} \frac{\partial v}{\partial y} - \frac{2}{3} \frac{\partial u}{\partial x} \right) \right] \end{cases}$$

$$\frac{\partial}{\partial \xi} (\vec{F}_v) = \begin{cases} L^0 \\ \frac{\partial u}{\partial \xi} \frac{\mu_e}{R_{ext}} \left\{ \frac{\partial v}{\partial y} + \frac{\partial u}{\partial x} \right\} + \mu \frac{M_{ext}}{R_{ext}} \left\{ \frac{\partial}{\partial \xi} \left(\frac{\partial u}{\partial y} \right) + \frac{\partial}{\partial \xi} \left(\frac{\partial v}{\partial x} \right) \right\} \\ \frac{\partial v}{\partial \xi} \frac{\mu_e}{R_{ext}} \left\{ \frac{4}{3} \frac{\partial v}{\partial y} - \frac{2}{3} \frac{\partial u}{\partial x} \right\} + \mu \frac{M_{ext}}{R_{ext}} \left\{ \frac{4}{3} \frac{\partial}{\partial \xi} \left(\frac{\partial v}{\partial y} \right) - \frac{2}{3} \frac{\partial}{\partial \xi} \left(\frac{\partial u}{\partial x} \right) \right\} \\ \frac{\partial u}{\partial \xi} \frac{\mu_e}{R_{ext}} \left[\frac{v}{R} \cdot \frac{\partial e}{\partial y} + u \left(\frac{\partial u}{\partial y} + \frac{\partial v}{\partial x} \right) + v \left(\frac{4}{3} \frac{\partial v}{\partial y} - \frac{2}{3} \frac{\partial u}{\partial x} \right) \right] + \mu \frac{M_{ext}}{R_{ext}} \left[\frac{v}{R} \cdot \frac{\partial}{\partial \xi} \left(\frac{\partial e}{\partial y} \right) + \frac{\partial u}{\partial \xi} \left(\frac{\partial u}{\partial y} + \frac{\partial v}{\partial x} \right) + u \left(\frac{\partial}{\partial \xi} \left(\frac{\partial u}{\partial y} \right) + \frac{\partial}{\partial \xi} \left(\frac{\partial v}{\partial x} \right) \right) \right] \\ \mu \frac{M_{ext}}{R_{ext}} \left[\frac{v}{R} \cdot \frac{\partial}{\partial \xi} \left(\frac{\partial e}{\partial y} \right) + \frac{\partial u}{\partial \xi} \left(\frac{\partial u}{\partial y} + \frac{\partial v}{\partial x} \right) + u \left(\frac{\partial}{\partial \xi} \left(\frac{\partial u}{\partial y} \right) + \frac{\partial}{\partial \xi} \left(\frac{\partial v}{\partial x} \right) \right) \right] \\ \frac{\partial v}{\partial \xi} \left(\frac{4}{3} \frac{\partial v}{\partial y} - \frac{2}{3} \frac{\partial u}{\partial x} \right) + v \left(\frac{4}{3} \frac{\partial}{\partial \xi} \left(\frac{\partial v}{\partial y} \right) - \frac{2}{3} \frac{\partial}{\partial \xi} \left(\frac{\partial u}{\partial x} \right) \right) \end{cases}$$

Remark:

- 1) The above uses the same stuff as $\frac{\partial E}{\partial \xi}$ thus we need do no further derivation. We have all the building blocks that we need.

- 2) In the code there will be NO MATMUL instead we will need $\frac{\partial}{\partial \xi} \left(\frac{\partial u}{\partial y} \right)$ and similar if composed at a tree since so many terms can common or zero.

Thus if we write this out fully

$$\frac{\partial R_v}{\partial \hat{g}} = \left\{ \begin{array}{l} \frac{\partial \phi}{\partial x} \left[G_{11} \left[\frac{\partial \phi_i}{\partial x} \right] + G_{12} \left[\frac{\partial \phi_i}{\partial y} \right] + \frac{\partial \bar{v}}{\partial g} [\phi_i] \right] + \\ \frac{\partial \phi_i}{\partial y} \left[G_{21} \left[\frac{\partial \phi_i}{\partial x} \right] + G_{22} \left[\frac{\partial \phi_i}{\partial y} \right] + \frac{\partial \bar{F}_v}{\partial g} [\phi_i] \right] \end{array} \right.$$

Surface term:

We have 4 terms to work out here $\frac{\partial R_s^L}{\partial \hat{g}_L}, \frac{\partial R_s^R}{\partial \hat{g}_R}, \frac{\partial R_s^L}{\partial \hat{g}_R}, \frac{\partial R_s^R}{\partial \hat{g}_L}$.

Recall R_s :

$$R_s^L = \left\{ -\phi_i^L \frac{1}{2} \left[(E_v^L + E_v^R) n_x + (F_v^L + F_v^R) n_y \right] - \frac{1}{2} \left([G_{11}^T \frac{\partial \phi}{\partial x} + G_{21}^T \frac{\partial \phi}{\partial y}] \cdot n_x + [G_{12}^T \frac{\partial \phi}{\partial x} + G_{22}^T \frac{\partial \phi}{\partial y}] \cdot n_y \right) (\hat{g}^L - \hat{g}^R) + \mu \frac{1}{2} (G_{11}^L + G_{22}^L + G_{11}^R + G_{22}^R) (\hat{g}^L - \hat{g}^R) ds \right.$$

$$R_s^R = \left\{ \phi_i^R \frac{1}{2} \left[(E_v^L + E_v^R) n_x + (F_v^L + F_v^R) \cdot n_y \right] - \frac{1}{2} \left([G_{11}^T \frac{\partial \phi}{\partial x} + G_{21}^T \frac{\partial \phi}{\partial y}] \cdot n_x + [G_{12}^T \frac{\partial \phi}{\partial x} + G_{22}^T \frac{\partial \phi}{\partial y}] \cdot n_y \right) (\hat{g}^L - \hat{g}^R) - \mu \frac{1}{2} (G_{11}^L + G_{22}^L + G_{11}^R + G_{22}^R) (\hat{g}^L - \hat{g}^R) ds \right.$$

First we consider R_s^L we have derived these for Vol. term.

$$\begin{aligned} \frac{\partial R_s^L}{\partial \hat{g}^L} = & \left\{ -\phi_i^L \frac{1}{2} \left[-\frac{\partial E_v}{\partial \hat{g}} n_x + \frac{\partial F_v}{\partial \hat{g}} \cdot n_y \right] \right. \\ & - \frac{1}{2} \left(\left[\frac{\partial G_{11}^T}{\partial x} \frac{\partial \phi}{\partial x} + \frac{\partial G_{21}^T}{\partial y} \frac{\partial \phi}{\partial y} \right] \cdot n_x + \left[\frac{\partial G_{12}^T}{\partial x} \frac{\partial \phi}{\partial x} + \frac{\partial G_{22}^T}{\partial y} \frac{\partial \phi}{\partial y} \right] \cdot n_y \right) (\hat{g}^L - \hat{g}^R) \\ & - \frac{1}{2} \left(\left[G_{11}^T \frac{\partial \phi}{\partial x} + G_{21}^T \frac{\partial \phi}{\partial y} \right] \cdot n_x + \left[G_{12}^T \frac{\partial \phi}{\partial x} + G_{22}^T \frac{\partial \phi}{\partial y} \right] \cdot n_y \right) \cdot [I][\phi_i] \\ & - \frac{1}{2} \left(\left[G_{11}^T \frac{\partial \phi}{\partial x} + G_{21}^T \frac{\partial \phi}{\partial y} \right] \cdot n_x + \left[G_{12}^T \frac{\partial \phi}{\partial x} + G_{22}^T \frac{\partial \phi}{\partial y} \right] \cdot n_y \right) \cdot [I][\phi_i] \\ & \left. + \mu \frac{1}{2} \left(\frac{\partial G_{11}}{\partial \hat{g}} + \frac{\partial G_{22}}{\partial \hat{g}} \right) (\hat{g}^L - \hat{g}^R) + \mu \frac{1}{2} (G_{11}^L + G_{22}^L + G_{11}^R + G_{22}^R) [I][\phi_i] \right\} \end{aligned}$$

Thus we are left only to ponder what do terms like
 $\frac{\partial G_{11}}{\partial \vec{g}}$ look like.

Well we know that each time we take a vector derivative we increase the Rank of the tensor.

Thus terms like

$$\frac{\partial G_{11}}{\partial \vec{g}} = \frac{\partial G_{11}}{\partial \vec{g}} \cdot \frac{\partial \vec{g}}{\partial \vec{g}} \text{ are Rank 3 tensors.}$$

Now it looks as though the dimensions won't match but that's not the case because we really ~~want~~ want things like

$$\frac{\partial (G_{11} \cdot (\vec{g}_1 \cdot \vec{g}_2))}{\partial \vec{g}} = \left[G_{11}[I] + \frac{\partial G_{11}}{\partial \vec{g}} \cdot (\vec{g}_1 \cdot \vec{g}_2) \right] \frac{\partial \vec{g}}{\partial \vec{g}} \text{ thus}$$

we can see that $\frac{\partial G_{11}}{\partial \vec{g}} \cdot (\vec{g}_1 \cdot \vec{g}_2)$ will become Rank 2

again thus we're ok.

We have 2 terms involving G 's thus we need to build the Rank 3 tensors for each G . We will

Denote $\frac{\partial G}{\partial \vec{g}}$ as $G'(\vec{g})$, Thus we can begin to work out what G' looks like for each G_{ij} term

Thus we write out the volume linearization.

$$\frac{\partial R_V}{\partial \hat{g}} = - \left\{ \frac{\partial \phi_i}{\partial x} \left[G_{11} \left[\frac{\partial \phi_j}{\partial x} \right] + G_{12} \left[\frac{\partial \phi_j}{\partial y} \right] + \frac{\partial E_V}{\partial \hat{g}} [\phi_j] \right] + \right. \\ \left. \frac{\partial \phi_i}{\partial y} \left[G_{21} \left[\frac{\partial \phi_j}{\partial x} \right] + G_{22} \left[\frac{\partial \phi_j}{\partial y} \right] + \frac{\partial F_V}{\partial \hat{g}} [\phi_j] \right] \right\}$$

Thus we can make some definitions that will be helpful for surface term

$$\frac{\partial E_V}{\partial \hat{g}} = G_{11} \left[\frac{\partial \phi_j}{\partial x} \right] + G_{12} \left[\frac{\partial \phi_j}{\partial y} \right] + \frac{\partial E_V}{\partial \hat{g}} [\phi_j]$$

$$\frac{\partial F_V}{\partial \hat{g}} = G_{21} \left[\frac{\partial \phi_j}{\partial x} \right] + G_{22} \left[\frac{\partial \phi_j}{\partial y} \right] + \frac{\partial F_V}{\partial \hat{g}} [\phi_j]$$

Surface terms.

We will work through these 1 at a time

$$R_S^L = \int -\phi_i^L \frac{1}{2} \left[(E_V^L + E_V^R) \cdot n_x + (F_V^L + F_V^R) n_y \right] - \text{Symflux} \\ + \rho \text{flux} \phi_i^L$$

$$\frac{\partial R_S^L}{\partial \hat{g}_L} = \int -\phi_i^L \frac{1}{2} \left[\left(\frac{\partial E_V^L}{\partial \hat{g}_L} \right) n_x + \left(\frac{\partial F_V^L}{\partial \hat{g}_L} \right) n_y \right] - \frac{\partial (\text{Symflux})}{\partial \hat{g}_L} \\ + \frac{\partial}{\partial \hat{g}_L} (\rho \text{flux}) \cdot \phi_i^L$$

$$\frac{\partial R_S^L}{\partial \hat{g}_R} = \int -\phi_i^L \frac{1}{2} \left[\left(\frac{\partial E_V^R}{\partial \hat{g}_R} \right) n_x + \left(\frac{\partial F_V^R}{\partial \hat{g}_R} \right) n_y \right] - \frac{\partial (\text{Symflux})}{\partial \hat{g}_R} \\ + \frac{\partial}{\partial \hat{g}_R} (\rho \text{flux}) \cdot \phi_i^L$$

$$R_S^R = \left\{ \rho^R \chi_2 \left[(E_v^L + E_v^R) n_x + (F_v^L + F_v^R) n_y \right] - \text{symvec} \right. \\ \left. - \phi_i^R \text{pflux} ds \right.$$

$$\frac{\partial R_S^R}{\partial \hat{g}_R} = \left\{ \rho^R \chi_2 \left[\frac{\partial E_v^R}{\partial \hat{g}_R} n_x + \frac{\partial F_v^R}{\partial \hat{g}_R} n_y \right] - \frac{\partial (\text{symvec})}{\partial \hat{g}_R} \right. \\ \left. - \phi_i^R \frac{\partial (\text{pflux})}{\partial \hat{g}_R} ds \right.$$

$$\frac{\partial R_S^R}{\partial \hat{g}_L} = \left\{ \rho^R \chi_2 \left[\frac{\partial E_v^L}{\partial \hat{g}_L} n_x + \frac{\partial F_v^L}{\partial \hat{g}_L} n_y \right] - \frac{\partial (\text{symvec})}{\partial \hat{g}_L} - \right. \\ \left. \phi_i^R \frac{\partial (\text{pflux})}{\partial \hat{g}_L} ds \right.$$

Thus we need to get 1st $\frac{\partial (\text{pflux})}{\partial \hat{g}_f}$

Linearization of pflux

$$\text{pflux} = \text{pen. } \frac{M_{\odot}}{R_{\odot} c} \begin{bmatrix} 0 \\ \tilde{A}_2 \Delta g_1 + \tilde{B} \Delta g_2 \\ \tilde{A}_3 \Delta g_1 + \tilde{C}_2 \Delta g_3 \\ \tilde{A}_4 \Delta g_1 + \tilde{B}_1 \Delta g_2 + \tilde{C}_{4t} \Delta g_3 + \tilde{D}_4 \Delta g_4 \end{bmatrix}$$

where $\tilde{C}_j = \tilde{C}_j (\theta, g_R)$ thus

we take

$$\frac{\partial \text{pflux}}{\partial \hat{g}} \cdot \frac{\partial \hat{g}}{\partial \hat{g}} = \frac{\partial \text{pflux}}{\partial \hat{g}} [\phi_j]$$

$$\frac{\partial p_{\text{flux}}}{\partial \vec{s}_L} = \text{pen. Res} \left[\begin{array}{l} \frac{\partial}{\partial \vec{s}_L} \cdot \Delta g_1 + \hat{A}_2 \frac{\partial (\Delta g)}{\partial \vec{s}_L} + \frac{\partial \tilde{B}_2 M_2}{\partial \vec{s}_L} \tilde{B}_2 \frac{\partial (\Delta g_2)}{\partial \vec{s}_L} \\ \frac{\partial \hat{A}_3}{\partial \vec{s}_L} \cdot \Delta g_1 + \hat{A}_3 \frac{\partial (\Delta g_1)}{\partial \vec{s}_L} + \frac{\partial \tilde{C}_3}{\partial \vec{s}_L} \cdot \Delta g_3 + \tilde{C}_3 \frac{\partial (\Delta g_3)}{\partial \vec{s}_L} \\ \frac{\partial \hat{A}_4}{\partial \vec{s}_L} \cdot \Delta g_1 + \hat{A}_4 \frac{\partial (\Delta g_1)}{\partial \vec{s}_L} + \frac{\partial \tilde{B}_4}{\partial \vec{s}_L} \Delta g_2 + \tilde{B}_4 \frac{\partial (\Delta g_2)}{\partial \vec{s}_L} + \\ \frac{\partial \tilde{C}_4}{\partial \vec{s}_L} \cdot \Delta g_3 + \tilde{C}_4 \frac{\partial (\Delta g_3)}{\partial \vec{s}_L} + \frac{\partial \tilde{D}_4}{\partial \vec{s}_L} \Delta g_4 + \tilde{D}_4 \frac{\partial (\Delta g_4)}{\partial \vec{s}_L} \end{array} \right]$$

The right will be the same except $\frac{\partial}{\partial \vec{s}_R}$

Thus we are now ready to write out explicitly the 4 jacobians:

$$\frac{\partial R^L}{\partial \vec{s}_L} = \int -\phi_i^L \lambda \left[\left([G_{11}] \left[\frac{\partial \phi_i^L}{\partial x} \right] + [G_{12}] \left[\frac{\partial \phi_i^L}{\partial y} \right] + \left[\frac{\partial E}{\partial s} \right] [\phi_i^L] \right) n_x + \left([G_{21}] \left[\frac{\partial \phi_i^L}{\partial x} \right] + [G_{22}] \left[\frac{\partial \phi_i^L}{\partial y} \right] + \left[\frac{\partial F}{\partial s} \right] [\phi_i^L] \right) n_y \right] + \phi_i^L \frac{\partial p_{\text{flux}}}{\partial \vec{s}_L} [\phi_i^L]$$

$$\frac{\partial R^L}{\partial \vec{s}_R} = \int -\phi_i^L \lambda \left[\left([G_{11}^R] \left[\frac{\partial \phi_i^R}{\partial x} \right]^R + [G_{12}^R] \left[\frac{\partial \phi_i^R}{\partial y} \right]^R + \left[\frac{\partial E^R}{\partial s} \right] [\phi_i^R] \right) n_x + \left([G_{21}^R] \left[\frac{\partial \phi_i^R}{\partial x} \right]^R + [G_{22}^R] \left[\frac{\partial \phi_i^R}{\partial y} \right]^R + \left[\frac{\partial F^R}{\partial s} \right] [\phi_i^R] \right) n_y \right] + \phi_i^L \frac{\partial p_{\text{flux}}}{\partial \vec{s}_R} [\phi_i^R]$$

The right side is exactly the same except it's on the right with the sign reversed.

The PO Residual (Viscous)

For the viscous $\rho=0$ residual we do the following.

For a face

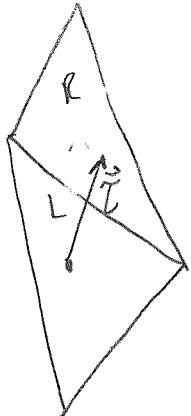
$$E_v^* = \left\{ \begin{array}{l} 0 \\ \frac{\mu_L + \mu_R}{2} \frac{M_\infty}{Re_\infty} \left(\frac{1}{3} \frac{\partial u}{\partial x} - \frac{2}{3} \frac{\partial v}{\partial y} \right) \\ \frac{\mu_L + \mu_R}{2} \frac{M_\infty}{Re_\infty} \left(\frac{\partial u}{\partial y} + \frac{\partial v}{\partial x} \right) \\ \frac{\mu_L + \mu_R}{2} \frac{M_\infty}{Re_\infty} \left(\frac{1}{Pr} \cdot \frac{\partial e}{\partial x} + \frac{(u_L + u_R)}{2} \left(\frac{1}{3} \frac{\partial u}{\partial x} - \frac{2}{3} \frac{\partial v}{\partial y} \right) + \frac{(v_L + v_R)}{2} \left(\frac{\partial u}{\partial y} + \frac{\partial v}{\partial x} \right) \right) \end{array} \right\}$$

$$F_v^* = \left\{ \begin{array}{l} 0 \\ \frac{\mu_L + \mu_R}{2} \frac{M_\infty}{Re_\infty} \left(\frac{\partial u}{\partial y} + \frac{\partial v}{\partial x} \right) \\ \frac{\mu_L + \mu_R}{2} \frac{M_\infty}{Re_\infty} \left(\frac{1}{3} \frac{\partial v}{\partial y} - \frac{2}{3} \frac{\partial u}{\partial x} \right) \\ \frac{\mu_L + \mu_R}{2} \frac{M_\infty}{Re_\infty} \left(\frac{1}{Pr} \cdot \frac{\partial e}{\partial y} + \frac{(u_L + u_R)}{2} \left(\frac{\partial u}{\partial y} + \frac{\partial v}{\partial x} \right) + \frac{(v_L + v_R)}{2} \left(\frac{1}{3} \frac{\partial v}{\partial x} - \frac{2}{3} \frac{\partial u}{\partial y} \right) \right) \end{array} \right\}$$

$$\text{Then } \tilde{F}^* = E_v^* n_x + F_v^* n_y$$

Thus the surface Normal $n_x, n_y, \frac{\partial u}{\partial y}, \frac{\partial v}{\partial y}$ etc.

How to compute



$$\frac{\partial \vec{r}}{\partial x} = \left[\frac{(\vec{r}_R - \vec{r}_L)}{|\vec{e}|^2} \right] \vec{e}_x$$

$$\frac{\partial \vec{r}}{\partial y} = \left[\frac{(\vec{r}_R - \vec{r}_L)}{|\vec{e}|^2} \right] \vec{e}_y$$

The P=0 viscous residual using Penalty formulation

As an alternative to the previously discarded Method for computing the p=0 viscous residual we will consider the following form given by K. Shah bazi, which looks like it is Based on the BR2 implementation by the MIT people.

\tilde{F}_V - Normal viscous flux at the face is given by

$$\tilde{F}_V = \int_{\Gamma} \nabla_0 \{ G_{i0} \} [\vec{g}_h] \cdot [\vec{n}] ds \quad \text{thus we need}$$

only an expression for ∇_0 as $\{ G_{i0} \} [\vec{g}_h]$ has been derived previously.

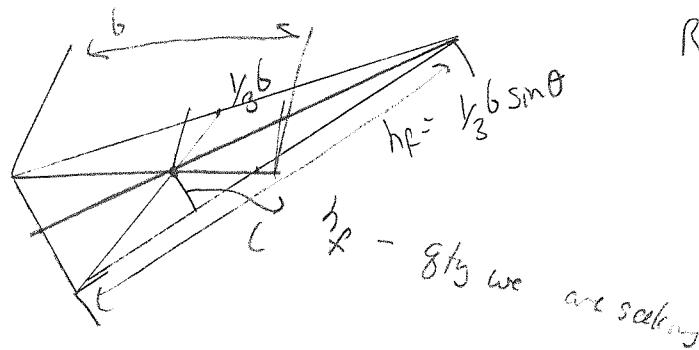
According to Shah bazi ∇_0 is the following

$$\nabla_0 = \begin{cases} \text{sum of } \perp \text{ distance from cell centers to the face f} \\ \text{on interior faces, take inverse of this } (\perp) \\ \perp \text{ distance from cell center to face + on Boundary} \\ \text{faces} \end{cases}$$

? What is the \perp distance from the cell center to the face.

- Consider a triangle as shown

$$h = b \sin \theta$$



$$\text{Recall } A = \frac{1}{2} C \cdot h$$

$$b \sin \theta = \frac{2A}{C} \Rightarrow$$

$$h_f = \frac{1}{3} \left(\frac{2A}{C} \right)$$

Thus the penalty parameter is

$$\text{for interior} \quad \left[\frac{1}{3} \left(\frac{2(A_{el} + A_{er})}{|\vec{n}_f|} \right) \right]^{-1}$$

$$\text{for Boundary} \quad \left[\frac{1}{3} \left(\frac{2(A_e)}{|\vec{n}_{fb}|} \right) \right]^{-1}$$

GMRES - Preconditioned Newton-Krylov Solver:

Following K. Shahzadi we will now extend our Newton Solver to follow a Krylov subspace method.
Notation x -vector $[J]$ -matrix, scalars will be underlined.

