A Matrix-Free High-Dimensional DG Approach for Mitigating the Rays-Effect in Phase-Space Advection.

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Model Problem:

$\vec{\Omega} \cdot \nabla f(X, \vec{\Omega}, E) = S(X, \vec{\Omega}, E)$



Figure: Snapshots showcasing the rays-effect in different numerical simulations.



The Strategy: The Generalized S_N methodology (GSN)

(Milan Holec)

General Coordinate System

Derive general change of coordinates at the continuous level aiming at mitigating ray effects at the discrete level.

Multi-Dimensional DG Discretization

Develop a novel high-order matrix-free multi-dimensional DG method.







Rotation of the Momentum Mesh: $\forall X \in K, \forall \omega \in [0, 2\pi], \forall \mu \in [-1, 1]$ $\vec{\Omega}(X, \omega, \mu, e) = R(\vec{\zeta}(X), \omega_0(X)) \begin{bmatrix} \cos(\omega)\sqrt{1-\mu^2} \\ \sin(\omega)\sqrt{1-\mu^2} \\ \mu \\ 0 \\ 0 \end{bmatrix}$

- Analytical $\vec{\zeta}(X) \Rightarrow$ Analytical-GSN,
- Numerical $\vec{\zeta}(X) \Rightarrow$ Flux-GSN.



$$\nabla f = J^{-T} \tilde{\nabla} f, \text{ and assuming that } \frac{\partial \mathbf{q}}{\partial \tilde{\mathbf{p}}} = 0, \text{ we get}$$

$$J^{-1} = \begin{pmatrix} \frac{\partial \mathbf{q}}{\partial \tilde{\mathbf{q}}} & \frac{\partial \mathbf{q}}{\partial \tilde{\mathbf{p}}} \\ \frac{\partial \mathbf{p}}{\partial \tilde{\mathbf{q}}} & \frac{\partial \mathbf{p}}{\partial \tilde{\mathbf{p}}} \end{pmatrix}^{-1} = \begin{pmatrix} \frac{\partial \mathbf{q}}{\partial \tilde{\mathbf{q}}} & 0 \\ \frac{\partial \mathbf{p}}{\partial \tilde{\mathbf{q}}} & \frac{\partial \mathbf{p}}{\partial \tilde{\mathbf{p}}} \end{pmatrix}^{-1} = \begin{pmatrix} \frac{\partial \mathbf{q}}{\partial \tilde{\mathbf{q}}} & 0 \\ -\frac{\partial \mathbf{p}}{\partial \tilde{\mathbf{p}}} - \frac{\partial \mathbf{p}}{\partial \tilde{\mathbf{q}}} \frac{\partial \mathbf{q}}{\partial \tilde{\mathbf{q}}} - 1 & \frac{\partial \mathbf{p}}{\partial \tilde{\mathbf{p}}} - 1 \end{pmatrix}$$
(1)
Thus,

$$\vec{\Omega}.\nabla f = \vec{\tilde{\Omega}}.J^{-T}\tilde{\nabla}f = J^{-1}\vec{\tilde{\Omega}}\cdot\tilde{\nabla}f$$
(2)



Three mesh data-structures are currently supported:

- Unstructured AMR curved mesh: using the mfem::Mesh class,
- Structured mesh: e.g. Cartesian mesh (very computationally efficient and almost zero memory footprint),
- Cartesian product mesh: enable simple construction of high-dimension meshes by representing a Cartesian product mesh between either structured and unstructured meshes without any additional memory footprint.





Mesh functions:

- GetCell $K \in \tau_h$ and $\hat{F} \in \partial K$: Returns an object representing a mesh cell,
- GetFaceNeighborInfo N_F(K): Returns a neighboring cell info based on a reference face.

Cell functions:

- ComputePhysicalCoordinates x_q := F(x̂_q): Compute the physical coordinates of a point in reference space,
- ComputeJacobian $J(\hat{\mathbf{x}}_q)$: Compute the Jacobian matrix of the cell mapping at a given point in reference space,
- **GetReferenceNormal** $\hat{\mathbf{n}}$: Returns the normal of a face in reference space.

 \rightarrow The simplicity of the mesh interface guarantees $easy\ support$ for new mesh data-structures and mesh data-structures existing in other libraries.



Simple Cartesian product mesh example



 \implies The 3D mesh has the same memory footprint as 2D + 1D (Not 2D × 1D).





Advantages

- Allow mixing structured and unstructured meshes,
- Low memory footprint,
- Tensor product elements by construction,
- Block diagonal Jacobians.



