

Adaptation of Curved Meshes in ALE Hydrodynamics

MultiMat 2019, Trento, Italy

9-13 September 2019



Vladimir Tomov

V. Dobrev, P. Knupp, Tz. Kolev, K. Mittal, and R. Rieben

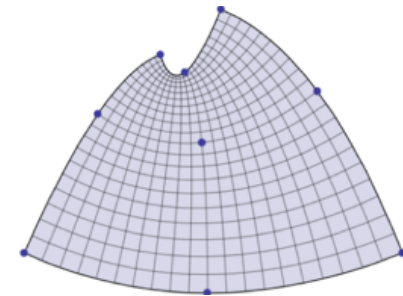


Overview and motivation

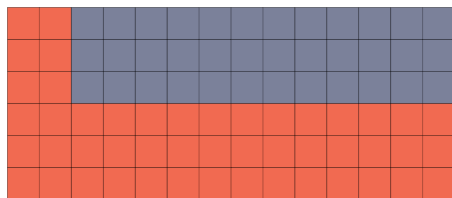
- General framework for mesh optimization.
 - Meshes are modified by node movement.
 - Extension of TMOP to curved meshes and adaptivity.
 - User targets (ideal geometry), mesh quality metrics, nonlinear optimization.
 - Algebraic routines - no geometrical operations in physical space.
- Application to multi-material ALE hydro.
 - Demonstration code - BLAST (high-order FE on curved grids).
 - Adaptivity to discrete features (interfaces, materials, shocks, etc).
 - Adaptive ALE triggers.

Discretization and ALE framework in BLAST

- Lagrange + remap, high-order finite elements.
- Curved meshes: $\mathbf{x} = (\mathbf{x}_1 \dots \mathbf{x}_N)^T$, $\mathbf{x}_q(\bar{\mathbf{x}}_q) = \sum_{i=1}^N \mathbf{x}_i \bar{w}_i(\bar{\mathbf{x}}_q)$
- Any number of Lagrangian steps between two ALE steps.

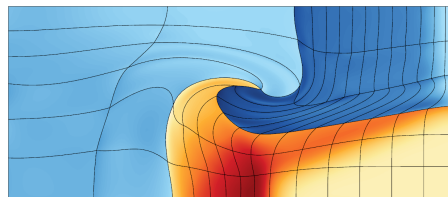


Example of a Q_2 element

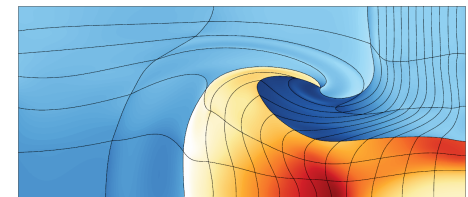


Triple point, Q3Q2, 84 elements

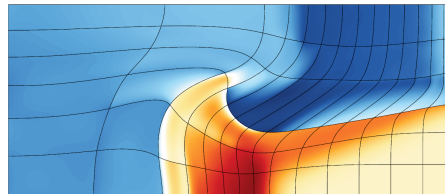
3000 Lagr
steps



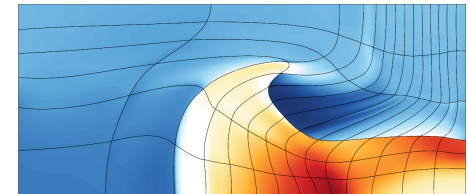
~6000 Lagr
steps



Remesh + remap step



1155 Lagr
steps



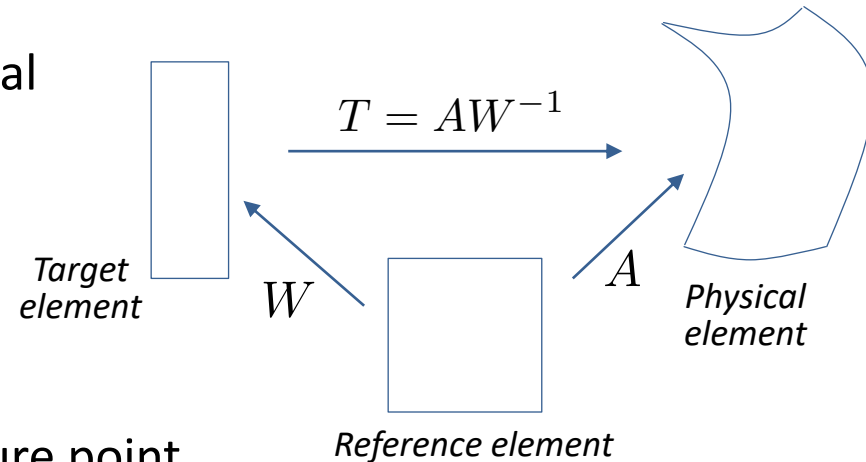
Towards what to optimize the mesh?
How often to perform ALE steps?

Target - Matrix Optimization Paradigm (TMOP)

- Target construction: the user defines ideal elements by specifying the Jacobians W .

- Minimize
$$\sum_{E \in \mathcal{M}} \int_{E_t} \mu(T(x_t))$$

$\mu(T(x_t))$ \swarrow
Mesh quality metric



- $T, \mu(T)$ are computed at every quadrature point.
- Default option: Newton's method (+ line search) to solve $\partial F(x) / \partial x = 0$.
 - Efficient parallel implementation in contrast to derivative-free methods.
- Requires calculation of $\partial \mu(T) / \partial T$ and $\partial^2 \mu(T) / \partial T^2$ for the metric.

Dobrev, Knupp, Kolev, Mittal, Tomov "The Target-Matrix Optimization Paradigm for High-Order Meshes", SIAM J. Sci. Comp, 2019.

TMOP mesh quality metrics

We have explored more than 60 metrics divided into 7 metric types

- Jacobian decomposition: $W = [\text{volume}] [\text{orientation}] [\text{skew}] [\text{aspect ratio}]$.

- Shape metrics – control over skew and aspect ratio.

Minimized when A is a scaled rotation of W .

$$\mu_2(T) = 0.5 \frac{|T|^2}{\det(T)} - 1$$

- Size metrics – control over volume.

Minimized when $\det(A) = \det(W)$.

$$\mu_{77}(T) = 0.5 \left(\det(T) - \frac{1}{\det(T)} \right)^2$$

- Alignment metrics – control over orientation and skew.

Minimized when $A = W * \text{Diag}$.

$$\mu_{30}(A, W) = |\mathbf{a}_1| |\mathbf{w}_1| - (\mathbf{a}_1 \cdot \mathbf{w}_1) + |\mathbf{a}_2| |\mathbf{w}_2| - (\mathbf{a}_2 \cdot \mathbf{w}_2)$$

- Implicit combinations.