Review of Basic Krylov Subspaces:

i) Consider a simple iteration with preconditioner M

$$\text{set } x_{k+1} = x_k + [M]^{-1}(b - [A]x_k)$$

If $M = I$ then this is Jacobi

Define

$$e_k = [A]^{-1}b - x_k \quad x_k = x_{k-1} + [M]^{-1}(b - [A]x_{k-1})$$

$$\text{If } [M]^{-1} \sim [A]^{-1} \text{ then } x_k = x_{k-1} + [M^{-1}]b - [M]^{-1}[A]x_{k-1}$$

$$e_k = [A^{-1}]b - x_{k-1} - [M]^{-1}b + [M]^{-1}[A]x_{k-1}$$

If we factor this, we have

$$= -(I - [M]^{-1}[A])x_{k-1} + \underbrace{([A]^{-1} - [M]^{-1})b}_{\text{Factor out } [A]^{-1} \text{ for the rig'}}$$

$$= -(I - [M]^{-1}[A])x_{k-1} + [A]^{-1}(I - [M]^{-1}[A])[A]^{-1}b$$

$$= (I - [M]^{-1}[A])([A]^{-1}b - x_{k-1}) \\ \equiv e_{k-1}$$

\Rightarrow

$$e_k = (I - [M]^{-1}[A])e_{k-1} = (I - [M]^{-1}[A])^2e_{k-2}, \dots = (I - [M]^{-1}[A])^k e_0$$

$$e_k = (I - [M]^{-1}[A])^k e_0$$

Taking the norm of both side

$$\|e_K\| = \|([I] - [M]^{-1}[A])^K e_0\| \leq \|([I] - [M]^{-1}[A])\|^K \|e_0\|$$

This \Rightarrow that if $\lim_{K \rightarrow \infty} \|([I] - [M]^{-1}[A])\| \rightarrow 0$ then the

iteration will converge. (There is a more rigorous proof than for any e_0 it will converge.)

Orthomin(1) method:

An improvement on simple iteration is to put dynamically computed parameters in the iteration.

$$x_{K+1} = x_K + \alpha_K (b - [A]x_K) \quad \text{where } r_{K+1} = b - [A]x_{K+1}$$

$$\alpha_K = \frac{\langle r_K, [A]r_K \rangle}{\langle [A]r_K, [A]r_K \rangle} \quad \text{etc.}$$

Recall that vector projection a onto b is given by

$(\vec{a} \cdot \vec{b})\hat{b}$ \hat{b} is unit vector in direction of b . Thus

$$\text{look closely at } \alpha_K = \frac{\langle r_K, [A]r_K \rangle}{\| [A]r_K \|^2} \approx \frac{(\vec{a} \cdot \vec{b})^2}{\| \vec{a} \|^2}$$

Thus it is the projection onto $[A]r_K$, then

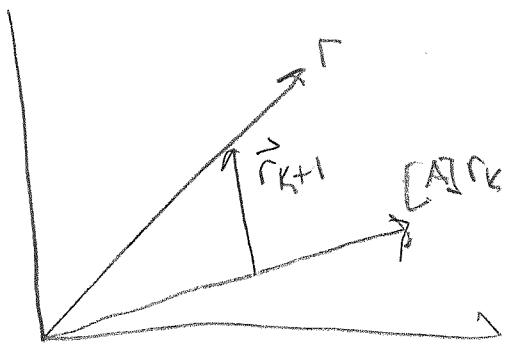
r_{K+1} is the orthogonal to $[A]r_K$ because the orthogonal component of \vec{a} to \vec{b} is our ex. is given

$$\therefore \vec{a}_\perp = \vec{a} - (\vec{a} \cdot \vec{b})\hat{b} \text{ which say}$$

$r_{K+1} = r_K - \alpha_K [A]r_K$ is just the orthogonal piece of r_K to $[A]r_K$.

Pictorially

for 2D- \vec{r}_{k+1}

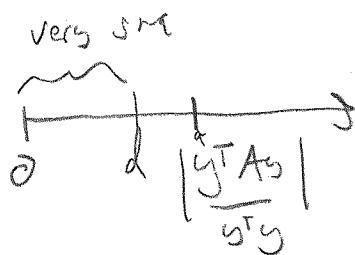


Theorem: The ℓ_2 -norm of the residual given by orthonormality decreases strictly monotonically for every initial 0 vector provided if and only if $0 \notin F(A)$ where $F(A) = \frac{\mathbf{y}^T A \mathbf{y}}{\mathbf{y}^T \mathbf{y}}$ for any vector \mathbf{y} . ($F(A)$ is kind of like energy $\rightarrow d$ for normalized \mathbf{y})

1) We show that ℓ_2 -norm of r_{k+1} decreases at each step.

- Because $0 \notin F(A)$ then it is a closed set
i.e. for any vector \mathbf{y} $\frac{\mathbf{y}^T A \mathbf{y}}{\mathbf{y}^T \mathbf{y}} \neq 0$ thus there is always a $d > 0$ such that $\left| \frac{\mathbf{y}^T A \mathbf{y}}{\mathbf{y}^T \mathbf{y}} \right| \geq d$ for all $\mathbf{y} \neq 0$

Pictorially



We now begin our proof. Start by taking

$$r_{k+1} = r_k - \alpha_k [A] r_k - \text{shown previously}$$

$$\text{take } \langle r_{k+1}, r_{k+1} \rangle = \|r_{k+1}\|^2 =$$

$$\begin{aligned} \langle r_k - \alpha_k [A] r_k, r_k - \alpha_k [A] r_k \rangle &= \|r_k\|^2 - 2\alpha_k \langle [A] r_k, r_k \rangle \\ &\quad + \alpha_k^2 \langle [A] r_k, [A] r_k \rangle \end{aligned}$$

$$\text{Recall the formula for } \alpha_k = \frac{\langle r_k, [A] r_k \rangle}{\langle [A] r_k, [A] r_k \rangle}$$

Expanding and simplifying we

$$\|r_{k+1}\|^2 = \|r_k\|^2 - 2 \frac{\langle r_k, A r_k \rangle^2}{\|A r_k\|^2} + \frac{\langle r_k, A r_k \rangle^2}{\langle A r_k, A r_k \rangle^2} \langle A r_k, A r_k \rangle$$

$$= \|r_k\|^2 - \frac{\langle r_k, A r_k \rangle^2}{\|A r_k\|^2} \quad \text{without loss of generality}$$

we can set

$$\langle r_k, A r_k \rangle^2 = |\langle r_k, A r_k \rangle|^2$$

$$= \|r_k\|^2 - \frac{|\langle r_k, A r_k \rangle|^2}{\|A r_k\|^2} \quad \text{this can be re-written as}$$

$$\text{recall } \|r_k\|^2 = r^T r$$

$$= \|r_k\|^2 \left(1 - \left| \frac{r_k^T A^T r_k}{r_k^T r_k} \right|^2 \cdot \frac{(r^T r)}{\|A r_k\|^2} \right)$$

Recalling our inequality $\left| \frac{r_k^T A^T r_k}{r_k^T r_k} \right|^* \geq d \Rightarrow$

further Schwartz inequality says $\|A\mathbf{r}_k\|^2 \leq \|A\mathbf{r}\|^2 / \|r_k\|^2$

gives

$$\|r_{k+1}\|^2 \leq \|r_k\|^2 \left(1 - d^2 \frac{\|r_k\|^2}{\|A\mathbf{r}\|^2 / \|r_k\|^2} \right) \Rightarrow$$

$$\|r_{k+1}\|^2 \leq \|r_k\|^2 \left(1 - \frac{d^2}{\|A\mathbf{r}\|^2} \right)$$

Remark: $\left(1 - \frac{d^2}{\|A\mathbf{r}\|^2} \right) < 1$ thus it is convergent and by that much at least.

thus orthonmin(1) converges to $\mathbf{r} = \mathbf{A}^{-1}\mathbf{b}$.

We are now 1 step closer to the Krylov methods.

Orthonmin(2):

Consider iterations as in orthonmin(1) by

$$\mathbf{x}_{k+1} = \mathbf{x}_k + \alpha_k \mathbf{r}_k \quad - \text{ in orthonmin(1) } \mathbf{r}_k = \mathbf{A}\mathbf{r}_k \\ \text{which gave } \mathbf{r}_{k+1} \perp \mathbf{A}\mathbf{r}_k$$

Remark: In orthonmin(1) α_k was chosen to minimize $\|r_{k+1}\|$, how?

$$\|r_{k+1}\|^2 = \langle \mathbf{r}_k - \alpha_k \mathbf{A}\mathbf{r}_k, \mathbf{r}_k - \alpha_k \mathbf{A}\mathbf{r}_k \rangle =$$

$$= \|r_k\|^2 - 2\alpha_k (\mathbf{A}\mathbf{r}_k, \mathbf{r}_k) + \alpha_k^2 \|\mathbf{A}\mathbf{r}_k\|^2 =$$

$$\frac{\partial}{\partial \alpha_k} \|\mathbf{r}_{k+1}\|^2 = -2 \langle \mathbf{A}\mathbf{r}_k, \mathbf{r}_k \rangle + 2\alpha_k \|\mathbf{A}\mathbf{r}_k\|^2 - \text{set } = 0 \\ \text{to find } \alpha_k \text{ that minimizes this residual.}$$

$$0 = \alpha_k \langle \mathbf{A}\mathbf{r}_k, \mathbf{r}_k \rangle + \beta_k \|\mathbf{A}\mathbf{r}_k\|^2 \text{ gives } \alpha_k = \frac{\langle \mathbf{A}\mathbf{r}_k, \mathbf{r}_k \rangle}{\langle \mathbf{A}\mathbf{r}_k, \mathbf{A}\mathbf{r}_k \rangle}$$

which we have shown gave us

$$\mathbf{r}_{k+1} \perp \mathbf{A}\mathbf{r}_k.$$

End Remark

Thus if we consider the more generic iteration.

$$\mathbf{x}_{k+1} = \mathbf{x}_k + \alpha_k \mathbf{p}_k,$$

Instead of trying to minimize $\|\mathbf{r}_{k+1}\|_2$ - we instead follow the orthogonality path of thinking but instead of force $\mathbf{A}\mathbf{p}_k$

we force $\mathbf{r}_{k+1} \perp \mathbf{A}\mathbf{p}_{k-1}$ so that it is orthogonal to the previous p-vector (i.e. takes history into account).

Thus define a new $\tilde{\mathbf{p}}_k$ vector such that

$$\tilde{\mathbf{p}}_k = \mathbf{r}_k - \frac{\langle \mathbf{A}\mathbf{r}_k, \mathbf{A}\mathbf{p}_{k-1} \rangle}{\langle \mathbf{A}\mathbf{p}_{k-1}, \mathbf{A}\mathbf{p}_{k-1} \rangle} \cdot \mathbf{p}_{k-1}, \text{ thus } \mathbf{r}_{k+1} \perp \text{Span}\{\mathbf{A}\mathbf{r}_k, \mathbf{A}\mathbf{p}_{k-1}\}$$

\mathbf{p}_k = projection of $\mathbf{A}\mathbf{r}_k$ onto $\mathbf{A}\mathbf{p}_{k-1}$. Does this give us some orthogonality.

$$\text{if yes: } \langle \mathbf{r}_{k+1}, \mathbf{A}\tilde{\mathbf{p}}_k \rangle = 0$$

to show

$$\langle \mathbf{r}_k - \alpha_k \mathbf{A}\mathbf{p}_k, \mathbf{A}\mathbf{r}_k - \beta_k \mathbf{A}\mathbf{p}_{k-1} \rangle = 0$$

$\mathbf{r}_k = \mathbf{A}\mathbf{x}_k$ & $\mathbf{A}\mathbf{p}_k = \mathbf{A}\mathbf{x}_k - \mathbf{A}\mathbf{r}_k$

lot of Algebra & it does come out

Further:

$$\langle r_{k+1}, A\hat{r}_{k+1} \rangle = \langle r_k, A\hat{r}_{k+1} \rangle - \alpha_k \langle A\hat{r}_k, A\hat{r}_{k+1} \rangle = 0$$

Thus the algorithm is given by

$$x_0, \quad r_0 = b - Ax_0, \quad \text{set } p_0 = r_0$$

for $k=1, 2$.

Compute $A\hat{r}_{k+1}$

$$x_k = x_{k-1} + \alpha_{k-1} p_{k-1}, \quad \alpha_{k-1} = \frac{\langle r_{k-1}, A\hat{r}_{k-1} \rangle}{\langle A\hat{r}_{k-1}, A\hat{r}_{k-1} \rangle}$$

$$\text{Compute } \hat{r}_k = r_{k-1} - \beta_{k-1} A\hat{r}_{k-1},$$

$$\text{set } p_k = \hat{r}_k - \beta_{k-1} p_{k-1}, \quad \beta_k = \frac{\langle A\hat{r}_k, A\hat{r}_{k-1} \rangle}{\langle A\hat{r}_{k-1}, A\hat{r}_{k-1} \rangle}$$

Repeat.

The above can be played with until (6) for symmetric systems is derived. However, we are not interested in that. We want something for non-symmetric Matrices.

GMRES:

We want a method that minimizes the ℓ_2 -norm of $\|r_{k+1}\|$ over the space $r_0 + \text{span}\{A\hat{r}_0, A\hat{r}_1, \dots, A\hat{r}_k\} = r_0 + \text{span}\{A^T r_0, A^T r_1, \dots, A^T r_k\}$.

The GMRES Method computes an orthonormal Basis to the Krylov Space given by $\text{span}\{r_0, Ar_0, \dots, A^{k-1}r_0\}$

Let us work out GMRES by considering the general example.

Consider Solving $[A]\{x\} = \{b\}$.

Let K_n denote the Krylov Subspace spanned by

$$\langle b, Ab, \dots, A^{n-1}b \rangle$$

Concept: At step n we shall approximate the exact solution $\{x^*\}$ by vector $x_n \in K_n$ that minimizes the norm of residual $\{r_n\} = \{b - Ax_n\}$.

This is a least squares problem.

- Definition of a least squares problem: Solve

$[Ax] = \{b\}$ - rectangular such that $\text{rows} > \text{cols}$.
we "solve" this by minimizing the 2-norm of $S\{b - Ax\}$.

Setting up the least squares problem via for GMRES.

Let K_n be the $\overset{\text{rows}}{m \times n}$ Krylov Matrix.

$$AK_n = \left[\begin{array}{c|c|c|c} Ab & A^2b & \cdots & A^n b \end{array} \right]$$

the column space is $A K_n$.

our goal is to find a vector $c \in \mathbb{C}^n$ - (real \mathbb{R}^n for \mathbb{C}^n)
such that

$$\| [A][k_n] \{c\} - b \|_2 = \text{minimum}, \quad \text{this could be done via}$$

QR factorization with $[A][k_n] = [Q][R]$

once you have $\{c\}$ set $x_n = [k_n] \{c\}$ and
you have your answer.

There is however a better way, use Arnoldi
procedure to construct a sequence of Krylov
~~vectors~~ matrices Q_n whose columns span $\mathbb{C}_1, \mathbb{C}_2, \dots$
span successive Krylov ~~spaces~~ subspaces \mathbb{K}_n . Then
we write $x_n = Q_n y$ and our problem is

$$\| A Q_n y - b \|_2 = \text{minimum}.$$

Using Arnoldi we can write $[A][Q_n] = [Q_{n+1}][\tilde{H}_n]$
where \tilde{H} is $(n+1) \times n$ upper-left section of the Hessenberg
matrix. The Arnoldi procedure is designed to
give the Hessenberg reduction $[A] = (\tilde{Q})[\tilde{H}](\tilde{Q})$.

The problem (goal) can be re-written as

$$\| [Q_{n+1}][\tilde{H}_n] \{y\} - b \|_2 = \text{minimum}.$$

Now we do some tricky stuff. Recall that
orthogonal matrices like Q_n have the
property $Q_n^T = Q_n^{-1}$, thus without
changing the norm $\|\cdot\|$ we can left multiply
by Q_n^T

giving.

$$\|\tilde{H}_{ny} - Q_{n+1}^T b\|_2 = \min.$$

by the construction of the krylov matrix

$$Q_{n+1}^T b = \|b\|_2 \left\{ \begin{matrix} 1 \\ 0 \\ \vdots \\ 0 \end{matrix} \right\}_n$$

Arnoldi's procedure ~~tells~~ shows that

$$A_n = \langle \vec{b}, A\vec{b}, \dots, A^{n-1}\vec{b} \rangle = \langle \vec{b}, \vec{b}_1, \dots, \vec{b}_n \rangle$$

thus Q_{n+1}^T has products that look $\|b\|_2 \vec{b}$ which

$$= \|b\|_2$$

Thus our final problem becomes the Least Squares
minimization of

$$\|\tilde{H}_{ny} - Q_{n+1}^T \|b\|_2 \left\{ \begin{matrix} 1 \\ 0 \\ \vdots \\ 0 \end{matrix} \right\}_n\|_2 = \min.$$

Thus our algorithm has 3 main parts

1). Find \tilde{H}, Q_{n+1}^T

2). Solve Least Squares

3). $x^{n+1} = Q_{n+1}^T y$

Step 1) This is the Arnoldi procedure as
outlined in the book by Trefethen

Arnoldi Procedure:

We need a way to find the Hessenberg Matrix \tilde{H}_n , and the vector $\{\tilde{g}_j\}_{j=1}^n \{\tilde{g}_n\}$. This the Arnoldi procedure.

Given \vec{v}

for $n=1, 2, 3, \dots$ — Note: for iteration n of GMRES we perform step n of Arnoldi.

$$v = [A]\{g_n\}$$

for $j=1, n$

$$\text{Then } h_{jn} = \langle \vec{v}, \tilde{g}_j \rangle = \tilde{H}_n(j, 1)$$

$$\vec{v} = \vec{v} - h_{jn} \tilde{g}_j$$

end

$$\text{end } h_{n+1,n} = \|\vec{v}\|$$

$$g_{n+1} = \frac{\vec{v}}{\|\vec{v}\|}$$

This ^{end} solves us with a least squares problem to solve namely

$$\|\tilde{H}_n y - \|b\| e_1\| = \min.$$

$$\tilde{H}_n = \begin{bmatrix} h_{11} & h_{12} & \cdots & h_{1n} \\ h_{21} & h_{22} & & \\ & \ddots & & \\ & & h_{n-1,n} & h_{n,n} \\ & & & h_{n+1,n} \end{bmatrix}$$

thus it's 1 row too

Big,

Which gives us an over determined system

written as

$$\tilde{H}_n y = \|b\| e_1$$

which must be solved.

$$x = \underline{x}_0 + [Q_n] \{y\}$$

Least Squares Problem: Let $\|b\|_2 = \beta$

$$[\tilde{A}_n] \{g\} = \beta \vec{z}(k+1) \quad \text{for the } k^{\text{th}} \text{ iteration of GIVES}$$

Note $\vec{z}_{k+1} = \vec{z} \begin{pmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{pmatrix}$ But as we go through and expand our basis it fills in.

The best way to solve this problem is by take the QR factorization of $[\tilde{A}_n]$ and solving $[R]g = \beta \vec{z}_{k+1}$ which is simple because we don't care about the Q part of $[\tilde{A}_n]$ we just need to get R part which we store in $[\tilde{A}_n]$ in the code.

Computation of R. If we had a general matrix then computing QR using Householder would be a good idea. However A_n is upper triangular further if we form R as we go through the Krylov space (we can save a lot of time).

Consider the matrix for $n=1$

$[\tilde{A}] = \begin{bmatrix} h_{11} \\ h_{21} \end{bmatrix}$ it needs to $\rightarrow \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$ thus we should use a givens rotation targeted at the R_{11} spot to make it zero.

Given we know how to compute the angle θ or more affly since $\cos(\theta)$ we can do the following.

$\begin{bmatrix} c & s \\ -s & c \end{bmatrix} \begin{bmatrix} h_{11} \\ h_{21} \end{bmatrix} : \rightarrow \begin{bmatrix} \|h\| \\ 0 \end{bmatrix}$ this is the given rotation. The method to compute θ come from B. P. G.

$$\Rightarrow \sqrt{\|h\|^2} c \cdot h_{11} + s \cdot h_{21}$$

$$\Rightarrow \theta = -s \cdot h_{11} + c \cdot h_{21}$$

Going a bit further we have essentially targeted spot 2d
thus this was easy our general multi-dimensional rotation
matrix is identity with $i_1 = c$, $j_1 = s$, $i_2 = -s$, $j_2 = c$

$$\begin{bmatrix} c & s \\ -s & c \\ & I \end{bmatrix}$$

Now consider when $n=2$.

$$[\tilde{H}]_2 = \begin{bmatrix} h_{11} & h_{12} \\ h_{21} & h_{22} \\ h_{31} & h_{32} \end{bmatrix} \quad \text{we scale to make } h_{21} = 0, h_{22} = 0,$$

Thus as before we set \hat{h}_{11} - (0.5 new value
of h_{11}) as $\hat{h}_{11} = (-h_{11} \sin \theta, h_{21})$ $\hat{h}_{21} \rightarrow 0$.

? what happens in 2nd column that's easy

$$\begin{bmatrix} c & s & 0 \\ -s & c & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} h_{11} & h_{12} \\ h_{21} & h_{22} \\ 0 & h_{32} \end{bmatrix} = \begin{bmatrix} \hat{h}_{11} & (c h_{12} + s h_{22}) \\ 0 & (-s h_{12} + c h_{22}) \\ 0 & h_{32} \end{bmatrix} \quad \begin{bmatrix} \hat{h}_{12} \\ \hat{h}_{22} \end{bmatrix}$$

But now we need to apply rotation for h_{32} .

$$\begin{bmatrix} 1 & 0 & 0 \\ 0 & c & s \\ 0 & -s & c \end{bmatrix} \begin{bmatrix} \hat{h}_{11} & \hat{h}_{12} \\ 0 & \hat{h}_{22} \\ 0 & h_{32} \end{bmatrix} \rightarrow \begin{bmatrix} \hat{h}_{11} & \hat{h}_{12} \\ 0 & (\hat{h}_{22} c + h_{32} s) \\ 0 & 0 \end{bmatrix}$$

If we did a few more it would be abundantly clear
it is. Already apparent that if we store
all columns $n-1$ then we can just apply
 $n-1$ gives rotations to column and when that
is done make a new angle for h_{n+1} and then
apply the next rotation and that is what's done in
the code.

Recall that we must also suitable deal with given rotations applied to the RHTS to set the system consistent.

consider $n=1$.

$$\begin{bmatrix} C & S \\ -S & C \end{bmatrix} \begin{bmatrix} \beta_1 \\ 0 \end{bmatrix} = \begin{Bmatrix} C\beta_1 + S \cdot 0 \\ -S\beta_1 + C \cdot 0 \end{Bmatrix} = \begin{Bmatrix} \hat{\beta}_1 \\ 0 \end{Bmatrix} \text{ now with } n=2$$

$$\begin{bmatrix} C & S & 0 \\ -S & C & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{Bmatrix} \beta_1 \\ 0 \\ 0 \end{Bmatrix} = \begin{Bmatrix} C\beta_1 \\ -S\beta_1 \\ 0 \end{Bmatrix}$$

Now apply the transform for $\hat{\beta}_2$

$$\begin{bmatrix} 1 & 0 & 0 \\ 0 & C & S \\ 0 & -S & C \end{bmatrix} \begin{Bmatrix} \hat{\beta}_1 \\ \hat{\beta}_2 \\ 0 \end{Bmatrix} = \begin{Bmatrix} \hat{\beta}_1 \\ C\hat{\beta}_2 \\ -S\hat{\beta}_2 \end{Bmatrix}$$

As $\hat{\beta}_1$ has not changed each time
we add the rotation for $\hat{\beta}_n, \hat{\beta}_{n+1}, \hat{\beta}_n$
we rotate $\hat{z}^{(n)}, \hat{z}^{(n+1)}$ as

$$\begin{bmatrix} C & S \\ -S & C \end{bmatrix} \begin{Bmatrix} \hat{z}^{(n)} \\ \hat{z}^{(n+1)} \end{Bmatrix}$$

How this is done is very evident in the code.

Re-projection:

once we have formed the $Ry = \hat{z}$

we solve for y . We now need to project this

back to X

$$X = X_0 + Q_n y$$

$$Q_n = \begin{bmatrix} \hat{g}_1 & \hat{g}_2 & \dots & \hat{g}_n \\ 1 & 1 & \dots & 1 \end{bmatrix}$$

Thus, we
see the same
pattern as with
if we can
do it as well.
expand the basis

Implementation issues:

Rather than solve for y at each Krylov step we estimate the linear residual, as $\frac{\|b\|_2}{\|b\|_2}$. If this is small enough, then step increases the Krylov space and get y and x or otherwise increase the space and continues.

