



Towards an Adaptive One-Shot Approach for Aerodynamic Shape Optimization

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Department of Mathematics**



From October 2010 on:

RWTH Aachen University

Dept. of Mathematics / Center for Comp. Eng. Science (CCES)



Towards an Adaptive One-Shot Approach for Aerodynamic Shape Optimization

Related Projects



- EU-Project NODESIM-CFD (Non-Deterministic Simulation for CFD-based Design Methodologies)
- DFG (German Research Foundation) Priority Program SPP 1253 'Optimization with PDEs'
- BMBF-Project DGHPOPT (Discontinuous Galerkin Methods for Robust Aerodynamic Design)



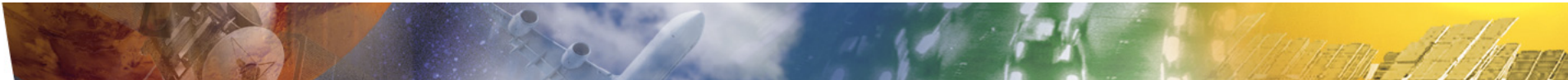
Title: „Adaptive One-Shot Methods for Robust Design“



Bundesministerium
für Bildung
und Forschung

Partners: Trier University, RWTH Aachen University ←HU B,
DLR, Airbus, MTU

→ Project starts October 2010

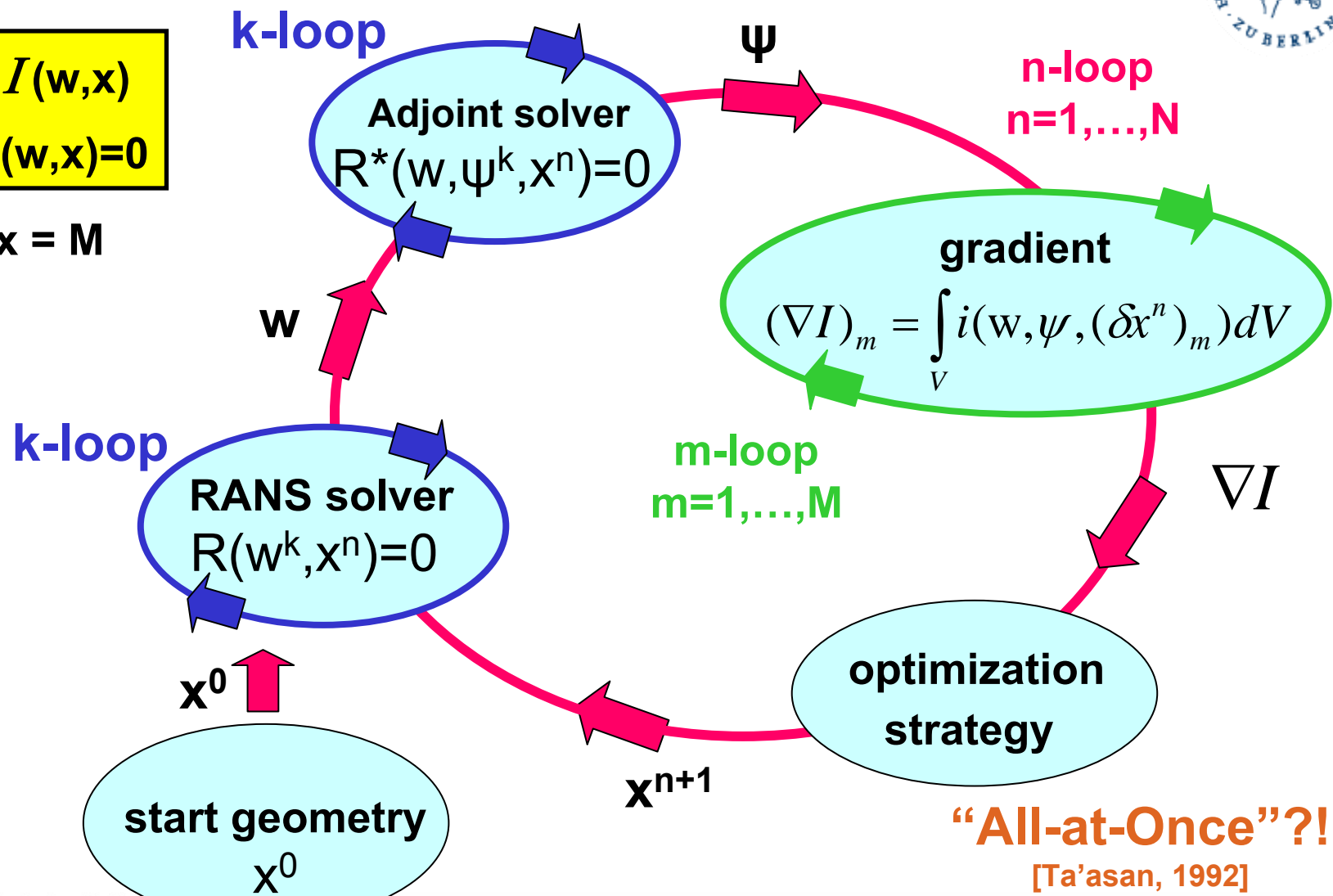


Nested approach



**min $I(w,x)$
s.t. $R(w,x)=0$**

dim $x = M$



“All-at-Once”?!

[Ta'asan, 1992]



Problem Statement



Goal: $\min_u f(y, u) \quad \text{s.t.} \quad c(y, u) = 0,$

where y and u are the state and design variables.

Given fixed point iteration $y_{k+1} = G(y_k, u)$ (e.g. pseudo-time stepping) to solve PDE $c(y, u) = 0$.

Assumptions:

- $\frac{\partial c}{\partial y}$ always invertible. IFT \Rightarrow given $u, \exists! y$ s.t. $c(y, u) = 0$.
- $G, f \in C^{2,1}$.
- G contractive: $\|G_y(y, u)\| = \|G_y^T(y, u)\| \leq \rho < 1$

One-Shot approach



$$L(y, \bar{y}, u) = f(y, u) + (G(y, u) - y)^T \bar{y}$$

$$= \underbrace{N(y, \bar{y}, u)} - y^T \bar{y}$$

shifted Lagrangian

Stationary point:

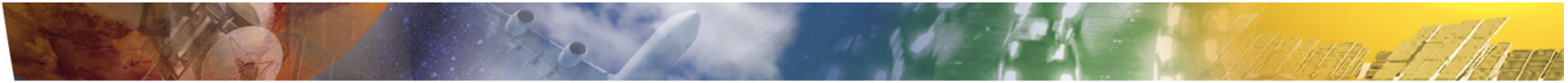
$$\begin{cases} L_{\bar{y}} = G(y, u) - y = 0 \\ L_y = N_y(y, \bar{y}, u)^T - \bar{y} = 0 \\ L_u = N_u(y, \bar{y}, u)^T = 0 \end{cases}$$

One-step one-shot (step $k+1$):

$$(OS) \begin{cases} y_{k+1} = G(y_k, u_k) & \text{primal update} \\ \bar{y}_{k+1} = N_y(y_k, \bar{y}_k, u_k)^T & \text{dual update} \\ u_{k+1} = u_k - B_k^{-1} N_u(y_k, \bar{y}_k, u_k)^T & \text{design update} \end{cases}$$

Aims: Choose B such that:

- **Convergence of (OS).**
- **Bounded retardation.**



Bounded retardation



Jacobian of the extended iteration:

$$J_* = \frac{\partial(y_{k+1}, \bar{y}_{k+1}, u_{k+1})}{\partial(y_k, \bar{y}_k, u_k)} \Big|_{(y^*, \bar{y}^*, u^*)} = \begin{pmatrix} G_y & 0 & G_u \\ N_{yy} & G_y^T & N_{yu} \\ -B^{-1}N_{uy} & -B^{-1}G_u^T & I - B^{-1}N_{uu} \end{pmatrix}$$

Whenever we can define B such that

$$\frac{1 - \rho(G_y)}{1 - \hat{\rho}(J_*)} < const, \quad \text{i.e.} \quad \mathcal{O}(opt) / \mathcal{O}(sim) < const$$

we have bounded retardation.

Necessary condition for contractivity



Eigenvalues of J_* are the zeros of the equation

$$\det((\lambda - 1)B + H(\lambda)) = 0$$

where

$$H(\lambda) = \left(-G_u^T (G_y^T - \lambda I)^{-1}, I \right) \begin{pmatrix} N_{yy} & N_{yu} \\ N_{uy} & N_{uu} \end{pmatrix} \begin{pmatrix} -(G_y - \lambda I)^{-1} G_u \\ I \end{pmatrix}.$$

Necessary (but not sufficient) condition for contractivity:

$$B = B^T \succ 0 \quad \text{and} \quad B \succ \frac{1}{2} H(-1).$$

[Griewank, 2006]



Exact penalty function: L^a

Remark:

Deriving (sufficient) conditions on B for J_* to have a spectral radius smaller than 1 has proven difficult.

Instead, we look for descent on the **augmented Lagrangian**

$$L^a(y, \bar{y}, u) := \underbrace{\frac{\alpha}{2} \|G(y, u) - y\|^2}_{\text{primal residual}} + \underbrace{\frac{\beta}{2} \|N_y(y, \bar{y}, u)^T - \bar{y}\|^2}_{\text{dual residual}} + \underbrace{N - \bar{y}^T y}_{\text{Lagrangian}}$$

where $\alpha > 0$ and $\beta > 0$.