SH+SZ, SH+AL, SZ+AL, SH+SZ+AL. $\mu_7(T) = |T - T^{-t}|^2$ $\mu_{14}(T) = |T - I|^2$

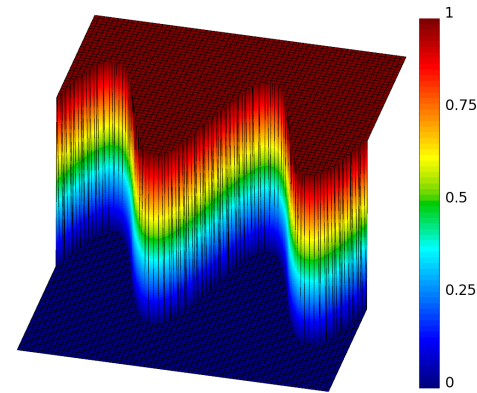
- Explicit combinations.

$$\mu(T) = \alpha \mu_i(T) + (1 - \alpha) \mu_j(T)$$

P. Knupp, “Algebraic mesh quality metrics”, SIAM J. Sci. Comp., 23(1):193-218, 2001.

Main steps in the adaptivity procedure

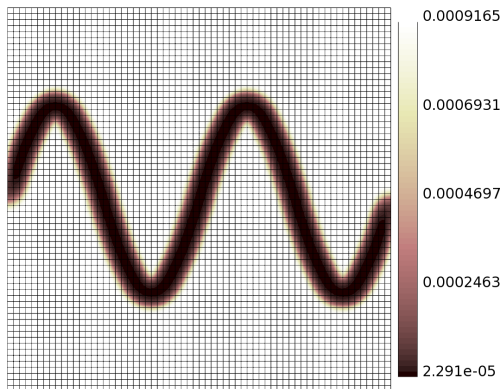
Example of adapting size and aspect ratio to a material interface



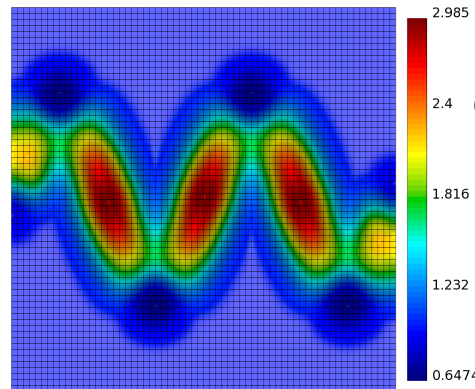
1. Start with simulation data
(material interface η here)

2. Choose adaptation goal
volume = ζ
orientation angle = θ
skew angle = ϕ
aspect ratio = ρ

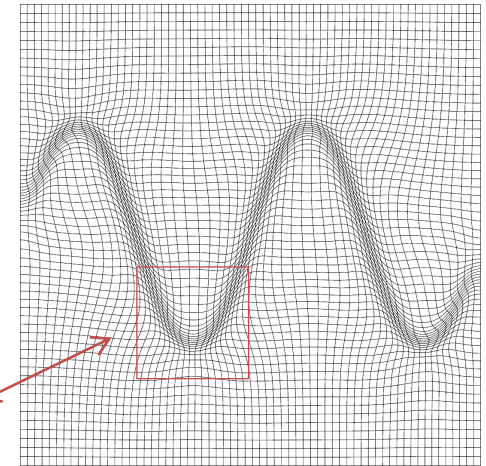
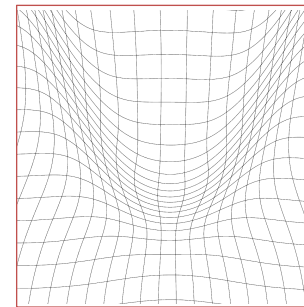
3. Transform into
geometric data on
the initial mesh



Size function $S(x) \approx |\nabla\eta|$



Aspect ratio $A(x) \approx |\eta_x/\eta_y|$



Choose quality
metric and optimize
the nonlinear
functional

Construct target
Jacobians

$$W(x) = \left(\frac{S(x)}{A(x)} \right)^{\frac{1}{2}} \begin{bmatrix} 1 & 0 \\ 0 & A(x) \end{bmatrix}$$

General formula in 2D:

$$X = \sqrt{\zeta} \begin{pmatrix} \frac{1}{\sqrt{\rho}} \cos \theta & \sqrt{\rho} \cos(\theta + \phi) \\ \frac{1}{\sqrt{\rho}} \sin \theta & \sqrt{\rho} \sin(\theta + \phi) \end{pmatrix}$$

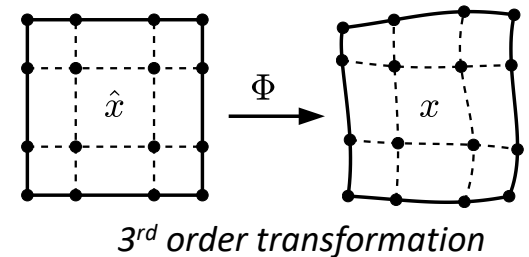
Adaptivity field values on intermediate meshes

The values of $\eta_0(x_0)$ are transferred on different meshes

- Iterative solvers use a series of intermediate meshes to reach convergence.
- Method 1: physical \rightarrow logical space interpolation.
 - Iterate over a set of candidate elements.
 - Invert the reference \rightarrow physical map for each.

$$\bar{x}_0^{n+1} = \bar{x}_0^n + A^{-1}(\bar{x}_0^n) [x - \Phi_{E_0}(\bar{x}_0^n)]$$

- Challenging parallel implementation.

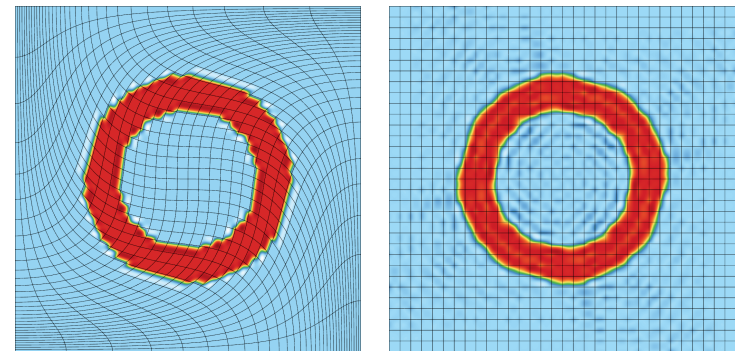


- Method 2: advection remap.
 - Define pseudo-time τ and mesh velocity u .

$$\tau \in [0, 1], \quad u = x - x_0$$

$$\frac{d\eta}{d\tau} = u \cdot \nabla \eta, \quad \eta(x_0, 0) = \eta_0(x_0)$$

- CG advection, no monotonicity treatment.