Further we cannot afford to store very large Krylov subspaces thus we store only m vectors after that we update X and restart the GMRES again the code makes this quite clear.

Force Output:

To compute the forces, we need to do integrals over each boundary faces. The pressure based forces will be computed as in the finite volume code. However, we need to be able to compute the viscous based forces.

Recall:

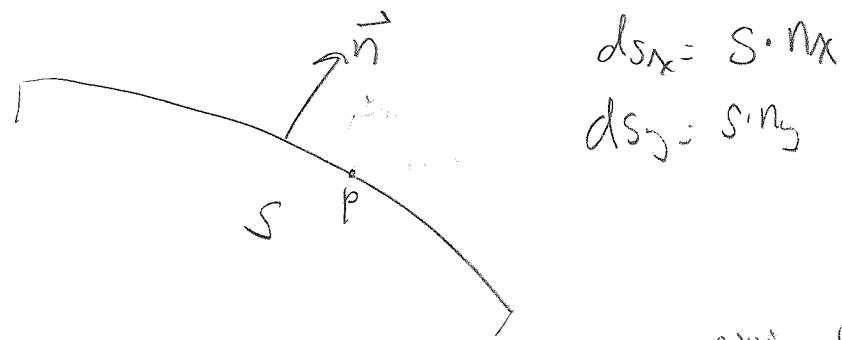
$$\tau_{xx} = \mu \left(\frac{1}{3} \frac{\partial u}{\partial x} - \frac{2}{3} \frac{\partial v}{\partial y} \right), \quad \tau_{xy} = \mu \left(\frac{\partial u}{\partial y} + \frac{\partial v}{\partial x} \right)$$

$$\tau_{yx} = \mu \left(\frac{\partial v}{\partial y} + \frac{\partial u}{\partial x} \right), \quad \tau_{yy} = \mu \left(\frac{4}{3} \frac{\partial v}{\partial y} - \frac{2}{3} \frac{\partial u}{\partial x} \right)$$

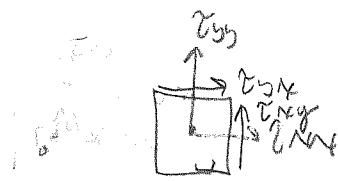
$$F_{vx} = \tau_{xx} \cdot A_{face \cdot nx} + \tau_{yx} \cdot A_{face \cdot ny}$$

$$F_{vy} = \tau_{yy} \cdot A_{face \cdot ny} + \tau_{xy} \cdot A_{face \cdot nx}$$

Ready the above formulas on finding the component of the surface area in the x, y dir.



Thus if I have a stress at a point P.



thus the force in the x-dir
 $\tau_{xx} \cdot ds_x + \tau_{yx} \cdot ds_y$.

That's why the normals go with the components it's not to put the stress in the right dir. but to get the proper component of the area in that dir.

This is 1 way to physically reason this formula.

Multi-grid Theory

Smoothing factors (Derivation)

Model Problem 1. $\nabla^2 u = f$

If we regard $L = -\nabla^2$, then a discrete operator L_h can be regarded as the finite difference approximation of L .

If we want to write L_h as an "iteration" operator, it would look like

$$\frac{1}{h^2} \begin{bmatrix} 1 & -4 & 1 \\ & 1 & \end{bmatrix} = L_h$$

which is the equivalent of
(Note this is NOT a Matrix)
It is written in "stencil Notation".

$$L_h: \frac{U_{i+1,j} - 2U_{ij} + U_{i-1,j}}{h^2} + \frac{U_{i,j+1} - 2U_{ij} + U_{i,j-1}}{h^2}$$

The above operator written stencil notation indicates that if the center point is ij then the spots occupied are the indices the top cent: $i, j+1$, etc. and the values there are the coefficients.

For an iterative scheme consider L_h split as

$$L_h^+ \bar{w}_h + L_h^- w_h = f_h, \quad \text{where } w_h \text{ is old approx to } u_h \\ \bar{w}_h \text{ is the new approx to } u_h.$$

$$\bar{w}_h = S_h w_h - \text{where } S_h \text{ is the smoothing operator.}$$

The Local Fourier Analysis is based on grid functions of the form.

$$\phi(\vec{\theta}, \vec{x}) = e^{i\vec{\theta} \cdot \vec{x}}, \quad \text{where } \vec{\theta}, \vec{x} \text{ are vectors of size } D \\ = e^{i\theta_1 \frac{x_1}{h_1}} e^{i\theta_2 \frac{x_2}{h_2}}, \quad D=2, \text{ for } D=3, \text{ for } 3D \text{ etc.}$$

Further

$$L_h \phi(\vec{\theta}, \vec{x}) = \tilde{L}_h(\vec{\theta}) \phi(\vec{\theta}, \vec{x}) \quad \text{with}$$

$$\tilde{L}_h = \sum_{\vec{k}} S_{\vec{k}} e^{i\vec{\theta} \cdot \vec{k}} \quad \text{where } \vec{k} = (k_1, k_2)$$

Let's illustrate how to derive $\tilde{L}_h(\vec{\theta})$ using the Laplacian

Ex 1. $\tilde{L}_h(\vec{\theta})$ for discrete Laplacian. $-\nabla^2 u$

a) Recall $\phi(\vec{\theta}, \vec{x}) = e^{i\theta_1 \frac{x_1}{h_1}} e^{i\theta_2 \frac{x_2}{h_2}}$. if

$h_1 = h_2$, then $e^{i\theta_1 \frac{x_1}{h_1}} e^{i\theta_2 \frac{x_2}{h_2}}$

b) Recall that the Laplacian (discrete) is given by

$$\frac{1}{h^2} (4u(x_i, y_i) - u(x_i+h, y_i) - u(x_i-h, y_i) - \\ u(x_i, y_i+h) - u(x_i, y_i-h))$$

Begin by $L_h \phi =$

$$= \frac{1}{h^2} [4\phi_{ii} - \phi(x_i+h, y_i) - \phi(x_i-h, y_i) - \\ \phi(x_i, y_i+h) - \phi(x_i, y_i-h)]$$

$$\phi(x_i+h, y_i) = e^{i\theta_1 \frac{(x_i+h)}{h}} e^{i\theta_2 \frac{y_i}{h}} = e^{i\theta_1} [e^{i\theta_1 \frac{x_i}{h}} e^{i\theta_2 \frac{y_i}{h}}] = \\ e^{i\theta_1} \phi(\vec{x}, \vec{\theta})$$

the rest of the terms follow

very similarly to sum.

$$L_h = \frac{1}{h^2} (4\phi - e^{i\theta_1}\phi + e^{-i\theta_1}\phi - e^{i\theta_2}\phi - e^{-i\theta_2}\phi) \Rightarrow$$

$$L_h = \tilde{L}_h(\vec{\theta}) \phi(\vec{\theta}, \vec{x})$$

$$\tilde{L}_h(\vec{\theta}) = \frac{1}{h^2} (4 - e^{i\theta_1} - e^{-i\theta_1} - e^{i\theta_2} - e^{-i\theta_2}), \text{ the imaginary part is}$$

the frequency, Damping factor is real part.

End Ex. 1.

If we apply an iterative smooth with a splitting such that $L_h = L_h^+ + L_h^-$ then if we write the smoothing operator as $\tilde{S}_h \phi(\vec{\theta}, \vec{x})$: $\tilde{S}_h(\vec{\theta}) \phi(\vec{\theta}, \vec{x})$

$$\tilde{S}_h = -\frac{\tilde{L}_h^-(\vec{\theta})}{\tilde{L}_h^+(\vec{\theta})}$$

We now have the tools needed to compute a smoothing factor.

Ex. Analysis G/S (Regular Not Red-Black).

$$L_h^+ L_h^- = \frac{-v_{i+1,j} + 4v_{ij} - v_{i-1,j}}{h^2} + \frac{v_{i,j+1} - v_{i,j-1}}{h^2}$$

where $m+1$ denotes an updated value.

$$L_h^+ = \frac{1}{h^2} \begin{bmatrix} 0 & & \\ -1 & 4 & 0 \\ & -1 & \end{bmatrix}, \quad L_h^- = \begin{bmatrix} -1 & & \\ 0 & 0 & -1 \\ 0 & & \end{bmatrix}$$

gives.

$$\tilde{L}_h^+ = \frac{1}{h^2} (4 - e^{-i\theta_1} - e^{-i\theta_2})$$

$$\tilde{L}_h^- = -\frac{1}{h^2} (e^{i\theta_1} + e^{i\theta_2})$$

$$\tilde{S}_h = -\frac{\tilde{L}_h(\theta)}{\tilde{L}_h^+(\theta)} = \frac{e^{i\theta_1} + e^{i\theta_2}}{(4 - e^{-i\theta_1} - e^{-i\theta_2})}$$

$$T_h = \left(-\frac{\pi}{4}, \dots, \frac{\pi}{2}\right) \text{ and}$$

$$\frac{\pi}{2}, \dots, \pi$$

$$\mu_{loc} = \max |\tilde{S}_h| \text{ such that } \theta \in T_h$$

μ_{loc} is readily the maximum of the absolute value or magnitude since it is complex.

$$\mu_{loc} = \max \left| \frac{e^{i\theta_1} + e^{i\theta_2}}{4 - e^{-i\theta_1} - e^{-i\theta_2}} \right| = .5 \text{ for } \theta_1 = \frac{\pi}{2}, \theta_2 = \arccos(\frac{4}{5}).$$

Let us now consider w -Jac. given as,

$$U_h^{m+1} = U_h^m + w(Z_h^{m+1} - U_h^m)$$

Note: in practice we'd do as $Z_h^{m+1} - U_h^m = \vec{r}$

$$U_h^{m+1} = U_h^m - w D^{-1}(\vec{r})$$

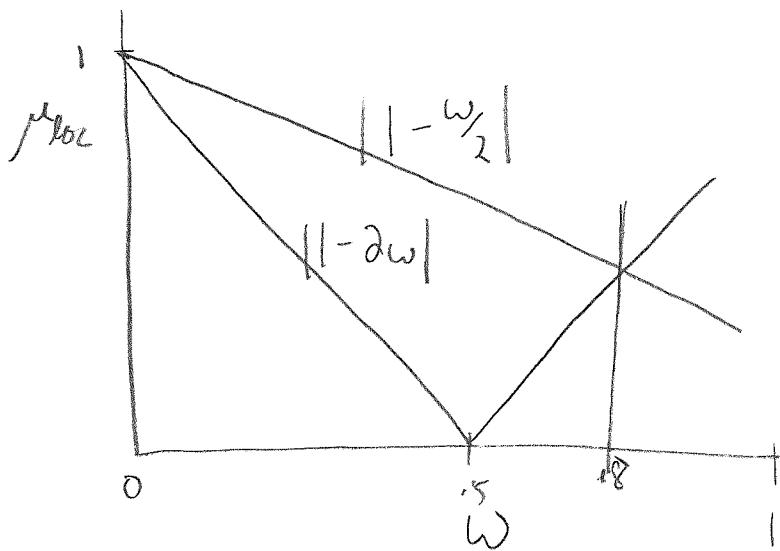
$$\vec{r} = \vec{A}\vec{x} - \vec{b}$$

$$\frac{4}{h^2} U_h^{m+1} = \frac{4U_h^m}{h^2 w} \therefore \frac{U^m}{h^2} i_{i+1,j} = \frac{U_{i-1,j}}{h^2} - \frac{U_{i,j+1}}{h^2} + \frac{U_{i,j-1}}{h^2} + 4 U_{i,j}^m$$

$$L_h^+ = \frac{1}{h} \begin{bmatrix} 0 & 6 \\ 0 & 0 \end{bmatrix}$$

$$L_h^- = \begin{bmatrix} -1 & & \\ -1 & 4(1 - \frac{4}{w}) & -1 \\ & -1 & \end{bmatrix}$$

If these are plotted, they look like



Thus the point where they meet is the absolute lowest possible μ_{loc} thus $w=.8$ is the optimal value for this problem as we use it as this for

(FD,

for $w=.8$

$$\mu_{loc}(.8) = \frac{3}{5} = .6 \text{ which is about as good as g/s Lexi=.5.}$$

However R10 G.S. has $\mu_{loc}=.25$ which is the best.

Thus we are motivated to examine a colored g/s type iteration for both parallel and "good" smoothing.

$$\tilde{S}_h(\vec{\theta}) = - \frac{\tilde{L}^-(\vec{\theta})}{L^+(\vec{\theta})}$$

$$L^+(\vec{\theta}) = \frac{4}{\omega}$$

$$L^-(\vec{\theta}) = -e^{-i\theta_1} - e^{i\theta_1} - e^{-i\theta_2} - e^{i\theta_2} + 4(1 - \frac{4}{\omega})$$

$$\tilde{S}_h(\vec{\theta}) = \frac{+e^{-i\theta_1} + e^{i\theta_1} + e^{-i\theta_2} + e^{i\theta_2} - 4(1 - \frac{4}{\omega})}{2 \cdot \frac{4}{\omega}}$$

$$= \cos(\theta_1) - i\sin(\theta_1) + \cos(\theta_1) + i\sin(\theta_1) + \cos(\theta_2) - i\sin(\theta_2) - 4(1 - \frac{4}{\omega})$$

$$\frac{4}{\omega}$$

$$= \frac{4}{\omega} (2\cos\theta_1 + \frac{\omega}{4} 2\cos(\theta_2)) + 1 - \frac{\omega}{4}$$

$$\hat{S}_h = 1 - \frac{\omega}{2} (2 - \cos(\theta_1) \cos(\theta_2))$$

The points of extrema are easy to find
possibilities

$$\theta_1 = \frac{\pi}{2}, \theta_2 = \frac{\pi}{2} \text{ gives } 1 - \frac{\omega}{2}$$

$$\theta_1 = \frac{\pi}{2}, \theta_2 = \pi \text{ gives } 1 - \frac{\omega}{2}(2 - 1) = 1 - \frac{\omega}{2}$$

$$\theta_1 = \pi, \theta_2 = \frac{\pi}{2} \text{ gives } 1 - \frac{\omega}{2}(2 - (-1) - (-1)) = 1 - 2\omega$$

$$\theta_1 = \pi, \theta_2 = \pi \text{ gives } 1 - \frac{\omega}{2}(2 - (-1) - (-1)) = 1 - 2\omega$$

thus

$$\mu_{\text{loc}} = \max(|1 - \frac{\omega}{2}|, |1 - 2\omega|).$$

An Inplace Approach to Do Matmul for $[A] = [L][U]$ stored it

1 - Matrix

Consider $[L][U]\{x\} = \{z\}$

Let's do a 4×4 example. We also work out

$$\begin{bmatrix} U_{11} & U_{12} & U_{13} & U_{14} \\ 0 & U_{22} & U_{23} & U_{24} \\ 0 & 0 & U_{33} & U_{34} \\ 0 & 0 & 0 & U_{44} \end{bmatrix} \begin{Bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{Bmatrix} = \begin{Bmatrix} \sum_{j=1}^N U_{1j} x_j \\ \sum_{j=1}^N U_{2j} x_j \\ \sum_{j=1}^N U_{3j} x_j \\ \sum_{j=1}^N U_{4j} x_j \end{Bmatrix} \quad l=1, 2, 3, 4 = \{y\}$$

$$\begin{bmatrix} 1 & 0 & 0 & 0 \\ L_{21} & 1 & 0 & 0 \\ L_{31} & L_{32} & 1 & 0 \\ L_{41} & L_{42} & L_{43} & 1 \end{bmatrix} \begin{Bmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \end{Bmatrix} = \left\{ y_i + \sum_{j=1}^{i-1} L_{ij} y_j \right\}$$

Now if we store $LU \rightarrow [A]$ then

$$[L][U]\{x\} \Rightarrow [L]\{y\} \quad \text{with } y = [U]\{x\}$$

$$\{y\} = \left\{ \sum_{j=1}^N A_{ij} x_j \right\}$$

$$\{z\} = \left\{ y_i + \sum_{j=1}^{i-1} A_{ij} y_j \right\}$$

Preconditioning:

Consider $[A]x = b$ we would like to Right Precondition this to to solve the Modified system. The following is known as Fiedler GMRES.

$$[A][M^{-1}]\hat{x} = b \quad \text{with} \quad [M]x = \hat{x}$$

Thus we need to redefine the Residual as

$$\tilde{r} = b - [A][M^{-1}]\hat{x}, \quad = Tb - [A]x, \quad \text{thus, the residual is unchange.}$$

$$[A][M^{-1}]x = b$$

$$[A][\hat{x}] = b$$

Applications to GMRES:

The above applies to GMRES.

1) We need to do the Residual as above

2) We have the product $[A]g_n \rightarrow [A][M^{-1}]g_n$

$$\text{thus } [A][M^{-1}]g_n = v, \text{ define } z_n = [M]^{-1}g_n$$

thus $v = [A]z_n$ with z_n the solution of

$$[M]z_n = g_n$$

3) After we set $\hat{x} = x_0 + [Q_n]g_n$ but we need x , thus $x = [M]^{-1}\hat{x} =$ that

$$x = x_0 + [M]^{-1}[Q_n]g_n \quad \text{thus}$$

Solve,

$$[M]x = \underbrace{[M]x_0}_{\text{vector, }} + \underbrace{[Q_n]g_n}_{\text{cols are } B_n^T} \quad \text{or}$$

$$\text{gette } x = x_0 + [Z_n]g_n$$

Thus for this we have 2 sets of vectors to
store. B, C. we still need to g's to do the normalization
the z's are computed only after we make the Krylov
space bigger.

A Generic and Efficient interpretation of Iterative methods

We wish to solve $[A]x = b$

There are 2 ways to view this

1). View as $[A]\{x\}^{k+1} = \{b\}$ where $\{x\}^{k+1} = \{x\}^k + \{e\}^k$
gives

$[M]\{e\}^k = \{b\} - [A]\{x\}^k$ - then take $[M]$ on the
LHS to be some approximation of A^{-1} as $[M] \approx [D]$ is
a Jacobi iteration.

- This method is more expensive because it uses
 $[A]\{x\}^k$ rather we should try another way.

2) View as $[A]\{x\} = \{b\}$ - factor $[A]$ as
 $[A] = [M] + [N]$ where $[M]$ multiplies x^{k+1} and N
multiplies x^k . Using the point of view in 1
and inserting $[M] + [N] = [A]$ we get the following..

$$[M]\{x\}^{k+1} - [N]\{x\}^k = \{b\} - [A]\{x\} \quad \text{gives}$$

$$[M]\{x\}^{k+1} = \{x\}^k + M(\{b\} - [A]\{x\}^k) \quad \text{gives}$$

$$\{x\}^{k+1} = \{x\}^k + M(\{b\} - [N]\{x\}^k) - \{x\}^k$$

yet another way to write this is
to add an under relaxation factor,

$$[M](\{x\}^{k+1} - \{x\}^k) = w(\{b\} - [A]\{x\}^k)$$

$$\{x\}^{k+1} = \{x\}^k + [M]w(\{b\} - ([M] + [N])\{x\}^k) =$$

$$\{x\}^{k+1} = (1-w)\{x\}^k + [M]w(\{b\} - [N]\{x\}^k)$$

To get Different Methods we select $[M]$ to be different thus.

Examples

- 1). $[M]$ = diagonal (or Block Diagonal) - we get Jacobi if $w \neq 1$ we get under relaxed Jacobi.
- 2). If $[M]$ = lower triangular part of $[A]$ we get G.S. if $w \neq 1$ we get SOR.
- 3). If $[M]$ = tri-diag of a line in the Mesh we get a line solve.

Naturally each choice of $[M]$ yields its corresponding choice of $[N]$.

The choices of $[N]$ for 1, 2 are easy.

How this applies to line-implicit solver.

In a line implicit solver we take a line of cells in the Mesh and solve the solution implicit along those lines. This results in a Block tri-diagonal system. Thus $[M]$ becomes this Block tri-diagonal Matrix. $[N]$ is the off diagonal faces that are Not in the line.

For example consider the following physical example.

Line 1			
10	13	5	14 15
9	1	4	12 14
		13	
8	9	3	10 13
9	8	2	11 12
4			11

These faces are not on the line.

Let's say we are on line 1.

for element 2 in line 1 we would have row 1 at

$$M = \begin{bmatrix} [JOD]_1 & [SOD]_{RL_1} \end{bmatrix}$$

for this gave element the row of $[N] =$

$[0, \dots, [SOD]_{RL_5}, \dots, [SOD]_{RL_6}]$ - these are the faces
on in the line,

It really is this simple. Just look at all
the faces on the element and use only
the off diagonals for the faces on that
element that are not in the line.

Implementation of the Thomas Algorithm for a line

Solver,

Our goal is to use the line solver and a
tool for smoothing in M6, and with GMRES.

Both of these approaches require the computation

of $[A]_{SU}$ or $[A]_X$. Thus we need to
do as much Thomas prepping as possible
but maintain an easy way to get the
linear residual with the lines.

From a text book Thomas for blocks can be written as

$$C_1' = B_1^{-1} C_1 \quad \text{for } [A, B, C] = R$$

$$R_1'' = B_1^{-1} R_1$$

For $j = 2, \dots, m-1$

$$B_j' = B_j - A_j C_{j-1}'$$

$$R_j'' = R_j - A_j R_{j-1}''$$

$$C_j' = B_j'^{-1} C_j$$

$$R_j'' = B_j'^{-1} R_j'$$

end

$$B_m' = B_m - A_m C_{m-1}'$$

$$R_m'' = R_m - A_m R_{m-1}''$$

$$R_m''' = B_m'^{-1} R_m'$$

For $j = m-1, \dots, 1$

$$R_j''' = R_j'' - C_j' R_{j+1}'''$$

end.

The most efficient method from Thomas Point of view is to over write the Jacobi-Dinger with $L U(B_j')$ and over the appropriate off diagonal with C_j' .

However this results in a difficulty computing the residual.

Thus we can compromise on the processing and factorization stages.

We note that the Thomas in block form is a Block LU Factorization.

As a setup procedure we will form $LU(B_j')$

and store this

Thus the setup loop is.

$$B_1' = B_1$$

For $j=2, 3, \dots, m-1$

$$B_j' = B_j - A_j \begin{pmatrix} B_{j-1}' \\ C_{j-1} \end{pmatrix}$$

$LU(B_j')$

end.

$$B_m' = B_m - A_m \begin{pmatrix} B_{m-1}' \\ C_{m-1} \end{pmatrix}$$

The residual calculation will involve going over the lines and computing.

for $j=2, m-1$

$$B_j = B_j' + A_j \begin{pmatrix} B_{j-1}' \\ C_{j-1} \end{pmatrix}$$

End.

Accessing the elements and faces in the grid.

	f_1	f_2	f_3	f_4	
physical	e_1	e_2	e_3	e_4	e_5
Boundary					

line Boundary

At ls we have only P, L so as we
 $\alpha_{face} = P_{ls_face}(ls)$

Linked list indicate.
ls - start
le - end.

As we move up the tree we for preprocessors
we want out c_{face} to stay by 1 so

for $j = 2, m-1$

$$c_{face} = 1 \cdot c_{face}(j-1)$$

$$a_{face} = 1 \cdot a_{face}(j-1)$$

end.

The O index is $ls_elem(j)$.

The solution loop is

$$R_i'' = B_i^{-1} R_i$$

For $j = 2, m-1$

$$R_j' = R_j - A_j R_{j-1}''$$

$$R_j'' = B_j'^{-1} R_j'$$

end

$$R_m' = R_m - A_m R_{m-1}''$$

$$R_m''' = B_m'^{-1} R_m'$$

For $j = m-1, \dots, 1$

$$C_j''' = B_j'^{-1} C_j''$$

$$R_j''' = R_j'' - C_j''' R_{j+1}'''$$

e

Block Thomas.