Find $u \in V_h$ such that:

$$\forall K \in \tau_h, \, \forall v_K \in V_K, \int_K u \vec{\Omega} \cdot \nabla v_K - \int_{\partial K} \vec{\Omega} \cdot \vec{n} u_{upwind} v_K = \int_K f \, v_K$$

Use matrix-free approach to mitigate the curse of dimensionality:

	Memory	Flops	Arithmetic Intensity
Sparse-Matrix	$\mathcal{O}(n(p+1)^{2d})$	$\mathcal{O}(n(p+1)^{2d})$	$\mathcal{O}(1)$
Matrix-Free	$\mathcal{O}(n(p+1)^d)$	$\mathcal{O}(n(p+1)^{2d})$	$\mathcal{O}(p^d)$
Matrix-Free with	$\mathcal{O}(n(p+1)^d)$	$\mathcal{O}(\mathit{nd}(p+1)^{d+1})$	$\mathcal{O}(dp)$
Sum Factorization			

 \Rightarrow Up to $\mathcal{O}((p+1)^d)$ speedup when compared to a Sparse-matrix approach.



Matrix-Free Algorithm for Advection

Volume contribution

- **1** Express integral in reference coordinates,
- 2 Use a quadrature rule to approximate the integral by a sum,
- 3 Transform the sum in a sequence of operations.

Volume contributions:

$$\mathbf{A}^{K} \approx \sum_{q} \omega_{q} det(J(\hat{\mathbf{x}}_{q})) \left(\hat{u}(\hat{\mathbf{x}}_{q}) \, \vec{\Omega}(\mathbf{x}_{q}) \right) \cdot J^{-T}(\hat{\mathbf{x}}_{q}) \hat{\nabla} \hat{v}(\hat{\mathbf{x}}_{q}) = G^{T} D_{K} B$$

where

$$B = \begin{bmatrix} \hat{\varphi}_{0}(\hat{\mathbf{x}}_{0}) & \dots & \hat{\varphi}_{N}(\hat{\mathbf{x}}_{0}) \\ \vdots & \ddots & \vdots \\ \hat{\varphi}_{0}(\hat{\mathbf{x}}_{Q}) & \dots & \hat{\varphi}_{N}(\hat{\mathbf{x}}_{Q}) \end{bmatrix}, \quad G = \begin{bmatrix} \hat{\nabla}\hat{\varphi}_{0}(\hat{\mathbf{x}}_{0}) & \dots & \hat{\nabla}\hat{\varphi}_{N}(\hat{\mathbf{x}}_{0}) \\ \vdots & \ddots & \vdots \\ \hat{\nabla}\hat{\varphi}_{0}(\hat{\mathbf{x}}_{Q}) & \dots & \hat{\nabla}\hat{\varphi}_{N}(\hat{\mathbf{x}}_{Q}) \end{bmatrix}, \quad D_{K} = \begin{bmatrix} \omega_{0}det(J(\hat{\mathbf{x}}_{0}))J^{-1}(\hat{\mathbf{x}}_{0})\vec{\Omega}(\mathbf{x}_{0}) & 0 \\ & \ddots & \\ 0 & & \omega_{Q}det(J(\hat{\mathbf{x}}_{Q}))J^{-1}(\hat{\mathbf{x}}_{Q})\vec{\Omega}(\mathbf{x}_{Q}) \end{bmatrix}$$

Matrix-free operator:

$$v_K = G^T D_K B u_K$$

Matrix-Free Algorithm for Advection

Face contribution

$$a_{K}^{\mathsf{face}}(u,v) = \sum_{\hat{F} \in \partial \hat{K}} \sum_{q} \omega_{q} |J(\hat{\mathbf{x}}_{q})| \operatorname{upwind} \left(\mathbf{a}(\mathbf{x}_{q}), J^{-T}(\hat{\mathbf{x}}_{q}) \hat{\mathbf{n}}, \hat{u}(\hat{\mathbf{x}}_{q}) \right) \cdot \llbracket \hat{v} \rrbracket (\hat{\mathbf{x}}_{q})$$

Express the face operator as a sequence of operations:

$$v_{K} = \sum_{\hat{F} \in \partial K} B_{\hat{F}}^{T} D_{K,\hat{F}} (B_{\hat{F}} u_{K}, \tilde{B}_{\hat{F}} P_{K,\hat{F}} u_{\mathcal{N}_{\hat{F}}(K)})$$

where

$$D_{K,\hat{F}}(u_{K}(\hat{\mathbf{x}}_{q}), u_{\mathcal{N}_{\hat{F}}(K)}(\hat{\mathbf{x}}_{q})) = \omega_{q} | J(\hat{\mathbf{x}}_{q}) | \text{upwind} \Big(\mathbf{a}(\mathbf{x}_{q}), J^{-T}(\hat{\mathbf{x}}_{q}) \hat{\mathbf{n}}, u_{K}(\hat{\mathbf{x}}_{q}), u_{\mathcal{N}_{\hat{F}}(K)}(\hat{\mathbf{x}}_{q}) \Big)$$