CG remap of a 3rd order field on 3rd order mesh

Differentiation of adaptive target matrices

Major difference compared to geometry-based optimization

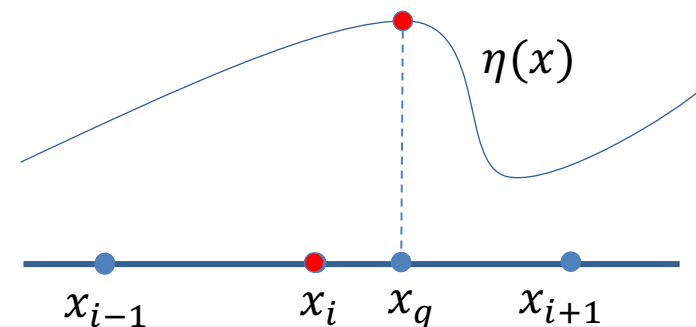
- As W depends on η , derivative-based solvers need its derivatives in \mathbf{x} .

$$F(\mathbf{x}) := \sum_{E \in \mathcal{M}} \int_{E_t} \mu(T(\mathbf{x}_t)) d\mathbf{x}_t = \sum_{E \in \mathcal{M}} \sum_{\mathbf{x}_q \in E_t} w_q \det(W(\bar{\mathbf{x}}_q)) \mu(T(\mathbf{x}_q))$$

$$\frac{\partial \mu(T)}{\partial x_{ij}} = \underbrace{\left(\nabla \bar{w}_i W^{-1}(\eta(\mathbf{x})) - A(\mathbf{x}) W^{-1} \frac{\partial W}{\partial \eta} \left(\nabla \eta \cdot \frac{\partial \mathbf{x}}{\partial x_{ij}} \right) W^{-1} \right)}_{\text{New term due to } r\text{-adaptivity}} : \frac{\partial \mu(T)}{\partial T}$$

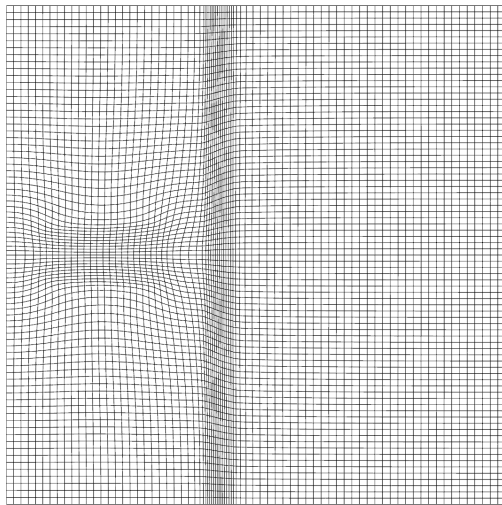
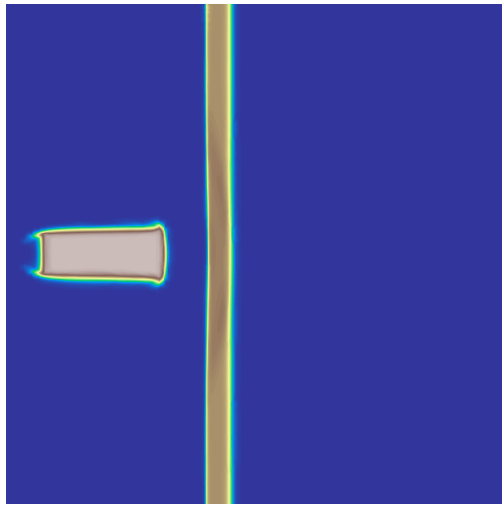
$$A(\mathbf{x}) = \sum_i \mathbf{x}_i \nabla \bar{w}_i(\bar{\mathbf{x}}), \quad \mathbf{x} = \sum_i \mathbf{x}_i \bar{w}_i(\bar{\mathbf{x}}), \quad \eta(\mathbf{x}) = \sum_i \eta_i w_i(\mathbf{x}), \quad \left[\frac{\partial \mu}{\partial T} \right]_{kl} = \frac{\partial \mu}{\partial T_{kl}}$$

- The above derivative is still an approximation. It doesn't consider transfer errors.

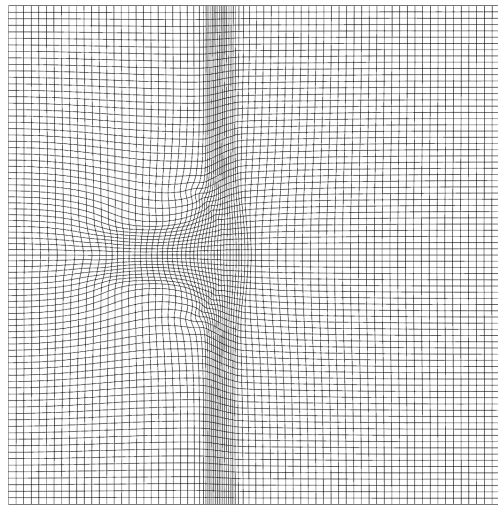
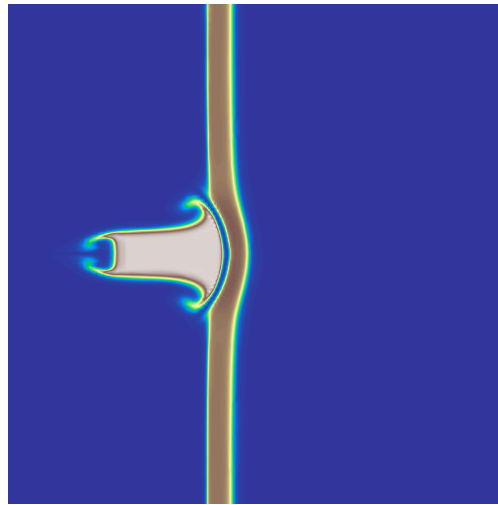