Consider Tri-diagonal Matrix stored $[A, B, C]x = f$

Pre-processing Matrix:

$$B'_1 = B_1$$

$$f_{0j} = 2, m.$$

$$B'_j = B_j - A_j (B'_{j-1} C_{j-1}) \rightarrow B'_j = B_j - A_j (P'_{j-1})$$

end.

Solution Procedure:

$$y_1 = B'^{-1}_1 f_1$$

for $j = 2, m-1$

$$y_j = B'^{-1}_j (f_j - A_j y_{j-1})$$

end.

$$y_m = B'^{-1}_m (f_m - A_m y_{m-1})$$

$$X_m = y_m$$

for $j = m-1, \dots, 1$

$$X_j = y_j - (B'^{-1}_j C_j)(X_{j+1}) \rightarrow X_j = y_j - z_j$$

where

$$[B'^{-1}_j] z_j = C_j X_{j+1}$$

Multi-Step ODE Integration:

Solving ODE's via multi-step methods
 Solving $y' = f(x, y)$ $y' = \frac{dy}{dx}$

Adams-Basforth.

- In contrast to single step methods A-B methods need a starting procedure to give y_0, \dots, y_{k-1} which are approx. solns at point $x_0 + h, \dots, x_0 + (k-1)h$ and then a multi-step procedure for computing $y(x_0 + kh)$. This is then applied recursively to all unknowns using k steps.

Explicit Adams Method.

Denote $x_i = x_0 + i h$.

We want numerical approximations at y_{n+1} and we know $y_n, y_{n-1}, \dots, y_{n-k+1}$

Equation $y' = f(x, y)$ $y(x_0) = y_0$ - known initial condition.

Integration of this from x_n to x_{n+1}

$$\int_{x_n}^{x_{n+1}} y'(t) dt = \int_{x_n}^{x_{n+1}} f(t, y(t)) dt \rightarrow$$

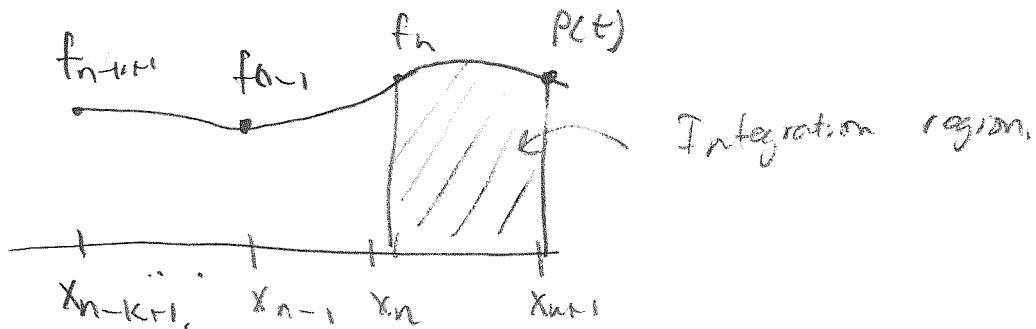
$$y(x_{n+1}) - y(x_n) = \int_{x_n}^{x_{n+1}} f(t, y(t)) dt$$

$$y(x_{n+1}) = y(x_n) + \int_{x_n}^{x_{n+1}} f(t, y(t)) dt$$

Since we know y_{n-k+1}, \dots, y_n then

$f(x_i, y_i)$ is known for $i = n-k+1, \dots, n$

The function $f_k(t)g_k(y(t))$ can then be replaced by the interpolation polynomial $P(t)$ that passes through $\{(x_i, f_i)\} i = n-k+1, n\}$



For the interpolation polynomial $P(t)$ we use Lagrange polynomials.

Normally we would express $P(t)$ as

$$P(t) = \sum_{k=1}^n \phi_k L_{k,n}(t) \quad \text{where } L_{k,n} = \prod_{j=0, j \neq k}^n \frac{(t - x_j)}{(x_k - x_j)}$$

However it is more convenient here to do the interpolation in divided difference form namely

$$P_n(t) = a_0 + a_1(t - t_0) + a_2(t - t_0)(t - t_1) + \dots$$

or in Backwards form

$$P_n(t) = b_0 + (x - x_n)b_1 + (x - x_n)(x - x_{n-1})b_2 + \dots$$

$$(x - x_0)(x - x_{n-1})(x - x_{n-2})b_3 + \dots (x - x_n) \dots (x - x_1)b_n. \quad \textcircled{1}$$

The form in $\textcircled{1}$ is going to be how we derive interpolation for Alans Bashford.

To see the connection between divided difference form and Lagrange form consider

$$P_K(x) = P_{K-1}(x) + g_{K,n}(x) \quad \text{for } n=1, 2, \dots, n \quad (1)$$

$$P_n = P_{n-1}(x) + g_n(x)$$

$$\text{where } g_n(x) = \frac{f(x)}{\prod_{j=0}^{K-1} (x - x_j)} \quad (2)$$

Using 1 and 2 respectively gives

$$P_n = ((a_0 + g_1) + g_2) + g_3 + \dots \quad \text{gives}$$

$$P_n = a_0 + a_1(x-x_0) + a_2(x-x_0)(x-x_1) + \dots (x-x_{n-1}) \cdots a_n$$

Recall that a given unique n interpolation polynomial of order n is given by

$$P_n = \sum_{j=0}^n f(x_j) \prod_{\substack{k=0 \\ k \neq j}}^{n-1} \frac{x - x_k}{x_j - x_k} \quad \text{we can permute the multipliers and additions due to associativity + commutativity}$$

$$P_n = \sum_{j=0}^n \left[\frac{f(x_j)}{\prod_{\substack{k=0 \\ k \neq j}}^{n-1} (x_j - x_k)} \left(\prod_{\substack{k=0 \\ k \neq j}}^{n-1} (x - x_k) \right) \right] \quad \text{thus comparing with (2) gets}$$

$$a_n = \sum_{j=0}^n \frac{f(x_j)}{\prod_{\substack{k=0 \\ k \neq j}}^{n-1} (x_j - x_k)}$$

Using the interpolation polynomial P and from lagrange polynomials we know $P_n(x_i) = f(x_i)$. Examining the polynomial we see

$$b_0 = f(x_n)$$

$$f_{n-1} = f(x_n) + (x_{n-1} - x_n)b_1 \Rightarrow b_1 = \frac{f_{n-1} - f_n}{x_{n-1} - x_n} = \frac{f_n - f_{n-1}}{x_n - x_{n-1}} =$$

$$f_{n-2} = f(x_n) + (x_{n-2} - x_n)f[x_n, x_{n-1}] + b_2(x_{n-2} - x_n)(x_{n-2} - x_{n-1})$$

$$b_2 = \frac{f_{n-2} - f(x_n) - (x_{n-2} - x_n)f[x_n, x_{n-1}]}{(x_{n-2} - x_n)(x_{n-2} - x_{n-1})}$$

$$\text{adding } \frac{f_{n-1} - f_n}{(x_{n-2} - x_n)(x_{n-2} - x_{n-1})} = 0 \text{ gives}$$

$$= \frac{f_{n-2} - f_{n-1}}{(x_{n-2} - x_{n-1})(x_{n-2} - x_n)} + \frac{f[x_n, x_{n-1}](x_{n-1} - x_{n-2})}{(x_{n-2} - x_n)(x_{n-2} - x_{n-1})} = \frac{f[x_n, x_{n-1}](x_{n-2} - x_n)}{(x_{n-2} - x_n)(x_{n-2} - x_{n-1})}$$

$$= \frac{f[x_{n-2}, x_{n-1}]}{x_{n-2} - x_n} \quad \cancel{\frac{f[x_n, x_{n-1}](x_{n-1} - x_{n-2})}{(x_{n-2} - x_{n-1})(x_{n-2} - x_n)}}$$

$$= \frac{f[x_{n-1}, x_{n-2}] - f[x_n, x_{n-2}]}{(x_n - x_{n-2})} = f[x_n, x_{n-1}, x_{n-2}] = b_2$$

Thus

$$P_n(x) = f[x_0] + f[x_0, x_{n-1}] (x - x_0) + f[x_0, x_{n-1}, x_{n-2}] (x - x_0)(x - x_{n-1}) \\ + \dots$$

Thus the interpolation polynomial is known completely ~~if~~ with the coefficients given by Newton divided differences.

If we consider even step sizes h then

$$x = x_0 + sh \quad s \in [0, 1]$$

Replacing this in our ~~polynomial~~ interpolation polynomial,

$$\text{B.C. } x_0 - (x_0 + sh) = -sh$$

$$P_n(x) = P_n(s) = f[x_0] + f[x_0 + sh, x_{n-1}] (sh) + f[x_0, x_{n-1}, x_{n-2}] (x_0 + sh - x_0) \\ (x_0 + sh - x_{n-1}) + \dots = f[x_0] - [f[x_{n-1}] - f[x_0]] s +$$

$$\frac{(f(x_{n-2}) - f(x_{n-1}) - f(x_{n-1}) - f(x_0))}{2!} x(s+1) sh + \dots$$

$$= f(x_0) + [f(x_{n-1}) - f(x_0)] s + \frac{s(s+1)}{2}$$

If we denote $f(x_{n-1}) - f(x_0) \equiv \nabla f$ and

$$f(x_{n-2}) - f(x_{n-1}) - f(x_{n-1}) - f(x_0) \equiv \nabla^2 f \text{ then}$$

we obtain the compact form of P_n in terms of binomial coefficients s of order j

$$P_n(x) = P(x_0 + sh) = \sum_{j=0}^{k-1} (-1)^j \binom{-s}{j} \nabla^j f_0 \text{ thus with}$$

$$\binom{-s}{j} = (-1)^j \frac{s(s+1)(s+2) + \dots (s+(j-1))}{j!}$$

Note : $-s$ terms come from terms like $x_{n-1} - x_n = -h$
 s terms come from $(x_{n-1} - x_n)(x_{n-2} - x_n) = (-h)(-2h) = 2h^2$

Example for $K=2$ $K=1$

$$p_n(t) = f_n - S \nabla^1 f_n$$

Using the expression in

$$y(X_{n+1}) = y(X_n) + \int_{X_n}^{X_{n+1}} f(t, y(t)) dt \quad \text{gives}$$

$$\begin{aligned} y(X_{n+1}) &= y(X_n) + h \sum_{j=0}^{K-1} \int_0^1 (-1)^j \binom{-s}{j} ds \nabla^1 f_n = y(X_n) + h \sum_{j=0}^{K-1} (-1)^j \int_0^1 \binom{-s}{j} ds \\ &= y(X_n) + h \sum_{j=0}^{K-1} \gamma_j \nabla^j f_n \quad \text{with } \gamma_j = (-1)^j \int_0^1 \binom{-s}{j} ds \end{aligned}$$

Let's do this for $K=1$

$$\gamma_0 = h \int_0^1 (1) ds = h(1-0) = h \quad \text{gives}$$

$$y(X_{n+1}) = y(X_n) + h f_n$$

for $K=2$ $j=0, 1$

$$\gamma_0 = h$$

$$\gamma_1 = - \int_0^1 s ds = \frac{s^2}{2} \Big|_0^1 = -\frac{1}{2}$$

$$y(X_{n+1}) = y(X_n) + h(f_n + -\frac{1}{2}(f_{n-1} - f_n)) = y(X_n) + h(\frac{3}{2}f_n - \frac{1}{2}f_{n-1})$$

for $K=3$
 $\binom{-s}{j} = (-1)^j \left[\frac{s(s+1) + \dots + s(s+(j-1))}{j!} \right] \quad j_{\max}=2$

$$\text{Need } \gamma_2 = \gamma_1 \quad \text{for } j=2 \quad \binom{-s}{2} = (1) \left[\frac{s(s+1)}{2} \right]$$

$$\gamma_2 = (-1) \int_0^1 \frac{s^2+s}{2} ds = \left. \frac{s^3}{6} + \frac{s^2}{4} \right|_0^1 = \frac{1}{6} + \frac{1}{4} = \frac{5}{12}$$

Thus as we find coefficients for lower order we keep finding them for then for higher order

so for $k=3$ $\gamma_0 = 1, \gamma_1 = \frac{1}{2}, \gamma_2 = \frac{5}{12}$ gives

$$\begin{aligned} y(x_{n+1}) &= y(x_n) + h \left(f_n - \frac{1}{2}(f_{n-1} - f_n) + \frac{5}{12}(f(x_{n-2}) - f(x_{n-1}) - f(x_{n-2})) \right. \\ &= y(x_n) + h \left(\frac{18}{12}f_n + \frac{5}{12}f_n - \frac{6}{12}f_{n-1} - \frac{10}{12}f_{n-1} + \frac{5}{12}f_{n-2} \right) \\ &= y(x_n) + h \left(\frac{23}{12}f_n - \frac{14}{12}f_{n-1} + \frac{5}{12}f_{n-2} \right). \end{aligned}$$

These all match the book and they all come from my math.

This is enough Adams Method we are really interested in BDF Formulas.

BDF Methods

These methods are not based on Integration (Quadrature) instead they numerically differentiates a function.

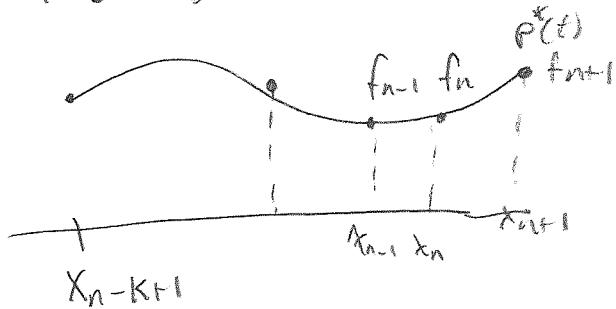
Assume approximations y_{n-k+1}, \dots, y_n are known to derive expression for y_{n+1} we use the interpolating

polynomial $g(x)$

$$g(x) = g(x_n + sh) = \sum_{j=0}^k (-1)^j (-s+1)_j^{\downarrow} y_{n+1-j}$$

one then asks where does this polynomial come from.

It is the same polynomial we have been using in Adams methods except it includes y_{n+1}, x_{n+1} in its domain



To derive this polynomial proceed as before (2 terms is enough to verify Back expression)

$$g(x) = a_0 + a_1(x - x_{n+1}) + a_2(x - x_{n+1})(x - x_n) + \dots$$

$$g(x_{n+1}) = f_{n+1} \Rightarrow a_0 = f_{n+1}$$

$$g(x_n) = f_n = f_{n+1} + a_1(x_n - x_{n+1}) \Rightarrow a_1 = \frac{f_{n+1} - f_n}{x_{n+1} - x_n} = f[x_{n+1}, x_n]$$

$$f_{n-1} = f_{n+1} + f[x_{n+1}, x_n](x_{n-1} - x_{n+1}) + a_2(x_{n+1} + x_{n-1})(x_{n-1} - x_n)$$

$$\frac{f_{n-1} - f_{n+1}}{(x_{n-1} - x_{n+1})(x_{n-1} - x_n)} - \frac{f[x_{n+1}, x_n](x_{n-1} - x_{n+1})}{(x_{n-1} - x_{n+1})(x_{n-1} - x_n)} = a_2$$

$$\text{add } + \frac{f_n - f_n}{(x_{n-1} - x_{n+1})(x_{n-1} - x_n)} \text{ gives}$$

$$\frac{(f_n - f_{n+1}) + (f_{n-1} - f_n)}{(x_{n-1} - x_{n+1})(x_{n-1} - x_n)} - \frac{f[x_{n+1}, x_n](x_{n-1} - x_{n+1})}{(x_{n-1} - x_{n+1})(x_{n-1} - x_n)} = a_2$$

$$+ \frac{f[x_n, x_{n-1}]}{(x_{n-1} - x_{n+1})} - \frac{f[x_{n+1}, x_n](x_{n+1} - x_n)}{(x_{n-1} - x_{n+1})(x_{n-1} - x_n)} - \frac{f[x_{n+1}, x_n](x_{n-1} - x_{n+1})}{(x_{n-1} - x_{n+1})(x_{n-1} - x_n)} = a_2$$

$$a_2 = \frac{(f[x_n, x_{n-1}] - f[x_{n+1}, x_n])}{x_{n-1} - x_{n+1}} = \frac{f[x_{n+1}, x_n] - f[x_n, x_{n-1}]}{x_{n+1} - x_n}$$

$$= f[x_{n+1}, x_n, x_{n-1}]$$

For $g(Nt+sh)$ and equal spacing $X_{n+1} - X_n = h$ we get the following

$$g(Nt+sh) = f_{n+1} + \frac{f_{n+1}-f_n}{h} (X_{n+sh} - X_{n+1}) + \frac{(f_{n+1}-f_n + f_n + f_{n-1})}{2h^2} (X_{n+sh} - X_{n+1})(X_{n+sh} - X_n) \\ \downarrow \\ \frac{(-1+s)^k}{2} (s^2 - s)$$

Thus again we have binomial coefficients except now they are given by

$$\frac{(-1)^k (s-1)(s-1+1) \dots (s-1+(k-1))}{k!}$$

check: $k=1$

$$(-1)^1 (-1)^1 (s-1) = (s-1) -$$

$$(-1)^2 (-1)^2 \frac{(s-1)(s-1+1)}{2} = \frac{s^2 - s}{2} \checkmark$$

Thus we can represent our polynomial

$$g(Nt+sh) = \sum_{j=0}^k (-1)^j \binom{-s+1}{j} \nabla^j y_{n+1} - \text{Note here we interp the solution } y \text{ not } y = f.$$

For BDF formulae we have a constraint the $\frac{dy}{dx}|_{x_{n+1}-r} = f(x_{n+1}-r)$

$f(x_{n+1}-r, y_{n+1}-r)$ for $r=1$ we get explicit formulae

for $r=0$ we get implicit formulae.

$$\frac{dy}{dx} = \frac{dy}{ds} \cdot \frac{ds}{dx} = \frac{dy}{ds} \Big|_{n+1} = f_{n+1} \Rightarrow h f_{n+1} = \sum_{j=0}^k (-1)^j \frac{d}{ds} \binom{-s+1}{j} \Big|_{s=1} \nabla^j y_{n+1}$$

Note x_{n+1} is $X(s=1)$

$$= \sum S_j^* \nabla^j y_{n+1} = f_{n+1} \cdot h \quad \text{this gives.}$$

we need S_j^*

$$\delta_j^* = (-1)^j \frac{d}{ds} \binom{-s+1}{j}$$

$$\text{Recall } (-1)^j \binom{-s+1}{j} = \frac{1}{j!} (s-1)s(s+1)\cdots(s+j-2)$$

$$\text{for } j=1 \quad \delta_1^* = 1$$

$$\text{for } j=2 \quad \delta_2^* = \frac{d}{ds} \binom{s^2-s}{2} \Big|_{s=1} = \frac{1}{2} (2s-1) \Big|_{s=1} = \frac{1}{2}$$

$$\delta_j^* = \begin{cases} 1 & j \geq 1 \\ 0 & j < 1 \end{cases}$$

Thus our formula is

$$\sum_{j=0}^k \delta_j^* \nabla^j y_{n+1} = h f_{n+1}$$

for $k=0$ we get $0 = h f_{n+1}$ - garbage value

for $k=1$ $y_{n+1} - y_n = h f_{n+1}$; BDF1

for $k=2$ $\frac{(y_{n+1} - y_n) - (y_n - y_{n-1})}{2} + y_{n+1} - y_n = h f_{n+1}$

$$\frac{y_{n+1} - 2y_n + \frac{1}{2}y_{n-1} + y_{n+1} - y_n}{2} = h f_{n+1}$$

$$\text{gives } \frac{3y_{n+1}}{2} - 2y_n + \frac{y_{n-1}}{2} = h f_{n+1} ; \text{BDF2}$$

for $k=3$

$$y_{n+1} - y_n + \frac{(y_{n+1} - y_n) - (y_n - y_{n-1})}{2} + \frac{(y_{n+1} - y_n + y_{n-1} - y_{n-2})}{3}$$

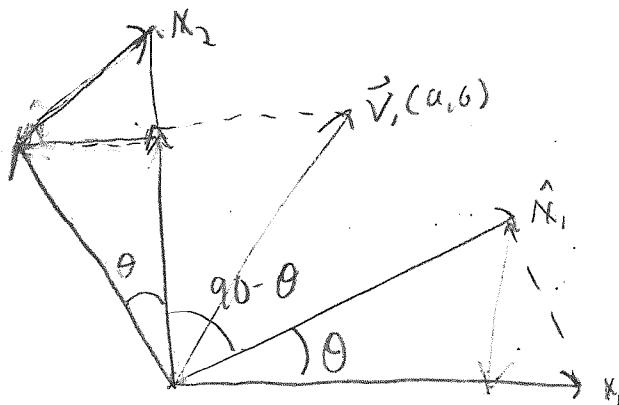
$$\frac{y_{n+1} + 2y_{n-1} - y_{n-2}}{3} = \frac{11}{6} y_{n+1} - 3y_n + \frac{3}{2} y_{n-1} - \frac{1}{3} y_{n-2}$$

; BDF 3.

Note: That compared to Adams we get K order accuracy (I have not yet proven this but I know from experience $K=2$: BDF-2 is 2nd order) not $K+1$ order. But we need to store solutions not residuals. Also we have yet to study the stability of BDF's v.s. Adams. However BDF's are well known for their amenability to stiff equations (which we have). Therefore we will begin time-accurate computations with BDF-2, then move to TRK type schemes.

Coordinate Transforms:

Consider going from 1 coordinate system to another i.e. from \hat{x}_1, \hat{x}_2 , \hat{X}_1, \hat{X}_2 with angle θ between the



given $\vec{V} \in (x_1, x_2)$ what are its components in \hat{x}_1, \hat{x}_2 $\vec{V} = \begin{bmatrix} a \\ b \end{bmatrix}$

\hat{x}_1 : The components of \vec{V} in \hat{x}_1
 $a \cos \theta + b \sin \theta$

\hat{x}_2 : The components of \vec{V} in \hat{x}_2
 $-a \sin \theta + b \cos \theta$

gives $[T] \begin{bmatrix} a \\ b \end{bmatrix} = \begin{bmatrix} c \\ d \end{bmatrix}$ where $[T] = \begin{bmatrix} \cos \theta & \sin \theta \\ -\sin \theta & \cos \theta \end{bmatrix}$

$$\vec{V}_{\hat{x}_1, \hat{x}_2} = [T] \vec{V} \Rightarrow \vec{V}_{x_1, x_2} = [T]^{-1} \{ \vec{V}_{\hat{x}_1, \hat{x}_2} \}$$

is this true. Let's check

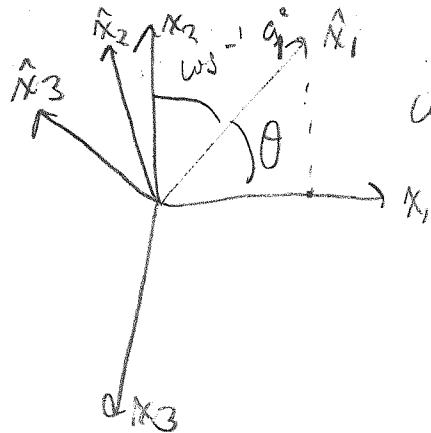
given $\vec{V}_{\hat{x}_1, \hat{x}_2} = \begin{bmatrix} c \\ d \end{bmatrix}$

x_1 : Components in x
 $c = \cos \theta - d \sin \theta$
 $d = -c \sin \theta + d \cos \theta \Rightarrow [T]^{-1} = \begin{bmatrix} \cos \theta & \sin \theta \\ -\sin \theta & \cos \theta \end{bmatrix}$

$$[T]^{-1} [T]^{-1} = \begin{bmatrix} \cos & \sin \\ -\sin & \cos \end{bmatrix} \begin{bmatrix} \cos & -\sin \\ \sin & \cos \end{bmatrix} = \begin{bmatrix} 1 & -\cancel{\cos \theta \sin \theta} \\ -\cancel{\sin \theta \cos \theta} & 1 \end{bmatrix} \checkmark$$

More formally:

We can define the Rotation Matrix in terms of direction cosines.



$$\cos \theta = \hat{i} \cdot \hat{x}_1$$

$$a_1^1 = \cos(\theta_{\hat{i} \cdot \hat{x}_1})$$

thus $\cos(a_1^1) = \theta_{\hat{i} \cdot \hat{x}_1}$ - angle between \hat{i} and \hat{x}_1 .