On tensor product finite elements, the B operator can be computed as:

$$v_{k_{1}...k_{6}} = B_{IK} u_{I} = \underbrace{\sum_{i_{1},...,i_{6}} u_{i_{1}...i_{6}} \varphi_{i_{1}}(x_{k_{1}}) \dots \varphi_{i_{6}}(x_{k_{6}})}_{O(p^{12}) = O(p^{2d})}$$
$$= \sum_{i_{6}} \varphi_{i_{6}}(x_{k_{6}}) \left(\dots \left(\underbrace{\sum_{i_{1}} \varphi_{i_{1}}(x_{k_{1}}) u_{i_{1}...i_{6}}}_{O(p^{7}) = O(p^{d+1})} \right) \right)$$
$$= \tilde{B}_{i_{6}k_{6}} \otimes \dots \otimes \tilde{B}_{i_{1}k_{1}} u_{i_{1}...i_{6}}$$



Benchmark Problem

v = Au

Theoretical data movements for the advection operator

Dimension		3D				6D			
Polynomial order		1	2	3	0	1	2	3	
Number of dofs per element		8	27	64	1	64	729	4096	
SpMV – Bytes per dof		260	560	1076	176	980	9740	52244	
PA – Bytes per dof		259	158.2	119.1	21520	2749.7	1094.8	638.6	
MF – Analytical mesh – Bytes per dof		16	16	16	16	16	16	16	
MF – Linear space mesh – Bytes per dof		40	23	19	208	19	16.3	16.1	
MF – Quadratic space mesh – Bytes per dof		97	40	26.1	664	26.1	16.9	16.2	

SpMV: Sparse-Matrix vector product, PA: Partial Assembly operator application, MF: Fully Matrix-Free operator application



Performance Benchmark: Mass Operator

CPU Machine: Quartz (OpenMP - 76.8GB/s)



SpMV: Sparse-Matrix vector product, PA: Partial Assembly operator application, MF: Fully Matrix-Free operator application p is the polynomial order, q is the number of quadrature points per dimension.



Performance Benchmark: Advection Operator

CPU Machine: Quartz (OpenMP - 76.8GB/s)



SpMV: Sparse-Matrix vector product, PA: Partial Assembly operator application, MF: Fully Matrix-Free operator application p is the polynomial order, q is the number of quadrature points per dimension.



Early GPU performance results (Amit Rotem)

CPU Machine: Quartz (OpenMP - 76.8GB/s), GPU Machine: Lassen (V100 - 900GB/s)



Main Takeaway:

Matrix-Free mass operator throughput is higher in 6D than 3D on GPU!



Rays-Effect Benchmark Problem I

Source Term:

- - Inflow function: $S_{in}(x, y, \omega) = 2$,
- \blacksquare Outflow only.





Standard High-Order DG on Benchmark Problem I

Scalar flux:

$$F(X) = \int u(X,\omega)d\omega$$



Figure: High order DG methods do not solve the rays-effect.



Comparing Standard with Cylindrical GSN

Benchmark Problem I: First Order





Rays-Effect Benchmark Problem II

Source Term:

- Inflow function: $S_{in}(x, y, \omega) = (x^2 + y^2)^4$,
- \blacksquare Outflow only.





Comparing "Standard" with "Polar" Coordinates

Benchmark Problem II: Second Order





Comparing Standard with Cylindrical GSN

Benchmark Problem II: impact of the polynomial order p with $n_{\vec{0}} = 16$





Rays-Effect Benchmark Problem III

Source Term:

- - Inflow function: $S_{in}(r, z, \omega, \phi) = 2$,
- Outflow only.





Benchmark III: Perfect Hohlraum in RZ spatial coordinates

Comparing "cylindrical" GSN with "spherical" GSN





Benchmark III: Perfect Hohlraum in RZ spatial coordinates

Comparing zeroth order in angle with high order in angle using spherical GSN





Net flux (First Moment):

$$\vec{F}(X) = \int_{\omega} p(X,\omega) u(X,\omega) d\omega$$

Flux-GSN algorithm:

- 1 Compute initial solution using analytical-GSN
- 2 Compute net flux
- 3 Fixed-point iteration until convergence
 - **1** Compute solution using flux-GSN with net flux: $\vec{\zeta}(X) = \vec{F}(X)$
 - 2 Compute net flux



Rays-Effect Benchmark Problem IV

Source Term:

- - Inflow function: $S_{in}(x, y, \omega) = 4 x$,
- Outflow only.





Flux-GSN example

Benchmark Problem IV





Main Takeaways

- The Analytical-GSN and Flux-GSN methodologies can efficiently mitigate the rays-effect at low computational cost.
- Matrix-free algorithms mitigates efficiently the computational cost of high-dimensional simulation.
- The higher the dimension the higher the throughput on GPU architectures.
- Tensor product meshes enable easy construction of arbitrary dimension meshes.

Future Work

- Use other quantities than net flux to inform flux-GSN's coordinate system.
- Improvement of matrix-free solvers and preconditioners.
- Extension to non-conforming meshes (AMR).



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