

Entropy stable notes

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1 Curved meshes

Assume non-affine geometric factors.

Let $\mathbf{F}(\mathbf{U})$ denote the flux matrix whose rows are

$$\mathbf{F}(\mathbf{U}) = \begin{pmatrix} \mathbf{F}_x \\ \mathbf{F}_y \end{pmatrix}.$$

The conservation law of interest is the following

$$\frac{\partial \mathbf{U}}{\partial t} + \nabla \cdot \mathbf{F}(\mathbf{U}) = 0,$$

where the divergence is taken over each column of $\mathbf{F}(\mathbf{U})$.

Let \mathbf{G} denote the Jacobian of the geometric mapping

$$\mathbf{G}_{ij} = \frac{\partial \hat{\mathbf{x}}_j}{\partial \mathbf{x}_i},$$

and let J denote the determinant of \mathbf{G} . One can show that

$$\hat{\nabla} \cdot (J\mathbf{G}^T) = 0$$

at the continuous level. We also have that the mapped normals obey the property

$$J\mathbf{G}\hat{\mathbf{n}}\hat{J}^f = \mathbf{n}J^f.$$

At the continuous level, the physical gradient and divergence satisfy

$$(\nabla u, \mathbf{v})_{D^k} = (J\mathbf{G}\hat{\nabla}u, \mathbf{v})_{\hat{D}}, \quad (\nabla \cdot \mathbf{u}, v)_{D^k} = (\hat{\nabla} \cdot (J\mathbf{G}^T \mathbf{u}), v)_{\hat{D}},$$

as well as a corresponding integration by parts property.

2 Flux differencing

Replace the flux derivative with

$$(\nabla \cdot \mathbf{F}(\mathbf{U}), \mathbf{V})_{D^k} \approx (\nabla \cdot \mathbf{F}_S(\mathbf{U}(\mathbf{x}), \mathbf{U}(\mathbf{x}'))|_{\mathbf{x}'=\mathbf{x}}, \mathbf{V})_{D^k}.$$

It is possible to remove the effect of geometric aliasing by evaluating the above term via

$$\left(\hat{\nabla} \cdot \mathbf{F}_S^k(\mathbf{U}(\mathbf{x}), \mathbf{U}(\mathbf{x}')) \Big|_{\mathbf{x}'=\mathbf{x}}, \mathbf{V} \right)_{\hat{D}}, \quad \mathbf{F}_S^k = \{\{J\mathbf{G}\}\} \mathbf{F}_S(\mathbf{U}(\mathbf{x}), \mathbf{U}(\mathbf{x}'))$$

Another alternative is to treat curvilinear grids using a skew-symmetric form, though this may not be strictly locally conservative.

2.1 Weight-adjusted DG

We define the curvilinear L^2 projection Π_N^J such that

$$(\Pi_N^J u, v)_{D^k} = (J \Pi_N^J u, v)_{\hat{D}} = (uJ, v)_{\hat{D}} = (u, v)_{D^k}.$$

Let the weight-adjusted projection operator P_N be defined as $P_N u = \Pi_N \left(\frac{1}{J} \Pi_N^J(uJ) \right)$. Note that P_N is self-adjoint with respect to the J -weighted L^2 inner product

$$(JP_N u, v) = \left(\Pi_N \left(\frac{1}{J} \Pi_N^J(uJ) \right), vJ \right) = \left(uJ, \Pi_N \left(\frac{1}{J} \Pi_N^J(vJ) \right) \right) = (uJ, P_N v).$$

Let $\Pi_N^J u$ be the L^2 projection of u with respect to the weighted (curvilinear) L^2 inner product. We observe in numerical experiments that for a fixed geometric mapping, $\|\Pi_N^J u - P_N u\|_{L^2(\Omega)} = O(h^{N+2})$. Because the difference between the L^2 and WADG projection is superconvergent, the results are indistinguishable for a fixed geometric mapping.

We can prove this bound using results from [1]. We first define the operator T_w^{-1} as follows

$$(wT_w^{-1}u, v)_{\hat{D}} = (u, v)_{\hat{D}}, \quad \forall v \in V_h.$$

This forms the basis of the weight-adjusted approximation of weighted L^2 inner products. The first theorem we need shows that $T_{1/J}^{-1}$ can be used to approximate weighted curvilinear L^2 inner products with order $(2N+2)$ accuracy.

Theorem 1. *Let $u \in W^{N+1,2}(D^k)$ and $v \in V_h(D^k)$. Then,*

$$\begin{aligned} & \left| (u, vJ)_{\hat{D}} - (T_{1/J}^{-1}u, v)_{\hat{D}} \right| \leq \\ & Ch^{2N+2} \|J\|_{L^\infty(D^k)} \left\| \frac{1}{J} \right\|_{L^\infty(D^k)}^2 \|J\|_{W^{N+1,\infty}(D^k)}^2 \|u\|_{W^{N+1,2}(D^k)} \|v\|_{W^{N+1,2}(D^k)}. \end{aligned}$$

Proof. The proof involves straightforward adaptations of Theorem 4, Theorem 5, and Theorem 6 in [1] to the reference element \hat{D} . \square

The next result we need is a generalized inverse inequality.

