

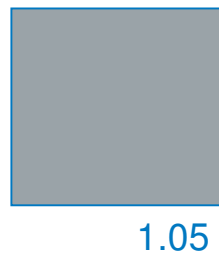


Continuous and Discrete adjoint methodologies within ESI CFD solvers

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- Rationale
- Continuous Adjoint Solver within PAM-FLOW
- Discrete Adjoint solver interfaced with CFD-ACE+
- Morphing

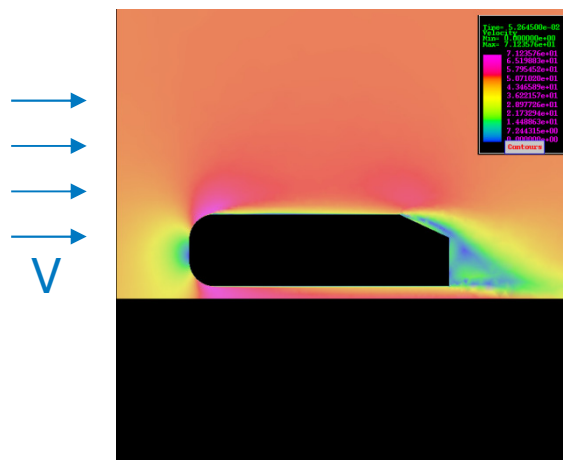
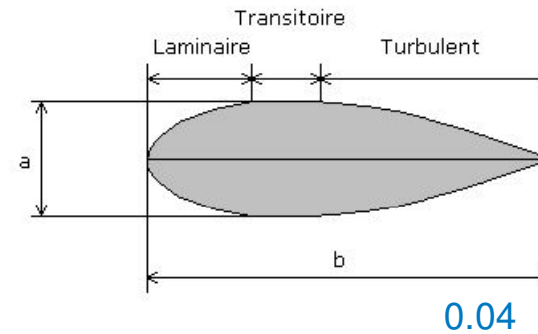
— Different problematics:



global optimization



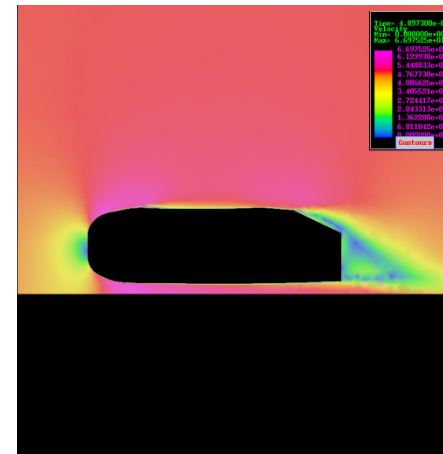
- 2500%



local improvement



- 17 %

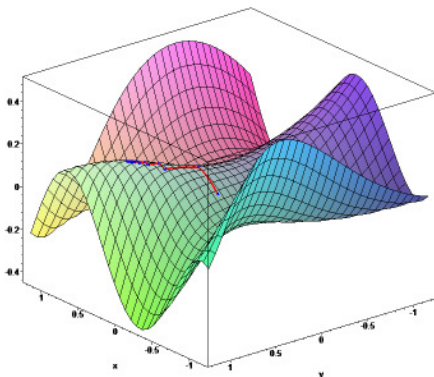


- **One would like to improve the performance of some given design wrt some criterion: the “cost function”**
 - may be lift, drag..
 - design parameters may be nodes coordinates, CAD parameters, level set position..
- **Standard numerical simulation provides a way to evaluate a design “a posteriori”**
- **Optimal design tools automatically select the best (or at least a better) design wrt some given criterion**

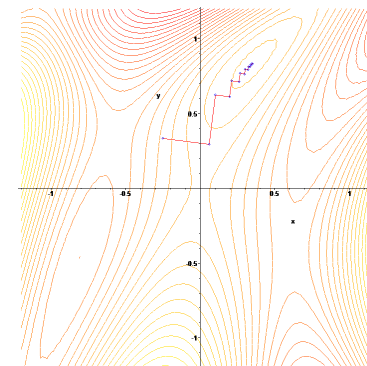
■ Different optimization methods:

- *non-gradient based* (e.g. genetic algorithms): slow but may succeed in finding a global optimum
- *gradient-based*: quicker but stop as soon as a local optimum is found

$$F(x, y) = \sin\left(\frac{1}{2}x^2 - \frac{1}{4}y^2 + 3\right) \cos(2x + 1 - e^y)$$



locally best descent direction



- **Different approaches for computing the gradient:**
 - *by Finite Differences → PAM-OPT*
 - *by using the adjoint state → PAM-FLOW Adjoint Solver, i-adjoint*

- **Both have their pro and cons**

By Finite Differences:

- Flexible, black box tool: very generic, no knowledge on the underlying application solver is needed
- But requires a number of runs proportional to the number of design parameters
- Not sustainable when it tends to be large (e.g. free shape optimization)
- In practice, used together with a surrogate model (for CPU savings), which introduces further approximation and complexity

$$\nabla_{\beta} I \approx \left(\overset{\text{CFD run 1}}{\frac{I_{\beta_1+\delta\beta_1} - I_{\beta_1}}{\delta\beta_1}}, \overset{\text{CFD run 2}}{\frac{I_{\beta_2+\delta\beta_2} - I_{\beta_2}}{\delta\beta_2}}, \dots, \overset{\text{CFD run n}}{\frac{I_{\beta_n+\delta\beta_n} - I_{\beta_n}}{\delta\beta_n}} \right)$$

- **By using the adjoint state:**

- Less generic: does require some knowledge of the underlying application code
- More complicated → requires a dedicated tool, the so-called « adjoint solver »
- But requires only one primal+one adjoint run → cost is independant on the number of design parameters
- Well suited for shape optimization

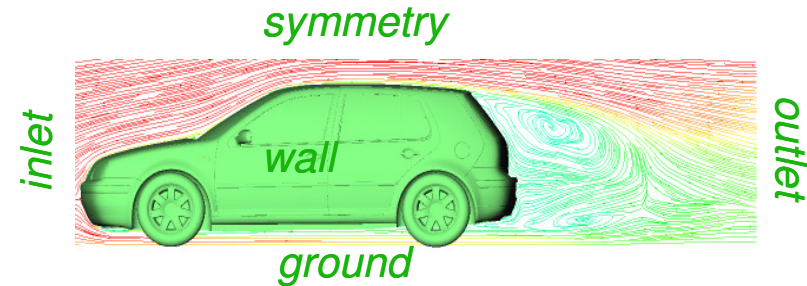
- **2 different approaches for computing the adjoint state:**
 - *Linearize/Dualize then Discretize → Continuous Adjoint Method*
 - *Discretize then Linearize/Dualize → Discrete Adjoint Method*

- **ESI adjoint solutions:**

- *Continuous adjoint solver embedded into PAM-FLOW (vertex-centered FV) (2006)*
- *Discrete adjoint library interfaced with CFD-ACE+ (cell-centered FV, multiphysics) (2012)*

Continuous adjoint solver

Incompressible Navier-Stokes:



$$\begin{cases} \nabla \cdot \{ (v v^\alpha) - \eta \nabla v^\alpha \} + \partial_\alpha p = 0 \\ \nabla \cdot v = 0 \end{cases}$$

mass & momentum conservation

$$\begin{cases} v = V & \text{on } \Gamma_{in} \\ v = 0 & \text{on } \Gamma_{wall} \cup \Gamma_{ground} \\ p n - \eta \partial_n v = F & \text{on } \Gamma_{out} \\ v \cdot n = 0 ; (\partial_n v) \cdot t^\alpha = 0, \alpha = 1, 2 & \text{on } \Gamma_{sym} \end{cases}$$

boundary conditions

— Optimization set-up:

volumic cost function

surfacic cost function

$$\left\{ \begin{array}{l} !I(\Omega, v^\alpha, p, S_\beta^\alpha, \tau_\beta^\alpha) = \int_{\Omega} j(v^\alpha, p, S_\beta^\alpha) + \int_{\partial\Omega} i(v^\alpha, \tau_\beta^\alpha n^\beta, n^\alpha) \\ \text{with } S_\beta^\alpha = \partial_\beta v^\alpha \text{ and } \tau_\beta^\alpha = p \delta_{\alpha\beta} - \eta \partial_\beta v^\alpha \\ \text{s.t. N - S equations + bcs} \end{array} \right.$$