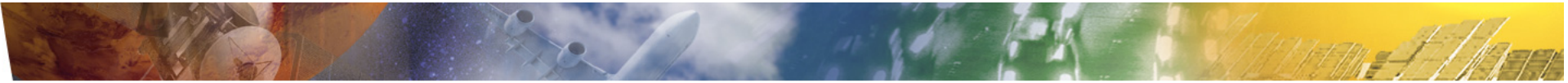


Correspondence condition

The full gradient of L^a is given by

$$\begin{bmatrix} \nabla_y L^a \\ \nabla_{\bar{y}} L^a \\ \nabla_u L^a \end{bmatrix} = -Ms(y, \bar{y}, u), \quad \text{where } s(y, \bar{y}, u) = \begin{bmatrix} G(y, u) - y \\ N_y(y, \bar{y}, u)^T - \bar{y} \\ -B^{-1}N_u(y, \bar{y}, u)^T \end{bmatrix}$$

$$\text{and } M = \begin{bmatrix} \alpha(I - G_y^T), & -I - \beta N_{yy}, & 0 \\ -I, & \beta(I - G_y), & 0 \\ -\alpha G_u^T, & -\beta N_{yu}^T, & B \end{bmatrix}.$$



Correspondence condition

Consequence (Correspondence condition):

There is a 1-1 correspondence between the stationary points of L^a and the roots of s if

$$\det[\alpha\beta(I - G_y^T)(I - G_y) - I - \beta N_{yy}] \neq 0,$$

for which it is sufficient that

$$\alpha\beta(1 - \rho)^2 > 1 + \beta \|N_{yy}\|.$$

[Hamdi, Griewank, 2008]

Descent condition



Theorem (Descent condition):

$s(y, \bar{y}, u)$ is a descent direction for all large positive B

if and only if

$$\alpha\beta\left(I - \frac{1}{2}(G_y + G_y^T)\right) > \left(I + \frac{\beta}{2}N_{yy}\right)\left(I - \frac{1}{2}(G_y + G_y^T)\right)^{-1}\left(I + \frac{\beta}{2}N_{yy}\right),$$

which is implied by $\sqrt{\alpha\beta}(1-\rho) > 1 + \frac{\beta}{2}\|N_{yy}\|$.

➤ Satisfied for $\beta = \frac{2}{c}$, $\alpha = \frac{2c}{(1-\rho)^2}$ with $c = \|N_{yy}\|$.

Theorem: A suitable B is given by:

$$B = \alpha G_u^T G_u + \beta N_{yu}^T N_{yu} + N_{uu}.$$

[Hamdi, Griewank, 2008]

One-step one-shot

Aerodynamic shape design



Descent for $\beta = \frac{2}{c}$, $\alpha = \frac{2c}{(1-\rho)^2}$ with $c = \|N_{yy}\|$.

(In practice choose $c = 1$, $\Rightarrow \beta = 2$, $\alpha \gg 1$.)

A suitable B is given by $B = \alpha G_u^T G_u + \beta N_{yu}^T N_{yu} + N_{uu}$.

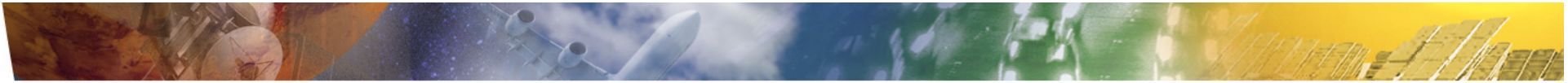
Instead BFGS updates for the Hessian

$$\nabla_u^2 L^a = \underbrace{\alpha G_u^T G_u + \beta N_{yu}^T N_{yu} + N_{uu}}_B + \underbrace{\alpha (G - y)^T G_{uu}}_{\rightarrow *0} + \underbrace{\beta (N_y^T - \bar{y})^T N_{yuu}}_{\rightarrow *0}$$

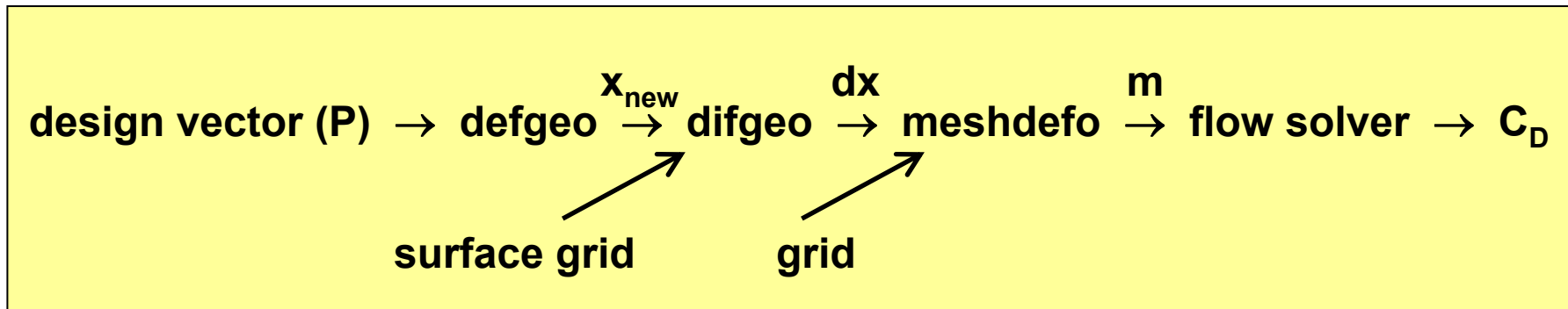
The gradient $\nabla_u L^a = \alpha (G - y)^T G_u + \beta (N_y - \bar{y})^T N_{yu} + N_u$

is evaluated by Algorithmic Differentiation (AD).

[Özkaya, Gauger, 2008]



Automatic Differentiation of Entire Design Chain



- Adjoint version of entire design chain by **ADOL-C / TAPENADE**
- TAUij (2D Euler) / ELAN (2D/3D RANS) + mesh deformation + parameterization

$$\frac{dC_D}{dP} = \frac{\partial C_D}{\partial m} \cdot \frac{\partial m}{\partial(dx)} \cdot \frac{\partial(dx)}{\partial x_{new}} \cdot \frac{\partial x_{new}}{\partial P} \quad \text{and} \quad \frac{\partial(dx)}{\partial x_{new}} = \frac{\partial(x_{new} - x_{old})}{\partial x_{new}} = Id$$

$\frac{\partial C_D}{\partial m}$: TAUij_AD / ELAN_AD
 $\frac{\partial m}{\partial(dx)}$: meshdefo_AD
 $\frac{\partial(dx)}{\partial x_{new}}$: defgeo_AD

[Özkaya, Gauger, 2008]

[Gauger, Walther, Özkaya, Moldenhauer, 2008]

Treatment of lift constraint by penalty multiplier method



$$\min_u C_D(y, u) \quad s.t. \quad C_L \geq C_{L, target} \quad \text{and} \quad y = G(y, u)$$

Penalty function for lift: $h = (C_{L, target} - C_L), \quad h \leq 0$

Redefine objective function: $f = C_D + \lambda h$

$$\min_u C_D(y, u) + \lambda h \quad ; \quad h \rightarrow 0$$

Update the penalty parameter in each one-shot step k :

$$\lambda_{k+1} = \lambda_k (1 + ch), \quad c > 0$$

$$h > 0 \Rightarrow \lambda \uparrow, \quad h < 0 \Rightarrow \lambda \downarrow$$

A good starting value is: $\lambda_0 = \frac{\|\nabla_u C_D\|}{\|\nabla_u h\|}$

Extension to Navier-Stokes (ELAN Code)



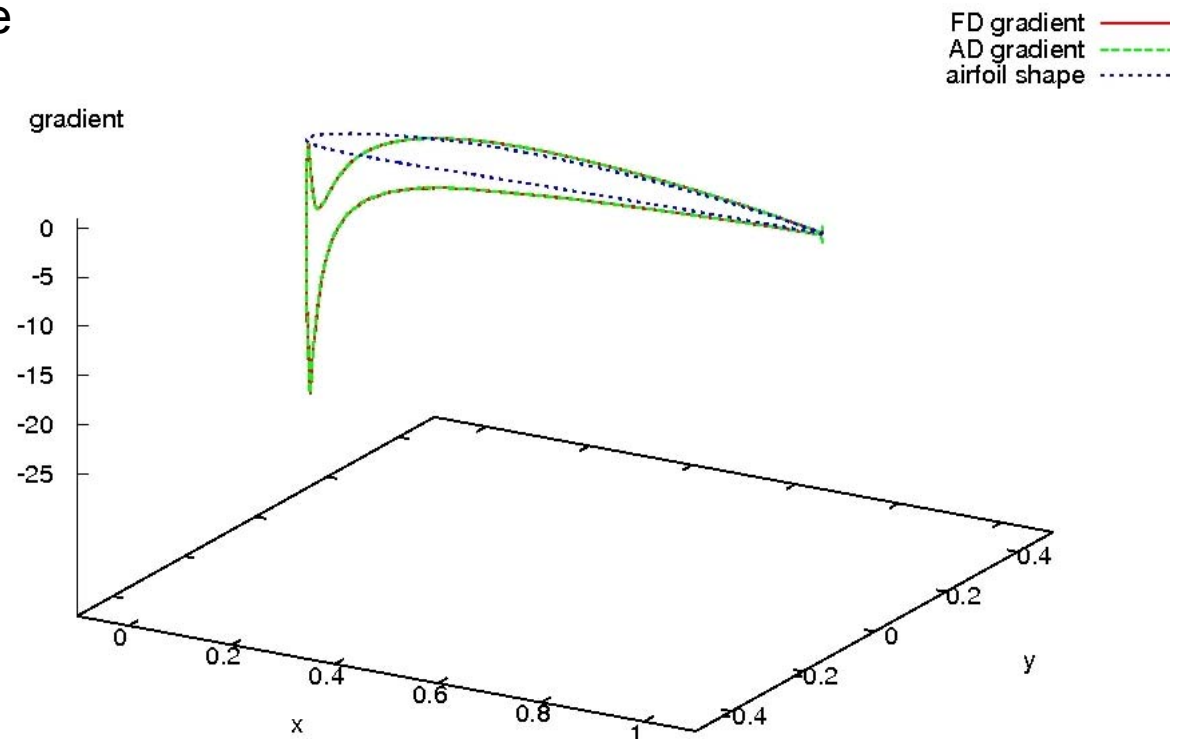
Flow Solver: ELAN (TU Berlin)

- 3D Navier-Stokes (RANS)
- incompressible with pressure correction
- multiblock
- $k-\omega$ (Wilcox) turbulence model (and others)
- Fortran (20.000 lines)

AD Tool: TAPENADE (INRIA)

- source to source
- reverse for **first derivatives**
- tangent on reverse for **second derivatives**

AD-FD Comparison



Extension to Navier-Stokes (ELAN Code)