Lemma 1. *Let $v \in P^N(D^k)$, and let $h = \text{diam}(D^k)$. Then,*

$$\|v\|_{W^{N+1,2}(D^k)} \leq C_N h^{-N} \|v\|_{L^2(D^k)}.$$

where C_N is independent of h .

Proof. The result is the consequence of a scaling argument and a Rayleigh quotient bound involving the largest eigenvalue of the generalized eigenvalue problem

$$\mathbf{K}_N \mathbf{u} = \lambda \mathbf{M} \mathbf{u},$$

where \mathbf{M} is the L^2 mass matrix over D^k and \mathbf{K}_N is the Gram matrix corresponding to the Sobolev inner product for $W^{N+1,2}(D^k)$. We note that the constant C_N depends on the largest eigenvalue, which in turn depends on the order N and dimension d . \square

We can now prove that $P_N u$ is superconvergent to the curvilinear L^2 projection $\Pi_N^J u$

Theorem 2. Let $u \in W^{N+1,2}(D^k)$. The difference between the L^2 projection $\Pi_N u$ and the weight-adjusted projection $P_N u$ is

$$\|\Pi_N u - P_N u\|_{L^2(D^k)} \leq C \|J\|_{L^\infty(D^k)} \left\| \frac{1}{J} \right\|_{L^\infty(D^k)}^2 \|J\|_{W^{N+1,\infty}(D^k)}^2 h^{N+2} \|u\|_{W^{N+1,2}(D^k)}.$$

where C is a mesh-independent constant.

Proof. Let $\Pi_N^J u$ be the L^2 projection over the curved element D^k , such that

$$(J\Pi_N^J u, v) = (uJ, v), \quad \forall v \in V_h.$$

By definition, $P_N u$ satisfies a similar property

$$(T_{1/J}^{-1} P_N u, v) = (uJ, v), \quad \forall v \in V_h.$$

Then, we have that

$$\|\Pi_N^J u - P_N u\|_{L^2(D^k)}^2 = (\Pi_N^J u - P_N u, vJ)_{\hat{D}}, \quad v = \Pi_N^J u - P_N u.$$

Because $v \in P^N(D^k)$, we can also evaluate the squared error as

$$\begin{aligned} \|\Pi_N^J u - P_N u\|_{L^2(D^k)}^2 &= |(\Pi_N^J u, vJ)_{\hat{D}} - (P_N u, vJ)_{\hat{D}}| \\ &= |(u, vJ)_{\hat{D}} - (P_N u, vJ)_{\hat{D}}| = \left| \left(T_{1/J}^{-1} P_N u, v \right)_{\hat{D}} - (JP_N u, v)_{\hat{D}} \right|. \end{aligned}$$

Applying Theorem 1 and Lemma 1 with $M = N$ then yields that

$$\begin{aligned} \|\Pi_N u - P_N u\|_{L^2(D^k)}^2 &\leq Ch^{2N+2} C_J \|u\|_{W^{N+1,2}(D^k)} \|v\|_{W^{N+1,2}(\hat{D})} \\ &\leq Ch^{N+2} C_J \|u\|_{W^{N+1,2}(D^k)} \|v\|_{L^2(D^k)}, \end{aligned}$$

where C_J is a mesh-independent constant depending on J . Dividing through by

$$\|v\|_{L^2(D^k)} = \|\Pi_N u - P_N u\|_{L^2(D^k)}$$

gives the desired result. \square

3 Limiting

Ignoring high order terms in the Taylor expansion, we have

$$u(\Pi_N v) - u = \frac{\partial u}{\partial v} (\Pi_N v - v).$$

We want to limit u with a compression towards the mean $u = \bar{u} + \theta(u - \bar{u})$ such that $|u(\Pi_N v)| \leq C|u|$.

One option: ensure $|u(\Pi_N v) - u(\bar{v})| \approx |u - u(\bar{v})|$ based on Taylor series.

$$u(\Pi_N v) - u(\bar{v})$$

Limit $\tilde{u} = \bar{u} + \theta(u - \bar{u})$ such that

$$\min \Pi_N v \geq \min v, \quad \max \Pi_N v \leq \max v.$$

Other options

- Adaptively choose time-step size?
- Expensive option: bisection or Newton algorithm for finding theta.

References

- [1] Jesse Chan, Russell J Hewett, and T Warburton. Weight-adjusted discontinuous Galerkin methods: wave propagation in heterogeneous media. *arXiv preprint arXiv:1608.01944*, 2016.
- [2] Jesse Chan, Russell J Hewett, and T Warburton. Weight-adjusted discontinuous Galerkin methods: curvilinear meshes. *arXiv preprint arXiv:1608.03836*, 2016.