— KKT theory:

- flow eqs
- bcs
- constitutive relations

$$\ell(\Omega, v^\alpha, p, S_\beta^\alpha, \tau_\beta^\alpha, w^\alpha, q, b_N, b_D, b_N^t, b_D^n, c_\beta^\alpha, d_\beta^\alpha) =$$

$$\begin{aligned}
 & I(\Omega, v^\alpha, p, S_\beta^\alpha, \tau_\beta^\alpha, w^\alpha, q) + \int_{\Omega} \nabla \cdot \left\{ (v v^\alpha) + (\tau_\beta^\alpha)_\beta \right\} w^\alpha \\
 & - \int_{\Omega} q \nabla \cdot v + \int_{\Gamma_{out}} \left\{ F - (\tau^\alpha \cdot n)_\alpha \right\} b_N + \int_{\Gamma_{in} \cup \Gamma_{wall} \cup \Gamma_{ground}} (v - \delta_{in} V) b_D + \\
 & - \int_{\Gamma_{sym}} (\tau^\alpha \cdot n) t^\alpha b_N^t + \int_{\Gamma_{sym}} (v \cdot n) b_D^N + \int_{\Omega} \left\{ \tau_\beta^\alpha - (p \delta_{\alpha\beta} - \eta \partial_\beta v^\alpha) \right\} c_\beta^\alpha \\
 & + \int_{\Omega} (S_\beta^\alpha - \partial_\beta v^\alpha) d_\beta^\alpha
 \end{aligned}$$

Continuous adjoint solver

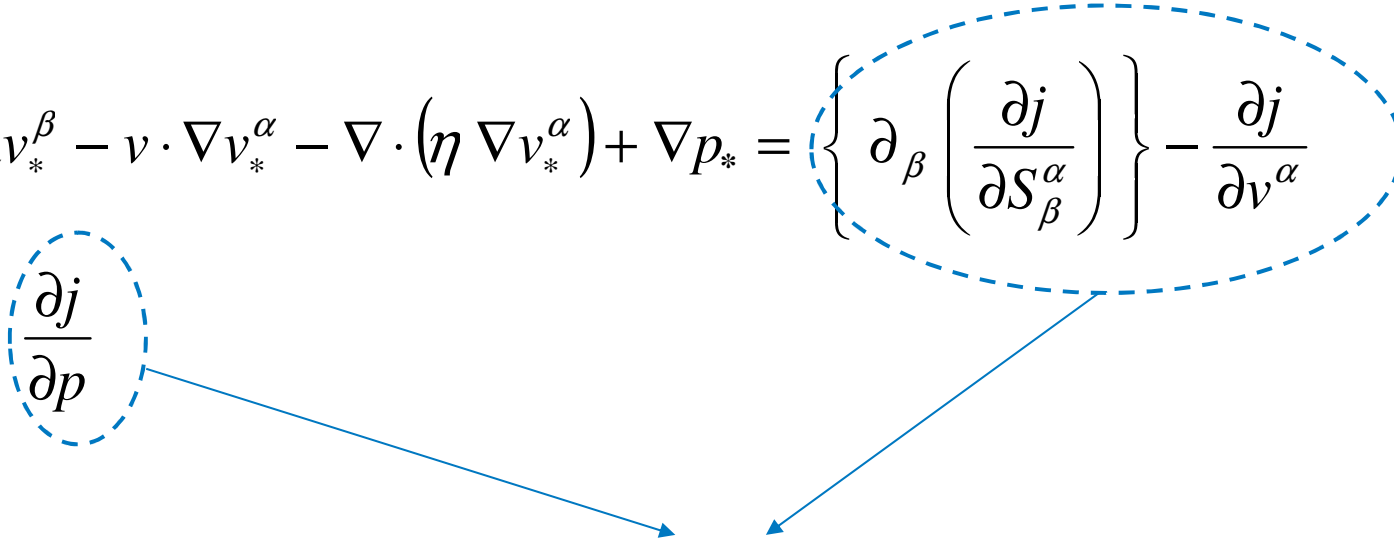
— KKT theory:

$$\frac{\partial \ell(\Omega, v^\alpha, p, S_\beta^\alpha, \tau_\beta^\alpha, q, w^\alpha, b_D, b_N, b_N^t, b_D^n, c_\beta^\alpha, d_\beta^\alpha)}{\partial (w^\alpha, q, b_D, b_N, b_N^t, b_D^n, c_\beta^\alpha, d_\beta^\alpha)} = 0 \quad \longrightarrow \quad \text{Flow equations + BCs}$$

$$\frac{\partial \ell(\Omega, v^\alpha, p, S_\beta^\alpha, \tau_\beta^\alpha, q, w^\alpha, b_D, b_N, b_N^t, b_D^n, c_\beta^\alpha, d_\beta^\alpha)}{\partial (v^\alpha, p, S_\beta^\alpha, \tau_\beta^\alpha)} = 0 \quad \longrightarrow \quad \text{Adjoint equations + BCs}$$

$$\frac{\partial \ell(\Omega, v^\alpha, p, S_\beta^\alpha, \tau_\beta^\alpha, q, w^\alpha, b_D, b_N, b_N^t, b_D^n, c_\beta^\alpha, d_\beta^\alpha)}{\partial \Omega} \quad \longrightarrow \quad \text{Shape derivative (0 at optimum)}$$

— Adjoint equations:

$$\left\{ \begin{array}{l} -v^\beta \partial_\alpha v_*^\beta - v \cdot \nabla v_*^\alpha - \nabla \cdot (\eta \nabla v_*^\alpha) + \nabla p_* = \left\{ \partial_\beta \left(\frac{\partial j}{\partial S_\beta^\alpha} \right) \right\} - \frac{\partial j}{\partial v^\alpha} \\ \nabla \cdot v_* = \frac{\partial j}{\partial p} \end{array} \right.$$


*cost function dependant
source terms*

— Adjoint bcs:

----- *cost function dependant source terms*

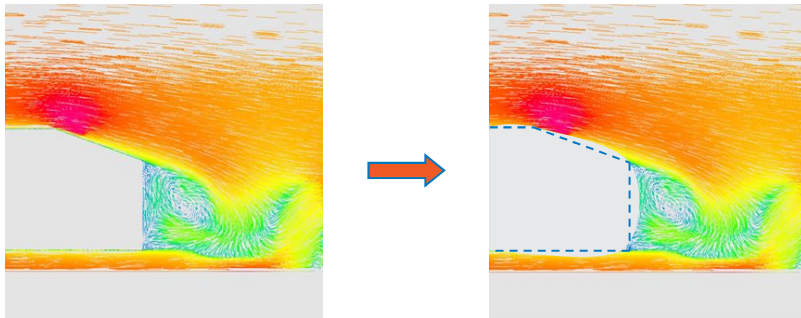
$$\left\{ \begin{array}{l}
 v_* = -\frac{\partial i}{\partial(\tau^\alpha \cdot n)} \text{ on } \Gamma_{in} \cup \Gamma_{wall} \cup \Gamma_{ground} \\
 p_* n - \eta \partial_n v_* = (v \cdot v_*) n + (v \cdot n) v_* + \frac{\partial i}{\partial v} + \left(\frac{\partial j}{\partial S_\beta^\alpha} n^\beta \right)_\alpha \text{ on } \Gamma_{out} \\
 v_* \cdot n = -\frac{\partial i}{\partial(\tau^\alpha \cdot n)} \cdot n ; (\eta \partial_n v_*) \cdot t^\alpha = -\frac{\partial i}{\partial v} \cdot t^\alpha - \left(\frac{\partial j}{\partial S_\beta^\alpha} n^\beta \right)_\alpha \cdot t^\alpha, \alpha = 1,2 \text{ on } \Gamma_{sym}
 \end{array} \right.$$