Thus we have a direction cosine for each vector unit vect \hat{i} relative to the origin ~~vector~~ coordinate system

e.g., $a_1^3 = \frac{\hat{x}_3 \cdot \hat{x}_1}{|\hat{x}_3|} = \cos(\theta_{\hat{x}_1 \cdot \hat{x}_3})$ this is the direction cosine

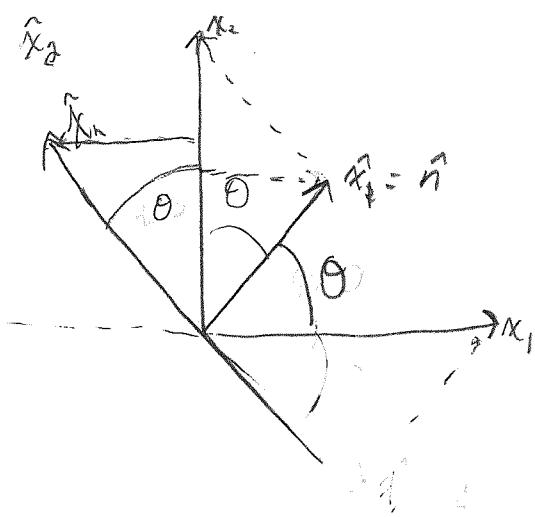
For 3D there are 3 of these

$$\begin{matrix}
 & \hat{i} & \hat{j} & \hat{k} \\
 a_i^1 & a_1^1 & a_2^1 & a_3^1 \\
 a_i^2 & a_1^2 & a_2^2 & a_3^2 \\
 a_i^3 & a_1^3 & a_2^3 & a_3^3
 \end{matrix}$$

This can be represented as a matrix,

$$\begin{bmatrix} a_1^1 & a_1^2 & a_1^3 \\ a_2^1 & a_2^2 & a_2^3 \\ a_3^1 & a_3^2 & a_3^3 \end{bmatrix} = [A]$$

A specific interest are rotations to a normal coordinate system



$$n_X \cos \theta \rightarrow n_X \sin \theta$$

$$n_X \sin \theta + n_Y \cos \theta$$

$$\begin{matrix} \hat{n}_X = 1 \\ \hat{n}_Y = 1 \end{matrix} \text{ i.e. } \|n\|_1, \|n\|_2 = 1$$

thus

$$\hat{n}_X \cos \theta = n_X \Rightarrow n_X = \cos \theta$$

$$\hat{n}_X \sin \theta = n_Y \Rightarrow n_Y = \sin \theta$$

$$-\hat{n}_Y \sin \theta = -n_Y = -n_Y \text{ we already}$$

$$\hat{n}_X \cos \theta = n_X \Rightarrow n_X \text{ now this}$$

Thus for transformations to and from a normal coordinate systems we have

$$[T]^{-1} = \begin{bmatrix} n_X & -n_Y \\ n_Y & n_X \end{bmatrix}, \quad T = \begin{bmatrix} n_X & n_Y \\ -n_Y & n_X \end{bmatrix}$$

Let's use a 2D version of our rotation matrix $[A]$ and see if we can work out what we discovered above.

$$a_1^1 = \cos(\theta_{\hat{n}_X}) = \frac{(1, 0) \cdot (n_X, n_Y)}{\|n\|_1 \| (1, 0) \|} = n_X$$

$$a_1^2 = \cos(\theta_{\hat{n}_Y}) = (0, 1) \cdot (n_X, n_Y) = n_Y$$

$$a_2^1 = \cos(\theta_{\hat{n}_X}) = (1, 0) \cdot (-n_Y, n_X) = -n_Y$$

$$a_2^2 = \cos(\theta_{\hat{n}_Y}) = (0, 1) \cdot (-n_Y, n_X) = n_Y$$

$\Rightarrow [A] = [T]^{-1}$ i.e. transform from $\hat{n}_X \rightarrow \hat{n}_Y$.

$$\begin{bmatrix} n_X & -n_Y \\ n_Y & n_X \end{bmatrix} \begin{bmatrix} \bar{v}_X \\ \bar{v}_Y \end{bmatrix} = \begin{bmatrix} v_X \\ v_Y \end{bmatrix} = \begin{matrix} a_1^1 \bar{v}_X + a_2^1 \bar{v}_Y \\ a_1^2 \bar{v}_X + a_2^2 \bar{v}_Y \end{matrix} \Rightarrow \bar{v}_j = a_j^i \bar{v}_i$$

So to transform unit vector $e_j = a_j^i \bar{e}_i$ or for the transpose $\bar{e}_i = a_j^i e_j$

Using these to manipulate tensors:

Let us first define a tensor component.

$$T_{ij} = \vec{e}_i \mathcal{T} \vec{e}_j \text{ ie } [1, 0, 0] \begin{bmatrix} \tilde{\alpha}_{11} & \tilde{\alpha}_{12} & \tilde{\alpha}_{13} \\ \tilde{\alpha}_{21} & \tilde{\alpha}_{22} & \tilde{\alpha}_{23} \\ \tilde{\alpha}_{31} & \tilde{\alpha}_{32} & \tilde{\alpha}_{33} \end{bmatrix} \begin{Bmatrix} 1 \\ 0 \\ 0 \end{Bmatrix} = [1, 0, 0] \begin{Bmatrix} \tilde{\alpha}_{11} \\ \tilde{\alpha}_{21} \\ \tilde{\alpha}_{31} \end{Bmatrix} = \tilde{\alpha}_{11}$$

So we need a way to go from

$$\vec{e} \rightarrow \vec{\tilde{e}} \quad \text{which takes use from } e_j \rightarrow \tilde{e}_j$$

$$[A]^T = \begin{bmatrix} a_1^1 & a_1^2 & a_1^3 \\ a_2^1 & a_2^2 & a_2^3 \\ a_3^1 & a_3^2 & a_3^3 \end{bmatrix}$$

$$\tilde{v} = [A]^T \{v\} = a_1^1 v_1 + a_1^2 v_2 + a_1^3 v_3 \\ a_2^1 v_1 + a_2^2 v_2 + a_2^3 v_3 \\ a_3^1 v_1 + a_3^2 v_2 + a_3^3 v_3$$

$\tilde{v}_i = a_i^j v_j$ here v_j, v_i etc are scalar components

To express T_{ij} by rotation from \tilde{T}_{ij}

$$e_i = a_i^j \tilde{e}_j \text{ gives}$$

$$T_{kl} = a_k^i \tilde{e}_i \mathcal{T} \cdot a_l^j \tilde{e}_j = a_i^k a_j^l \tilde{T}_{ij}$$

$$T_{11} = a_1^1 a_1^1 \tilde{T}_{11}$$

Thus for 2D

$$\tilde{T} = \begin{bmatrix} \tilde{T}_{11} & \tilde{T}_{12} \\ \tilde{T}_{21} & \tilde{T}_{22} \end{bmatrix}$$

$$T_{11} = a_1^1 \cdot (a_1^1 \tilde{T}_{11} + a_2^1 \tilde{T}_{12}) + a_2^1 (\tilde{T}_{21} a_1^1 + \tilde{T}_{22} a_2^1)$$

$$\begin{bmatrix} a_1^1 & a_2^1 \\ a_1^2 & a_2^2 \end{bmatrix} \begin{bmatrix} \tilde{T}_{11} & \tilde{T}_{12} \\ \tilde{T}_{21} & \tilde{T}_{22} \end{bmatrix} \begin{bmatrix} a_1^1 & a_1^2 \\ a_2^1 & a_2^2 \end{bmatrix} = \begin{bmatrix} \tilde{T}_{11} a_1^1 + \tilde{T}_{12} a_2^1 \\ \tilde{T}_{21} a_1^1 + \tilde{T}_{22} a_2^1 \end{bmatrix}$$

$$\text{give } T_{11} = a_1^1 (a_1^1 \tilde{T}_{11} + a_2^1 \tilde{T}_{12}) + a_2^1 (\tilde{T}_{21} a_1^1 + \tilde{T}_{22} a_2^1)$$

Thus we can say the transformation from $\tilde{x} \rightarrow x$ of tensor \tilde{T} is given by the following
concurrent Matrix Notation.

$$[\tilde{T}] = [A][\tilde{T}][A]^T \text{ and } \tilde{T} = [A]^{-1}[\tilde{T}][A]^{-T} \text{ however}$$

$[A]$ is orthogonal thus $[A]^{-1} = [A]^T$ and $[A]^{-T} = [A]$ so
 $\tilde{T} = [A]^T[\tilde{T}][A]$ - thus we simply figure out

$$[A] \text{ as } \begin{bmatrix} \cos(\theta_{\tilde{x}_1}^{x_1}) & \cos(\theta_{\tilde{x}_1}^{x_2}) & \cos(\theta_{\tilde{x}_1}^{x_3}) \\ \cos(\theta_{\tilde{x}_2}^{x_1}) & \cos(\theta_{\tilde{x}_2}^{x_2}) & \cos(\theta_{\tilde{x}_2}^{x_3}) \\ \cos(\theta_{\tilde{x}_3}^{x_1}) & \cos(\theta_{\tilde{x}_3}^{x_2}) & \cos(\theta_{\tilde{x}_3}^{x_3}) \end{bmatrix}$$

Note: These are best computes as do products of
old $\hat{e}_1, \hat{e}_2, \hat{e}_3$ and new $\tilde{x}_1, \tilde{x}_2, \tilde{x}_3$.

Ex: Rotation from Cartesian to Normal Axis

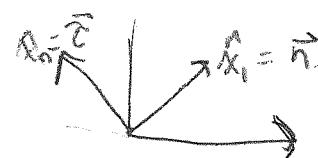
Since on thing we are interested in is the rotation
from cartesian coordinates to normal axes we will use
this as a nice 2D Example.
Consider the viscous stress tensor.

$$\begin{bmatrix} T_{xx} & T_{xy} \\ T_{yx} & T_{yy} \end{bmatrix}$$

If we want the component of this in the \tilde{x} direction
we can 1). Rotate the tensor, 2) Find the traction
in cartesian coordinates and then dot product with \tilde{x} .

Method 1:

a) Find $[A]$



$$a_1^1 = \cos(\theta_{\hat{n}}^{x_1}) = \frac{(1, 0)(n_x, n_y)}{1} = n_x$$

$$a_1^2 = \cos(\theta_{\hat{n}}^{x_2}) = (0, 1)(n_x, n_y) = n_y$$

$$a_2^1 = \cos(\theta_{\hat{n}}^{x_1}) = (1, 0)(-n_y, n_x) = -n_y$$

$$a_2^2 = \cos(\theta_{\hat{n}}^{x_2}) = (0, 1)(-n_y, n_x) = n_x$$

$$\begin{bmatrix} n_x & -n_y \\ n_y & n_x \end{bmatrix} = [A]$$

$$\begin{bmatrix} n_x & -n_y \\ -n_y & n_x \end{bmatrix} \begin{bmatrix} \bar{\epsilon}_{xx} & \bar{\epsilon}_{xy} \\ \bar{\epsilon}_{yx} & \bar{\epsilon}_{yy} \end{bmatrix} \begin{bmatrix} n_x & -n_y \\ n_y & n_x \end{bmatrix} = \begin{bmatrix} n_x & n_y \\ -n_y & n_x \end{bmatrix} \begin{bmatrix} 2n_x n_y + \bar{\epsilon}_{xy} \bar{\epsilon}_{yy} & -\bar{\epsilon}_{xx} n_y + \bar{\epsilon}_{xy} n_x \\ \bar{\epsilon}_{yx} n_x + \bar{\epsilon}_{yy} n_y & -\bar{\epsilon}_{xy} n_y + \bar{\epsilon}_{yy} n_x \end{bmatrix}$$

$$= \begin{bmatrix} n_x^2 \bar{\epsilon}_{xx} + n_x n_y \bar{\epsilon}_{xy} + n_x n_y \bar{\epsilon}_{yx} + \bar{\epsilon}_{yy} n_y^2 & -n_x n_y \bar{\epsilon}_{xy} + n_x^2 \bar{\epsilon}_{xy} - \bar{\epsilon}_{yy} n_y^2 + 2 \bar{\epsilon}_{yy} n_x n_y \\ -n_y n_x \bar{\epsilon}_{xx} - \bar{\epsilon}_{xy} n_y^2 + \bar{\epsilon}_{yx} n_x^2 + \bar{\epsilon}_{yy} n_x n_y & \bar{\epsilon}_{xx} n_y^2 - (\bar{\epsilon}_{xy} n_x n_y - \bar{\epsilon}_{yy} n_x n_y) + \bar{\epsilon}_{yy} n_x^2 \end{bmatrix}$$

Method 2:

$$\begin{bmatrix} -n_y & n_x \end{bmatrix} \begin{bmatrix} \bar{\epsilon}_{xx} & \bar{\epsilon}_{xy} \\ \bar{\epsilon}_{yx} & \bar{\epsilon}_{yy} \end{bmatrix} \begin{bmatrix} n_x \\ n_y \end{bmatrix} = \begin{cases} \bar{\epsilon}_{xx} n_x + \bar{\epsilon}_{xy} n_y \\ \bar{\epsilon}_{yx} n_x + \bar{\epsilon}_{yy} n_y \end{cases} = \bar{\epsilon}_{xx} n_x n_y - \bar{\epsilon}_{xy} n_y^2 + \dots \bar{\epsilon}_{yy} n_x^2 + \bar{\epsilon}_{yy} n_x n_y$$

Note: The above and the off. diagonals from 1 are exactly the same thus to get a shear stress tangent to a wall with normal \hat{n} we can use either method (by 2) is more computationally efficient.

$$\text{If } \bar{\epsilon}_{yx} = \bar{\epsilon}_{xy} \text{ the } \bar{\epsilon}_w = (n_y n_x)(-\bar{\epsilon}_{xx}) + \bar{\epsilon}_{xy}(n_x^2 - n_y^2) + \bar{\epsilon}_{yy} n_x n_y$$

Computing Coefficient of Friction:

Using the tensor Math. we can compute the Stress component tangential to the surface.

$$[A] = \begin{bmatrix} n_x & n_y \\ n_y & n_z \end{bmatrix}$$

$$\bar{\tau}_{\text{normal}} = [A]^T [\tau] [A] =$$

$$\begin{bmatrix} n_x & n_y \\ -n_y & n_z \end{bmatrix} \begin{bmatrix} \tau_{xx} & \tau_{xy} \\ \tau_{xy} & \tau_{yy} \end{bmatrix} \begin{bmatrix} n_x & n_y \\ n_y & n_z \end{bmatrix} =$$

$$\begin{bmatrix} n_x^2 \tau_{xx} + 2n_x n_y \tau_{xy} + n_y^2 \tau_{yy} & -n_x n_y \tau_{xx} + \tau_{xy}(n_x - n_y) + \tau_{yy} n_x n_y \\ -n_y n_x \tau_{xx} + \tau_{xy}(n_x^2 - n_y^2) + \tau_{yy} n_x n_y & \tau_{xx} n_y^2 - \tau_{xy} n_y n_z - \tau_{yy} n_x n_z + \tau_{yy} n_x^2 \end{bmatrix}$$

$\tau_w = \frac{\partial u}{\partial x}$
 $C_f \approx \frac{\tau_w}{b p \omega} \approx \frac{\text{Aspect Ratio}}{\text{Lc} \cdot \text{Reynolds Number}}$

$\bar{\mu} \frac{\partial u}{\partial x}$ Mod
 Lc, aspect ratio Mod

$F \frac{\bar{\mu} \frac{\partial u}{\partial x}}{2 \text{ Re } \cdot \text{ Mod}}$

Computing viscous lift forces.

1) Compute traction vector in cartesian coordinates

$$\begin{bmatrix} \tau_{xx} & \tau_{xy} \\ \tau_{xy} & \tau_{yy} \end{bmatrix} \begin{bmatrix} n_x \\ n_y \end{bmatrix} = \{S\} \text{ traction vector.}$$

$$S_x = (\tau_{xx} n_x + \tau_{xy} n_y)$$

$$S_y = (\tau_{xy} n_x + \tau_{yy} n_y)$$

Then we have to integrate these tractions over the surface

$$F_{xv} = \int S_x \, ds$$

$$F_{yv} = \int S_y \, ds$$

$$C_{xv} = \frac{F_{xv}}{\frac{1}{2} \rho \omega U^2 C_{ref}} = \frac{\mu \bar{\mu} \left(\frac{4}{3} \frac{\partial \bar{U}}{\partial x} - \frac{2}{3} \frac{\partial \bar{U}}{\partial S} + \frac{\partial \bar{U}}{\partial S} + \frac{\partial \bar{V}}{\partial T} \right) \frac{a \bar{x}}{L_{ref}}}{\frac{1}{2} \rho \omega U^2 a \bar{S} M \bar{R} \text{ Lcft Coef}}$$

$$= \frac{\bar{\mu}(c)}{k_2} \frac{\mu_{\text{ext}}}{g_{\text{ext}} \text{Mol Frct}} \frac{1}{\text{Mol Frct}} = \frac{\bar{\mu}(c)}{\frac{k_2}{2} R e \mu_{\text{ext}} \text{Mol Frct}}$$

Unsteady Solution using BDF2:

The formula has been derived previously and for

$$[\underline{M}] \frac{\partial \vec{g}}{\partial t} + R(\vec{g}) = 0 \quad \text{gives Note: Super script } n \text{ denotes time level } \Delta t.$$

$$\frac{[\underline{M}]}{\Delta t} \left(\frac{3}{2} \vec{g}^{n+1} - 2\vec{g}^n + \frac{1}{2} \vec{g}^{n-1} \right) + R(\vec{g}^{n+1}) = 0$$

This makes up the time accurate residual defined as $R_t(\vec{g}^{n+1}, \vec{g}^n, \vec{g}^{n-1}) = 0$

Thus our new non-linear problem is given as

$$R_t(\vec{g}^{n+1}, \vec{g}^n, \vec{g}^{n-1}) = 0$$

Application of Newton's Method

$$\left[\frac{\partial R_t}{\partial \vec{g}^{n+1}} \right] \vec{g}_{IK}^{n+1} = -R(\vec{g}_{IK}^{n+1}, \vec{g}^n, \vec{g}^{n-1})$$

where subscript IK denotes our Newton iteration index.

$$\frac{\partial R_t}{\partial \vec{g}^{n+1}_K} = \left(\frac{3}{2} \frac{[\underline{M}]}{\Delta t} + \left[\frac{\partial \vec{R}}{\partial \vec{g}^{n+1}_K} \right] - 0 + 0 \right)$$

The time accurate residual can further be broken up

$$\text{as } R(\vec{g}_K^{n+1}) + \frac{3}{2} \frac{[\underline{M}]}{\Delta t} (\vec{g}^{n+1}) + S(\vec{g}^n, \vec{g}^{n-1}) = R_t$$

where $S(\vec{g}^n, \vec{g}^{n-1})$ is a source term given by

$$\vec{S}(\vec{g}^n, \vec{g}^{n-1}) = -2 \frac{[\underline{M}]}{\Delta t} \vec{g}^n + \frac{[\underline{M}]}{2\Delta t} \vec{g}^{n-1}$$

Moving Mesh's - Ensuring conservation of gts over a time step

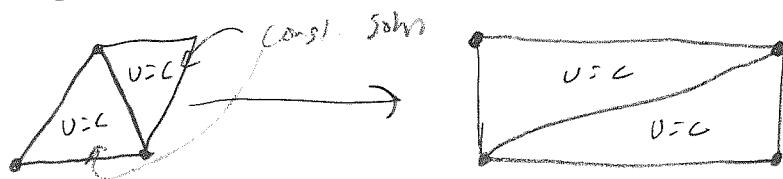
The GCL:

Start with the Euler Equations in moving coordinates

$$\frac{d(A\vec{v})}{dt} + \int_{B(t)} (\vec{F}(\vec{v}) - \vec{x}\vec{v}) \cdot \vec{n} dB = 0 \quad (1)$$

Say we go from,

where c is a uniform soln.



Insert in to (1)

$$\frac{dA\vec{v}}{dt} - \int_{B(t)} \vec{x}\vec{v} \cdot \vec{n} dB = 0$$

gives

$$\frac{dA}{dt} - \int_{B(t)} \vec{x} \cdot \vec{n} dB = 0 \quad - \text{This the GCL equation.}$$

For ODF1, \vec{V}_c

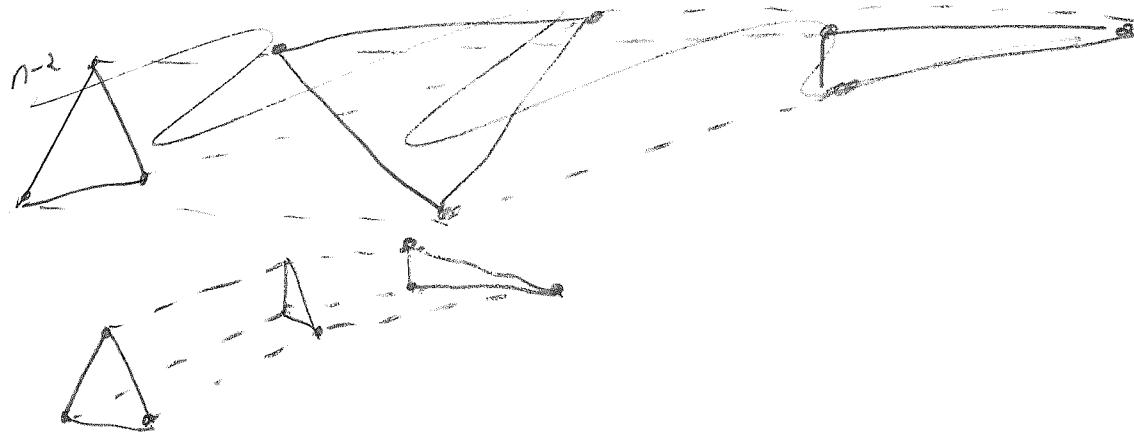
$$\frac{\vec{A}^n - \vec{A}^{n-1}}{\Delta t} = \int_{B(t)} \vec{x} \cdot \vec{n} dB - \text{solve for } V_c \approx$$

$$\frac{d(A\vec{v})}{dt} + \int_{B(t)} [\vec{F}(\vec{v}) \cdot \vec{n} - V_c \vec{U}] dB = 0 \quad \text{where } V_c \text{ is soln of}$$

To do this correctly GCL must be solved w.th
same temporal accuracy as the flow.