Example of r-adaptivity in an impact simulation

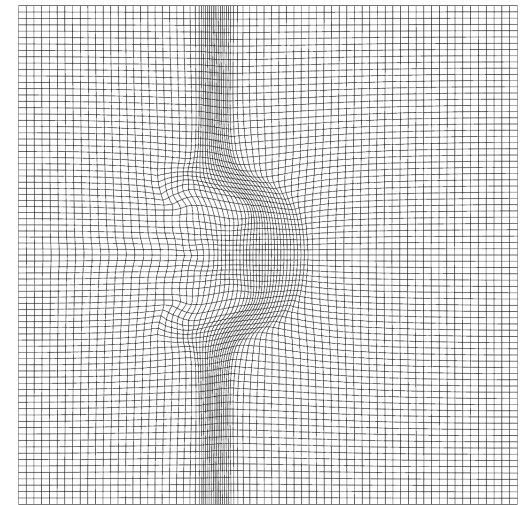
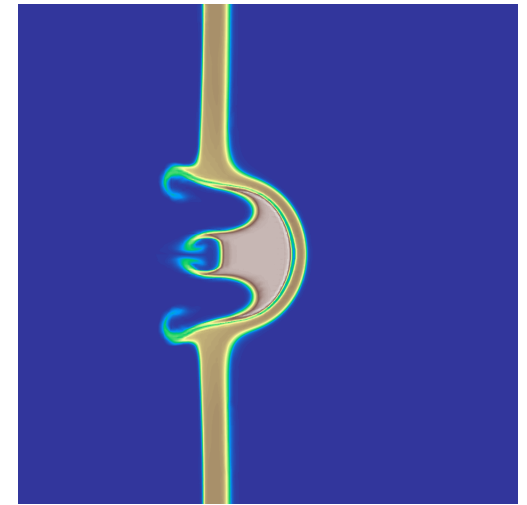
45000 Lagrange steps / 80 ALE steps / 690 pseudo advection steps



$t = 0.5$



$t = 2.0$



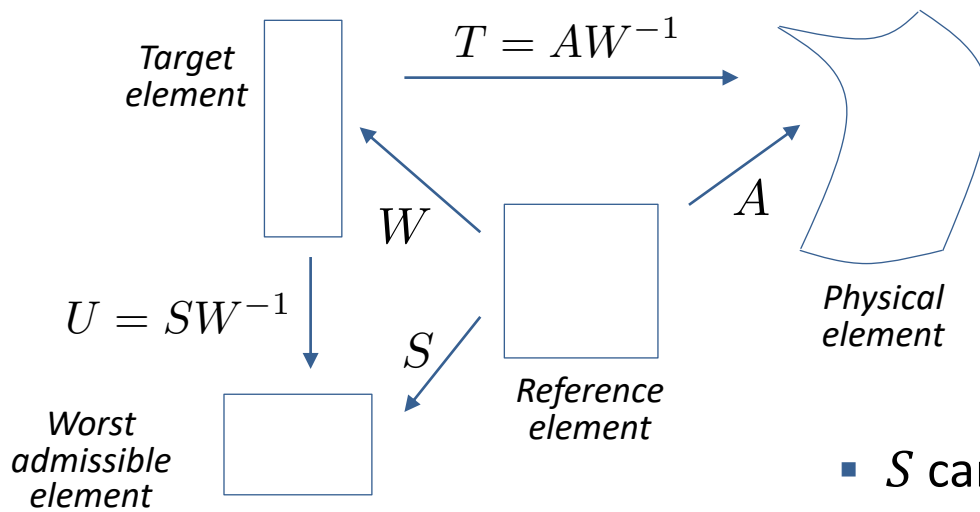
$t = 4.0$

TMOP-based quality detection and ALE triggers

User-defined admissible local quality can trigger the ALE step

- Too few ALE steps - deterioration of mesh quality can cause simulation failure.
- Too frequent - affects accuracy (remap is artificial transport).
- ALE frequency must be based on mesh quality.
 - Lagrangian steps don't always deteriorate mesh quality!
- The user defines admissible local quality.

Jacobian S of the reference \rightarrow *worst admissible* element transformation.



- ALE step is triggered whenever
$$\mu(T) > \mu(U)$$

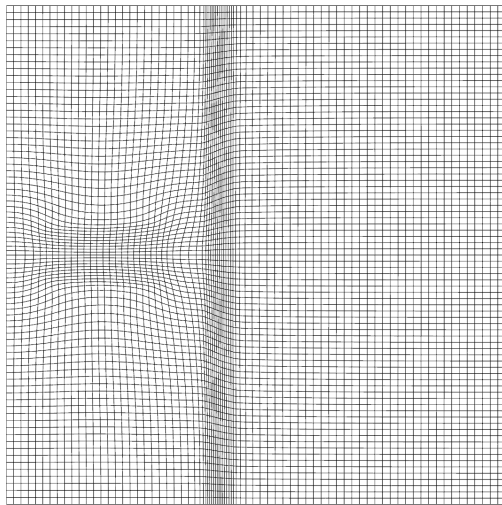
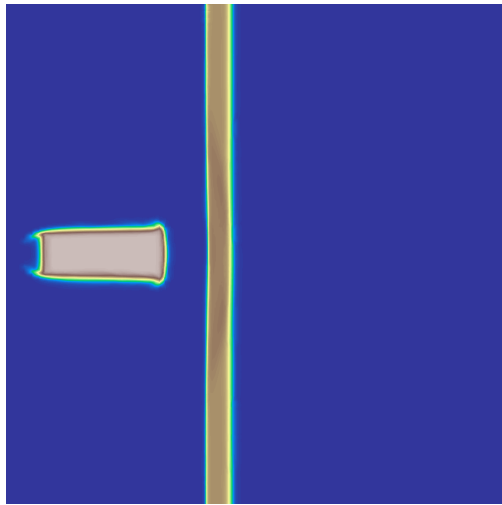
- S and W must be in sync!
 - Might get stuck otherwise.

- S can be adapted through η .

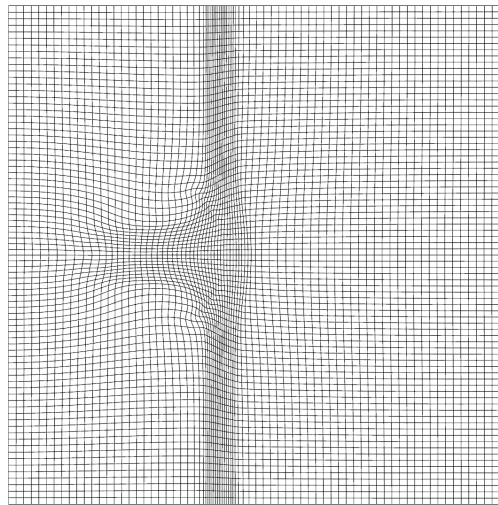
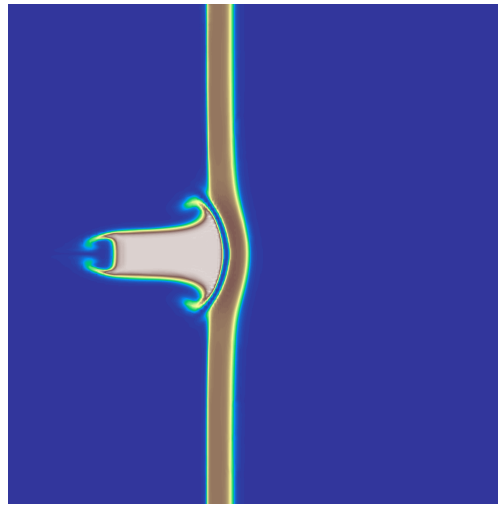
$S = [\text{volume}] [\text{orientation}] [\text{skew}] [\text{aspect ratio}]$.