Continuous adjoint solver

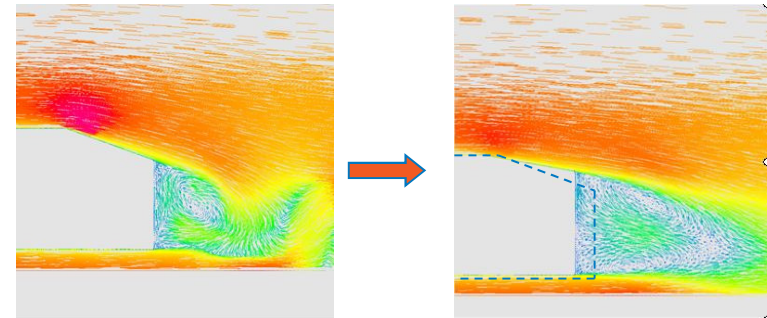
- Shape derivative: $\frac{\partial \ell}{\partial \Omega} = \frac{\partial I}{\partial \Omega} - \int_{\Gamma_{wall}} \left\{ \eta (\nabla v^\alpha \cdot \nabla v_*^\alpha) + S_\beta^\alpha \frac{\partial j}{\partial S_\beta^\alpha} \right\} (\varphi \cdot n)$

derivative wrt the profile

derivative wrt the physics



keep the flow / change the shape



keep the shape / change the flow

Continuous adjoint solver

Application to Aero Force:

$$I = \int_{\Gamma_{wall}} \{ p(n \cdot d) - \eta \partial_n (v \cdot d) \} = \int_{\Gamma_{wall}} (\tau^\alpha \cdot n)_\beta \cdot d$$

cost function

$$\begin{cases} -v^\beta \partial_\alpha v_*^\beta - v \cdot \nabla v_*^\alpha - \nabla \cdot (\eta \nabla v_*^\alpha) + \nabla p_* = 0 \\ \nabla \cdot v_* = 0 \end{cases}$$

source term

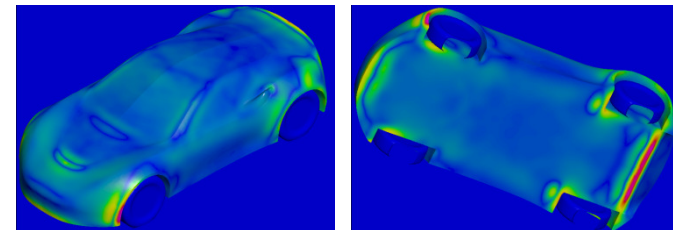
adjoint system

$$\begin{cases} v_* = -d & \text{on } \Gamma_{wall} \\ v_* = 0 & \text{on } \Gamma_{in} \cup \Gamma_{ground} \\ p_* n - \eta \partial_n v_* = (v \cdot v_*) n + (v \cdot n) v_* & \text{on } \Gamma_{out} \\ v_* \cdot n = 0 ; (\eta \partial_n v_*) \cdot t^\alpha = 0, \alpha = 1, 2 & \text{on } \Gamma_{sym} \end{cases}$$

adjoint bcs

$$\frac{\partial \ell}{\partial \Omega} = - \int_{\Gamma_{wall}} \eta (\nabla v^\alpha \cdot \nabla v_*^\alpha) (\varphi \cdot n)$$

shape derivative



Continuous adjoint solver

cost function

— **Pressure Drop:**
$$I = + \int_{\Omega} \eta (\nabla v^\alpha)^2 = - \int_{\Gamma_{in} \cup \Gamma_{out}} \{ p + v^2/2 \} (v \cdot n) - \eta \partial_n v^2 = - \int_{\Gamma_{wall}} v^2/2 (v \cdot n) + (\tau^\alpha \cdot n)_\beta \cdot v$$

$$\begin{cases} -v^\beta \partial_\alpha v_*^\beta - v \cdot \nabla v_*^\alpha - \nabla \cdot (\eta \nabla v_*^\alpha) + \nabla p_* = 0 \\ \nabla \cdot v_* = 0 \end{cases}$$

adjoint system

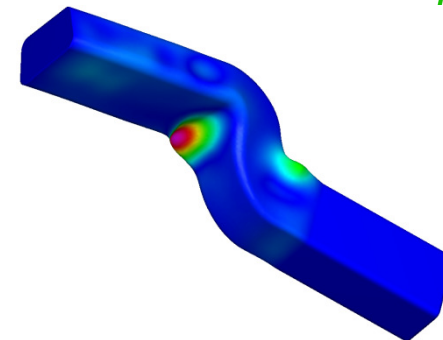
$$\begin{cases} v_* = 0 & \text{on } \Gamma_{wall} \\ v_* = -V & \text{on } \Gamma_{in} \\ p_* n - \eta \partial_n v_* = (v \cdot v_*) n + (v \cdot n) v_* \\ & - (v^2/2) n - v (v \cdot n) \\ & - F & \text{on } \Gamma_{out} \end{cases}$$

source terms

adjoint bcs

$$\frac{\partial \ell}{\partial \Omega} = - \int_{\Gamma_{wall}} \eta (\nabla v^\alpha \cdot \nabla v_*^\alpha) (\varphi \cdot n)$$

shape derivative



Continuous adjoint solver

- Some complication: turbulent viscosity

Smagorinsky model

$$\begin{cases} \eta = \eta + \eta_t \\ \eta_t = g(S_\beta^\alpha) \end{cases}$$

- KKT: $\ell(\Omega, v^\alpha, p, S_\beta^\alpha, \tau_\beta^\alpha, w^\alpha, q, b_N, b_D, b_N^t, b_D^n, c_\beta^\alpha, d_\beta^\alpha, \eta_t, \mu) =$

new variables

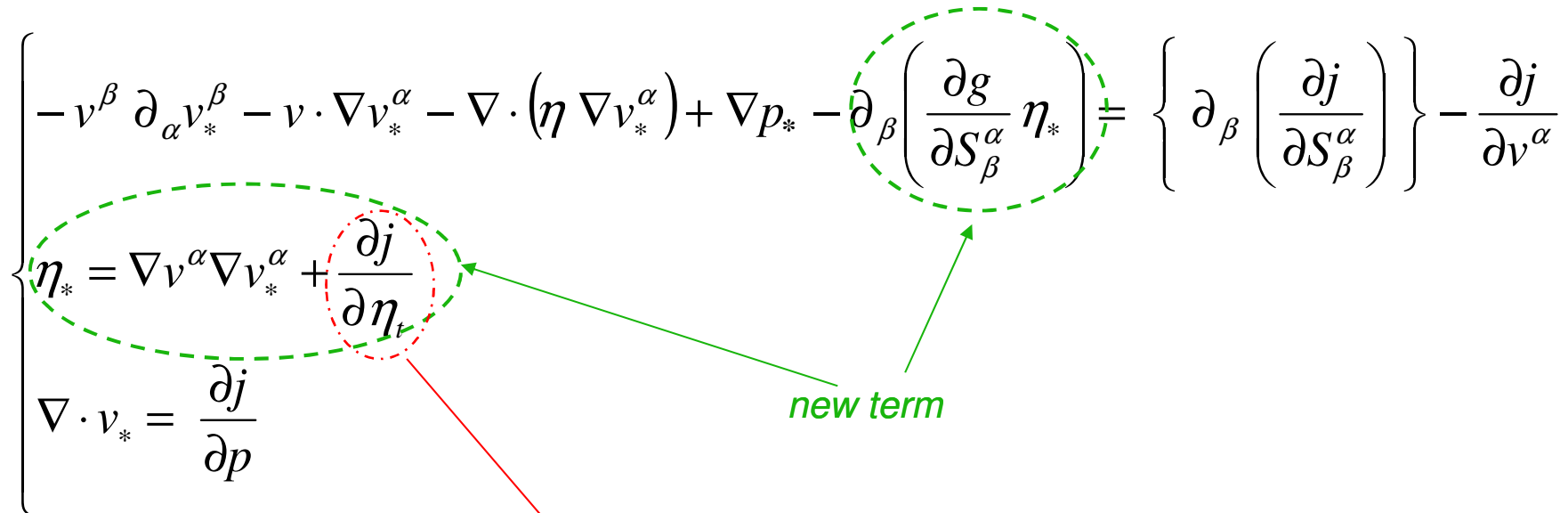
$$\ell_0(\Omega, v^\alpha, p, S_\beta^\alpha, \tau_\beta^\alpha, w^\alpha, q, b_N, b_D, b_N^t, b_D^n, c_\beta^\alpha, d_\beta^\alpha)$$

turbulent lagrangian

$$+ \int_{\Omega} \{ g(S_\beta^\alpha) - \eta_t \} \mu$$

standard lagrangian

— Modified adjoint equations:

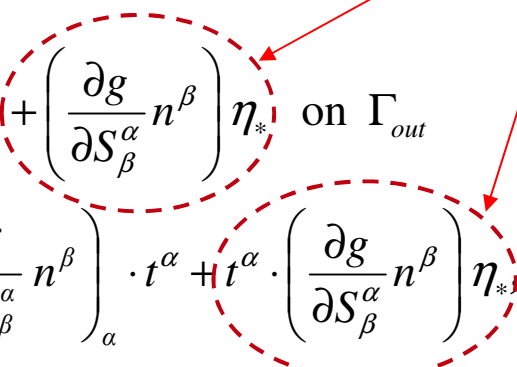
$$\left\{ \begin{array}{l} -v^\beta \partial_\alpha v_*^\beta - v \cdot \nabla v_*^\alpha - \nabla \cdot (\eta \nabla v_*^\alpha) + \nabla p_* - \partial_\beta \left(\frac{\partial g}{\partial S_\beta^\alpha} \eta_* \right) = \left\{ \partial_\beta \left(\frac{\partial j}{\partial S_\beta^\alpha} \right) \right\} - \frac{\partial j}{\partial v^\alpha} \\ \eta_* = \nabla v^\alpha \nabla v_*^\alpha + \frac{\partial j}{\partial \eta_*} \\ \nabla \cdot v_* = \frac{\partial j}{\partial p} \end{array} \right.$$


volumetric cost function is allowed to depend on turbulent viscosity

— Modified adjoint bcs:

$$\begin{cases}
 v_* = -\frac{\partial i}{\partial(\tau^\alpha \cdot n)} \quad \text{on } \Gamma_{in} \cup \Gamma_{wall} \\
 p_* n - \eta \partial_n v_* = (v \cdot v_*) n + (v \cdot n) v_* + \frac{\partial i}{\partial v} + \left(\frac{\partial j}{\partial S_\beta^\alpha} n^\beta \right)_\alpha + \left(\frac{\partial g}{\partial S_\beta^\alpha} n^\beta \right) \eta_* \quad \text{on } \Gamma_{out} \\
 v_* \cdot n = -\frac{\partial i}{\partial(\tau^\alpha \cdot n)} \cdot n ; (\eta \partial_n v_*) \cdot t^\alpha = -\frac{\partial i}{\partial v} \cdot t^\alpha - \left(\frac{\partial j}{\partial S_\beta^\alpha} n^\beta \right)_\alpha \cdot t^\alpha + t^\alpha \cdot \left(\frac{\partial g}{\partial S_\beta^\alpha} n^\beta \right) \eta_* \quad \alpha = 1, 2 \quad \text{on } \Gamma_{sym}
 \end{cases}$$

new terms



— Modified shape derivative:

$$\frac{\partial \ell}{\partial \Omega} = \frac{\partial I}{\partial \Omega} - \int_{\Gamma_{wall}} \left\{ \tilde{\eta} (\nabla v^\alpha \cdot \nabla v_*^\alpha) + S_\beta^\alpha \left(\frac{\partial j}{\partial S_\beta^\alpha} + \frac{\partial j}{\partial \eta_t} \frac{\partial g}{\partial S_\beta^\alpha} \right) \right\} (\varphi \cdot n)$$

new term

$$\tilde{\eta} = \eta + S_\beta^\alpha \frac{\partial g}{\partial S_\beta^\alpha}$$

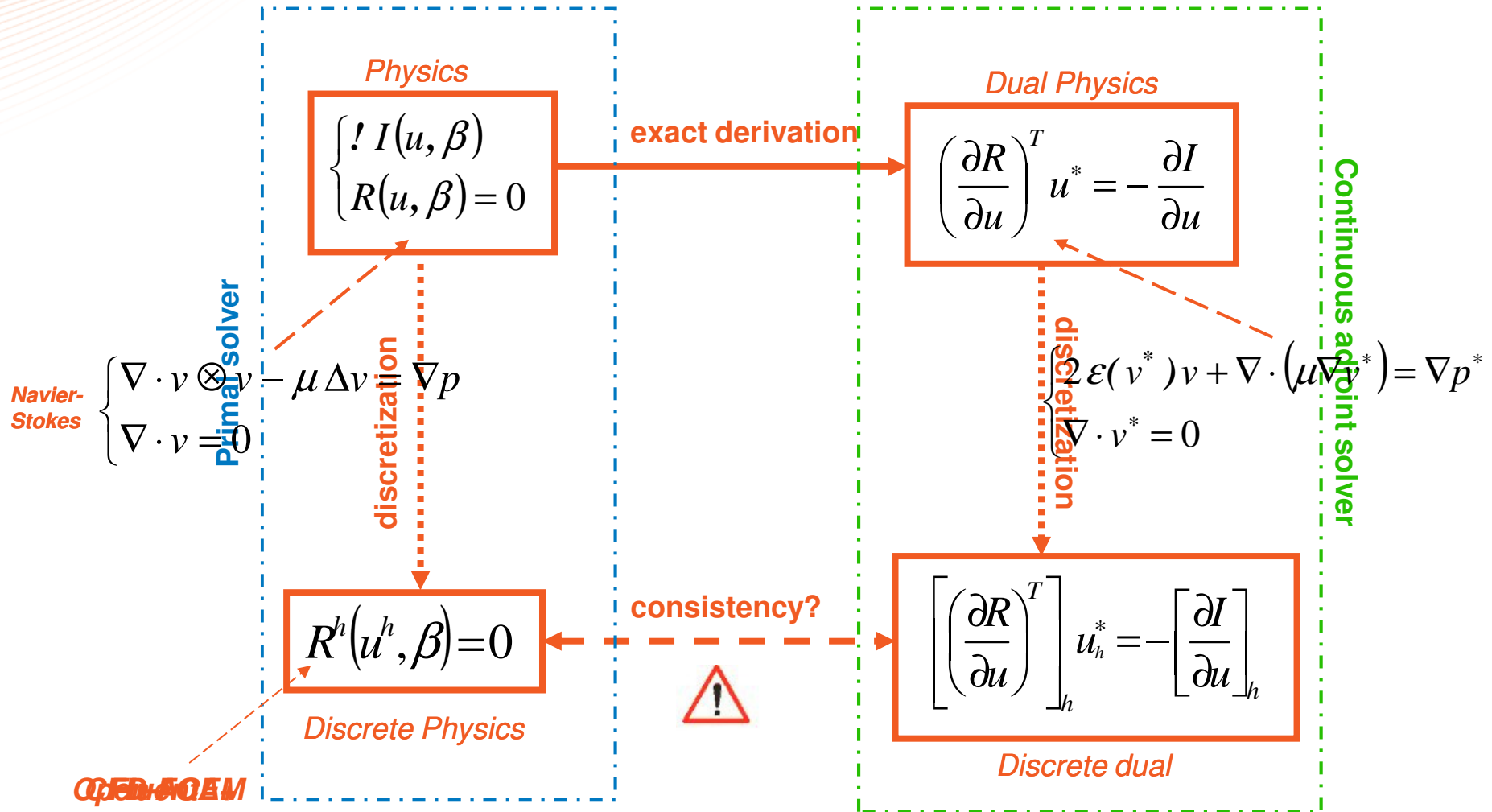
*linearized
turbulent
viscosity*

Continuous adjoint solver

— More complications..

- turbulence models (k-epsilon, Spalart-Allmaras..)
- law of the wall
- natural convection (+Temperature equation)
- MHD
- Chemistry ..