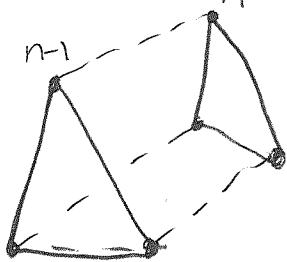
For BDF2

$$\frac{3}{2}A^n - \frac{2}{3}A^{n-1} + \frac{1}{6}A^{n-2} = \sum_{i=1}^3 \vec{V}_e \cdot \vec{B}_i = 0 \quad \int_{B(e)} \vec{x} \cdot \vec{B} d\Omega$$



$$= \frac{\gamma_1}{\Delta t} (A^n - A^{n-1}) + \frac{\gamma_2}{\Delta t} (A^{n-1} - A^{n-2}) =$$

$$= \frac{\gamma_1}{\Delta t} A^n + \left(\frac{\gamma_2 - \gamma_1}{\Delta t} \right) A^{n-1} - \frac{\gamma_2}{\Delta t} A^{n-2} - \text{watch } \cancel{\text{Gauss}}$$



$$(A^n - A^{n-1}) = \Delta t \cdot \sum_{i=1}^3 S_{e_i}^n /$$

$$(A^{n-1} - A^{n-2}) = \Delta t \cdot \sum_{i=1}^3 S_{e_i}^{n-1}$$

where S_{e_i} is area swept by edge e_i



$$= \frac{\delta_1}{\Delta t} \sum_{i=1}^3 S_i^{n-1} + \frac{\delta_2}{\Delta t} \sum_{i=1}^3 S_i^{n-1/n-2}$$

$$= \delta_1 \sum_{i=1}^3 \frac{S_i^{n-1}}{\Delta t} + \delta_2 \sum_{i=1}^3 \frac{S_i^{n-1/n-2}}{\Delta t}$$

Electromagnetics

Ref: E.J. Rothwell, M.J. Cloud, Electromagnetics, CRC Press, ①
Boca Raton, FL, 2009

1). Introduction

- Fundamental difference between the field point of view and mechanical point of view.

ME Mechanical says you can describe the system by the particle charges, position & momenta.

Field instead says the system is described by field variables \vec{E} , \vec{D} , \vec{B} , \vec{H} - the field point of view is the EM phenomena affect all space.

- Unlike charged particle Mechanics the field point of view like Fluid Mechanics is not represented by a finite set of state variables
 - e.g. for a Mechanical system of N particles you have $6N$ state vars.

- Field is described by functions of continuous variables.

- Field Theory description

- Need 2 types of fields

1). Mediating field generated by the source

2). Field describing the source itself.

- In free-space E, B are mediating field while source or current

- Fields are unobservable

- Need link to mechanics to observe

Lorentz force provides the link and allows us to observe the field.

- Constitutive Relations

- describe effect of supporting medium on field.

2) Sources of E-M field.

- We are interested in Macroscopic E-M thus we want the effects of sources given by continuous sources (e.g. charge + (current densities))
 - we know on a micro-scope level
 - 1). Charge is fundamental property of matter.
 - 2). charge is quantized (exists in discrete quantum amounts)
 - 3). Quantum is assoc to smallest sub-atomic part.
 - 4). Charge is invariant with speed (mass is not)
 - 5). Charge is the source of E-M field, field is entity that carry energy + momentum away from charge via propagating waves.

- For problems on our scale of interest, we can do an ~~an~~ averaging space as long as enough particles are in the laboratory size we can regard this as a continuum.

- Averaging

Need convenient weighting function.

Consider using gaussian.

$$f(\vec{r}) = (\pi a^2)^{-\frac{3}{2}} e^{-\vec{r}^2/a^2}$$

$$\int f(\vec{r}) dV = 1.$$

a- ~~out~~ averaging radius

for micro-scope quantity $\vec{F}(\vec{r}, t)$

$$\langle F(\vec{r}, t) \rangle = \int F(\vec{r} - \vec{r}', t) f(\vec{r}') dV' - \vec{r}' \text{ is origin.}$$

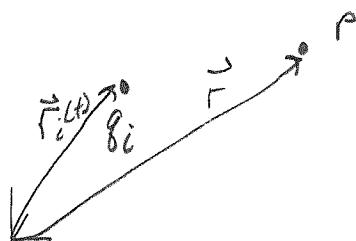
Where \vec{r}' - is some origin, and V' is volume surrounding that origin.

Macroscopic Volume charge density.

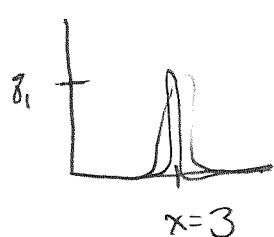
- We do not distinguish between "free" charge that is unattached to molecular structure, and the charge found near the surface of a conductor.
- Ignore dipole nature of polarizable materials.
- For "free-space" E-M assume charge has 3 DoF (volume charge) 2 DoF (surface " ") 1 DoF (line & ")
- Typically microscopic variations have length scale of 10^{-10} m.
 - for solids, liquids, dense gases. $a = 10^{-8}$ m is good contain $\sim 10^6$ particles \Rightarrow continuous

The volume density of charge can be written as

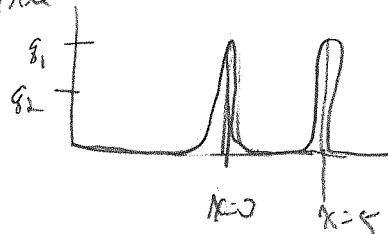
$$\rho(\vec{r}, t) = \sum_i q_i \delta(\vec{r} - \vec{r}_i(t)) \quad - \text{each of these is charge as point } i$$



In 1D, for $q_i : i = 1, r_1 = 3$.



for 2 particle



$$i=1, q_1, r_1=3$$

$$i=2, r_2=5,$$

This is a summed microscopic quantity. So we apply it
assume distribution and average.

$$\rho(\vec{r}, t) = \langle \rho_i(\vec{r}_i, t) \rangle = \int \sum_i g_i \delta(\vec{r} - \vec{r}_i) \cdot f(\vec{r}_i) dV_i$$

$$\rho(\vec{r}, t) = \sum_i g_i f(\vec{r} - \vec{r}_i(t))$$

Total charge in volume.

$$Q(t) = \int_V \rho(\vec{r}, t) dV = \int \sum_i g_i f(\vec{r} - \vec{r}_i(t)) dV =$$

$$\sum_i g_i \\ \vec{r}_i(t) \in V$$

~~Macro~~ Macroscopic Current Density

- charge in motion is called current.

$$\vec{v}_i(t) = \frac{d\vec{r}_i}{dt}$$

$$\vec{j}^o(\vec{r}, t) = \sum_i g_i \vec{v}_i(t) \delta(\vec{r} - \vec{r}_i(t))$$

Again apply ~~average~~ spatial averaging at time

t. - this eliminate uncorrelated motion on scale
at averaging radius

$$\vec{j}(\vec{r}, t) = \langle \vec{j}^o(\vec{r}, t) \rangle = \int \sum_i g_i \vec{v}_i(t) \delta(\vec{r} - \vec{r}_i(t)) f(r_{ave}) dV / V_{ave}$$

$$= \sum_i g_i \vec{v}_i(t) f(\vec{r} - \vec{r}_i(t))$$

- Assume sufficiently large a gives

$$\vec{j}(\vec{r}, t) = \rho(\vec{r}, t) \vec{v}(\vec{r}, t)$$

(5) Current flux $I(t)$

$$I(t) = \int_S \vec{J}(\vec{r}, t) \cdot \hat{n} dS = \sum_i g_i f_i(\vec{r}_i, t) \cdot \hat{n} \int_S f(\vec{r} - \vec{r}_i, t) dS$$

↓
deform
surface.

- Many types of current.

- each described by $\vec{J} = \rho \vec{v}$. Isolated charged particles in space give convection currents, Neg-charged particles in background are called conduction currents. Electrolytic are current, results from the flow of positive or negative ions through a fluid.

- \vec{J} Impressed vs. Secondary sources.

- this depends on action setting charge in motion.

- Impressed (or primary) are independent of the field they source.

- Secondary result from interactions between the source fields and the medium in which the field field exists.

Surface + Line Sources:

- Surface charge is a continuous volume charge,

distributed in a thin layer. If we assign the charge density in a cylinder on the surface as $\rho_s(\vec{r}, t)$ then we write the surface density as $\rho_s(\vec{r}, t)$

Then we write the volume charge is

$$\rho(\vec{r}, w, t) = \rho_s(r, e) \Delta w / \Delta S -$$

where Δ - thickness and w is the distance \perp to S inside cylinder.

The density function $f(x, \Delta)$

$$\int_{-\infty}^{\infty} f(x, \Delta) dx = 1 \quad \lim_{\Delta \rightarrow 0} f(x, \Delta) = \delta(x).$$

The take for example. $f(x, \Delta) = \frac{e^{-x^2/\Delta^2}}{\Delta \sqrt{\pi}}$

with this the total charge in a cylinder normal to the surface is

$$dQ(t) = \int_{-\infty}^{\infty} \rho_s(r, t) dS f(w, \Delta) dw + j_s(r, t) dS$$

$$\varphi(t) = \int_S \rho_s(\vec{r}, t) dS$$

The Line charge is similar see text.

Surface Current Density: Defined the same as charge.

$$\vec{j}(\vec{r}, w, t) = \vec{j}_s(\vec{r}, t) f(w, \Delta)$$

$$dI(t) = \int_{-\infty}^{\infty} [\vec{j}_s(\vec{r}, t) \cdot \hat{n}_E] dS f(w, \Delta) = j_s(r, t) \cdot \hat{n}_E(r) dS$$

This is the total current flowing through a strip of width $dr \perp S$ at \vec{r} .

Charge Conservation:

(7)

Net charge in any closed system remains the same with time.

- Essentially we are deriving a ctg equation for charge.

Using Reynolds transport

$$\frac{DQ}{Dt} = \frac{D}{Dt} \int_V \rho dV = \int_{V(t)} \frac{\partial \rho}{\partial t} dV + \oint_S \rho \vec{V} \cdot d\vec{S} = 0$$

$$= \int_V \frac{\partial \rho}{\partial t} dV + \oint_S \vec{j}(\vec{r}, t) dS = 0 \quad - \text{using divergence theorem}$$

$$= \int_V \frac{\partial \rho}{\partial t} + \vec{\nabla} \cdot \vec{j}(\vec{r}, t) dV = 0 \quad \text{gives}$$

$$\frac{\partial \rho}{\partial t} + \vec{\nabla} \cdot \vec{j}(\vec{r}, t) = 0$$

Ex. Using ctg

$$\text{given } \rho = \rho_0 r e^{-\beta t}$$

$$\frac{\partial}{\partial t} \int_V \rho dV = +\pi \int_V \rho_0 r e^{-\beta t} r^2 dr = -\oint_S \vec{J}_r \hat{n} \cdot d\vec{S}$$

$$\text{using calc text: } dS = r \sin\theta \, dr \, r \, d\phi$$

$$-\iint_S \vec{J}_r r^2 \sin\theta \, dr \, d\phi = \vec{J}_r a^2 \left(\frac{(-1 - 1)(+i)}{\cos(0i) \cdot \cos(0)} \right) = -4\pi a^2 \vec{J}_r (a)$$

$$4\pi \int_0^a -\rho_0 \beta r^3 e^{-\beta t} dr = 74\pi \beta \rho_0 \frac{a^4}{4} e^{-\beta t} = 18\pi \beta \rho_0 a^2$$

$$\vec{J}_r = \beta \rho_0 \frac{a^2}{4} e^{-\beta t} \quad a = r \text{ since}$$

$$\vec{j} = \epsilon \beta \rho_0 \frac{a^2}{4} e^{-\beta t}$$

$$\nabla \cdot \vec{J} = \frac{1}{r^2} \frac{\partial}{\partial r} (r^2 J_r) \cdot \cancel{\left(\frac{A r^8}{4} \beta \rho_0 r e^{-\beta t} \right)} = \beta \rho_0 r e^{-\beta t}$$

$$\vec{v} = \frac{\vec{J}}{S} = \frac{\cancel{\frac{\beta \rho_0}{4} r^2 e^{-\beta t}}}{\cancel{\rho_0 r e^{-\beta t}}} = \frac{\cancel{\beta r}}{\cancel{4}} = \vec{v}$$

$$\frac{\partial \rho}{\partial t} = -\beta \rho r e^{-\beta t} + \beta \rho r e^{-\beta t} = 0 \quad \checkmark \text{ this verifies conservation.}$$

Magnetic charges:

Created Magnetic fields are created only by time varying magnetic fields

- Elemental Source is magnetic dipole,
- So far we have found no magnet charge
- Even though these guys don't exist we will use them for convenience,

(9)

Maxwell's Equation (Minkowski)

$$\vec{\nabla} \times \vec{E}(\vec{x}, t) = -\frac{\partial}{\partial t} \vec{B}(\vec{x}, t) \quad - \text{Faraday's Law}$$

$$\vec{\nabla} \times \vec{H}(\vec{x}, t) = \vec{J}(\vec{x}, t) + \frac{\partial}{\partial t} (\vec{D}(\vec{x}, t)) \quad - \text{Ampere's Law}$$

$$\nabla \cdot \vec{B}(\vec{x}, t) = 0 \quad - \text{Gauss's Law}$$

$$\nabla \cdot \vec{D}(\vec{x}, t) = \rho(\vec{x}, t) \quad - \text{Gauss's Magnetic Law}$$

\vec{E} - Electric field - strength } Also use continuity equation

\vec{B} - Magnetic flux density } i.e. charge conservation

\vec{J} - current density

ρ - charge density

\vec{H} - magnetic field

\vec{D} - Electric Excitation

$$\frac{\partial \rho}{\partial t} + \vec{\nabla} \cdot \vec{J} = 0$$

Inter dependance:

$$\vec{\nabla} \cdot (\vec{\nabla} \times \vec{E}) = \vec{\nabla} \cdot \left(-\frac{\partial \vec{B}}{\partial t} \right)$$

$$\text{Recall that } \vec{\nabla} \cdot (\vec{\nabla} \times \vec{E}) = 0 \quad \text{Divergence of curl} = 0$$

$$\frac{\partial}{\partial t} (\vec{\nabla} \cdot \vec{B}) = 0 \quad - \text{I.P. rate of change of divergence in time} = 0$$

$$\text{Thus } \vec{\nabla} \cdot \vec{B} = C_B(\vec{x}) \quad - \text{i.e. the divergence } \vec{B} \text{ is only}$$

a function of space.

We choose $C_B(\vec{x}) = 0$ gives

$$\vec{\nabla} \cdot \vec{B} = 0$$

Similar work can be done on Ampere's law to get,

$$\vec{\nabla} \cdot (\vec{\nabla} \times \vec{H}) = \vec{\nabla} \cdot \vec{J} + \frac{\partial}{\partial t} (\vec{D}) \quad \text{gives}$$

$$\downarrow \quad = -\frac{\partial \rho}{\partial t} + \vec{\nabla} \cdot \frac{\partial}{\partial t} (\vec{J}) = \frac{\partial}{\partial t} (\rho - \vec{\nabla} \cdot \vec{J}) = 0$$

I.e. $\rho \cdot \vec{J} \cdot \vec{D} = C_D$ take $C_D = 0$ gives

$$\vec{J} \cdot \vec{D} = \rho$$

If we can define a time prior to which C_B and C_D are both = to zero then the setting of $(C_B, C_D = 0)$ is perfectly valid because the $(C_B, C_D > 0)$ is not changing in time. We will regard this setting as initial conditions for Ampere's Law and Faraday's Law.

Constitutive Relations:

To close the system a set of constitutive relations must be applied.

- Relations split: 1) for the EM field only + the others for mechanical interaction between sources + fields

- Involve - parameters + operators.

- If the relations involve time derivative of integrals the medium is temporally dispersive.

Many types of Materials - see Pg. 28 for description

General form,

$$\left. \begin{aligned} \vec{D} &= \vec{D}[\vec{E}, \vec{B}] \\ \vec{H} &= \vec{H}[\vec{E}, \vec{B}] \end{aligned} \right\} \text{ i.e. these are related to } \vec{E}, \vec{B} \text{ in some mathematical way.}$$

For now we will restrict ourselves to linear isotropic media.

$$\text{i.e. } \vec{D} = \epsilon \vec{E}, \vec{B} = \mu \vec{H}$$

$$\text{For conducting Media } \vec{J} = \sigma \vec{E}$$

For a Vacuum we have ϵ_0 - permittivity of free space
 μ_0 - permeability of free space.

Thus for linear isotropic Media we will define our
 ϵ, μ as $\epsilon = \epsilon_r \epsilon_0$ $\mu = \mu_r \mu_0$ - i.e. relative
permittivity and permeability.

Recall. $c = \frac{1}{(\mu_0 \epsilon_0)^{1/2}}$ Dimensionless.

$$\mu_0 = 4\pi \times 10^{-7} \text{ T/m}$$

$$\epsilon_0 = 8.854 \times 10^{-12} \text{ F/m}$$

For Now this is all we need for Maxwell's Equations
constitutive relations.

Solving Linear Maxwell's Equation:

() Maxwell's Equations

$$\left. \begin{aligned} \vec{\nabla} \times \vec{E} &= -\frac{\partial}{\partial t} (\vec{B}) \\ \vec{\nabla} \times \vec{H} &= \vec{J} + \frac{\partial}{\partial t} (\vec{D}) \end{aligned} \right\} \text{with consistency condition}$$

$$\vec{\nabla} \cdot \vec{B} = 0$$

$$\vec{\nabla} \cdot \vec{D} = \rho$$

charge conservation

$$\frac{\partial \rho}{\partial t} + \vec{\nabla} \cdot \vec{J} = 0$$

for Linear isotropic materials we can write the following constitutive relations.

$$\vec{D} = \epsilon \vec{E}, \quad \vec{B} = \mu \vec{H} \quad \text{with Ohms law} \quad \vec{J} = \sigma \vec{E}$$

$$\left. \begin{aligned} \vec{\nabla} \times \vec{E} &= -\frac{\partial}{\partial t} (\vec{B}) \\ \vec{\nabla} \times (\frac{1}{\mu} \vec{B}) &= \vec{J} + \frac{\partial}{\partial t} (\epsilon \vec{E}) \end{aligned} \right\} \text{or} \quad \textcircled{1}$$

$$\left. \begin{aligned} \vec{\nabla} \times \vec{E} &= -\frac{\partial}{\partial t} (\vec{B}) \\ \vec{\nabla} \times \vec{B} &= \mu \vec{J} + \epsilon \mu \frac{\partial}{\partial t} (\vec{E}) \end{aligned} \right\} \text{Second form } \textcircled{1}$$

Alternatively we can rewrite this for \vec{E}, \vec{H} ala, Hesthaven + Warburton,

$$\left. \begin{aligned} \vec{\nabla} \times \vec{E} &= -\frac{\partial}{\partial t} (\mu \vec{H}) \\ \vec{\nabla} \times \vec{H} &= \vec{J} + \frac{\partial}{\partial t} (\epsilon \vec{E}) \end{aligned} \right\}$$

Using Ohms Law.

$$\left. \begin{aligned} \vec{\nabla} \times \vec{E} &= -\frac{\partial}{\partial t} (\mu \vec{H}) \\ \vec{\nabla} \times \vec{H} &= \sigma \vec{E} + \frac{\partial}{\partial t} (\epsilon \vec{E}) \end{aligned} \right\} \quad \textcircled{3}$$

- We prefer this form or we solve for magnetic field \vec{H} .

We will work with ③ ~~also~~

Introducing our relative permittivity and permeability give

$$\vec{\nabla} \times \vec{E} = -\mu_r \mu_0 \frac{\partial}{\partial t} (\vec{H})$$

$$\vec{\nabla} \times \vec{H} = \vec{J} + \epsilon_r \epsilon_0 \frac{\partial}{\partial t} (\vec{E})$$

Non Dimensionalization.

$$\vec{E}^* = \frac{\vec{E}}{E_0}, \quad \vec{H}^* = \frac{\vec{H}}{H_0}, \quad \vec{J}^* = \frac{\vec{J}}{J_0}$$

$$x^* = \frac{x}{L_{\text{rot}}} \quad T = \frac{t}{L_{\text{rot}}/C_0}$$

As usual we won't be able to specify E_0, H_0, J_0 explicitly.

With out introducing extra N/D groups, rather we will seek to get $E_0(H_0, \mu_0, \epsilon_0)$.

$$\frac{E_0}{L_{\text{rot}}} \vec{\nabla}^* \vec{E}^* = -\mu_r \mu_0 \frac{H_0}{L_{\text{rot}}} \frac{\partial}{\partial t} (\vec{H}^*) \Rightarrow E_0 = \mu_0 C_0 H_0 = \frac{\mu_0}{\sqrt{\mu_0 \epsilon_0}} H_0 = \sqrt{\frac{\mu_0}{\epsilon_0}} H_0$$

define $\sqrt{\frac{\mu_0}{\epsilon_0}} = Z_0$ give $E_0 = Z_0 H_0$ gives

$$\vec{E}^* = \frac{\vec{E}}{Z_0 H_0} \quad \text{thus our N/D equations}$$

$$\vec{\nabla}^* \vec{E}^* = -\mu_r \frac{\partial}{\partial t} (\vec{H}^*)$$

$$\frac{H_0}{L_{\text{rot}}} \vec{\nabla} \times \vec{H} = \frac{J_0 \vec{J}^*}{L_{\text{rot}}} + \epsilon_r \epsilon_0 Z_0 \frac{H_0}{L_{\text{rot}}} \frac{\partial}{\partial t} (\vec{E}^*)$$

$$\vec{\nabla}^* \vec{H}^* = L_{\text{rot}} \frac{J_0}{H_0} \vec{J}^* + \epsilon_r \epsilon_0 \sqrt{\frac{H_0}{\epsilon_0}} \cdot \sqrt{\frac{H_0}{\mu_0}} \frac{1}{L_{\text{rot}}} \frac{\partial}{\partial t} (\vec{E}^*)$$

$$J_0 = \frac{H_0}{L_{\text{rot}}} \quad \text{give } \vec{J}^* = \boxed{\frac{\vec{J} L_{\text{rot}}}{H_0}}$$

$$\vec{\nabla}^* \vec{H}^* = \vec{J}^* + \epsilon_r \frac{\partial}{\partial t} (\vec{E}^*)$$

Thus Dropping the $(\cdot)^*$ Notation Maxwell's Equations Become,

$$\vec{\nabla} \times \vec{E} = -\mu_r \frac{\partial}{\partial t} (\vec{H})$$

$$\vec{\nabla} \times \vec{H} = \vec{J} + \epsilon_r \frac{\partial}{\partial t} (\vec{E})$$

thus law $\vec{J}^* = \vec{\sigma} \vec{E}^*$, $\vec{J} = \vec{\sigma} \vec{E}$
Drop \vec{J}^*

Now we should Reconsider writing these equations
in some kind of Divergence form.

It can be shown that $\vec{\nabla} \times \vec{E} = -\vec{\nabla} \cdot (\vec{e}_i \times \vec{E})_{i=1,2,3}$

Thus gives,

$$\epsilon_r \frac{\partial}{\partial t} (\vec{E}) - \vec{\nabla} \times \vec{H} = \vec{J} = \epsilon_r \frac{\partial}{\partial t} (\vec{E}) + \vec{\nabla} \cdot (\vec{e}_i \times \vec{H})_{i=1,2,3} = 0$$

$$\mu_r \frac{\partial \vec{H}}{\partial t} + \vec{\nabla} \times \vec{E} = 0 = \mu_r \frac{\partial \vec{H}}{\partial t} - \vec{\nabla} \cdot (\vec{e}_i \times \vec{E})_{i=1,2,3}$$

This can be verified as follows. But

- we will do it only for $\epsilon_r \frac{\partial}{\partial t} (\vec{E}) - \vec{\nabla} \times \vec{H} = \vec{J}$

$$\epsilon_r \frac{\partial}{\partial t} (E_x) - \underbrace{\frac{\partial H_z}{\partial y} + \frac{\partial H_y}{\partial z}}_{\sim \vec{\nabla} \times \vec{H}(1)} = J_x$$

$$\epsilon_r \frac{\partial}{\partial t} (E_y) + \frac{\partial H_z}{\partial x} - \frac{\partial H_x}{\partial z} = J_y$$

$$\epsilon_r \frac{\partial}{\partial t} (E_z) - \frac{\partial H_y}{\partial x} + \frac{\partial H_x}{\partial y} = J_z$$

$$\begin{vmatrix} i & j & k \\ 1 & 0 & 0 \\ H_x & H_y & H_z \end{vmatrix} = 0\hat{i} - H_z\hat{j} + H_y\hat{k} \Rightarrow \vec{\nabla} \cdot (\vec{e}_i \times \vec{H}) = -\vec{\nabla} \times \vec{H}_i$$

Thus we can write Maxwell's as

$$\frac{\partial}{\partial t} (\vec{g}) + \nabla \cdot \vec{F}(\vec{g}) = S$$

$$g = \left\{ \begin{array}{l} \vec{H} \\ \epsilon_r \vec{E} \end{array} \right\}, F_i = \left\{ \begin{array}{l} (-\vec{e}_i \times \vec{E})_{i=1,2,3} \\ (\vec{e}_i \times \vec{H}) \end{array} \right\}$$

Using this form of Maxwell's Equations

we have,

$$\frac{\partial \vec{E}}{\partial t} + \nabla \cdot \vec{F}(\vec{E}) = \vec{S}$$

For 2D problems we have, 2 form TM, TG polaris

TM, H_x, H_y, E_z all else zero

TE, E_x, E_y, H_z all else zero.