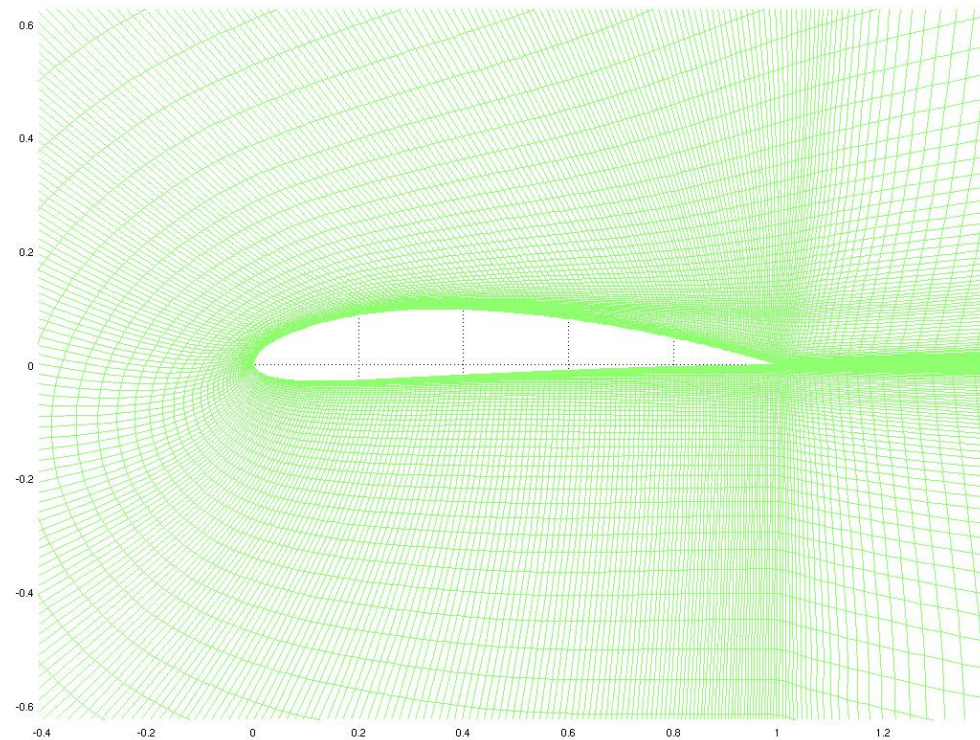
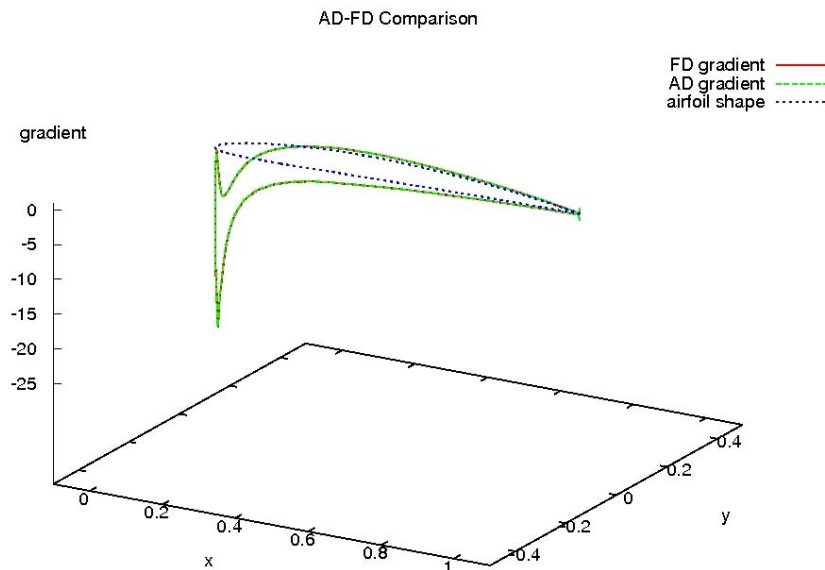


Drag reduction with lift constraint

- NACA 4412
- $Re = 1.000.000$, $\alpha = 5.1^\circ$
- RANS
- k- ω (Wilcox) turbulence model
- 300 surface mesh points

Approaches for Optimization

- one-shot method
- entire design chain differentiated
- gradient smoothing
- penalty multiplier method



Extension to Navier-Stokes (ELAN Code)



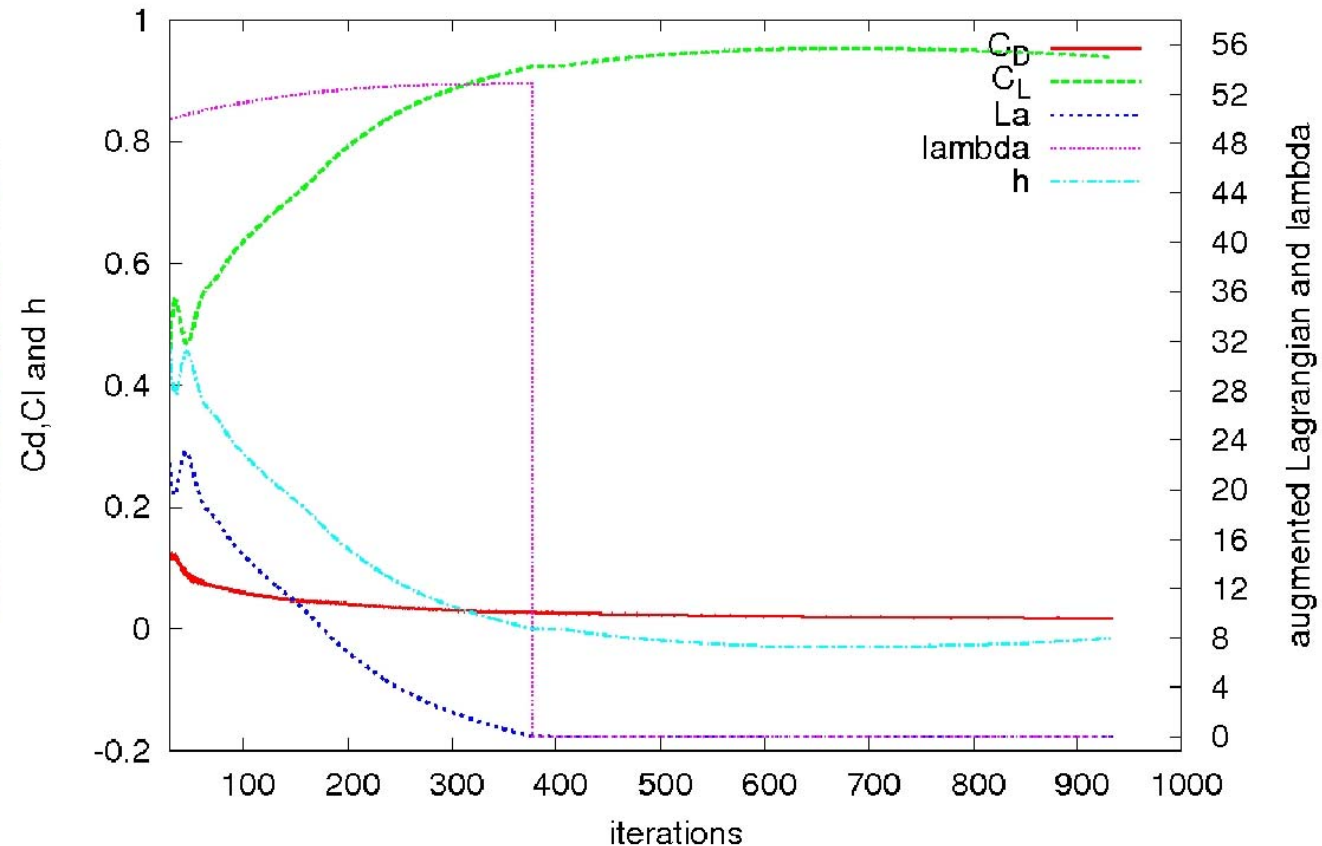
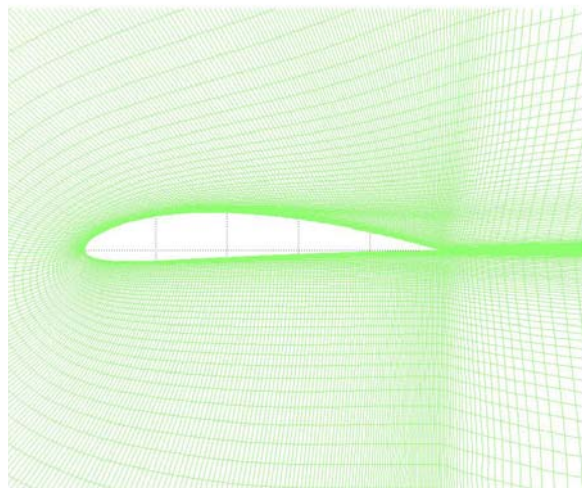
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Augmented Lagrangian and aerodynamic coefficients



Extension to Navier-Stokes (ELAN Code)