Continuous adjoint solver



Continuous adjoint solver

— Pros:

- *Relatively easy-to-implement*
- *Independant of the numerical scheme of the application code*
- *CPU and memory efficient*

— Cons:

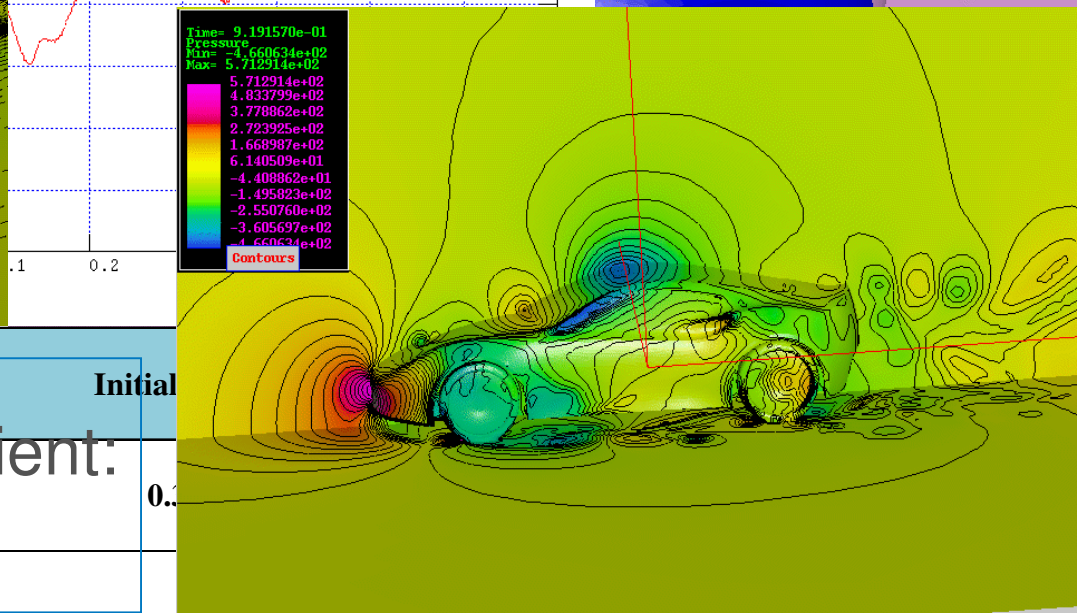
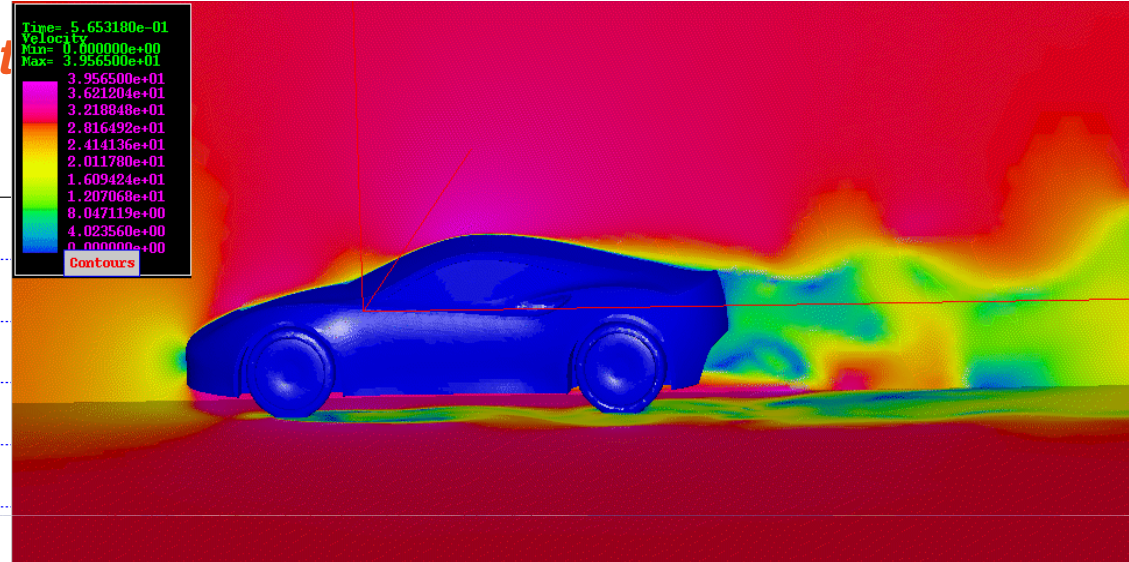
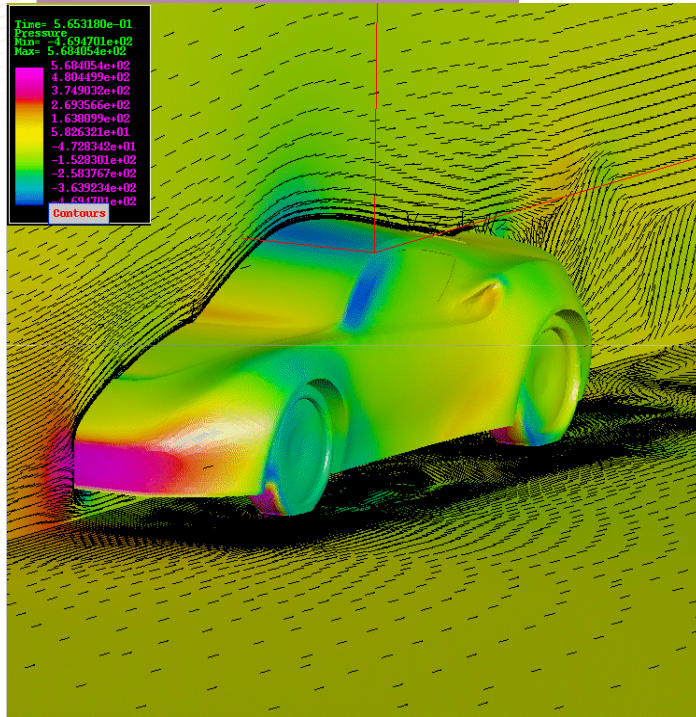
- *Gradient inconsistency: the computed adjoint state is not the adjoint state of the computed physical field*
- *Requires by hand differentiation of the underlying physical model → may be tricky (turbulence models..)*
- *High cost maintenance: any model addendum in the primal solver requires a specific development effort counterpart in the adjoint solver*

Continuous adjoint solver

- **Enriched with converters in 2010 so that it can accommodate results of alternative CFD codes**
 - the CFD may be run using OpenFOAM or Star-CCM+ and the adjoint using PAM-FLOW
- **Both academic and industrial proof of value**
- **Integrated within ESI Visual process environment**
- **Only tet mesh**

