- **Critical Survey on High Resolution Monotonic Schemes**
 - Basic analysis framework

• 1-D SCL of
$$\frac{\partial u}{\partial t} + \frac{\partial f(u)}{\partial x} = 0 \rightarrow u_j^{n+1} = u_j^n - \frac{\Delta t}{\Delta x} \left(F_{j+1/2} - F_{j-1/2} \right)$$
 or $\frac{du_j}{dt} = -\frac{1}{\Delta x} \left(F_{j+1/2} - F_{j-1/2} \right)$

 \bullet Monotonicity constraint as a way to design $F_{{}_{j+1\!/\!2}}$

 $\min(u_{j-1}, u_j, u_{j+1}) \le u(x) \le \max(u_{j-1}, u_j, u_{j+1}) \text{ or } \min(u_j, u_{j+1}) \le u_{j+1/2} \le \max(u_j, u_{j+1}), \ x_{j-1/2} \le x \le x_{j+1/2}$

- One-dimensional l_1 or l_{∞} -stability is realized by imposing TVD stability (FCT, TVD, MUSCL, LED) or TVB stability (ENO and WENO).
- → Avoid numerical oscillations across discontinuous region while maintaining expected order of accuracy in smooth region

Multi-dimensional extension

• 2-D SCL of
$$\frac{\partial u}{\partial t} + \frac{\partial f(u)}{\partial x} + \frac{\partial g(u)}{\partial y} = 0 \rightarrow \frac{du_{i,j}}{dt} = -\frac{1}{\Delta x} (F_{i+1/2,j} - F_{i-1/2,j}) - \frac{1}{\Delta y} (G_{i,j+1/2} - G_{i,j-1/2})$$

• Monotonicity constraint by dimensional splitting approach

$$(x - dir) \min(u_{i-1,j}, u_{i,j}, u_{i+1,j}) \le u(x, y_j) \le \max(u_{i-1,j}, u_{i,j}, u_{i+1,j})$$
$$\min(u_{i-1,j}, u_{i+1,j}) \le u_{i+1,j} \le \max(u_{i-1,j}, u_{i,j}, u_{i+1,j})$$

$$\min(u_{i,j}, u_{i+1,j}) \le u_{i+1/2,j} \le \max(u_{i,j}, u_{i+1,j}), \ x_{i-1/2,j} \le x \le x_{i+1/2,j}$$

$$\begin{array}{l} (u_{i,j-1}, u_{i,j}, u_{i,j+1}) \leq u(x_i, y) \leq \max(u_{i,j-1}, u_{i,j}, u_{i,j+1}) \\ \min(u_{i,j}, u_{i,j+1}) \leq u_{i,j+1/2} \leq \max(u_{i,j}, u_{i,j+1}), \ y_{i,j-1/2} \leq y \leq y_{i,j+1/2} \end{array}$$

(l

• Critical Survey (cont'd)

- Any missing physics for multi-D flows?
 - Multi-dimensional monotonicity and multi-dimensional numerical flux
- Intrinsic one-dimensionality of total variation
 - $TV(u) = \int_{-\infty}^{\infty} |u'(x)| dx = \sum_{j=-\infty}^{\infty} |u_j u_{j-1}| = 2(\sum \text{maxima} \sum \text{minima})$

$$\xrightarrow{TV \text{ in multiple dimensions}} TV(u) = \int_{V} \left\| \nabla u \right\|_{p} ds \text{ with } \left\| \nabla u \right\|_{1} = \left| \frac{\partial u}{\partial x} \right| + \left| \frac{\partial u}{\partial y} \right|, \quad \left\| \nabla u \right\|_{2} = \sqrt{\left(\frac{\partial u}{\partial x} \right)^{2} + \left(\frac{\partial u}{\partial y} \right)^{2}}, \dots$$

- Two piecewise linear distributions (two-peaks and one-ridge) on equilateral triangular mesh with unit length (Jameson, 1995)
 - $\rightarrow TV_{two-peaks} < TV_{one-ridge}$ confirming that straightforward extession of 1-D TVD is not proper to handle multi-dimensional oscillations.