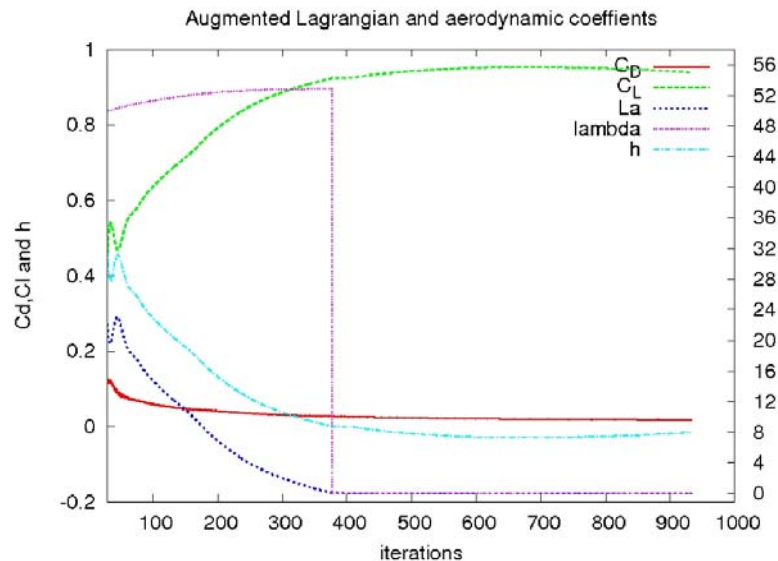
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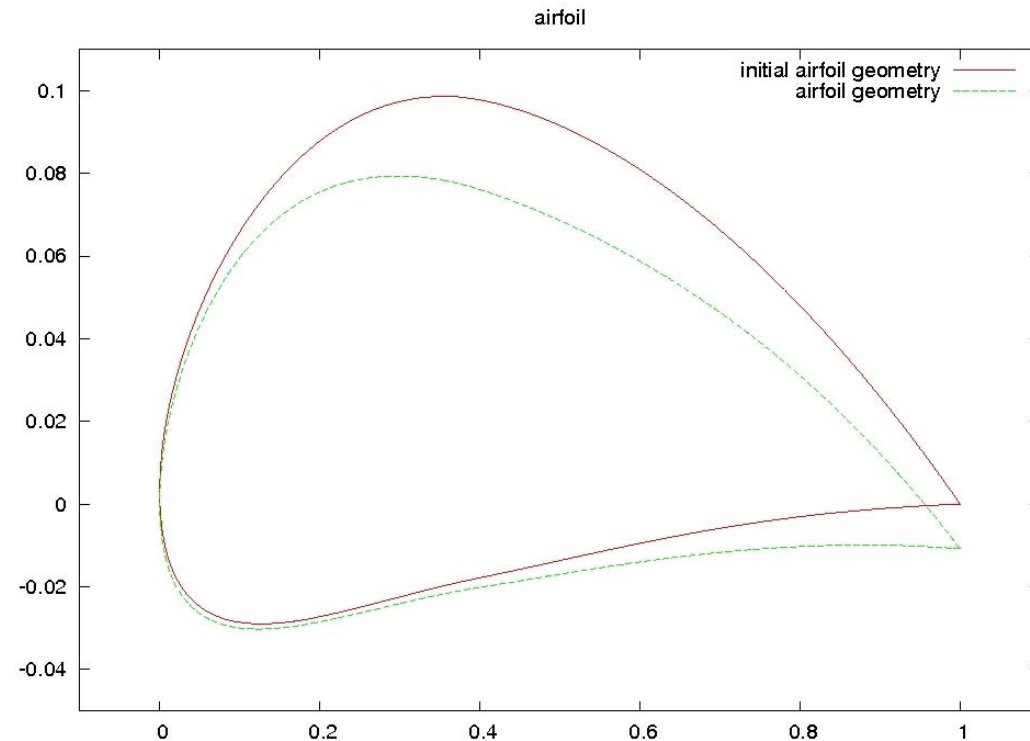
Approaches for Optimization

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- entire design chain differentiated
- gradient smoothing
- penalty multiplier method

5% drag reduction



Retardation-Factor = 3



[Özkaya, Gauger, 2009]



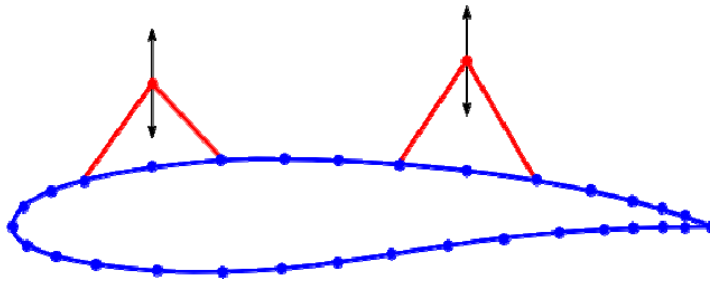
Ingredients for Efficient One-Shot Approach

- **Shape Derivatives:**

$$dF_\ell(\Omega)[V] = \int_{\Gamma} \langle V, n \rangle \left[\langle \nabla p_\ell n, n \rangle + \operatorname{div}_{\Gamma} (p_\ell - (\psi^T w_H) u) \right] dS$$

[Schmidt, Ilic, Gauger, Schulz, 2008]

- **Gradient Smoothing / Preconditioning:**



$$\bar{G} - \frac{\partial}{\partial \xi} \varepsilon \frac{\partial}{\partial \xi} \bar{G} = G$$

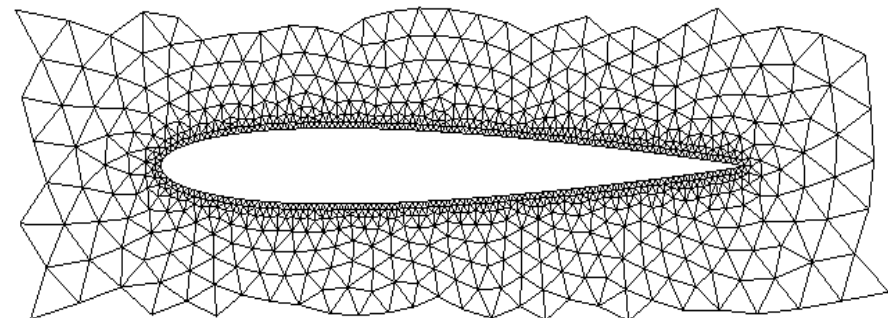
[Jameson et al., 1994 ff.], ..., [Schmidt, Ilic, Gauger, Schulz, 2008]

- **Multilevel-Parameterization:**

Dual Weighted Residual (DWR)

[Rannacher et al., 1996], [Giles 1999], ...

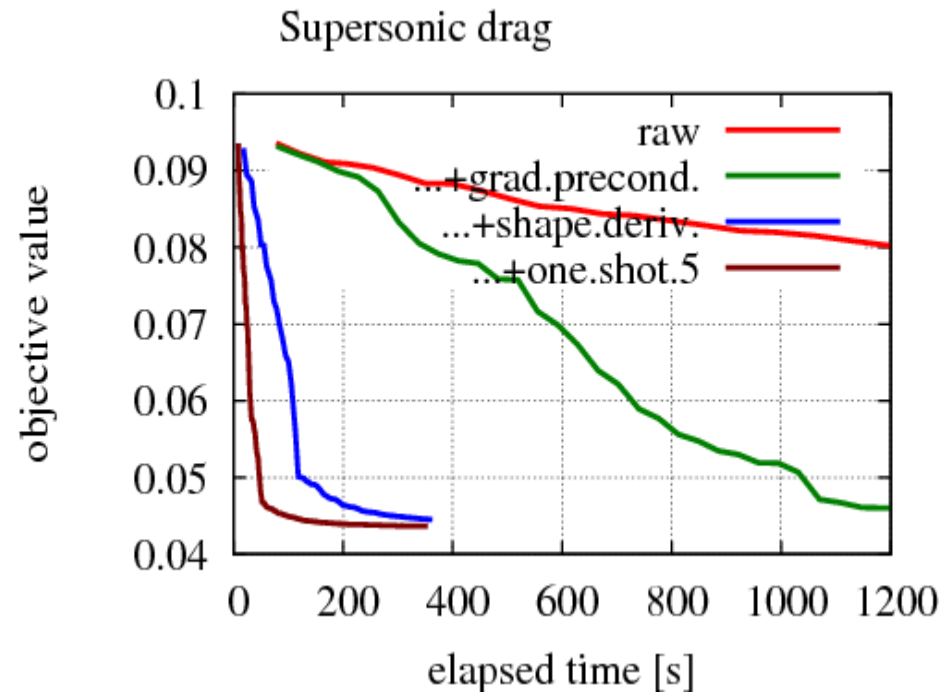
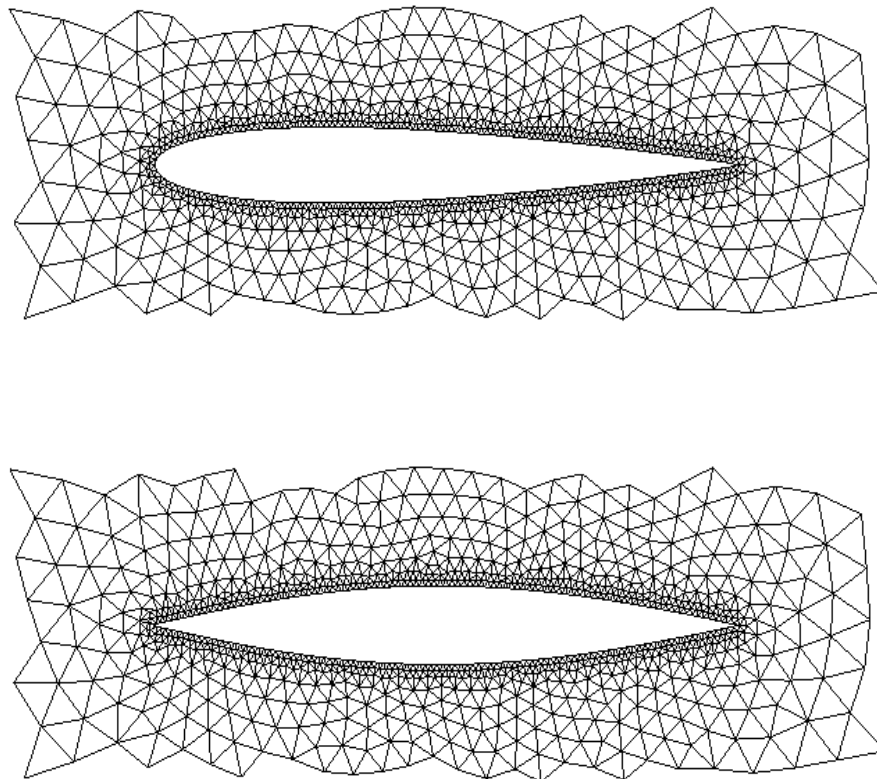
[Vollmer, Gauger, 2005], [Kroll, Gauger et al., 2007]