Continuous adjoint solver

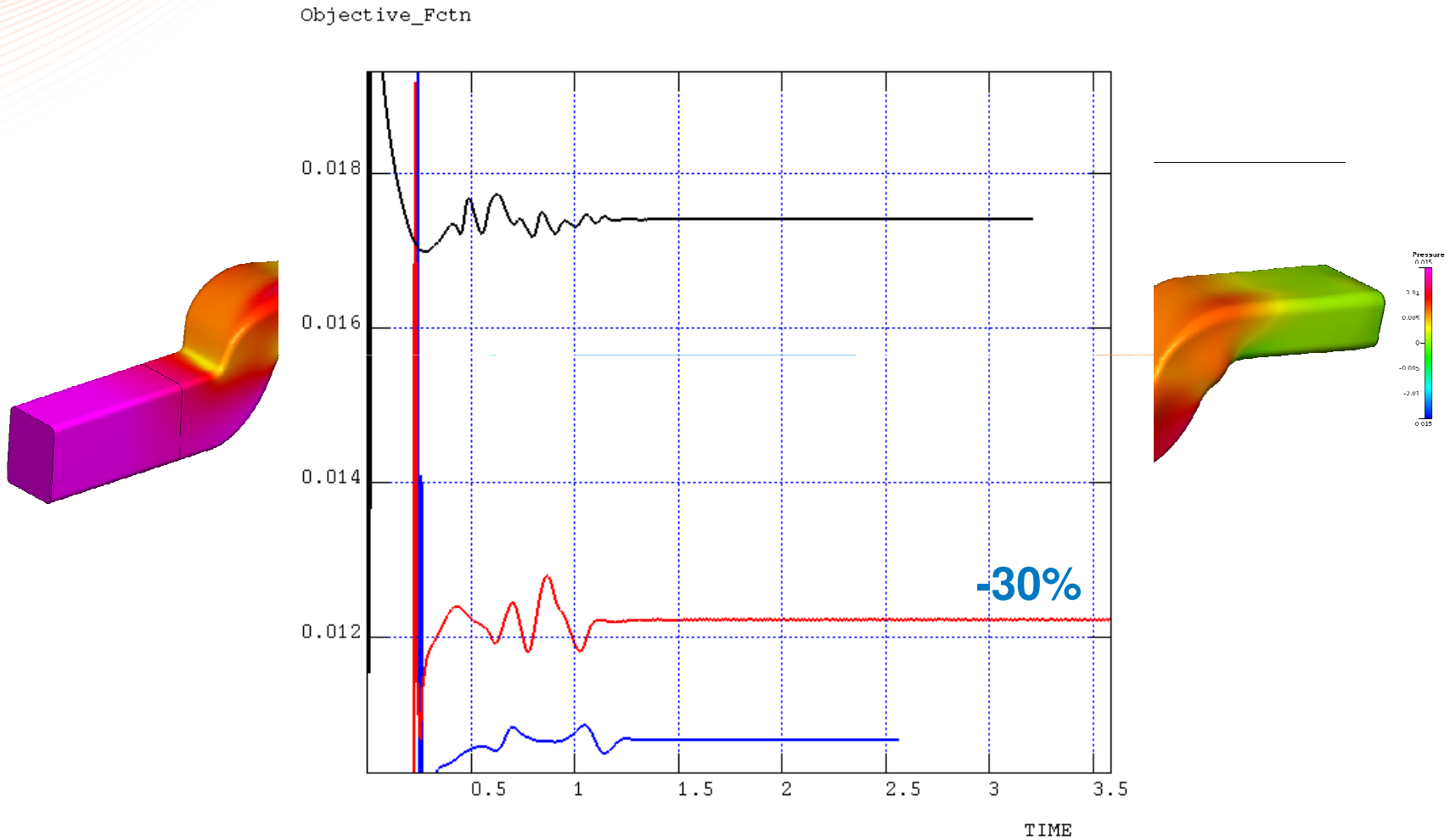
Drag reduct



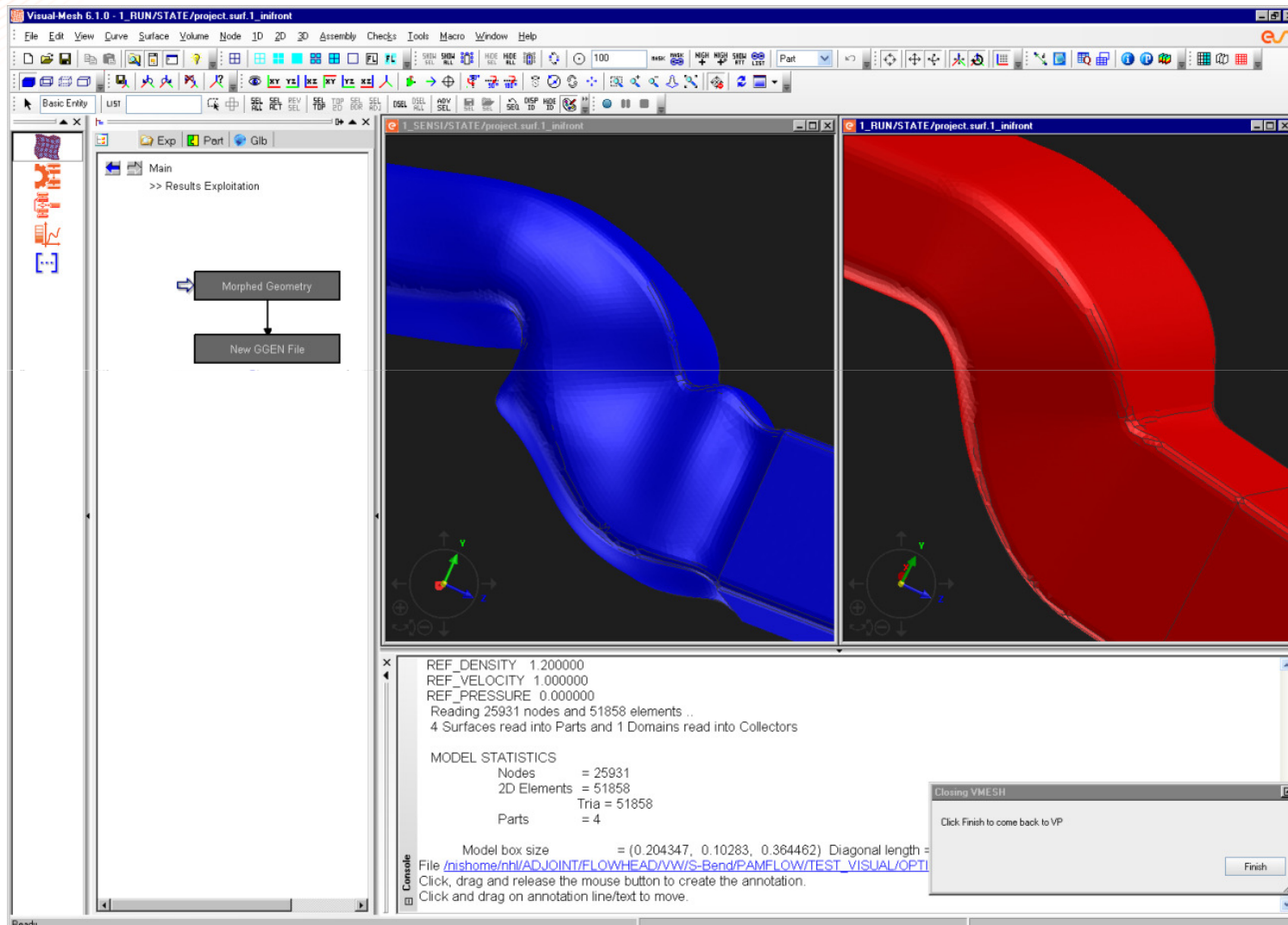
Initial	Final
Predicted drag coefficient:	0.342
Drag coefficient	0.342
$C_d = 0.342$	

ce
ce

Continuous adjoint solver



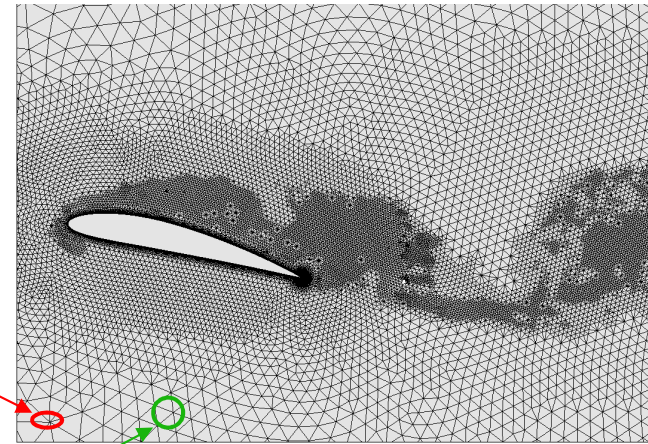
Continuous adjoint solver



- Optimization set-up:

$$\begin{cases} ! I(x, u) \\ s.t. \quad R(\tilde{x}, \tilde{u}) = 0 \end{cases}$$

mesh nodes
coordinates



DOF vector: (v_1, v_2, v_3, p)

- KKT theory: $\ell(x, u, u^*) = I(x, u) + (u^*)^T R(x, u)$

Discrete adjoint solver

- KKT theory:

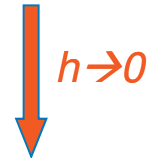
$$\frac{\partial \ell(x, u, u^*)}{\partial u} = \frac{\partial I(x, u)}{\partial u} + \left(\frac{\partial R(x, u)}{\partial u} \right)^T u^* = 0 \quad \longrightarrow \quad \text{discrete adjoint equation}$$

$$\frac{\partial \ell(x, u, u^*)}{\partial x} = \frac{\partial I(x, u)}{\partial x} + \left(\frac{\partial R(x, u)}{\partial x} \right)^T u^* \quad \longrightarrow \quad \text{sensitivity vector}$$

- Discrete vs. Continuous shape derivative:

discrete

$$\frac{\partial \ell}{\partial x} = \left(\frac{\partial I}{\partial x} \right)^T + \left(\frac{\partial R}{\partial x} \right)^T u^*$$



BUT:

$$\left(\frac{\partial I}{\partial x} \right)^T \neq \frac{\partial I}{\partial \Omega}$$

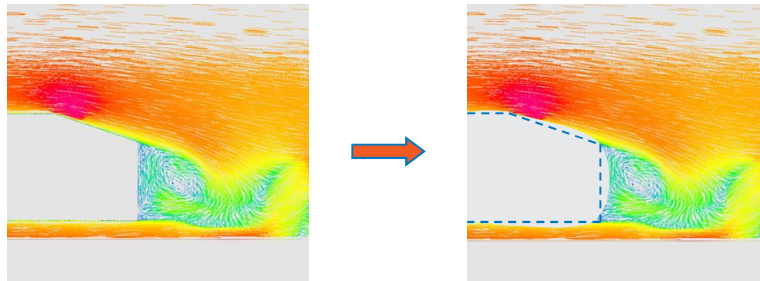
continuous

$$\frac{\partial \ell}{\partial \Omega} = \frac{\partial I}{\partial \Omega} - \int_{\Gamma_{wall}} \left\{ \eta (\nabla v^\alpha \cdot \nabla v_*^\alpha) - S_\beta^\alpha \frac{\partial j}{\partial S_\beta^\alpha} \right\} (\varphi \cdot n)$$

Discrete adjoint solver

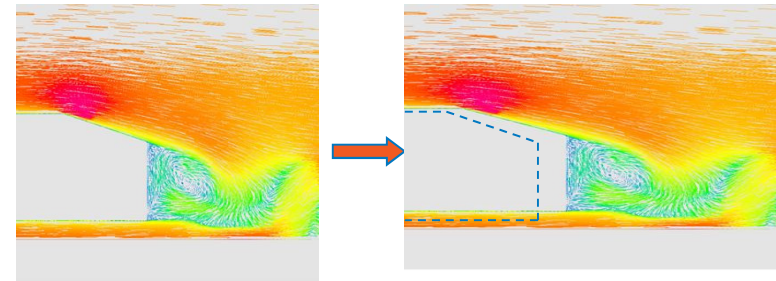
— Indeed:

$$\frac{\partial I}{\partial \Omega} \quad \text{Lie derivative}$$



keep the flow / change the shape

$$\left(\frac{\partial I}{\partial x} \right)^T \quad \text{Sensitivity to the node positions}$$



advect the flow as shape changes

— They are connected:

$$\left(\frac{\partial I}{\partial x} \right)^T \rightarrow \frac{\partial I}{\partial \Omega} - \left(\frac{\partial I}{\partial u} \right) (\varphi \cdot \nabla u) - \left(\frac{\partial I}{\partial U_{wall}} \right) (\varphi \cdot \nabla U)$$

— Similarly:

$$\left(\frac{\partial R}{\partial x}\right)^T u^* \rightarrow \frac{\partial(R, u^*)}{\partial \Omega} - \left(\left(\frac{\partial R}{\partial u}\right)^T u^*, (\varphi \cdot \nabla u) \right) - \left(\left(\frac{\partial R}{\partial U_{wall}}\right)^T u^*, (\varphi \cdot \nabla U) \right)$$

— Hence:

$$\begin{aligned} \frac{\partial \ell}{\partial x} &\rightarrow \frac{\partial I}{\partial \Omega} - \left(\left(\frac{\partial R}{\partial U_{wall}}\right)^T u^* + \left(\frac{\partial I}{\partial U_{wall}}\right)^T, (\varphi \cdot \nabla U) \right) \\ &+ \underbrace{\frac{\partial(R, u^*)}{\partial \Omega}}_{\rightarrow 0} - \left(\underbrace{\left\{ \left(\frac{\partial R}{\partial u}\right)^T u^* + \left(\frac{\partial I}{\partial u}\right)^T \right\}}_0, (\varphi \cdot \nabla u) \right) \end{aligned}$$

— Finally:

$$\frac{\partial \ell}{\partial x} \approx \frac{\partial I}{\partial \Omega} - \left(\left(\frac{\partial R}{\partial U_{wall}}\right)^T u^* + \left(\frac{\partial I}{\partial U_{wall}}\right)^T, (\varphi \cdot \nabla U) \right)$$

3 choices for computing the shape derivative:

<i>discrete</i>	$\frac{\partial \ell}{\partial x} = \left(\frac{\partial I}{\partial x} \right)^T + \left(\frac{\partial R}{\partial x} \right)^T u^*$	→	exact
<i>continuous</i>	$\frac{\partial \ell}{\partial \Omega} = \frac{\partial I}{\partial \Omega} - \int_{\Gamma_{wall}} \left\{ \eta (\nabla v^\alpha \cdot \nabla v_*^\alpha) - S_\beta^\alpha \frac{\partial j}{\partial S_\beta^\alpha} \right\} (\varphi \cdot n)$	→	valid at convergence
<i>hybrid</i>	$\frac{\partial \ell}{\partial x} \approx \frac{\partial I}{\partial \Omega} - \left(\left(\frac{\partial R}{\partial U_{wall}} \right)^T u^* + \left(\frac{\partial I}{\partial U_{wall}} \right)^T, (\varphi \cdot \nabla U) \right)$	→	good (?) compromise if one can not easily move the nodes

Discrete adjoint solver

- The adjoint matrix:

$$\left(\begin{array}{ccc|c}
 \frac{\partial R_{v_1}}{\partial v^1} & \frac{\partial R_{v_2}}{\partial v^1} & \frac{\partial R_{v_3}}{\partial v^1} & \frac{\partial R_p}{\partial v^1} \\
 \frac{\partial R_{v_1}}{\partial v^2} & \frac{\partial R_{v_2}}{\partial v^2} & \frac{\partial R_{v_3}}{\partial v^2} & \frac{\partial R_p}{\partial v^2} \\
 \frac{\partial R_{v_1}}{\partial v^3} & \frac{\partial R_{v_2}}{\partial v^3} & \frac{\partial R_{v_3}}{\partial v^3} & \frac{\partial R_p}{\partial v^3} \\
 \hline
 \frac{\partial R_{v_1}}{\partial p} & \frac{\partial R_{v_2}}{\partial p} & \frac{\partial R_{v_3}}{\partial p} & \frac{\partial R_p}{\partial p}
 \end{array} \right) = \left(\begin{array}{c|c}
 \mathbf{A} & \mathbf{B} \\
 \hline
 \mathbf{B}' & \mathbf{C}
 \end{array} \right)$$

- Typical block stencil:

		2		
2	1	2		
1	0	1		
2	1	2		
		2		

- Huge, (not so) sparse, unsymmetric, indefinite matrix
- Hard to solve (saddle-point system)

- Use an optimal preconditioner (DDM, Multigrid, Subdomain deflation)