• MLP Schemes

- More refined numerical strategy is necessary for non-oscillatory schemes in multi-dimensional flows.
 - Most oscillation-free schemes have been developed largely based on one dimensional flow physics $(u_t + f(u)_x = 0)$.
 - Dimensional splitting TVD schemes do not guarantee monotonicity at vertex point.
 - See the works by C. Kim *et al.* (2005, 2008, 2010), and others
- Massing flow physics in non grid-aligned flow distributions





< Do the values at vertexes satisfy monotonicty? >

- Role of vertex values under linear distribution
- Local extrema always appear at vertex point under linear distribution. → treat cell-centered and cell-vertex point simultaneously

- MLP condition: $u_{neighbor}^{\min} \le u(x, y)|_{(x,y)\in T_{i,j} \text{ or } T_0} \le u_{neighbor}^{\max}$
 - Applying MLP condition to each vertex point of the target $cell(T_{i,j} \text{ or } T_o)$ to have

$$\min\left(u_{i,j}, u_{i+1,j}, u_{i,j+1}, u_{i+1,j+1}\right) \le u(x, y)\Big|_{i+1/2, j+1/2} \le \max\left(u_{i,j}, u_{i+1,j}, u_{i,j+1}, u_{i+1,j+1}\right)$$
$$\min_{T_k \in S_{v_j}} (u_k) \le u(x, y)\Big|_{v_j} \le \max_{T_k \in S_{v_j}} (u_k) \quad \text{with } S_{v_j} = \{T_k | v_j \in T_k \text{ for } v_j \text{ of } T_0\}$$

 \rightarrow Impose the above inequality as additional constraint in designing MLP limiters

• MLP Limiters on Structured Meshes

• TVD-MUSCL vs. MLP

From MUSCL-type slope limiting, the left/right cell-interface values are given by

- $u_{i+1/2,j}^{L} = u_{i,j} + 0.5 \phi_{i,j}(r_L) \Delta u_{i-1/2,j}$ and $u_{i+1/2,j}^{R} = u_{i+1,j} 0.5 \phi_{i+1,j}(r_R) \Delta u_{i+3/2,j}$ with $\phi(r) = r\phi(1/r)$ and $r_L = \Delta u_{i+1/2,j} / \Delta u_{i-1/2,j}, r_R = \Delta u_{i+1/2,j} / \Delta u_{i+3/2,j}$
- TVD limiting region based on 1-D analysis: $\Phi_{TVD}(r) = \max(0, \min(2, 2r))$
- MLP limiting region to treat multi-dimensionality: $\Phi_{MLP}(r) = \max(0, \min(\alpha, \alpha r))$
 - Basic form: $\phi_{_{MLP}}(r) = \max(0, \min(\alpha, \alpha r, \beta(r)))$
 - α : multi-dimensional restriction coefficient to determine the upper bound of MLP limiting region
 - β : charactersitic interpolation coefficient to determine local variation (slope or higher than 2nd-order)



 $u_{i+1/2,j}^{L}$

- Determination of multi-dimensional restriction coefficient, α
 - (S1) Each cell-vertex value of the target cell $T_{i,j}$ is estimated by

$$u_{i+k_{1}/2,j+k_{2}/2} = u_{i,j} + \Delta u_{i+k_{1}/2,j}^{x} + \Delta u_{i,j+k_{2}/2}^{y} = u_{i,j} + 0.5k_{1}\phi(r_{x})\Delta u_{i-1/2,j} + 0.5k_{2}\phi(r_{y})\Delta u_{i,j-1/2}$$
$$= u_{i,j} + (1+r_{xy})\Delta u_{i+k_{1}/2,j}^{x}$$

with $r_x = \Delta u_{i+1/2,j} / \Delta u_{i-1/2,j}$, $r_y = \Delta u_{i,j+1/2} / \Delta u_{i,j-1/2}$, $r_{xy} = \Delta u_{i,j+k_2/2}^y / \Delta u_{i+k_1/2,j}^x$ and $k_1, k_2 = \pm 1$