Example of r-adaptivity in an impact simulation

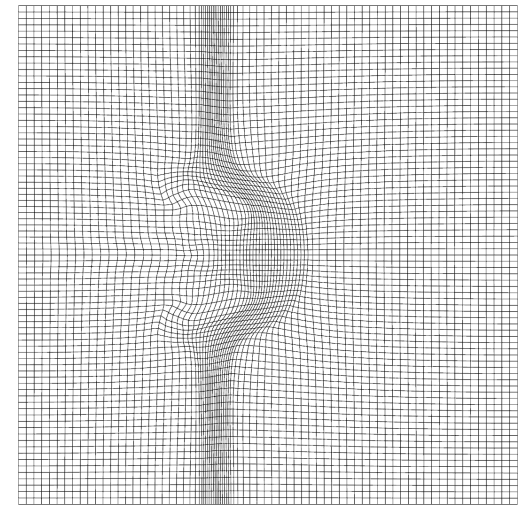
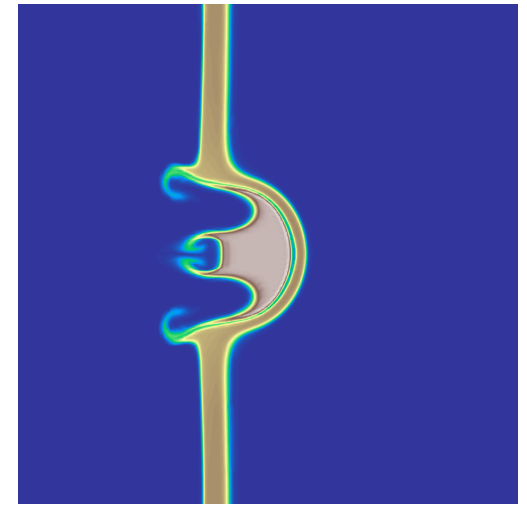
45000 Lagrange steps / 80 ALE steps / 690 pseudo advection steps



$t = 0.5$



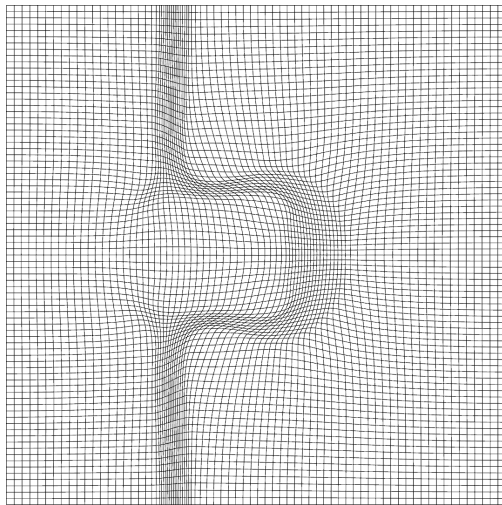
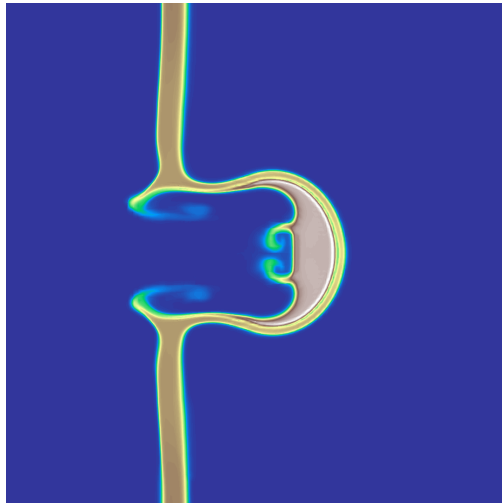
$t = 2.0$



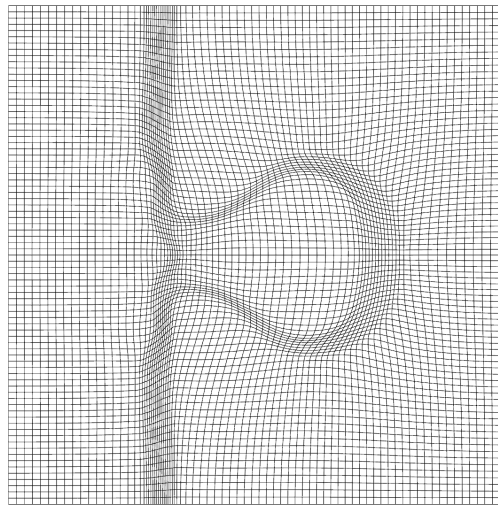
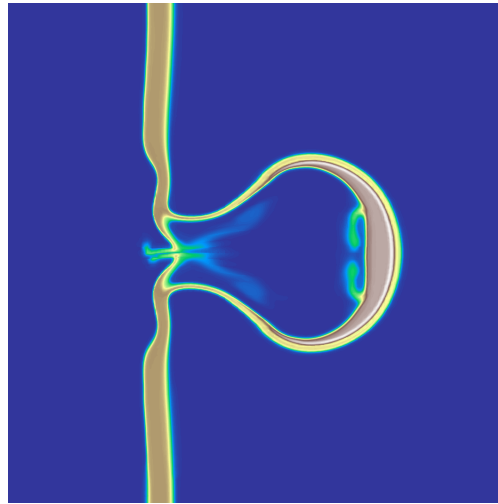
$t = 4.0$