TM:

$$\mu_r \frac{\partial H^x}{\partial z} + \frac{\partial E_z}{\partial y} = 0$$

$$\mu_r \frac{\partial H^y}{\partial z} + \frac{\partial E_z}{\partial x} = 0$$

$$\epsilon_r \frac{\partial E_z}{\partial z} - \frac{\partial H^y}{\partial x} + \frac{\partial H_x}{\partial y} = J_z \sim \sigma E_z \quad \text{using Ohm's Law}$$

$$\vec{F}_{TM} = \left\{ \begin{array}{l} (0, E_z) \\ (-E_z, 0) \\ (-H_y, H_x) \end{array} \right\} \quad S_{TM} = \left\{ \begin{array}{l} 0 \\ 0 \\ J_z \end{array} \right\}$$

TE:

$$\mu_r \frac{\partial H_z}{\partial z} + \frac{\partial E_y}{\partial x} - \frac{\partial E_x}{\partial y} = 0$$

$$\epsilon_r \frac{\partial E_x}{\partial z} - \frac{\partial H_z}{\partial y} = J_x$$

$$\epsilon_r \frac{\partial E_y}{\partial z} + \frac{\partial H_z}{\partial x} = J_y$$

$$\vec{F}_{TE} = \left\{ \begin{array}{l} (E_y, -E_x) \\ (0, -H_z) \\ (H_z, 0) \end{array} \right\}$$

$$S_{TE} = \left\{ \begin{array}{l} 0 \\ J_x \\ J_y \end{array} \right\}$$

DG Formulation for TMI: Maxwell's:

$$\frac{\partial(\vec{\phi})}{\partial t} + \nabla \cdot \vec{F}_{TM} = \vec{s}$$

Begin by $\langle \phi_i(t) \rangle = 0$

$$\int_{\Omega_e} \phi_i \frac{\partial(\vec{\phi})}{\partial t} d\Omega_e + \int_{\Omega_e} \nabla \cdot \vec{F}_{TM} \phi_i d\Omega_e - \int_{\Omega_e} \vec{s} \cdot \phi_i d\Omega_e = 0$$

For one element i we have.

$$\int_{\Omega_e} \phi_i \frac{\partial(\vec{\phi})}{\partial t} d\Omega_e + \int_{\Omega_e} \nabla \cdot \vec{F}_{TM} \phi_i d\Omega_e = \int_{\Omega_e} \vec{s} \cdot \phi_i d\Omega_e$$

Do integration by parts on second term

$$\int_{\Omega_e} \phi_i \frac{\partial(\vec{\phi})}{\partial t} d\Omega_e - \int_{\Omega_e} \vec{\nabla} \phi_i \cdot \vec{F}_{TM} d\Omega_e + \oint_{\partial\Omega_e} \phi_i \vec{F}_{TM} \cdot \hat{n} ds = \int_{\Omega_e} \vec{s} \cdot \phi_i d\Omega_e$$

Time term. Volume Resid. Surface Resid.

$$\text{Introduce } \vec{\phi} = \sum_j \hat{\phi}_j \phi_j = \vec{\phi}_s$$

$$\vec{\phi} = [\vec{\phi}] \{ \hat{\phi}_j \} \quad [\vec{\phi}] = \begin{bmatrix} 0 & 0 & \dots & 0 \\ 0 & 0 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & 0 \end{bmatrix} \quad \{ \hat{\phi}_j \} = \begin{cases} \text{Interior} \\ \text{Boundary} \end{cases}$$

$$\int_{\Omega_e} \phi_i [\vec{\phi}] d\Omega_e \cdot \frac{\partial \{ \hat{\phi}_j \}}{\partial t} - \int_{\Omega_e} \vec{\nabla} \phi_i \cdot \vec{F}_{TM} (\{ \hat{\phi}_j \} \vec{\phi}_s) +$$

$[M]$

$$\oint_{\partial\Omega_e} \vec{F}_{TM} (\{ \hat{\phi}_j \} \vec{\phi}_s) \cdot \hat{n} ds = \int_{\Omega_e} \vec{s} \cdot \phi_i d\Omega_e$$

SR ST

Mass Matrix: This has been done previously and we have for the Euler and Navier-Stokes equations given a computation + storage and implementation scheme.

Volume Residual:

$$\int_{\Omega_e} \vec{\nabla} \cdot \phi_i \cdot \vec{F}_{\text{Int}}(\tilde{\vec{g}}) \, d\Omega_e.$$

Here for each ϕ_i we should have a vector of size 3.

Thus for a ϕ_i we get

$$\int_{\Omega_e^{\text{Standard/tri/gquad}}} \left(\frac{\partial \phi_i}{\partial x}, \frac{\partial \phi_i}{\partial y} \right) \cdot \begin{cases} (0, E_Z) \\ (-E_Z, 0) \\ (-H_Y, H_X) \end{cases} \, d\Omega_e^{\text{Standard}}, \text{ for}$$

Using Quadrature.

$$R_V \{ \cdot \} = \sum_{K=1}^{N_{GP}} \left\{ \begin{array}{l} \frac{\partial \phi_i}{\partial y} \cdot E_Z \\ -\frac{\partial \phi_i}{\partial x} \cdot E_Z \\ -\frac{\partial \phi_i}{\partial x} H_Y + \frac{\partial \phi_i}{\partial y} H_X \end{array} \right\} w(K) \text{Det}_J(\xi_K, \eta_K)$$

$\xi_K, \eta_K = \xi_K, \eta_K$

Further we will bring in the μ_r, ϵ_r to the flux as

$$R_V \{ \cdot \} = \sum_{K=1}^{N_{GP}} \left\{ \begin{array}{l} \frac{\partial \phi_i}{\partial y} \cdot E_Z \frac{1}{\mu_r} \\ -\frac{\partial \phi_i}{\partial x} \cdot E_Z \frac{1}{\mu_r} \\ -\frac{\partial \phi_i}{\partial x} \frac{H_Y}{\epsilon_r} + \frac{\partial \phi_i}{\partial y} \frac{H_X}{\epsilon_r} \end{array} \right\} w(K) \text{Det}_J(\xi_K, \eta_K)$$

$\xi_K, \eta_K = \xi_K, \eta_K$

Surface Residual.

$$\oint \phi_i \vec{F}_M \cdot \hat{n} ds :$$

We Since we have discontinuous basis functions there is the usual ambiguity. Thus for a face we have

$$\int \phi_i \vec{F}_M^* ds \approx \sum_{K=1}^{N_{GP}} \phi_i|_{S_K} \vec{F}^*(\vec{\theta}_L, \vec{\theta}_R)|_{S_K} w(K) \text{ Det} J_{\text{face}}$$

The only ? is what do we do for a numerical flux

\vec{F}^* = numerical flux, for maxwell's equation.

To derive a numerical flux function the first thing that we need is the eigen values. recall that we have the normal flux vectors \vec{A} as

$$\vec{E}_{\vec{n}} = \left\{ \begin{array}{l} \frac{E_x \hat{n}_y}{\mu_r} \\ \frac{-E_z \hat{n}_x}{\mu_r} \\ -H_x \frac{\hat{n}_z}{\epsilon_r} + H_z \frac{\hat{n}_x}{\epsilon_r} \end{array} \right\} \quad \text{which can be written as}$$

$$= \begin{bmatrix} 0 & 0 & \frac{\hat{n}_y \mu_r}{\epsilon_r} \\ 0 & 0 & -\frac{\hat{n}_x}{\mu_r} \\ \frac{\hat{n}_y}{\epsilon_r} & -\frac{\hat{n}_x}{\epsilon_r} & 0 \end{bmatrix} \begin{Bmatrix} H_x \\ H_y \\ E_z \end{Bmatrix} = [\hat{A}] \{ \vec{g} \}$$

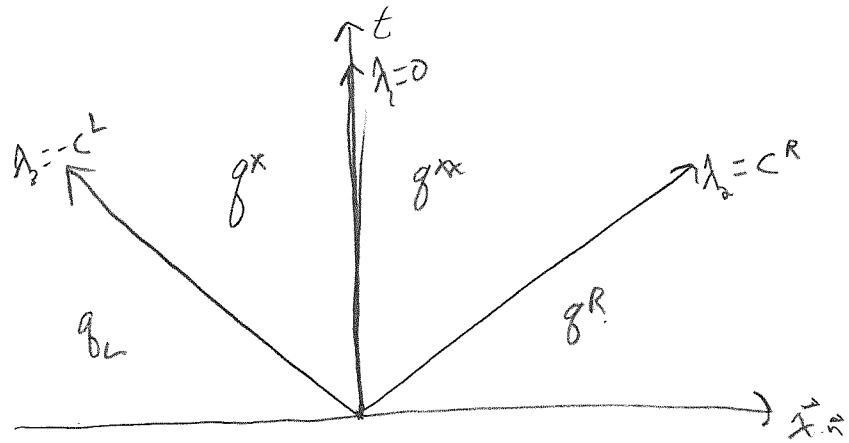
The eigen values of $[\hat{A}]$ are

$$|\lambda I - \hat{A}| = \begin{vmatrix} \lambda & 0 & -\frac{\hat{n}_y \mu_r}{\epsilon_r} \\ 0 & \lambda & \frac{\hat{n}_x}{\mu_r} \\ -\frac{\hat{n}_y}{\epsilon_r} & \frac{\hat{n}_x}{\epsilon_r} & \lambda \end{vmatrix} = \lambda \left(\lambda^2 - \frac{\hat{n}_x^2}{\epsilon_r \mu_r} \right) - \frac{\hat{n}_y^2}{\mu_r} \left(\frac{\hat{n}_x}{\epsilon_r} \lambda \right) = 0$$

$$\lambda \left(\lambda^2 - \frac{1}{\epsilon_r \mu_r} \right) = 0 \quad \lambda_1 = 0, \lambda_2 = c, \lambda_3 = -c$$

$$\lambda^2 = \frac{1}{\epsilon_r \mu_r} = c^2$$

The wave Diagram



We can apply the Rankine-Hugoniot jump conditions.

$$\lambda=0: -\partial(g^* - g^{**}) + (F(g^*) - F(g^{**})) = 0$$

$$\lambda=c: -c(g^{**} - g_R) + [F(g^{**}) - F(g^R)] = 0$$

$$\lambda=c: -[c(g^* - g^L)] + [F(g^L) - F(g^*)] = 0$$

$$= -c(g^* - g^L) - [F(g^*) - F(g^L)] = 0$$

$$= c(g^* - g^L) + [F(g^*) - F(g^L)] = 0$$

We note that across the contact discontinuity wave $F(g^*) = F(g^{**})$
gives a system of equations for $F(g^*)$ and g^*, g^{**}

The 1st equation:

$$F(g^*) - F(g^{**}) = 0 \Rightarrow F(g^{**}) = F(g^*) \text{ since } c$$

$$F(g) = \hat{A}g \text{ the } \hat{A}g^* = \hat{A}g^{**} \Rightarrow g^* = g^{**} \text{ for}$$

linear problems

Using Maple

$$F(g^*) = F(g)^* = \frac{c_R c_L g_L + c_R F_L - c_R c_L g_R + F_R c_L}{(c_L + c_R)}$$

which can be re-written as

$$\frac{c_R F_L + c_L F_R + c_R c_L (g_L - g_R)}{(c_L + c_R)}$$

Special Case $C_L = C_R$ (contains the const. medium)

$$\frac{\partial (F_L + F_R)}{\partial \hat{r}} + \frac{\partial (E_L - E_R)}{\partial \hat{r}} = k_2 (F_L + F_R) + C(E_L - E_R) \text{ which}$$

is the L-F type flux, which is exact for linear problem.

$$F_{TM}^* = \frac{1}{2} \left(\left\{ \begin{array}{l} \frac{E_x^L \hat{n}_y}{\mu r} \\ -\frac{E_x^L \hat{n}_x}{\mu r} \\ -\frac{H_y^L \hat{n}_x}{\mu r} + \frac{H_x^L \cdot \hat{n}_y}{\epsilon r} \end{array} \right\} + \left\{ \begin{array}{l} \frac{E_x^R \hat{n}_y}{\mu r} \\ -\frac{E_x^R \hat{n}_x}{\mu r} \\ -\frac{H_y^R \hat{n}_x}{\epsilon r} + \frac{H_x^R \cdot \hat{n}_y}{\epsilon r} \end{array} \right\} \right) + \frac{1}{2} \left\{ \begin{array}{l} H_x^L - H_x^R \\ H_y^L - H_y^R \\ E_x^L - E_x^R \end{array} \right\}$$

Note: B.C. will be enforced weakly as usual.

Linearization:

$$\frac{\partial F_{TM}^*}{\partial \hat{r}_c} = \begin{bmatrix} \frac{1}{2} C & 0 & \frac{1}{2} \frac{\hat{n}_y}{\mu r} \\ 0 & \frac{1}{2} C & -\frac{1}{2} \frac{\hat{n}_x}{\mu r} \\ \frac{1}{2} \frac{\hat{n}_y}{\epsilon r} & -\frac{1}{2} \frac{\hat{n}_x}{\epsilon r} & \frac{1}{2} C \end{bmatrix}$$

$$\frac{\partial F_{TM}^*}{\partial \hat{r}_R} = \begin{bmatrix} -\frac{1}{2} C & 0 & \frac{1}{2} \frac{\hat{n}_y}{\mu r} \\ 0 & -\frac{1}{2} C & -\frac{1}{2} \frac{\hat{n}_x}{\mu r} \\ \frac{1}{2} \frac{\hat{n}_y}{\epsilon r} & -\frac{1}{2} \frac{\hat{n}_x}{\epsilon r} & -\frac{1}{2} C \end{bmatrix}$$

$$\frac{\partial p}{\partial t} + p_0$$

$$\frac{\partial v_3}{\partial t}$$

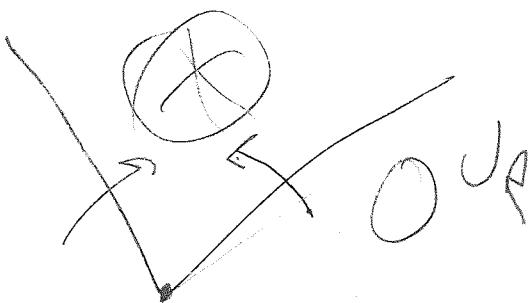
$$[X]\{w\}$$

$$[X]^{-1}\{w\} = \{w\}$$

$$\{w\} = \begin{bmatrix} w_1 \\ w_2 \end{bmatrix} \quad \begin{bmatrix} p_0 & p_0 \\ -a & a \end{bmatrix} \begin{bmatrix} w_1 \\ w_2 \end{bmatrix} = \begin{bmatrix} p_0 w_1 + p_0 w_2 \\ -a w_1 + a w_2 \end{bmatrix} = \begin{bmatrix} p_0 \\ 0 \end{bmatrix} + \begin{bmatrix} p_0 \\ -a \end{bmatrix} \begin{bmatrix} w_1 \\ w_2 \end{bmatrix}$$

$$\begin{bmatrix} \frac{L}{2p_0} & -\frac{L}{2a} \\ + & \frac{1}{2a} \end{bmatrix} \begin{bmatrix} p_L \\ v_L \end{bmatrix} = \begin{bmatrix} p_L \\ v_L \end{bmatrix} = \begin{bmatrix} \frac{p_L}{2p_0} - \frac{v_L}{2a} \\ \frac{p_L}{2a} + \frac{v_L}{2a} \end{bmatrix}$$

$$\frac{p_0 s}{2p_0} - \frac{v}{2a} p_0 + \frac{p_0 s}{2a} + \frac{v}{2a} p_0 = s$$



$$\nabla \cdot \vec{\mu}^H =$$

Scattered field TM Maxwell's Equations

$$\vec{E} = \vec{E}^i + \vec{E}^s, \quad \vec{H} = \vec{H}^i + \vec{H}^s$$

regarding \vec{E}^i a particular solution to Maxwell's equations

$$\mu_r \frac{\partial H_x^i}{\partial t} + \frac{\partial E_z^i}{\partial y} = 0$$

$$\mu_r \frac{\partial H_y^i}{\partial z} - \frac{\partial E_x^i}{\partial x} = 0$$

$$\epsilon_r \frac{\partial E_x^i}{\partial t} - \frac{\partial H_y^i}{\partial x} + \frac{\partial H_x^i}{\partial z} = 0$$

The total formulation is given as

$$\mu_r \frac{\partial H_x^i}{\partial t} + \mu_r \frac{\partial H_x^s}{\partial z} + \frac{\partial E_z^i}{\partial y} + \frac{\partial E_z^s}{\partial y} = 0 \rightarrow$$

using $\frac{\partial E_z^i}{\partial y} = -\mu_r \frac{\partial H_x^i}{\partial t}$ gives

$$\boxed{\mu_r \frac{\partial H_x^s}{\partial t} + (\mu_r - \mu_r^i) \frac{\partial H_x^i}{\partial t} + \frac{\partial E_z^s}{\partial y} = 0}$$

$$\mu_r \frac{\partial H_y^s}{\partial z} + \mu_r \frac{\partial H_y^i}{\partial z} - \frac{\partial E_x^i}{\partial x} - \frac{\partial E_x^s}{\partial x} = 0$$

using $\frac{\partial E_x^i}{\partial x} = \mu_r^i \frac{\partial H_y^i}{\partial z}$ gives

$$\boxed{\mu_r \frac{\partial H_y^s}{\partial z} + (\mu_r - \mu_r^i) \frac{\partial H_y^i}{\partial z} - \frac{\partial E_x^s}{\partial x} = 0}$$

$$\epsilon_r \frac{\partial E_y^s}{\partial z} + \epsilon_r \frac{\partial E_y^i}{\partial z} = \frac{\partial H_x^i}{\partial x} - \frac{\partial H_x^s}{\partial y} + \frac{\partial H_x^s}{\partial z} + \frac{\partial H_x^i}{\partial y} = 0$$

using $-\epsilon_r^i \frac{\partial E_y^i}{\partial z} = -\frac{\partial H_x^i}{\partial y} + \frac{\partial H_x^i}{\partial z}$ gives

$$\boxed{\epsilon_r \frac{\partial E_y^s}{\partial z} + (\epsilon_r - \epsilon_r^i) \frac{\partial E_y^i}{\partial z} - \frac{\partial H_x^s}{\partial z} + \frac{\partial H_x^s}{\partial y} = 0}$$

Scattered B.C. on solid metallic surface.

Recall to set $E_z = 0$ on a metallic boundary we have

$$E_z^R = -E_z^S \quad \text{using scattered field formulation}$$

we have

$$E_z^{iR} + E_z^{sR} = -E_z^{iL} - E_z^{sL} =$$

We seek E_z^{sR} , $E_z^{iR} = E_z^{iL}$. This is known since

$$\boxed{E_z^{sR} = -2E_z^{iL} - E_z^{sL}} \quad \text{this is our new B.C.}$$

for scattering. Note we will project E_z^i to the nodes at every time step.

Also note that this is the only mode

by which scattering enters the equations for a vacuum medium illuminating a vacuum medium.

Linearizations:

Volume Resid.:

$$F = \begin{Bmatrix} 0 \\ -\frac{\bar{E}_z}{\mu_r} \\ -\frac{H_y}{\bar{k}_r} \end{Bmatrix}, \quad g = \begin{Bmatrix} \frac{\bar{E}_z}{\mu_r} \\ 0 \\ \frac{H_y}{\bar{k}_r} \end{Bmatrix}$$

$$\frac{\partial E}{\partial g} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & -\frac{1}{\mu_r} \\ 0 & -\frac{1}{\bar{k}_r} & 0 \end{bmatrix}$$

$$\frac{\partial G}{\partial g} = \begin{bmatrix} 0 & 0 & \frac{1}{\mu_r} \\ 0 & 0 & 0 \\ \frac{1}{\bar{k}_r} & 0 & 0 \end{bmatrix}$$

Plane wave solutions.

$$\phi = \phi_0 e^{-i \vec{k}(\omega) \cdot (\vec{x} + \vec{y})}$$

\vec{k} is the wave vector i.e

$$k_x = \omega \cos(\theta) \hat{x} + \cancel{\sin(\theta) \hat{y}}$$

$$k_y = \omega \sin(\theta)$$

$$\text{Re}(\phi) = \text{Re} \left(\phi_0 [\cos(\vec{k} \cdot \vec{r}) - i \sin(\vec{k} \cdot \vec{r})] \right) =$$

$$= \phi_0 \cos(\omega \cos \theta \cdot x + \omega \sin \theta \cdot y)$$

We need to figure out how to analyze this as a radar type wave.

Boundary Conditions:

For any Boundary in Maxwell's equations we require continuity in the tangential ~~the~~ components of the fields

$\hat{n} \times (\vec{E}_1 - \vec{E}_2) = 0$, $\hat{n} \times (\vec{H}_1 - \vec{H}_2) = 0$. Also the normal fluxes must be equal to the surface charge or current densities i.e.

$$\hat{n} \cdot (\vec{B}_1 - \vec{B}_2) = J_S, \quad \hat{n} \cdot (\vec{D}_1 - \vec{D}_2) = P_S.$$

In the case of a perfectly conducting Boundary i.e. a "solid" surface of metal. It has no surface charges. But the fields cannot penetrate the Boundary,

For general materials we have

$$\hat{n} \times (\vec{E}_1 - \vec{E}_2) = 0, \quad \hat{n} \times (\vec{H}_1 - \vec{H}_2) = 0$$

$$\hat{n} \cdot (\vec{B}_1 - \vec{B}_2) = 0, \quad \hat{n} \cdot (\vec{D}_1 - \vec{D}_2) = P_S$$

This is because they support No surface charges or currents

This express

- 1). Continuity of tangential field components
- 2). Continuity of Normal fluxes as
- 3). discontinuity of Normal field

For a perfect's conducting Surface in 2D TM region

$$\hat{n} \times \vec{E} = 0$$

$$\mu_0 \hat{n} \cdot \vec{H} = 0 \quad \text{why?}$$

$$\hat{n} \times \vec{E} = \begin{vmatrix} \hat{i} & \hat{j} & \hat{k} \\ n_x & n_y & 0 \\ 0 & 0 & E_z \end{vmatrix} = 0\hat{i} - (n_y)E_z\hat{j} + 0\hat{k} = 0 \Rightarrow E_z = 0 \text{ on Boundary.}$$

i.e. E_z is diachar B.C. set $E_z = -E_{z0}$

For $\vec{n} \cdot \vec{H} = 0$, we simply have the mirror condition.