- Noth that, with linear subcell approximation, we only need to check the upper bound of the maximum vertex value and the lower bound of the minimum vertex value. Thus, r_{xy} is assumed to be positive.
- (S2) Obtain the neighboring minimum and maximum values by checking all cell-averaged values sharing the same vertex point $(i + k_1 / 2, j + k_2 / 2)$

$$u_{i+k_1/2,j+k_2/2}^{\min} = \min\left(u_{i,j}, u_{i+k_1,j}, u_{i,j+k_2}, u_{i+k_1,j+k_2}\right), u_{i+k_1/2,j+k_2/2}^{\max} = \max\left(u_{i,j}, u_{i+k_1,j}, u_{i,j+k_2}, u_{i+k_1,j+k_2}\right)$$

• (S3) Enforce the MLP limiting condition with $\phi(r) = \phi_{MLP}(r) = \min(\alpha, \alpha r)$ into $u_{i+k_1/2, j+k_2/2}$

$$\begin{aligned} u_{i+k_{1}/2,j+k_{2}/2}^{\min} &\leq u_{i+k_{1}/2,j+k_{2}/2} \leq u_{i+k_{1}/2,j+k_{2}/2}^{\max} \to u_{i+k_{1}/2,j+k_{2}/2}^{\min} \\ \frac{u_{i+k_{1}/2,j+k_{2}/2}^{\min} - u_{i,j}}{1+r_{xy}} &\leq \Delta u_{i+k_{1}/2,j}^{x} \leq \frac{u_{i+k_{1}/2,j+k_{2}/2}^{\max} - u_{i,j}}{1+r_{xy}} \quad \text{or} \end{aligned}$$

$$\frac{u_{i+k_1/2,j+k_2/2}^{\min} - u_{i,j}}{1 + r_{xy}} \le 0.5k_1\phi_{MLP}(r_x)\Delta u_{i-1/2,j} \le \frac{u_{i+k_1/2,j+k_2/2}^{\max} - u_{i,j}}{1 + r_{xy}}$$

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Determination of multi-dimensional restriction coefficient, α (cont'd) • (S4) Obtain the range of α for local maximum case i) $0 < r_x < 1$, $0 \le 0.5k_1 \alpha \Delta u_{i+1/2,j} \le \frac{u_{i+k_1/2,j+k_2/2}^{\max} - u_{i,j}}{1+r} \rightarrow 0 \le \alpha \le \frac{2(u_{i+k_1/2,j+k_2/2}^{\max} - u_{i,j})}{k_1(1+r_m)\Delta u_{i+1/2,j}}$ ii) $r_x > 1$, $0 \le \frac{k_1 \alpha}{2r} \Delta u_{i+1/2,j} \le \frac{u_{i+k_1/2,j+k_2/2}^{\max} - u_{i,j}}{1+r} \to 0 \le \alpha \le \frac{2r_x (u_{i+k_1/2,j+k_2/2}^{\max} - u_{i,j})}{k_x (1+r_x) \Delta u_{i+1/2,j}}$ Thus, we have $0 \le \alpha_{\lim ax} \le \frac{2 \max(1, r_x) (u_{i+k_1/2, j+k_2/2}^{\max} - u_{i,j})}{k_1 (1 + r_{yy}) \Delta u_{i+1/2, j}}$ • (S5) Obtain the range of α for local minimum case Since $\Delta u_{i+k_1/2,j}^x < 0$ (local minimum), $\frac{u_{i+k_1/2,j+k_2/2}^{\min} - u_{i,j}}{1+r} \le 0.5k_1\phi_{MLP}(r_x)\Delta u_{i-1/2,j} \le 0$ i) $0 < r_x < 1$, $\frac{u_{i+k_1/2,j+k_2/2}^{\min} - u_{i,j}}{1+r} \le 0.5k_1\alpha\Delta u_{i+1/2,j} \le 0 \rightarrow 0 \le \alpha \le \frac{2(u_{i+k_1/2,j+k_2/2}^{\min} - u_{i,j})}{k_1(1+r_m)\Delta u_{i+1/2,j}}$ ii) $r_x > 1$, $\frac{u_{i+k_1/2, j+k_2/2}^{\min} - u_{i,j}}{1+r_{m}} \le \frac{k_1 \alpha}{2r} \Delta u_{i+1/2, j} \le 0 \rightarrow 0 \le \alpha \le \frac{2r_x (u_{i+k_1/2, j+k_2/2}^{\min} - u_{i,j})}{k_x (1+r_x) \Delta u_{i+1/2, j}}$ Thus, we have $0 \le \alpha_{\text{lmin}} \le \frac{2 \max(1, r_x) (u_{i+k_1/2, j+k_2/2}^{\min} - u_{i,j})}{k_1 (1 + r_{xv}) \Delta u_{i+1/2, j}}$