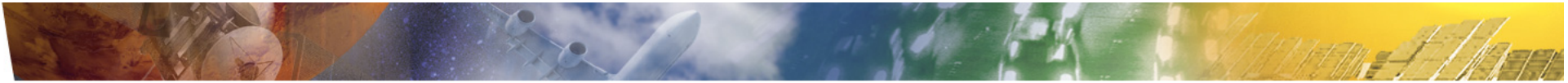


Efficient One-Shot Approach

- NACA0012, $M=2.0$, $\alpha=0^\circ$, TAU (Euler)
- Drag Reduction

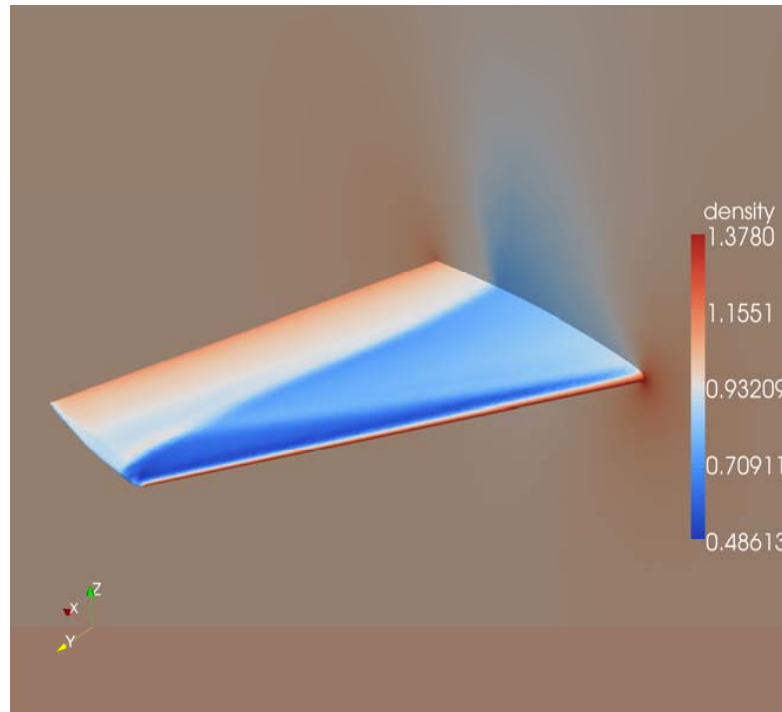


[Schmidt, Ilic, Gauger, Schulz, 2008]



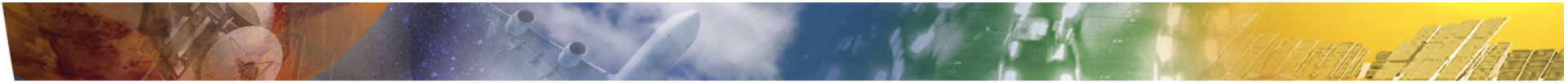
Efficient One-Shot Approach

- ONERA M6, $M=0.83$, $\alpha=3.01^\circ$, TAU (Euler)
- Drag reduction by
- Constant lift



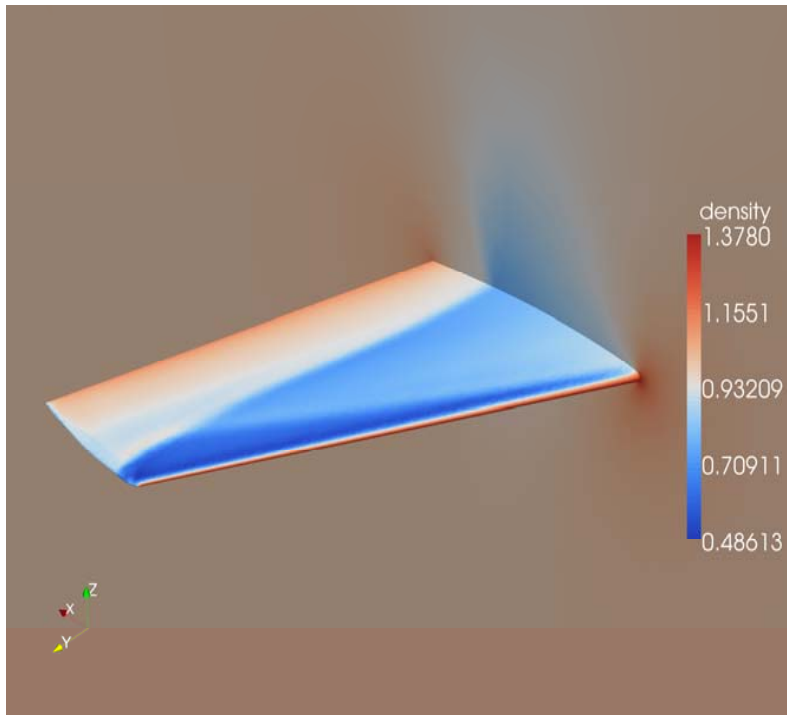
- 867.168 points for volume mesh
- Design variables:
- **All 18.285 surface points!**
- Approach:
- **Shape Derivatives**
- **Gradient Smoothing / Preconditioning**
- **One Shot**

[Illic, Gauger, Schmidt, Schulz, 2009]

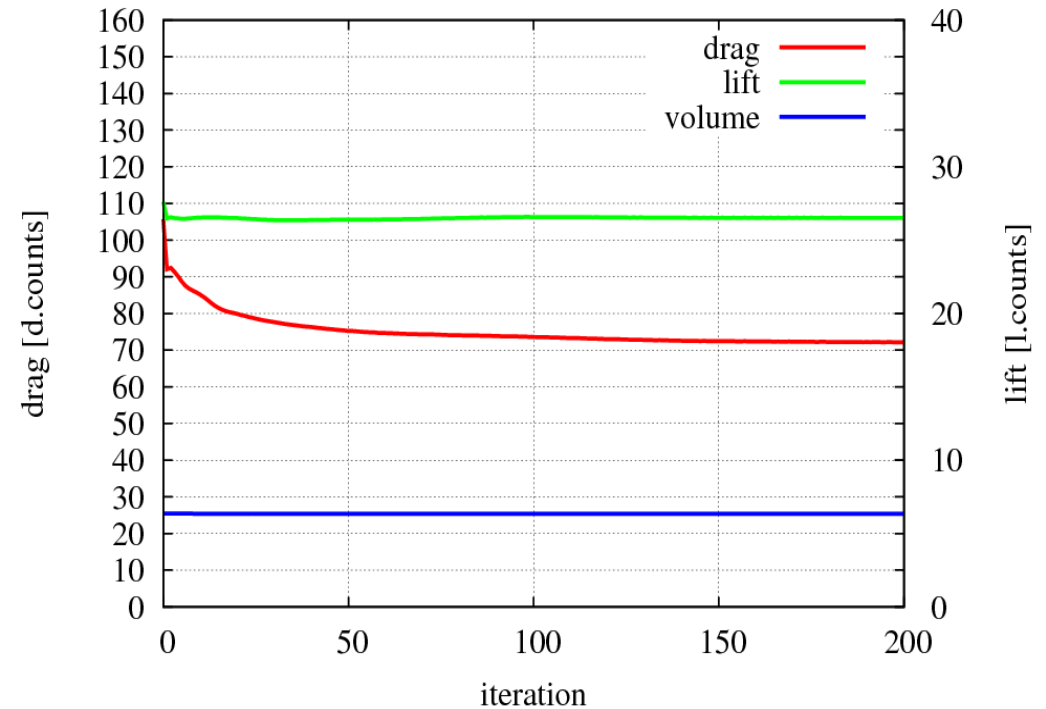


Efficient One-Shot Approach

- ONERA M6, $M=0.83$, $\alpha=3.01^\circ$, TAU (Euler)
- Drag reduction by
- Constant lift



Optimization history



$\mathcal{O}(\text{opt}) / \mathcal{O}(\text{sim}) = 5$ (wall clock time)
 $= 2$ (# iterations)

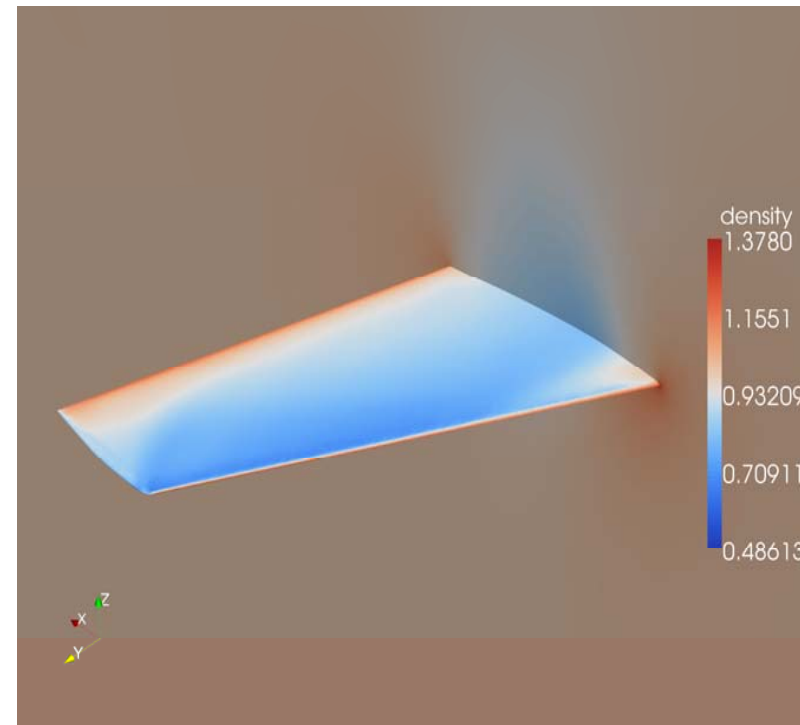
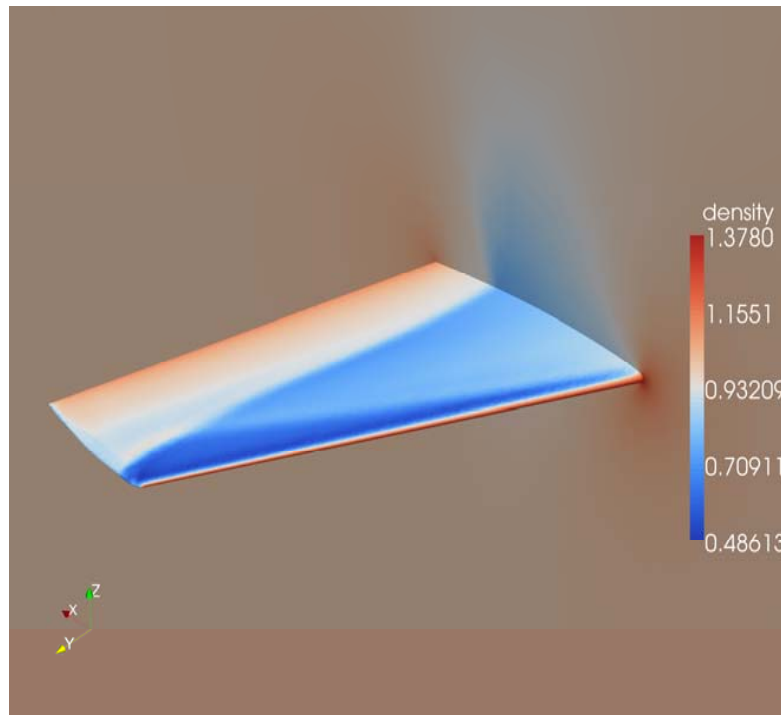
[Illic, Gauger, Schmidt, Schulz, 2009]