Example of r-adaptivity in an impact simulation

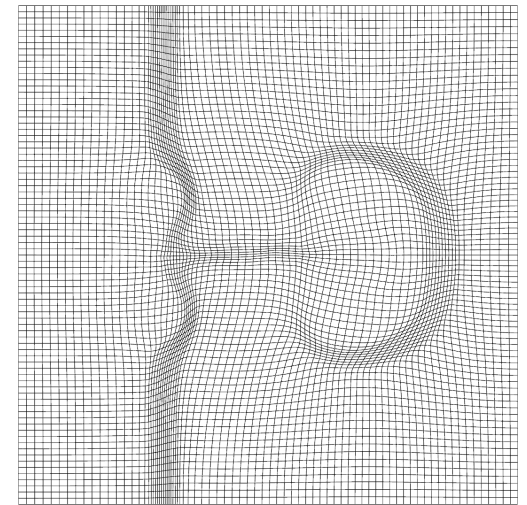
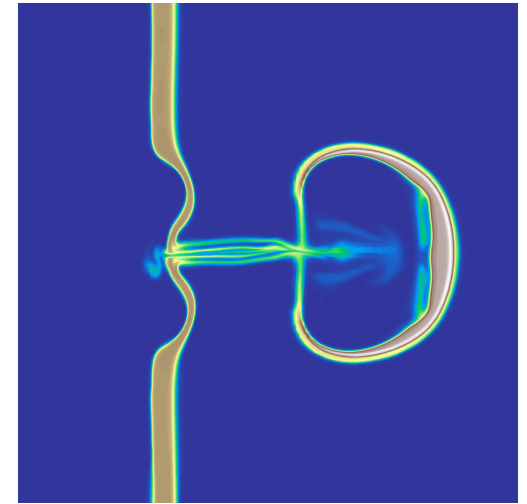
45000 Lagrange steps / 80 ALE steps / 690 pseudo advection steps



$t = 6.0$



$t = 8.0$

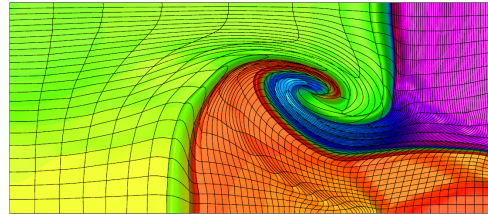


$t = 10.0$

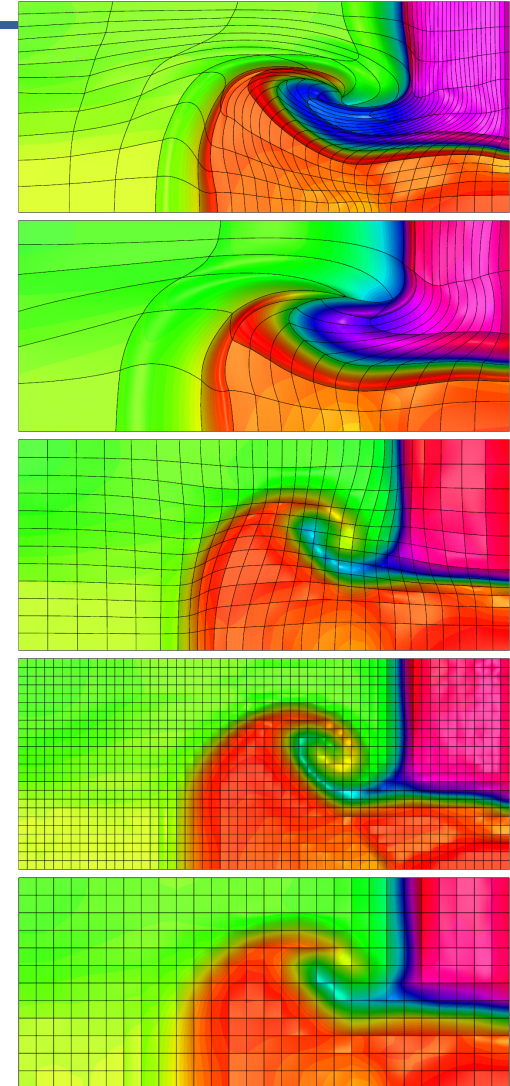
A more quantitative example

Solutions on different meshes are compared through interpolation

- Triple point to time 5, Q2Q1.
Skew angle trigger at $\pi/4$.

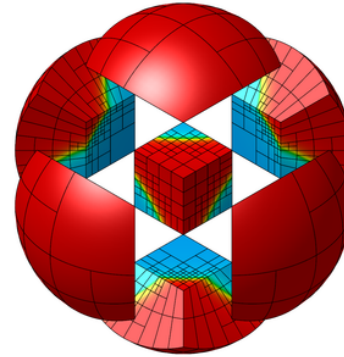


Method	Refs	L Cycles	Runtime	# ALE	Error
Lagrangian	2	93 833	-	0	0
Lagrangian	1	18 482	266	0	0.069
Lagrangian	0	3 034	11.2	0	0.138
Adapted to interfaces	1	1 577	54.4	19	0.099
Eulerian	2	1 508	134	21	0.098
Eulerian	1	802	18.5	11	0.143

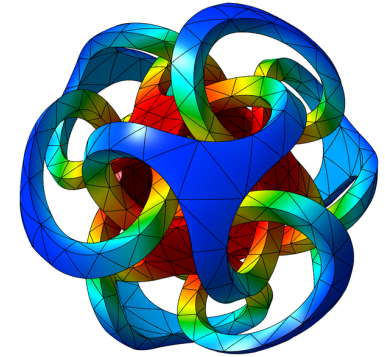


MFEM open source implementation

- All presented methods are (or will be) available in MFEM.
- MFEM contains **12** 2D metrics, **7** 3D metrics, all metric derivatives, **6** target construction methods.
- User interface provided by the ***mesh_optimizer*** and ***pmesh_optimizer*** miniapps.
 - Choice of target construction / quality metric / adaptivity fields / parameters.
 - Visualization through GLVis.



mfem.org



glvis.org

V. Dobrev, P. Knupp, Tz. Kolev, K. Mittal, V. Tomov, “The target-matrix optimization paradigm for high-order meshes”, SISC, 2018.

V. Dobrev, P. Knupp, Tz. Kolev, V. Tomov, “Towards simulation-driven optimization of high-order meshes by the target-matrix optimization paradigm”, IMR 2018 Proceedings.

Summary and future work

- The TMOP framework can be beneficial in ALE hydro.
 - Flexible adaptivity options.
 - Simulation-based ALE triggers.
- General framework for improving quality of high-order curved meshes.
 - Point-wise quality metrics + target constructions.
 - Sub-element control over shape / size / alignment.
- Extension to r-adaptivity based on discrete adaptivity fields.
 - Interpolation / advection to obtain values of η on intermediate meshes.
 - Additional derivative terms in the nonlinear solvers.
- Future work:
 - Approximate preservation of discrete surfaces.
 - Combination of TMOP and AMR adaptivity (hr-adaptivity).
 - Improved nonlinear solvers, physical interpolation, general TMOP components.