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- Determination of multi-dimensional restriction coefficient, α (cont'd)
 - (S6) Obtain the range of α from (S4) and (S5) with $\alpha \ge 1$

$$1 \le \alpha = \min(\alpha_{\max}, \alpha_{\min}) \le \left| \frac{2 \max(1, r_x)}{(1 + r_{xy}) \Delta u_{i+1/2, j}} \right| \min\left(\left| u_{i+k_1/2, j+k_2/2}^{\max} - u_{i, j} \right|, \left| u_{i+k_1/2, j+k_2/2}^{\min} - u_{i, j} \right| \right),$$

and choose the upper bound as
$$\alpha = \left| \frac{2 \max(1, r_x)}{(1 + r_{xy}) \Delta u_{i+1/2, j}} \right| \min\left(\left| u_{i+k_1/2, j+k_2/2}^{\max} - u_{i, j} \right|, \left| u_{i+k_1/2, j+k_2/2}^{\min} - u_{i, j} \right| \right)$$

- Notice that if $r_{xy} = 0$ (1-D situation), it recovers the 1-D TVD region.
- **Determination of interpolation coefficient, β**
 - β using conventional TVD-MUSCL or LED slopes
 - MLP with minmod limiter is the same as TVD minmod limiter with $\alpha = 1 = \beta$.

MLP with van Leer:
$$\beta_L = \frac{2r_L}{1 + r_L}$$
, $\beta_R = \frac{2r_R}{1 + r_R}$

- MLP with superbee: $\beta_{L/R} = \max(1, r_{L/R})$
- Any other TVD-MUSCL or LED slopes with $\beta(r)|_{r=1} = 1$ can be used.
- β using polynomial interpolation
 - Consider higher-order polynomial of $u(x) = a_0 + a_1x + a_2x^2 + \dots + a_nx^n$, $x_{j-1/2} \le x \le x_{j+1/2}$
 - MLP3 (slope limiting using 2rd-order polynomial)

For
$$u(x) = a_0 + a_1 x + a_2 x^2$$
 with $u_{i+l} = \int_{x_{i+l-1/2}}^{x_{i+l+1/2}} u(x) dx$ $(l = 0, \pm 1)$,

Determination of interpolation coefficient, β (cont'd)

- β using polynomial interpolation
 - MLP3 (slope limiting using 2rd-order polynomial)

$$u_{i+1/2}^{L} = u(x_{i+1/2}) = \frac{-u_{i-1} + 5u_i + 2u_{i+1}}{6} = u_i + 0.5 \frac{\Delta u_{i-1/2} + 2\Delta u_{i+1/2}}{3} = u_i + 0.5\beta(r_L)\Delta u_{i-1/2}$$

Thus, we have $\beta_{L/R} = \beta(r_{L/R}) = \frac{1+2r_{L/R}}{3}$.

- MLP5 (slope limiting using 4th-order polynomial)

Similarly, with $u(x) = a_0 + a_1 x + a_2 x^2 + a_3 x^3 + a_4 x^4$ and $u_{i+l} = \int_{x_{i+l-1/2}}^{x_{i+l+1/2}} u(x) dx$ $(l = 0, \pm 1, \pm 2)$,

$$u_{i+1/2}^{L} = u(x_{i+1/2}) = u_{i} + 0.5 \frac{-2\Delta u_{i-3/2} + 11\Delta u_{i-1/2} + 24\Delta u_{i+1/2} - 3\Delta u_{i+3/2}}{30} = u_{i} + 0.5\beta(r_{L})\Delta u_{i-1/2}$$

$$\begin{cases} \beta_L = \beta(r_L) = \frac{-2/r_{L(i-1)} + 11 + 24r_L - 3r_Lr_{L(i+1)}}{30} \\ -2/r_{P(i-1)} + 11 + 24r_P - 3r_{P(i-1)}r_P \end{cases}$$