Efficient One-Shot Approach

- Initial geometry
- $C_D^{\text{init}} = 106$ drag counts
- $C_L^{\text{init}} = 27.6$ lift counts
- Optimized geometry
- $C_D^{\text{opt}} = 72$ drag counts
- $C_L^{\text{opt}} = 26.5$ lift counts

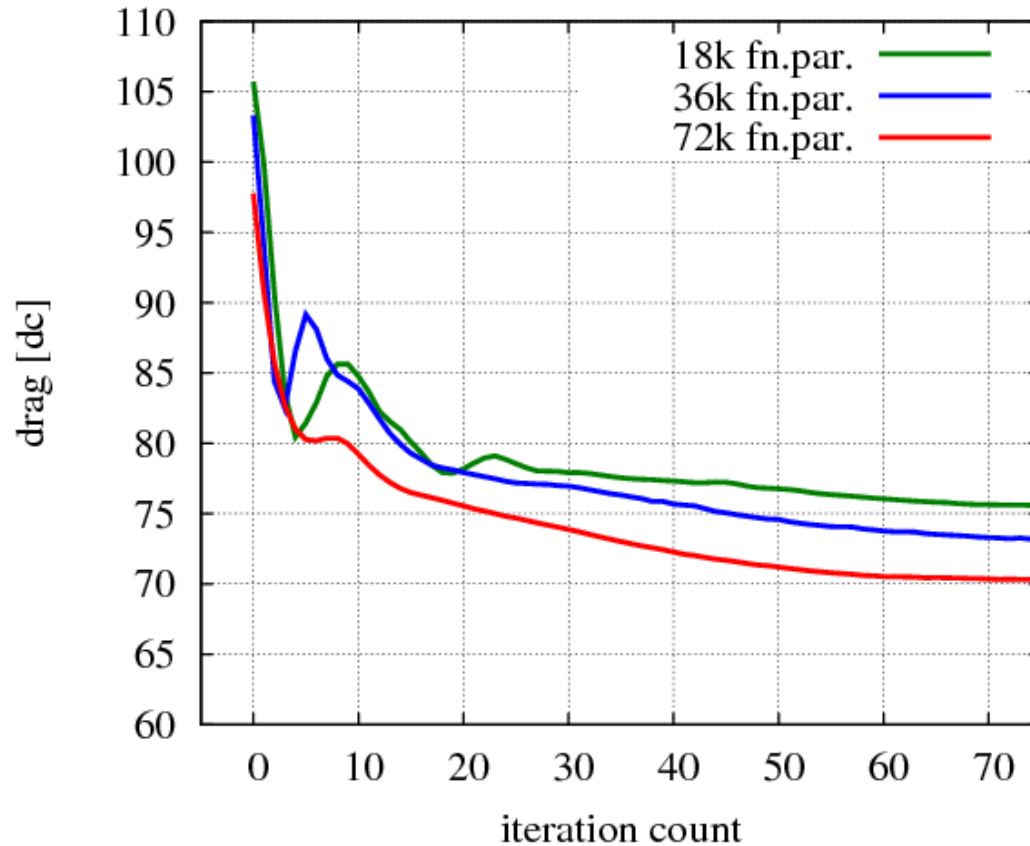
32% Drag reduction



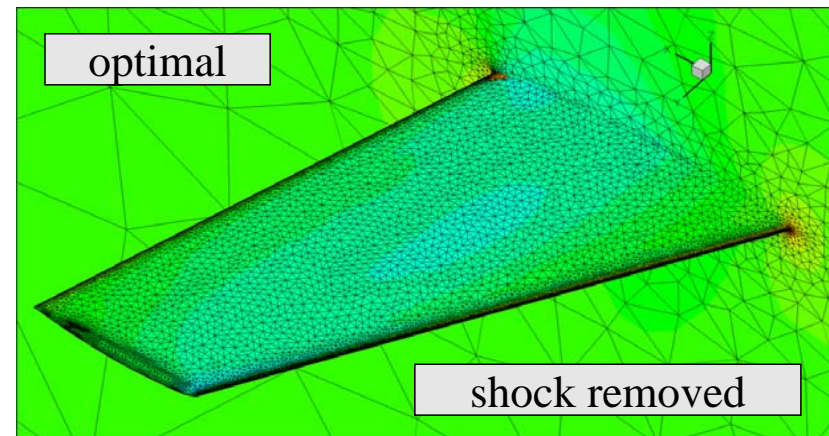
Scaling With Number of Parameters



Transonic drag reduction 3D

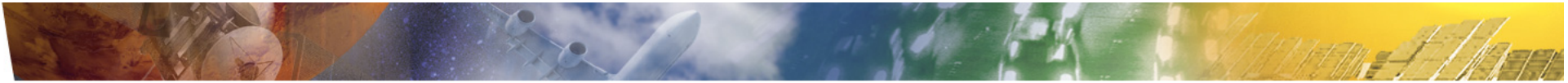


optimal drag =
induced drag (planform)
+ spurious drag (numerics)



optimization to simulation
time ~5

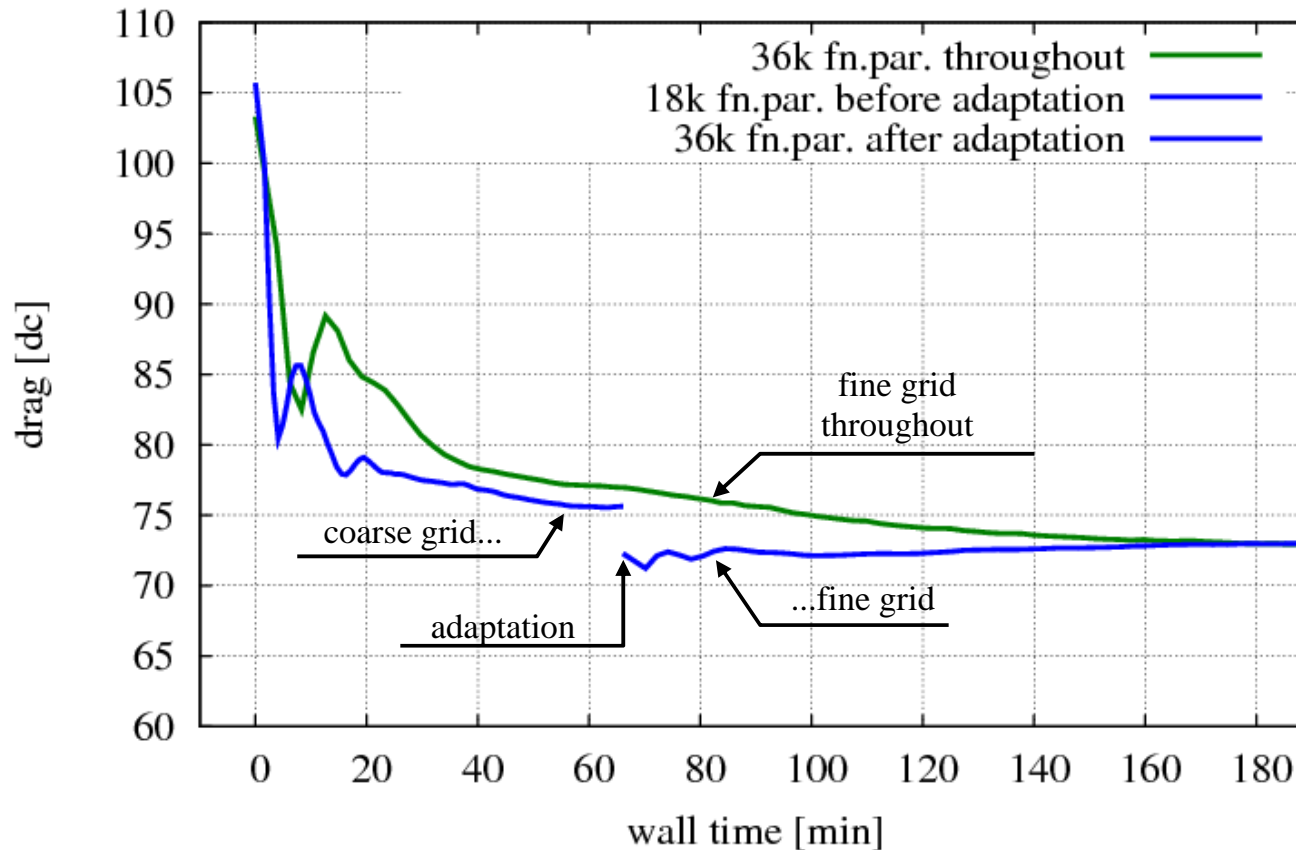
[Illic, Gauger, Schmidt, Schulz, 2009]



Multilevel Descent

- 2-level: coarse grid **18k** design parameters, fine **36k**

Transonic drag reduction, 3D multilevel



- 2-level iteration brings factor **~2** in optimization time

[Ilic, Gauger, Schmidt, Schulz, 2009]



Dual (Adjoint) Weighted Residual Approach (DWR)

Idea stems from *Rannacher et al.* in **FEM** context.

Transfer to **FVM** by *Venditty & Darmofal*, but repeated extrapolation between certain mesh levels (coarse H , fine h) in practice not handy.

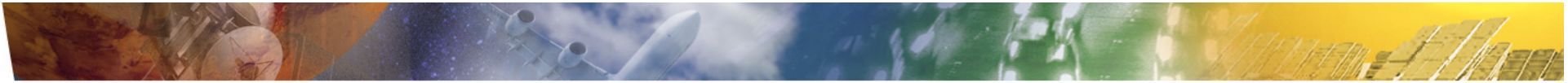
Therefore, instead of $I_h(U_h^H) - I_h(U_h) \approx (\psi_h^H)^T R_h(U_h^H)$,

we consider $I(U_h) - I(U) \approx \psi_h^T R(U_h)$.