CASC

Center for Applied
Scientific Computing



**Lawrence Livermore
National Laboratory**

Disclaimer

This document was prepared as an account of work sponsored by an agency of the United States government. Neither the United States government nor Lawrence Livermore National Security, LLC, nor any of their employees makes any warranty, expressed or implied, or assumes any legal liability or responsibility for the accuracy, completeness, or usefulness of any information, apparatus, product, or process disclosed, or represents that its use would not infringe privately owned rights. Reference herein to any specific commercial product, process, or service by trade name, trademark, manufacturer, or otherwise does not necessarily constitute or imply its endorsement, recommendation, or favoring by the United States government or Lawrence Livermore National Security, LLC. The views and opinions of authors expressed herein do not necessarily state or reflect those of the United States government or Lawrence Livermore National Security, LLC, and shall not be used for advertising or product endorsement purposes.

Combinations of metrics and limiting terms

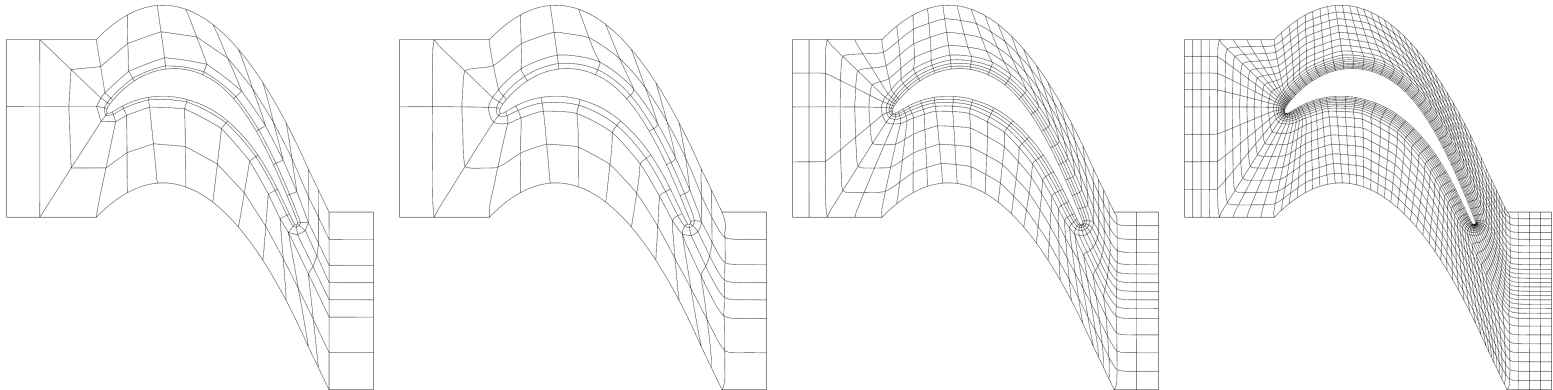
All terms are normalized relative to the unit value

- Users expect similar displacement under mesh refinement / change of units.
- Users expect reasonable, $O(1)$ adjustable constants for each problem.

$$F(x) = \alpha \frac{1}{n} \frac{\sum_{E(x)} \int_{E_t} \mu_{i_1}(T)}{\sum_{E(x_0)} \int_{E_t} \mu_{i_1}(T_0)} + \dots \beta \frac{1}{n} \frac{\sum_{E(x)} \int_{E_t} \mu_{i_n}(T)}{\sum_{E(x_0)} \int_{E_t} \mu_{i_n}(T_0)} + \varepsilon \frac{\sum_E \int_{E_t} \frac{(x-x_0)^2}{d^2}}{\sum_E \int_{E_t} 1}$$

Refs	Final F	μ part	Limiting part	Max displacement
0	0.7548	0.6915	0.0632	0.0216
1	0.7542	0.6913	0.0629	0.0217
2	0.7541	0.6912	0.0628	0.0217

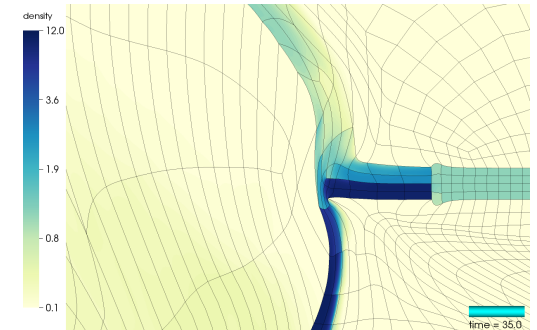
*Behavior under refinement
for fixed d 4th order mesh,
Shape optimization*



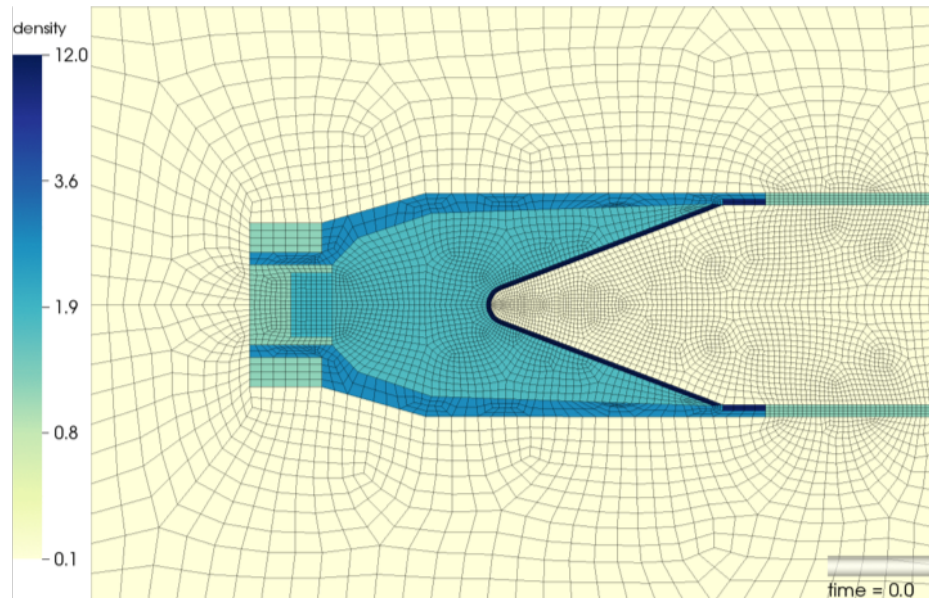
Feature preservation and local optimization

- Local optimization by using space-dependent d .
No mesh motion for $d \rightarrow 0$.
- Applicable when the starting mesh has certain desirable features.