Thus, we have

$$\beta_R = \frac{2 + r_{R(i+1)} + 1 + 2 + r_R - 2 + r_{R(i-1)} + r_R}{30}$$

MLP slope limiting in multiple dimensions

• *x*-directional cell-interface values and fluxes

$$u_{i+1/2,j}^{L} = u_{i,j} + 0.5\phi_{MLP(i,j)}(r_{L})\Delta u_{i-1/2,j} = u_{i,j} + 0.5\max\left(0,\min\left(\alpha_{L},\alpha_{L}r_{L},\beta_{L}\right)\right)\Delta u_{i-1/2,j} \\ u_{i+1/2,j}^{R} = u_{i+1,j} - 0.5\phi_{MLP(i+1,j)}(r_{R})\Delta u_{i+3/2,j} = u_{i+1,j} - 0.5\max\left(0,\min\left(\alpha_{R},\alpha_{R}r_{R},\beta_{R}\right)\right)\Delta u_{i+3/2,j} \right\} \rightarrow F_{i+1/2,j}(u_{i+1/2,j}^{L},u_{i+1/2,j}^{R})$$

- **MLP Limiters on Unstructured Meshes**
 - Multi-dimensional unstructured meshes excludes direct estimation of α, β.
 - Multi-dimensional limited linear reconstruction for the target cell T_O $u_O(\mathbf{r}) = u_O + \nabla u_O \cdot (\mathbf{r} - \mathbf{r}_O) \rightarrow L[u_O(\mathbf{r})] = u_O + \phi_{\text{MLP}, T_O} \nabla u_O \cdot (\mathbf{r} - \mathbf{r}_O)$
 - Gradient ∇u_o is estimated by least square method using the cell-averaged values of the cell T_o and its neighborhoods T_A, T_B, T_C .
 - The same MLP condition is enforced to determine the limiter function $\phi_{\text{MLP},T_{0}}$

since local extrema appear at vertex points.

Apply the MLP condition to each vertex
$$v_i \in T_O$$

 $u_{v_i}^{\min} \leq L\left[u_O(\mathbf{r}_{v_i})\right] = u_O + \phi_{\mathrm{MLP},v_i} \nabla u_O \cdot (\mathbf{r}_{v_i} - \mathbf{r}_O) \leq u_{v_i}^{\max}$,
where $u_{v_i}^{\min} = \min_{T_k \in S_{v_i}} (u_k)$, $u_{v_i}^{\max} = \max_{T_k \in S_{v_i}} (u_k)$,
and $S_{v_i} = \{T_k \mid v_i \in T_k \text{ for } v_i \in T_o\}$.
 $\rightarrow u_{v_i}^{\min} - u_O \leq \phi_{\mathrm{MLP},v_i} \nabla u_O \cdot (\mathbf{r}_{v_i} - \mathbf{r}_O) \leq u_{v_i}^{\max} - u_O$
Since $\mathrm{Sgn}(u_{v_i}^{\min} - u_O) \neq \mathrm{Sgn}(u_{v_i}^{\max} - u_O)$,
 $0 \leq \phi_{\mathrm{MLP},v_i} \leq \max\left(\frac{u_{v_i}^{\min} - u_O}{\nabla u_O \cdot (\mathbf{r}_{v_i} - \mathbf{r}_O)}, \frac{u_{v_i}^{\max} - u_O}{\nabla u_O \cdot (\mathbf{r}_{v_i} - \mathbf{r}_O)}\right)$.



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Determination of MLP-u slope limiters on unstructured meshes

• (S1) Estimate a local gradient ∇u_o using a least-square approach and

reconstruct the linear distribution within the target cell T_o .

$$u_{O}(\mathbf{r}) = u_{O} + \nabla u_{O} \cdot (\mathbf{r} - \mathbf{r}_{O})|_{A,B,C} \rightarrow [\mathbf{L}_{1} \quad \mathbf{L}_{2}][\nabla u_{O}] = [\Delta u] \text{ with}$$