Now the idea (by *R. Dwight*) is, to interpret the discretization error $R(U_h)$ as dissipation error. This yields:

$$I(U_h) - I(U) \approx \psi_h^T \left(k^{(2)} \frac{\partial R}{\partial k^{(2)}} + k^{(4)} \frac{\partial R}{\partial k^{(4)}} \right)$$

[*R. Dwight, JCP, 2008*]



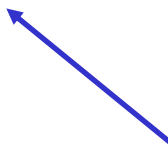
Dual (Adjoint) Weighted Residual Approach (DWR)

The (global) value

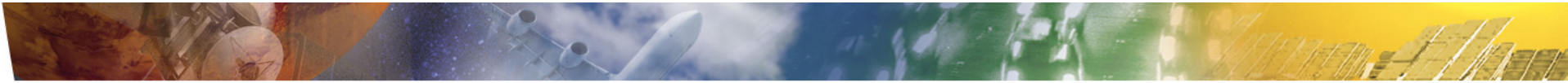
$$\psi^T \left(k^{(2)} \frac{\partial R}{\partial k^{(2)}} + k^{(4)} \frac{\partial R}{\partial k^{(4)}} \right),$$

is a scalar product over the computational mesh, i.e. we have a summation over all mesh cells of terms

$$\psi_{i,j}^T \left(k_{i,j}^{(2)} \frac{\partial R_{i,j}}{\partial k^{(2)}} + k_{i,j}^{(4)} \frac{\partial R_{i,j}}{\partial k^{(4)}} \right).$$



Sensor for mesh adaptation
(Local dual weighted residual)



(Local) Adjoint-based Error Estimate / Sensor for Mesh Adaptation by DWR

Sensor

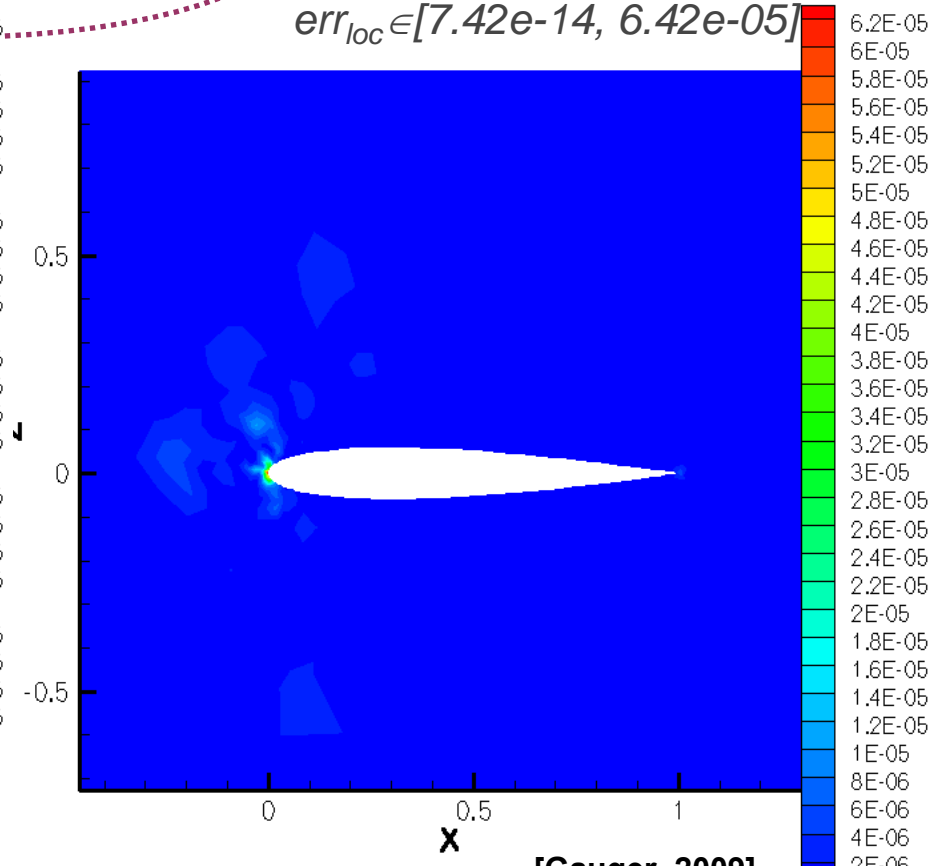
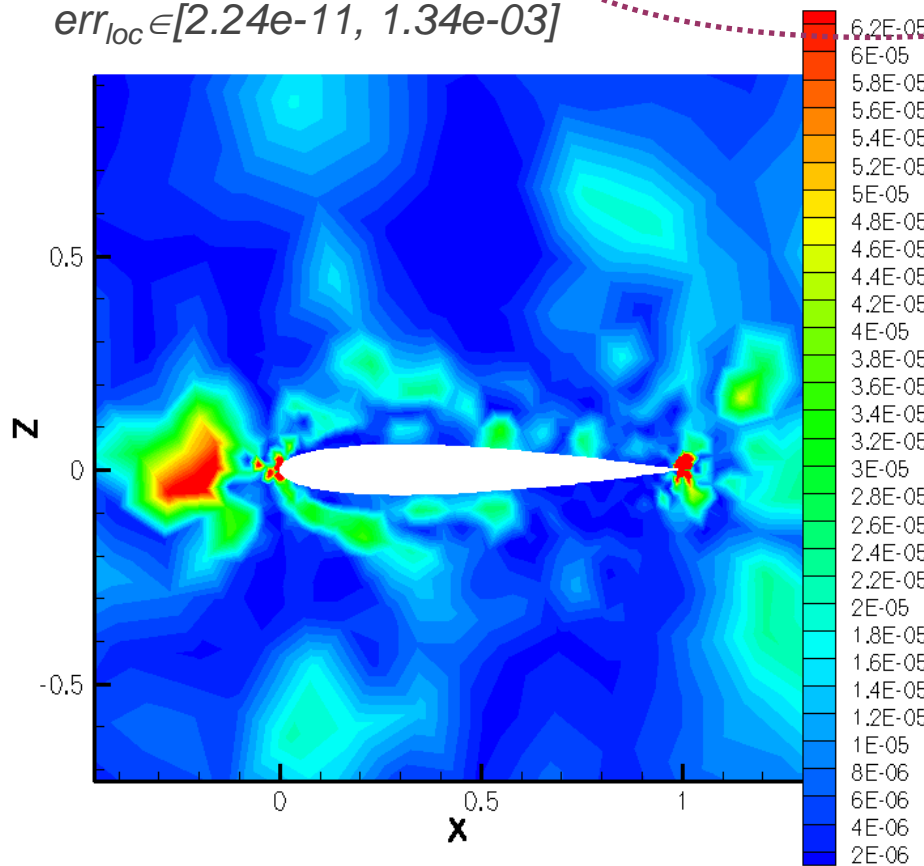
$$\text{abs} \left[\psi_{i,j}^T \left(k_{i,j}^{(2)} \frac{\partial R_{i,j}}{\partial k^{(2)}} + k_{i,j}^{(4)} \frac{\partial R_{i,j}}{\partial k^{(4)}} \right) \right]$$

Lift

$err_{loc} \in [2.24e-11, 1.34e-03]$

Drag

$err_{loc} \in [7.42e-14, 6.42e-05]$



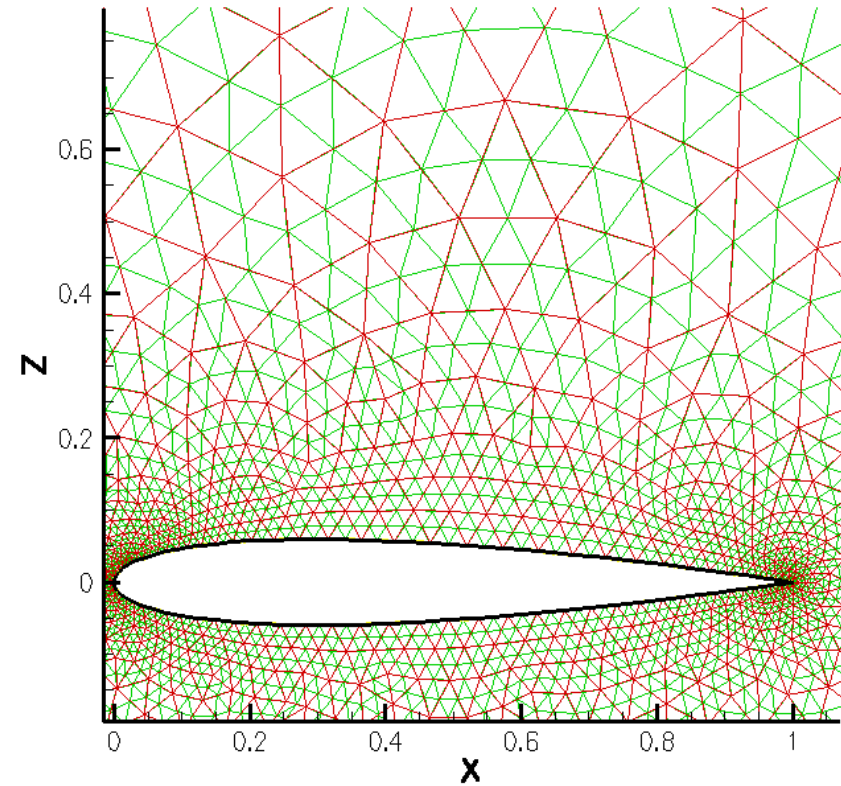
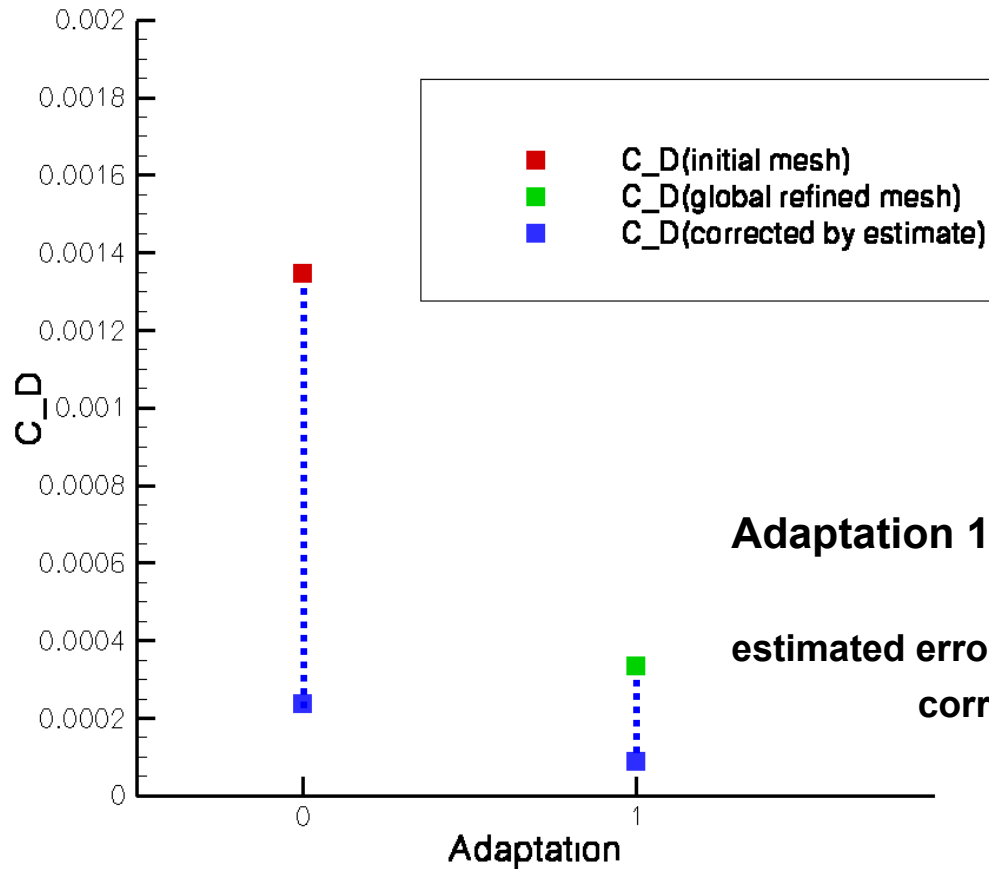
(NACA0012 Ma = 0.5, $\alpha = 1.0^\circ$)