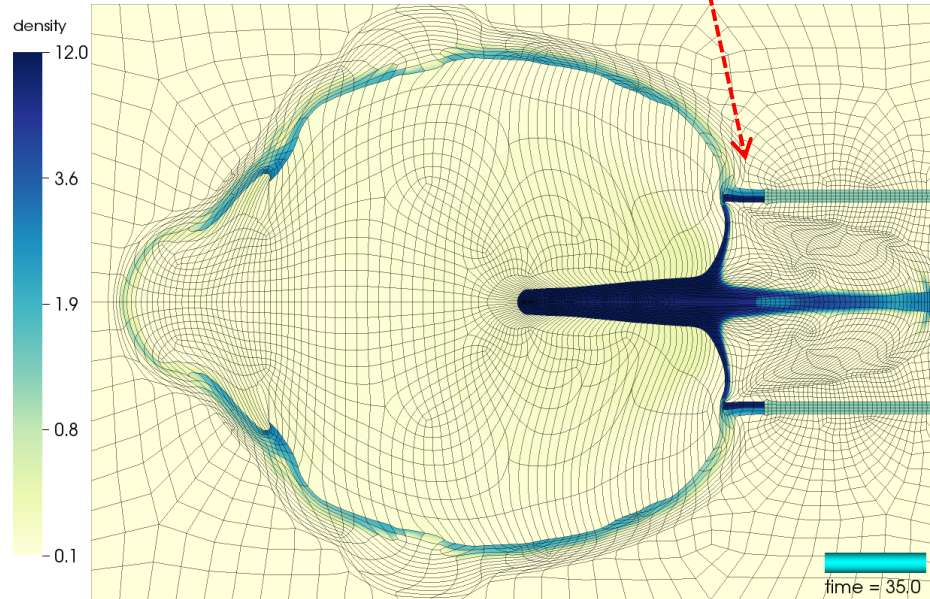
$$\sum_E \int_{E_t} \frac{(x - x_0)^2}{d^2}$$



Shaped charge simulation on an unstructured NURBS mesh, Shape+Size optimization



Initial mesh and density



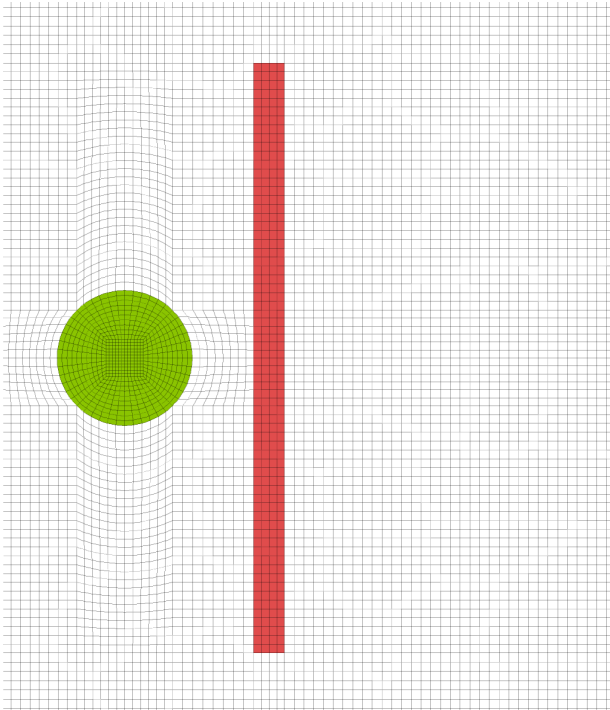
Mesh and density at final time

Feature preservation in moving mesh applications

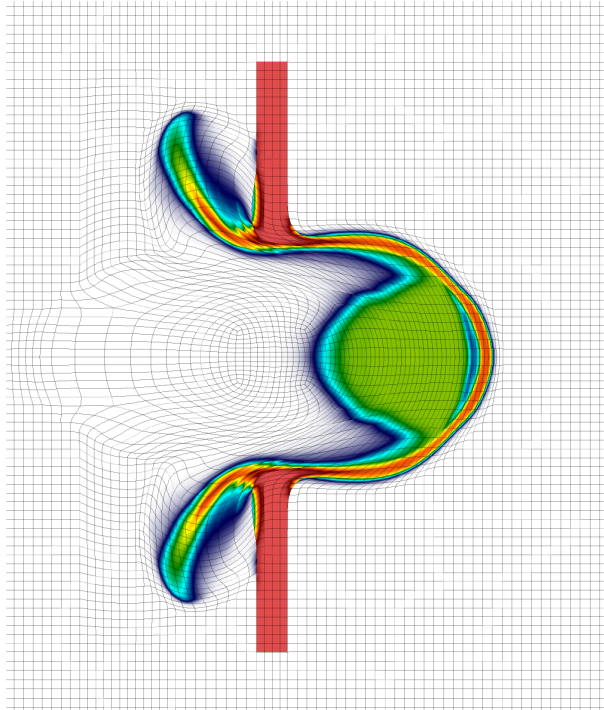
- Optimization can be adapted to the problem dynamics.
Example: $d \sim \alpha [\text{mesh displacement}]$ in ALE simulations.
- Allows tradeoffs between mesh quality feature preservation.

$$\sum_E \int_{E_t} \frac{(x - x_0)^2}{d^2}$$

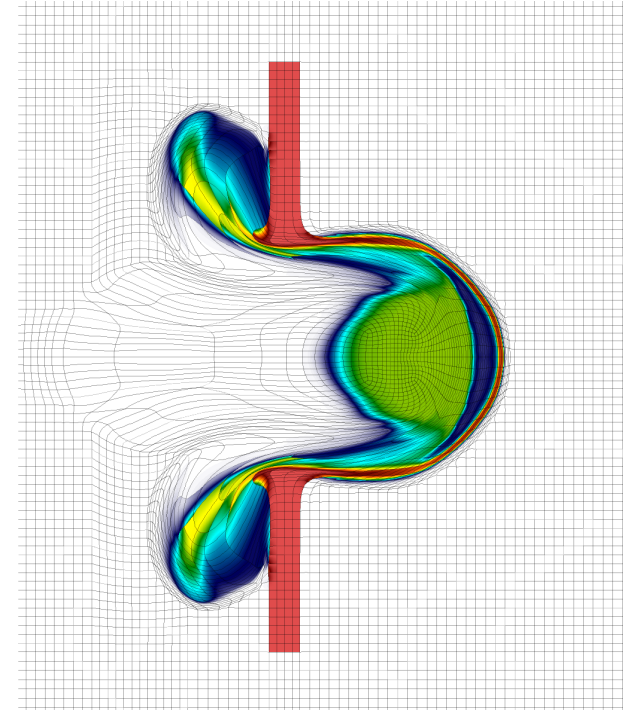
High-velocity impact simulation, Shape+Size optimization



Initial condition



Higher d – better mesh / more diffusion



Lower d – worse mesh / less diffusion