$$\mathbf{L}_{1} = \begin{bmatrix} \Delta x_{OA} \\ \Delta x_{OB} \\ \Delta x_{OC} \end{bmatrix}, \quad \mathbf{L}_{2} = \begin{bmatrix} \Delta y_{OA} \\ \Delta y_{OB} \\ \Delta y_{OC} \end{bmatrix}, \quad [\nabla u_{O}] = \begin{bmatrix} (\nabla u_{O})_{x} \\ (\nabla u_{O})_{y} \end{bmatrix} \text{ and } [\Delta u] = \begin{bmatrix} u_{A} - u_{O} \\ u_{B} - u_{O} \\ u_{C} - u_{O} \end{bmatrix}$$
Thus, we have $[\nabla u_{O}] = \frac{1}{l_{1} l_{22} - l_{12}^{2}} \begin{bmatrix} l_{22}(\mathbf{L}_{1} \cdot [\Delta u]) & -l_{12}(\mathbf{L}_{2} \cdot [\Delta u]) \\ l_{11}(\mathbf{L}_{2} \cdot [\Delta u]) & -l_{12}(\mathbf{L}_{1} \cdot [\Delta u]) \end{bmatrix} \text{ with } l_{ij} = \mathbf{L}_{i} \cdot \mathbf{L}_{j}.$

• (S2) For each vertex $v_i \in T_o$, search neighboring maximum and minimum cell-averaged values, and determine the permissible range of ϕ_{MLP,v_i} by applying the MLP condition.

$$u_{v_i}^{\min} = \min_{T_k \in S_{v_i}} (u_k), \ u_{v_i}^{\max} = \max_{T_k \in S_{v_i}} (u_k) \quad \text{with } S_{v_i} = \{T_k \mid v_i \in T_k \text{ for } v_i \in T_O\} \text{ gives}$$

$$0 \le \phi_{\text{MLP}, v_i} \le \min(r_{v_i}, 1) \text{ with } r_{v_i} = \begin{cases} \frac{u_{v_i}^{\max} - u_O}{\nabla u_O \cdot (\mathbf{r}_{v_i} - \mathbf{r}_O)} & \text{if } \nabla u_O \cdot (\mathbf{r}_{v_i} - \mathbf{r}_O) > 0\\ \frac{u_{v_i}^{\min} - u_O}{\nabla u_O \cdot (\mathbf{r}_{v_i} - \mathbf{r}_O)} & \text{if } \nabla u_O \cdot (\mathbf{r}_{v_i} - \mathbf{r}_O) < 0 \end{cases}$$

Similar to minmod limiting, r_{v_i} is the ratio of the maximum (or minimum) allowable variation to the estimated variation at the vertex $v_i \in T_o$.

- Determination of MLP-u slope limiters on unstructured meshes (cont'd)
 - (S3) For each vertex $v_i \in T_O$, determine ϕ_{MLP,v_i}

i) MLP-u1 limiter \rightarrow Take the upper bound of the limiting region

$$\phi_{\text{MLP-ul},v_i} = \Phi(r_{v_i}), \text{ where } \Phi(r) = \begin{cases} \min(1, r) & r > 0, \\ 0 & r = 0. \end{cases}$$

ii) MLP-u2 limiter \rightarrow Make MLP-u1 limiter function Φ_{MLP-u1} differentiable for steady-state computations

. Approximate min(1, r) by a smooth function $f_v(r) = (r^2 + 2r)/(r^2 + r + 2)$ _Venkat, and apply $f_v(r)$ to $\Phi_{\text{MLP-ul}}(r)$ with ε to avoid clipping

$$\Phi_{\mathrm{MLP-u2}}\left(\frac{\Delta_{+}}{\Delta_{-}}\right) = \begin{cases} \frac{1}{\Delta_{-}} \left(\frac{\left(\Delta_{+}^{2} + \varepsilon^{2}\right)\Delta_{-} + 2\Delta_{-}^{2}\Delta_{+}}{\Delta_{+}^{2} + 2\Delta_{-}^{2} + \Delta_{-}\Delta_{+} + \varepsilon^{2}}\right) & r \neq 0, \\ 1 & r = 0. \end{cases}$$

where $r = \Delta_+ / \Delta_-$, $\Delta_+ = u_{v_j}^{\min} - u_O$ or $u_{v_j}^{\max} - u_O$, and $\Delta_- = \nabla u_O \cdot (\mathbf{r}_{v_i} - \mathbf{r}_O)$.

. $\boldsymbol{\varepsilon}$ is determined by relfecting local flow physics

- In nearly uniform regions, ε is large enough to prevent unnecessary operation of the limiter.