[Gauger, 2009]

Adjoint-based (Global) Error Estimate and Correction

NACA0012 (Euler flow)

Ma = 0.5, $\alpha = 1.0^\circ$



Adaptation 1:

$C_D(\text{global refined mesh}) = 0.00033382$

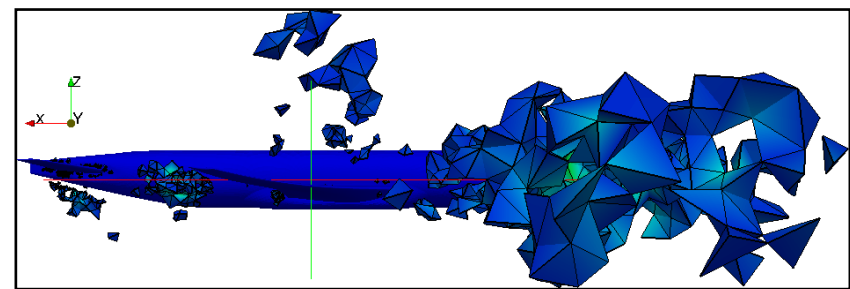
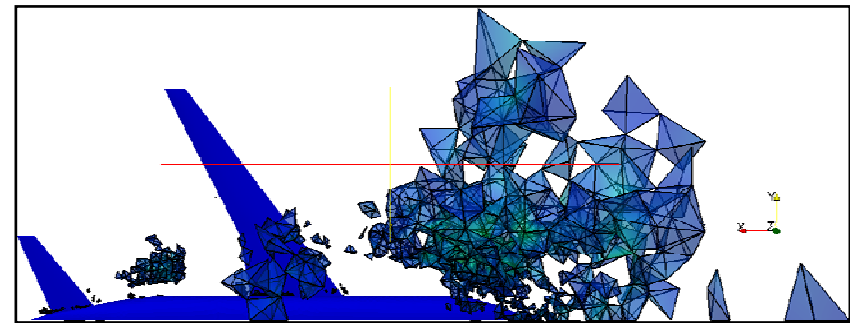
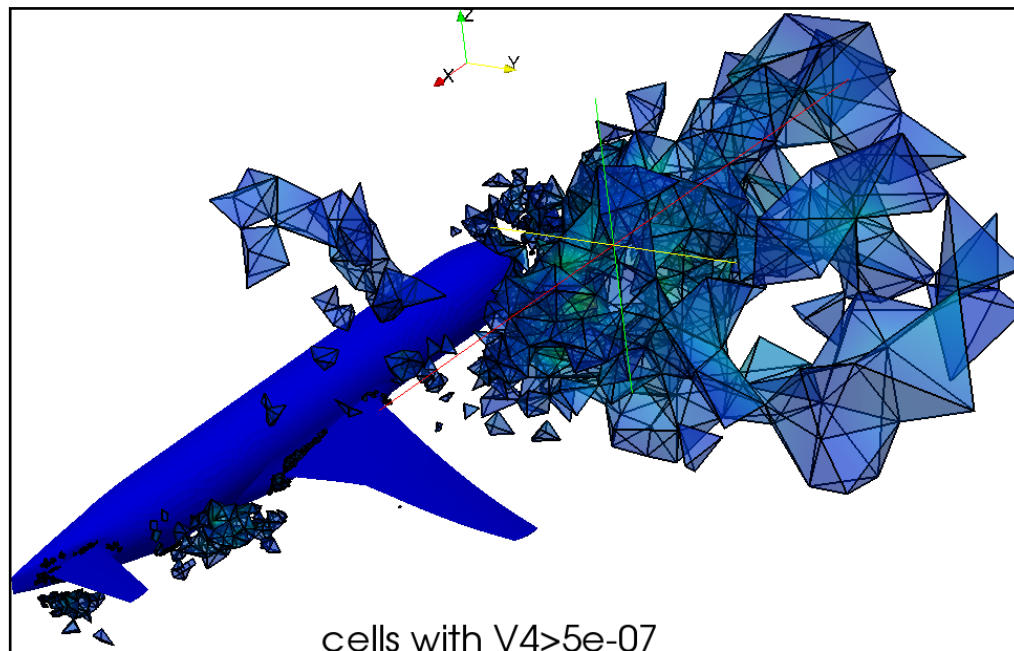
estimated error = $\Psi^*[(dRdk2 * k2) + (dRdk4 * k4)] = -0.00024721$

corrected C_D for global refined mesh = 0.00008661

[Gauger, 2009]

(Local) Adjoint-based Error Estimate

- Adjoint-based error estimates coupled to SOLAR
- Manually performed for the DPW4 meshes
- Error estimate based on the artificial viscosities k_2 and k_4
- Only field cells with sensor $> 5e-07$ are plotted in color



[Crippa, 2009]

Adjoint-based Error Estimate and Adaptation

Error estimator and mesh adaptation indicator based on adjoints and explicitly added artificial dissipation

HIRENASD Case (SFB 401)

C_d (initial mesh) = $1.181e-02$

Adjoint-based Adaptation:

C_d (7.5% of cells refined) = $1.179e-02$

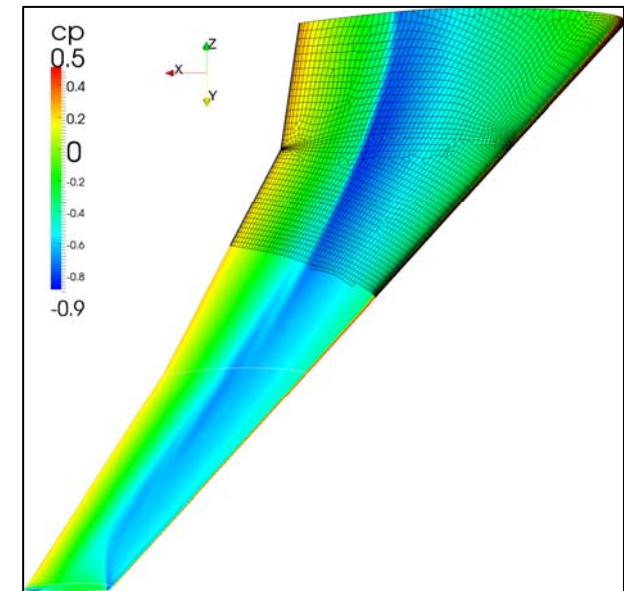
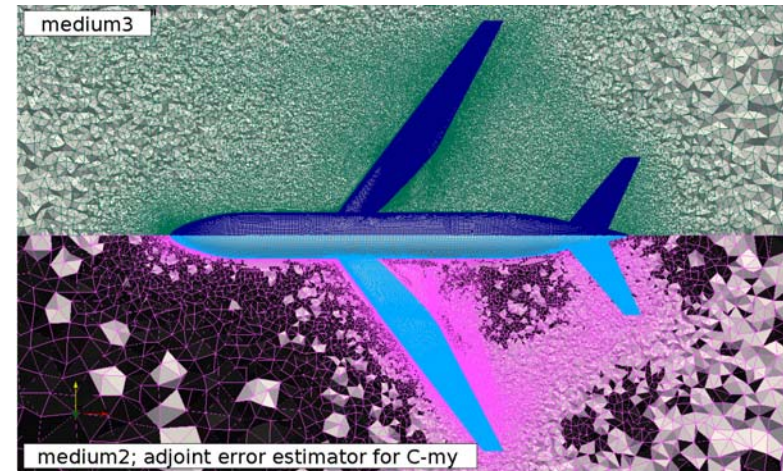
C_d (15% of cells refined) = $1.175e-02$

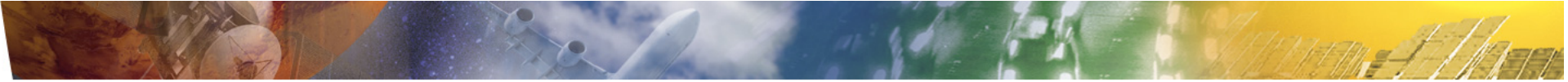
C_d (globally refined mesh) = $1.171e-02$

(Global) Error estimate for initial mesh = $-1.431e-04$

⇒ Corrected value for initial mesh = $1.167e-02$

[Gauger, Orlt, 2010]





Outlook

- **Redo one-shot theory in function spaces for coupling with adaptivity**
- **Combine one-shot with adaptivity in FVM as well as DG context (DLR PADGE Code used in BMBF Project DGHPOPT)**
- ...

Thanks!