Thus for perfectly conducting surface (i.e. BC type = 2)
we have, for the ghost cell values,

$$E_{Zg} = -E_Z$$

$$H_{Xg} = H_X - \alpha n_X (H_X n_X + H_Y n_Y) \quad \left. \right\} \text{Same as veloci in CFD.}$$

$$H_{Yg} = H_Y - \alpha n_Y (H_X n_X + H_Y n_Y)$$

Far field,

$$\text{Silver-Müller B.C. : } \vec{n} \times \vec{E} \cdot \vec{Z}_0 + \vec{n} \times (\vec{n} \times \vec{H}) = 0$$

$$\left| \begin{array}{ccc} i & j & k \\ n_x & n_y & 0 \\ H_x & H_y & 0 \end{array} \right| = (n_x H_y - H_x n_y) \hat{k}$$

$$\left| \begin{array}{ccc} i & j & k \\ n_x & n_y & 0 \\ 0 & 0 & T \end{array} \right| = n_x T \hat{i} - n_y T \hat{j} + 0 \hat{k}$$

$$\left| \begin{array}{ccc} i & j & k \\ n_x & n_y & 0 \\ 0 & 0 & E_z \end{array} \right| = 2(n_y E_z) - j(E_z n_x)$$

gives 2 eqns.

$$Z_0 E_z \cdot n_y + n_x^2 H_y - H_x n_x n_y = 0$$

$$-Z_0 E_z n_x - n_y n_x H_y + H_x n_y^2 = 0$$

$$n_x H_y = 0 \quad \left\{ \begin{array}{l} x\text{-face} \\ n_x E_z = 0 \end{array} \right.$$

$$n_y E_z = 0 \quad \left\{ \begin{array}{l} y\text{-face} \\ n_x H_y = 0 \end{array} \right.$$

The above is implemented as 2 separate B.C.
for xfaces, y-faces.

Non-Linear P multigrid:

For clarity we will define $R_p(U_p^n)$ - as non-linear residual and r_p to be the multi-grid residual.

In general the non-linear equations have the form

$$R_p(U_p^n) = S_p, \text{ and the residual } r_p = S_p - R(U_p^n)$$

Note: in the case $p=p_{\max}$ $S_p=0$, $r_p = -R(U_p^n)$.

The coarse level source term is given as

$$S_{p-1} = I_p^{p-1} r_p, \quad U_{p-1}^n = I_p^{p-1} U_p^n.$$

2-level Procedure:

- 1) Do some smoothing on fine level and get $R(U_p^n)$ from correction equation if we had \tilde{U}_p^{n+1} then $R(U_p^{n+1}) = S_p - \tilde{U}_p^{n+1}$ satisfies this

Thus,

$$R(U_p^{n+1}) - R(U_p^n) = S_p - R(U_p^n) \quad - \text{correction equation}$$

i.e. This measures how far we need to go to correct current value of U_p^n to make it satisfy $R(U_p^{n+1}) = S_p$.

Restrict this to the coarse level.

$$R(U_{p-1}^n) - R(I_p^{p-1} U_p^n) = I_p^{p-1} (S_p - R(U_p^n))$$

~~$U_{p-1}^n = I_p^{p-1} U_p^n$~~ thus our coarse r_p solve is

$$R(U_{p-1}^n) = I_p^{p-1} r_p + R(U_{p-1}^n) = D_{p-1}$$

Iterate on this gives a correction $U_p^{n+1} = U_p^n + I_p^{p-1} (U_{p-1}^n - I_p^{p-1} U_p^n)$.
 error between U_p^n and U_p^{n+1} .

To really get multigrid we would apply this

$$\text{Again to } R_{p-1}(U_{p-1}^n) = D_{p-1}$$

generate some iterations for U_{p-1}^n
generate residual as.

$$R_{p-1} = D_{p-1} - R_{p-1}(U_{p-1}^n)$$

$$R_{p-2}(U_{p-2}^n) = R(I_{p-2}^{p-2} U_{p-1}^n) = I_{p-1}^{p-2} F_{p-1}$$

$$R_{p-2}(U_{p-2}^n) = I_{p-1}^{p-2} F_{p-1} + R_{p-2}(I_{p-2}^{p-2} U_{p-1}^n)$$

This generates the correction

$$U_{p-1}^n = U_{p-1}^n + I_{p-2}^{p-1} (U_{p-2}^n - I_{p-1}^{p-2} U_{p-1}^n)$$

Implementation Note:

We the form of our prolongation is just add to those nodes. We can easily see the following.

$$U_p^{n+1} = U_p^n + I_{p-1}^p (U_{p-1}^n - I_{p-1}^{p-1} U_p^n) =$$

$$U_p^n + I_{p-1}^p [U_{p-1}^n + I_{p-2}^{p-1} (U_{p-2}^n - I_{p-1}^{p-2} U_{p-1}^n) - I_{p-1}^{p-1} U_p^n]$$

This equation shows that as we generate a correction on a level and it's correction it can be directly prolonged to the next level as seen by splitting in the following way.

$$U_p^{n+1} = U_p^n + \underbrace{I_{p-1}^p [U_{p-1}^n - I_{p-1}^{p-1} U_p^n]}_{p-1\text{-correction}} + \underbrace{I_{p-1}^p I_{p-2}^{p-1} (U_{p-2}^n - I_{p-1}^{p-2} U_{p-1}^n)}_{p-2\text{-correction to level } p}$$

These can be prolonged on the fly.

$$U_p^{n+1} = U_p^n + \Delta U_p^n + I_{p-1}^p (I_p^{p-1} U_p^{n-1} + \Delta U_{p-1}^n - I_p^{p-1} U_p^n) + I_{p-1}^p I_{p-2}^p (\Delta U_{p-2}^n)$$

$$\frac{\partial R_{p-1}}{\partial I_p^{p-1} U_p^n} \Delta U_{p-1}^n = I_{p-1}^{p-1} r_p + R_{p-1} (I_p^{p-1} U_p^n)$$

TVM Filter:

TVM: Total Variation Minimization.

g_f : Filter solution

g_o : Unfilter solution.

$$g_f = \min_{g_f} \int_{\Omega_K} |\nabla g_f| d\Omega + \frac{\lambda}{2} \|g_f - g_o\|_{L_2(\Omega_K)}$$

Where

$$|\nabla g_f| = \sqrt{(\frac{\partial g_f}{\partial x})^2 + (\frac{\partial g_f}{\partial y})^2}$$

$$\|g_f - g_o\|_{L_2(\Omega_K)} = \int_{\Omega_K} (g_f - g_o)^2 d\Omega_K$$

Note: Each of the above operations is done per field.

L_2 -norm term is a control factor for balancing filtering procedure vs original solution. I.e. The filtered solution should be as close as possible to the original sol.

1st minimize the above functional giving Euler-Lagrange equation.

$$\nabla \cdot \left(\frac{\nabla g_f}{|\nabla g_f| + \lambda} \right) - \lambda (g_f - g_o) = 0 \text{ with B.C. } \frac{\partial g_f}{\partial n} = 0 \text{ on } \partial \Omega_K \text{ & } g_f$$

Now discretize with weighted residuals

$$\int_{\Omega_K} \phi_j \nabla \cdot \left(\frac{\nabla g_f}{|\nabla g_f| + \lambda} \right) d\Omega_K - \int_{\Omega_K} \phi_j \lambda (g_f - g_o) d\Omega_K$$

↓
I.O.P

$$\frac{\partial u}{\partial e} = - \int \frac{\nabla \phi_j \cdot \nabla g_f}{|\nabla g_f| + \lambda} d\Omega_K + \int \phi_j \frac{\nabla g_f \cdot \hat{n}}{|\nabla g_f| + \lambda} ds - \int \lambda \phi_j (g_f - g_o) d\Omega_K$$

Note: The surface term is kept there to allow for possible implementation

Tuneable constants:

$$\alpha = 20,000 e^{-1 \nabla g_0} + 10^{-6}$$

$$\lambda = \frac{\beta}{\int_{\Omega_K} (\tilde{g}_f - \bar{g}_f)^2 d\Omega_K + \beta} \quad \text{where } \bar{g}_f = \frac{1}{|\Omega_K|} \int_{\Omega_K} g_f d\Omega_K \rightarrow \text{Avg. Sol.}$$

yields stiff system as (using) $q_f = \sum_{j=1}^N q_{fj}; q_j$

$$M \frac{d\tilde{g}_f}{dt} + R_f(\tilde{g}_f) = 0$$

To solve consider Rosenbrock

$$(1 + \mu \Delta t J_0) K_1 = -\Delta t R_f(\tilde{g}_f)$$

$$(1 + \mu \Delta t J_0) K_2 = -\Delta t R_f(\tilde{g}_f + \frac{2}{3} \mu \Delta t J_0 K_1) + \frac{4}{3} \mu \Delta t J_0 K_1$$

$$\tilde{g}_f^{n+1} = \tilde{g}_f^n + \frac{1}{6} K_1 + \frac{3}{4} K_2$$

$$J_0 = \left[\frac{\partial R_f}{\partial \tilde{g}_f} \right]_{\tilde{g}_f^n}$$

TVM Filter Surface term:

In the integration by parts stuff we have.

$$M \frac{\partial \Phi}{\partial t} = - \int \frac{\nabla \phi_j \cdot \nabla g_f}{|\nabla g_f| + \alpha} d\Omega_K + \oint \phi_j \frac{\nabla g_f \cdot \vec{n}}{|\nabla g_f| + \alpha} d\partial\Omega_K - \int \lambda \phi_j (g_f - g_o) d\Omega_K$$

\Downarrow
 $\int \frac{\nabla \phi_j \cdot \nabla g_f}{|\nabla g_f| + \alpha} d\Omega_K$

We are seeking

$$\oint \phi_j \frac{\nabla g_f \cdot \vec{n}}{|\nabla g_f| + \alpha} d\Omega_K \approx \left\{ \llbracket \phi_j \rrbracket \left\{ \frac{\nabla g_f}{|\nabla g_f| + \alpha} \right\} \cdot \vec{n} \right\}_+ +$$

$$\llbracket g_f \rrbracket \left\{ \begin{bmatrix} G_{f11} & G_{f12} \\ G_{f21} & G_{f22} \end{bmatrix} \nabla \phi_j \right\} - \left\{ G_{f11} \right\} \nabla (g_f^L - g_f^R) \llbracket \phi_j \rrbracket d\Omega_K$$

on a perfield basis ie for a field w .

$$\approx \left\{ \llbracket \phi_j \rrbracket \left(\frac{\nabla w_f \cdot \vec{n}}{|\nabla w_f| + \alpha} \right) \right\}_+ + \llbracket g_f \rrbracket \left\{ \begin{bmatrix} G_{f11}^w & G_{f12}^w \\ G_{f21}^w & G_{f22}^w \end{bmatrix} \nabla \phi_j \right\}_{\vec{n}} - \left\{ G_{f11}^w \right\} \nabla (g_f^L - g_f^R) \llbracket \phi_j \rrbracket$$

$$\frac{\partial \Omega_{12}}{\partial \Omega_{12}}, \quad G_{f11}^w = \frac{1}{(|\nabla w_f| + \alpha)} - \frac{(\partial w_f)^2}{(|\nabla w_f| + \alpha)^3}, \quad G_{f12}^w = -\frac{\frac{\partial w_f}{\partial x} \frac{\partial w_f}{\partial y}}{(|\nabla w_f| + \alpha)^3}, \quad G_{f22}^w = \frac{1}{(|\nabla w_f| + \alpha)} - \frac{(\partial w_f)^2}{(|\nabla w_f| + \alpha)^3}$$

$$\approx \oint \llbracket \phi_j \rrbracket \left\{ \frac{\nabla w_f \cdot \vec{n}}{|\nabla w_f| + \alpha} \right\} + \llbracket w_f \rrbracket \left\{ (G_{f11} \frac{\partial \phi_j}{\partial x} + G_{f12} \frac{\partial \phi_j}{\partial y}) \hat{i}_x + (G_{f21} \frac{\partial \phi_j}{\partial x} + G_{f22} \frac{\partial \phi_j}{\partial y}) \hat{i}_y \right\}$$

$$- \left\{ G_{f11} + G_{f22} \right\} \nabla (g_f^L - g_f^R) \llbracket \phi_j \rrbracket d\Omega_{12}$$

We will proceed by writing this term out piece by piece for a general field.

Term 1: The regular flux.

For the Left

$$\phi_j \cdot \frac{1}{2} \left[\left(\frac{\partial w_f}{\partial x} \right)_L + \left(\frac{\partial w_f}{\partial x} \right)_{R+2} \right] \hat{n}_x + \frac{1}{2} \left[\left(\frac{\partial w_f}{\partial y} \right)_{L+2} + \left(\frac{\partial w_f}{\partial y} \right)_{R+2} \right] \hat{n}_y$$

negative for right.

Term 2:

For both Left and Right

$$(w_f^L - w_f^R) \frac{1}{2} \left[\left(G_{f,11}^w \frac{\partial \phi_j}{\partial x} + G_{f,12}^w \frac{\partial \phi_j}{\partial y} \right)_L + \left(G_{f,11}^w \frac{\partial \phi_j}{\partial x} + G_{f,12}^w \frac{\partial \phi_j}{\partial y} \right)_{R+2} \right] \hat{n}_x +$$
$$\frac{1}{2} \left[\left(G_{f,21}^w \frac{\partial \phi_j}{\partial x} + G_{f,22}^w \frac{\partial \phi_j}{\partial y} \right)_L + \left(G_{f,21}^w \frac{\partial \phi_j}{\partial x} + G_{f,22}^w \frac{\partial \phi_j}{\partial y} \right)_{R+2} \right] \hat{n}_y$$

Term 3:

For Left.

$$\frac{1}{2} \left[\left(G_{f,11}^w + G_{f,22}^w \right)_L + \left(G_{f,11}^w + G_{f,22}^w \right)_{R+2} \right] \cdot \nabla \phi_j (w_f^L - w_f^R)$$

TVM Filter Linearization:

If we define R_f as

$$R_f = - \int_{S_{LK}} \frac{\nabla \phi_i \cdot \nabla \vec{g}_f}{|\nabla \vec{g}_f| + d} - \int_{M_L} \lambda \beta_i (\vec{g}_f - \vec{g}_o) dS_{LK} - \text{Note: No surface term here.}$$

(A)

Then we define J as.

$$\left[\frac{\partial R_f}{\partial \vec{g}} \right] = \int_{S_{LK}} \left(\frac{\partial R_f}{\partial g_x} \cdot \frac{\partial g_x}{\partial \vec{g}} + \frac{\partial R_f}{\partial g_y} \cdot \frac{\partial g_y}{\partial \vec{g}} \right) dS_{LK} - \int_{M_L} \frac{\partial R_f}{\partial \vec{g}_f} \cdot \frac{\partial \vec{g}_f}{\partial \vec{g}} dM_L$$

This makes it a simple matter of finding $\frac{\partial R_f}{\partial g_x}$ and $\frac{\partial R_f}{\partial g_y}$.
 In this case no field's R_f depends on any other field.

Thus $\frac{\partial R_f}{\partial g_x}$ is diagonal

$$\begin{bmatrix} \frac{\partial R_f}{\partial g_{x_1}} & 0 & 0 & 0 \\ 0 & \frac{\partial R_f}{\partial g_{x_2}} & 0 & 0 \\ 0 & 0 & \frac{\partial R_f}{\partial g_{x_3}} & 0 \\ 0 & 0 & 0 & \frac{\partial R_f}{\partial g_{x_4}} \end{bmatrix}$$

Thus we can write the $\frac{\partial R_f}{\partial g_x}$ for a field and it is the same for each.

Consider a generic field w then for any w .

$$\frac{\partial R_f}{\partial w_{K_f}} = \frac{\partial}{\partial w_{K_f}} \left[- \frac{\nabla \phi_i \cdot \nabla w_f}{|\nabla w_f| + d} \right]$$

$$\frac{\partial R_{fw}}{\partial (w_{M_f})} = \frac{\partial}{\partial (w_{M_f})} \left[- \frac{\nabla \phi_i \cdot \nabla w_f}{|\nabla w_f| + d} \right]$$

$$\frac{\partial R_f}{\partial w_f} = \frac{\partial}{\partial w_f} \left[- \lambda(w_f) \phi_i (w_f - w_o) \right].$$

Thus we see that parts ① and ③ actually are the $\frac{\partial R_f}{\partial w_{xf}}$, $\frac{\partial R_f}{\partial w_{yf}}$ terms from above because as with viscous fluxes we regard R_f as $R_f(\nabla w, \omega)$ where the gradient is a separable variable.

Details:

First we will work out $\frac{\partial R_f}{\partial(w_{xf})}$ and $\frac{\partial R_f}{\partial(w_{yf})}$

$$\frac{\partial R_f}{\partial(w_{xf})} = \frac{\partial}{\partial(w_{xf})} \left[\frac{\frac{\partial \phi_i}{\partial x} \frac{\partial w_f}{\partial x} + \frac{\partial \phi_i}{\partial y} \cdot \frac{\partial w_f}{\partial y}}{\sqrt{\left(\frac{\partial w_f}{\partial x}\right)^2 + \left(\frac{\partial w_f}{\partial y}\right)^2} + \alpha} \right]$$

$$\text{define } \sqrt{\left(\frac{\partial w_f}{\partial x}\right)^2 + \left(\frac{\partial w_f}{\partial y}\right)^2} = |\nabla w_f|$$

$$= \frac{\partial \phi_i}{\partial x} \left(|\nabla w_f| + \alpha \right) - \left(\frac{\partial \phi_i}{\partial x} \cdot \frac{\partial w_f}{\partial x} \right) \cdot \left[\frac{1}{|\nabla w_f|} \frac{\partial w_f}{\partial x} \right] - \frac{\partial \phi_i}{\partial y} \cdot \frac{\partial w_f}{\partial y} \left[\frac{1}{|\nabla w_f|} \frac{\partial w_f}{\partial x} \right]$$

$$[|\nabla w_f| + \alpha]^2$$

$$\frac{\partial R_f}{\partial(w_{yf})} = \frac{\partial}{\partial(w_{yf})} \left[\frac{\frac{\partial \phi_i}{\partial x} \cdot \frac{\partial w_f}{\partial x} + \frac{\partial \phi_i}{\partial y} \cdot \frac{\partial w_f}{\partial y}}{\sqrt{\left(\frac{\partial w_f}{\partial x}\right)^2 + \left(\frac{\partial w_f}{\partial y}\right)^2} + \alpha} \right] =$$

$$= - \frac{\partial \phi_i}{\partial x} \cdot \frac{\partial w_f}{\partial x} \left(\frac{1}{|\nabla w_f|} \frac{\partial w_f}{\partial y} \right) + \frac{\partial \phi_i}{\partial y} \cdot \left(|\nabla w_f| + \alpha \right) - \frac{\partial \phi_i}{\partial y} \cdot \frac{\partial w_f}{\partial y} \left(\frac{1}{|\nabla w_f|} \frac{\partial w_f}{\partial y} \right)$$

$$[|\nabla w_f| + \alpha]^2$$

We will take $\frac{\partial R_f}{\partial \hat{w}_f}$ directly for practical reasons, this way these notes will match ~~exactly~~ very closely to the code.

$$\begin{aligned}\frac{\partial R_f}{\partial \hat{w}_f} &= \frac{\partial}{\partial \hat{w}_f} \left[\lambda(\hat{w}_f) \phi_i (\hat{w}_f - w_0) \right] \\ &= \phi_i \left[\frac{\partial \lambda}{\partial \hat{w}_f} (\hat{w}_f - w_0) + \lambda(\hat{w}_f) \frac{\partial \hat{w}_f}{\partial \hat{w}_f} \right]\end{aligned}$$

$$\frac{\partial \lambda}{\partial \hat{w}_f} = \frac{1}{\left[\sum_{j \in \mathcal{N}_K} (\hat{w}_f - \bar{w}_j)^2 d_{jk} \right]^2} \cdot \left[\sum_{j \in \mathcal{N}_K} 2(\hat{w}_f - \bar{w}_j) \cdot \left\{ \frac{\partial w}{\partial \hat{w}_f} - \frac{1}{\sum_{j \in \mathcal{N}_K}} \sum_{j \in \mathcal{N}_K} \phi_j d_{jk} \right\} \right]$$

Thus we will need to build and store $\frac{\partial \lambda}{\partial \hat{w}_f}$

Shock Detection.

1). Person and Peacor Element-wise Resolution Indicator.

$$S_K = \frac{\langle g - \tilde{g}, g - \tilde{g} \rangle_{L^2(\Omega_K)}}{\langle \tilde{g}, \tilde{g} \rangle_{L^2(\Omega_K)}}$$

$$\text{where } \tilde{g} = \sum_{j=1}^n \tilde{g}_j \phi_j$$

$$\tilde{g} = \sum_{j=1}^{\tilde{M}} \tilde{g}_j \phi_j \quad \text{when } \tilde{M} = \theta \text{ at Node } p-1,$$

2). Jump indicator

$$S_K = \frac{1}{|\partial\Omega_K|} \int_{\partial\Omega_K} \left| \frac{\tilde{g}^+ - \tilde{g}^-}{\sqrt{2(g^+ + g^-)}} \right| dS.$$

Remark: This can be done for as many fields as you like but I will experiment with using density which should not be zero

Where Does the Euler - Lagrange Eqn Come from?

This is quite simple. It is a variational calculus principle very closely related to energy methods in Structural Dynamics and Mechanics.

The statement

$$S = \int_{t_1}^{t_2} [V\dot{\theta} + \frac{1}{2}I\ddot{\theta}^2 - \theta_0] dt$$

is a functional that we would like the minimum of. Thus we take the variation and set the total Variation=0 to find the minima (or stationary point).

Let's derive this procedure by a simple example and then we'll see how the E/L eqn is derived and then it can be applied to our functional.

Consider a general functional $L = \int f(t, g, \dot{g}) dt$ where t is a single independent variable and $\dot{g} = \frac{dg}{dt}$.

$$\delta L = \delta \int f(t, g, \dot{g}) dt = \int \frac{\partial f}{\partial t} \delta t + \frac{\partial f}{\partial g} \delta g + \frac{\partial f}{\partial \dot{g}} \delta \left(\frac{dg}{dt} \right) dt \quad \textcircled{D}$$

Integration by parts of the 2nd term.

Integration by parts of the 2nd term.

$$U = \frac{\partial f}{\partial \dot{g}}, \quad dV = d(\delta \dot{g}) \rightarrow \text{Linear operators can be reversed (assumed)} \quad \text{see S.O. notes D.H.}$$

$$dU \left(\frac{df}{d\dot{g}} \right) dt, \quad V = \delta \dot{g} \quad \text{gives No variation at end points (part of Var calc)}$$

$$UV \Big|_{t_1}^{t_2} - \int V dU \rightarrow \delta \dot{g} \frac{\partial f}{\partial \dot{g}} \Big|_{t_1}^{t_2} - \int_{t_1}^{t_2} \delta \dot{g} \frac{\partial f}{\partial \dot{g}} dt \quad \textcircled{D}$$

using \textcircled{D} in \textcircled{D}.

$$\delta L = \int \left[\frac{\partial f}{\partial g} - \frac{\partial f}{\partial \dot{g}} \left(\frac{dg}{dt} \right) \right] \delta g dt,$$

Thus if we want $\delta L = 0$ then f must satisfy

$$\frac{\partial f}{\partial g} - \frac{\partial f}{\partial \dot{g}} \left(\frac{dg}{dt} \right) = 0 \quad \text{--- E/L.}$$

Applying the our function $\vec{g} \rightarrow \nabla g$, $b \rightarrow \mu_b$,

$$\frac{\partial f}{\partial g} \rightarrow \frac{\partial (\sqrt{\nabla g \cdot \nabla g})}{\partial \nabla g} \rightarrow \frac{1}{2} \cdot \frac{(\nabla g + \nabla g)}{\sqrt{\nabla g \cdot \nabla g}} = \frac{\nabla g}{|\nabla g|}$$

$$\frac{\partial f}{\partial g} = \frac{\lambda}{2} \cdot (\nabla g - g_0) \cdot (1)$$

Thus we have

$$\nabla \cdot \left(\frac{\nabla g}{|\nabla g|} \right) - \lambda (g - g_0) = 0$$

We add the α term
for complex implementation,

$$\nabla \cdot \left(\frac{\nabla g}{|\nabla g| + \alpha} \right) - \lambda (g - g_0) = 0$$

That is really simple.