- In fluctuating regions, ε is smaller than local flow variation to activate the limiter.

$$\varepsilon_{MLP-u2}^{2} = \frac{K_{1}}{1+r} (\Delta u_{v_{i}})^{2} \text{ with } r = \frac{\Delta u_{v_{i}}}{K_{2} (\Delta x)^{1.5}}, \ \Delta u_{v_{i}} = u_{v_{i}}^{\max} - u_{v_{i}}^{\min}, \text{ and } K_{1} = K_{2} = 5.0$$

- **Determination of MLP-u slope limiters on unstructured meshes (cont'd)**
 - (S4) Determine the limited slope within the cell T_o to satisfy the local maximum principle.

$$L[u_O(\mathbf{r})] = u_O + \phi_{\mathrm{MLP},T_O} \nabla u_O \cdot (\mathbf{r} - \mathbf{r}_O) \text{ with } \phi_{\mathrm{MLP},T_O} = \min_{\forall v_i \in T_O} \phi_{\mathrm{MLP},v_i}$$

- Stability of MLP schemes
 - l_{∞} stability by the local maximum principle

For multi-dimensional nonlinear scalar conservation law of $\partial u / \partial t + \partial f(u) / \partial x + \partial g(u) / \partial y = 0$, a fully discrete scheme using the MLP limiters for *linear reconstruction* over T_o satisfies the local maximum principle under a suitable CFL condition.

If
$$u_{neighbor}^{\min,n} \le u_{T_o}^n \le u_{neighbor}^{\max,n}$$
, then $u_{neighbor}^{\min,n} \le u_{T_o}^{n+1} \le u_{neighbor}^{\max,n}$

- $u_{neighbor}^{\min/max,n}$ is the minimum/maximum cell-averaged value over the MLP stencil, S_{T_j} , given by $S_{T_j} = \{T_k | v_i \in T_k \text{ for any } v_i \in T_j\}.$

- $\phi_{_{MLP}}$ is less diffusive than conventional limiters on regular triangular/tetrahedral meshes.

• Performances of MLP

At *t* = 1.0

• Ex1: 2-D linear wave equation					-	At $l = 1.0$
on triangular meshes	Scheme	Grid	L_{∞}	Order	L_1	Order
	Barth's Limiter MLP-u1	20x20x2	4.0857E-01	-	1.8795E-01	-
$u_t + \mathbf{a} \cdot \nabla u = 0, \ \mathbf{a} = (1, 2)$		40x40x2	2.3275E-01	0.81	1.1570E-01	0.70
with		80x80x2	1.3716E-01	0.76	6.6048E-02	0.81
i) smooth IC:		160x160x2	7.7957E-2	0.81	3.6023E-02	0.87
$u_0(x,y) = \sin(2\pi x)\sin(2\pi y)$		20x20x2	1.7544E-01		3.3721E-02	
ii) discontinuous IC:		40x40x2	6.6036E-02	1.41	6.5248E-03	2.37
$u_0(x, y) = \begin{cases} 1 & \text{if } -0.5 \le x, y \le 0.5 \\ 0 & \text{otherwise} \end{cases}$		80x80x2	2.3412E-02	1.50	1.2439E-03	2.39
		160x160x2	8.0831E-03	1.53	2.5402E-04	2.29
	MLP-u2	20x20x2	2.5789E-01		7.0173E-02	
		40x40x2	1.0727E-01	1.27	1.6780E-02	2.06
		80x80x2	4.3619E-02	1.30	4.1919E-03	2.00
		160x160x2	1.7198E-02	1.34	4.1919E-03	2.11
	Unlimited	20x20x2	3.2729E-02		1.7253E-02	
		40x40x2	6.5138E-03	2.33	3.4741E-03	2.31
		80x80x2	1.4691E-03	2.15	8.0518E-04	2.11
		160x160x2	3.5323E-04	2.06	1.9720E-04	2.03

Aerodynamic Simulation & Design Laboratory, SNU

Advanced Computational Fluid Dynamics, 2019 Spring

Performances of MLP

- Ex2: 2-D steady Euler euqations
 - Inviscid transonic flow over NACA0012 airfoil
 - Freestream Mach number = 0.8, angle of attack = 1.25°
 - RoeM numerical flux with LU-SGS implicit time integration
 - 24,041 triangular elements



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