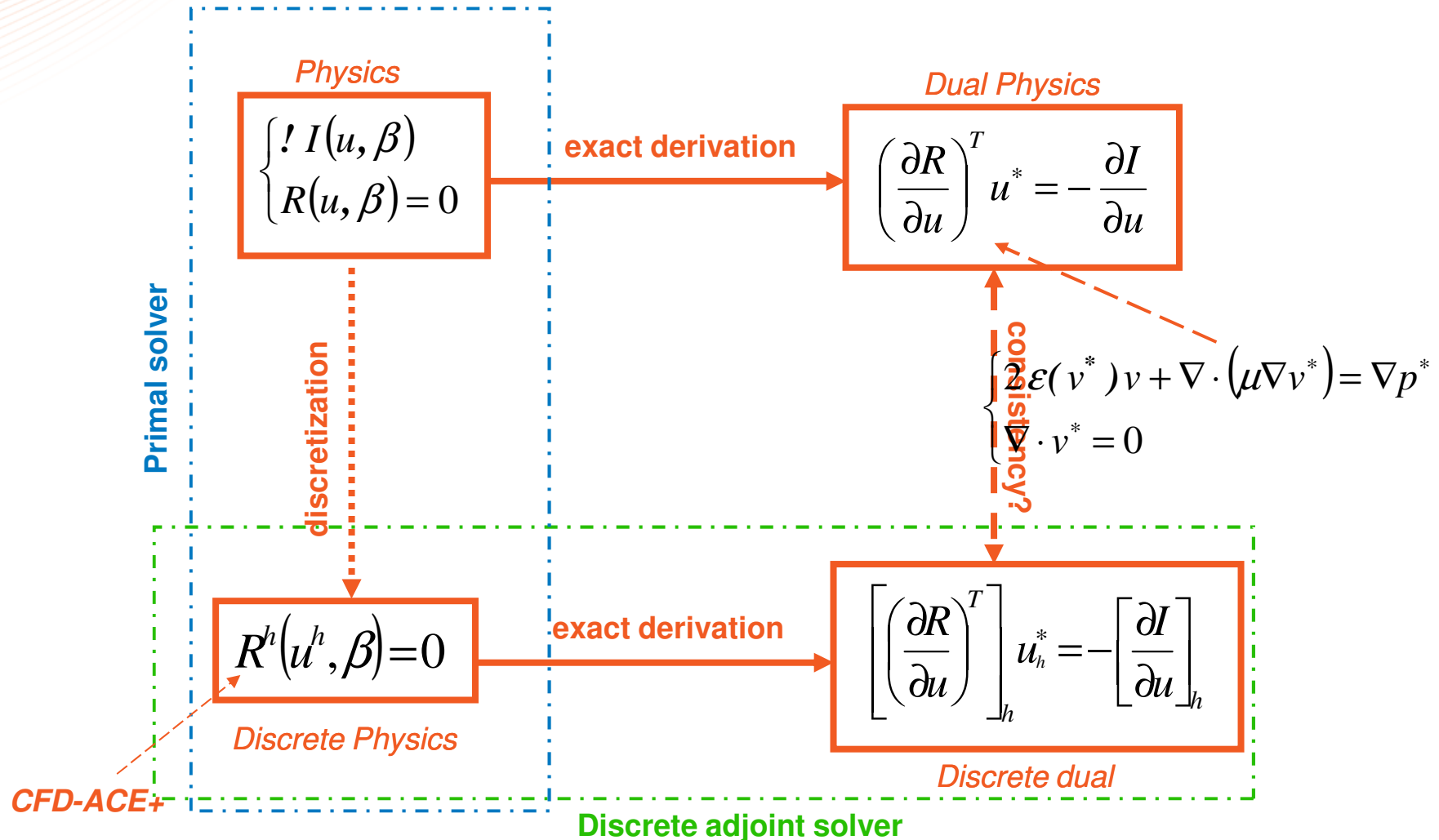
- Or a segregated-like approach:
$$P(x^{n+1} - x^n) = \left(\frac{\partial I}{\partial u}\right)^T - \left(\frac{\partial R}{\partial u}\right)^T x^n$$

$$P^{-1} = \begin{pmatrix} I & -D_A^{-1}B \\ 0 & I \end{pmatrix} \begin{pmatrix} I & 0 \\ 0 & (B'D_A^{-1}B - C)^{-1} \end{pmatrix} \begin{pmatrix} I & 0 \\ B' & -I \end{pmatrix} \begin{pmatrix} (D_A + A)^{-1} & 0 \\ 0 & I \end{pmatrix}$$

$$D_A = \alpha \text{DIAG}(A)$$

- If matrix has to be assembled, out of coring may be needed

Discrete adjoint solver



Discrete adjoint solver

- **Pros:**

- *Gradient consistency: the computed adjoint state is the real adjoint of the computed physical field*

- **Cons:**

- *Depends on the very numerical scheme of the application code*
- *How to build the discrete adjoint operator?*

Discrete adjoint solver

- Different approaches for building the discrete adjoint operator:
 - *By hand*
 - *Automatic (Algorithmic) Differentiation*

Discrete adjoint solver

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to

(PAM-FLOW) the final cut!

$$\sum_{\alpha=1}^3 \sum_k \sum_l \left(\frac{\partial \mathcal{R}_k^v}{\partial u_k^*} - \int_{\Omega} \frac{\partial S_k}{\partial u_k^*} \right) \frac{\partial u_k^*}{\partial x} u_k^*$$

$$- \sum_{\alpha=1}^3 \sum_k \frac{\partial \mathcal{R}_k^p}{\partial p_k^*} \frac{\partial p_k^*}{\partial x} p_k^*$$

$$- \sum_k \sum_l \frac{\partial \mathcal{R}_k^v}{\partial p_l^*} \frac{\partial p_l^*}{\partial x} p_l^*$$

$$- \sum_{\alpha=1}^3 \sum_k \int_{\Omega} \frac{\partial \mathcal{I}_k}{\partial p_k^*} \frac{\partial p_k^*}{\partial x}$$

$$- \sum_{\alpha=1}^3 \sum_k \int_{\Omega} \frac{\partial \mathcal{I}_k}{\partial u_k^*} \frac{\partial u_k^*}{\partial x}$$

$$\left(- \sum_{\alpha=1}^3 \sum_k \int_{\Omega} \frac{\partial \mathcal{I}_k}{\partial p_k^*} \frac{\partial p_k^*}{\partial x} \right)$$

$$- \sum_k \int_{\Omega} \frac{\partial \mathcal{I}_k}{\partial p_k^*} \frac{\partial p_k^*}{\partial x}$$

$$\sum_{\alpha=1}^3 \left(\frac{\partial \mathcal{R}_k^v}{\partial u_k^*} - \int_{\Omega} \frac{\partial S_k}{\partial u_k^*} \right)^T u_k^*$$

$$- \sum_k \left(\frac{\partial \mathcal{R}_k^p}{\partial p_k^*} \right)^T p_k^*$$

$$= \frac{\partial \mathcal{J}}{\partial u_k^*}$$

$$+ \sum_k \left(\frac{\partial \mathcal{R}_k^p}{\partial p_k^*} \right)^T p_k^* - \sum_k \left(\frac{\partial \mathcal{R}_k^p}{\partial p_k^*} \right)^T p_k^*$$

$$= \frac{\partial \mathcal{J}}{\partial p_k^*}$$

$$\frac{\partial \mathcal{J}}{\partial u_k^*} = \frac{\partial}{\partial u_k^*} \left(\int_{\Omega} (\nabla \mu \nabla^h v) \right) + (\nabla^h v \cdot \nu)_i + (\nabla^h p)_i + \sum (\theta(v_i, y_i, \phi_i) - p(v_i, \phi_i) / (y_i \phi_i)) + \sum (\theta(v_i + \omega_i) / 2, c_i) - \frac{p(v_i, \phi_i) / (y_i \phi_i)}{2}$$

re of

$$\left(\frac{\partial \mathcal{R}_k^v}{\partial u_k^*} \right)^T u_k^*$$

$$= - \nabla \mu \nabla u_k^* + \int_{\Omega} S_k u_k^* - \int_{\Omega} \frac{\partial S_k}{\partial u_k^*} u_k^*$$

$$- (\nabla^h v)_i \nabla_i^h u_k^* + \dots$$

$$+ \int_{\Omega} S_k u_k^* A^T(u) v^*$$

$$\left(\frac{\partial \mathcal{R}_k^p}{\partial p_k^*} \right)^T p_k^* = + \nabla^h v + \sum_{j \neq i} R_{ij}(v, p) (p_j - p_i)$$

$$\left(\frac{\partial \mathcal{R}_k^p}{\partial u_k^*} \right)^T p_k^* = - \nabla^h p_k^* + \int_{\Omega} p_k^* \nu + \dots$$

$$- (\nabla \mu \nabla^h v)_i + \delta R_{i, \alpha}^*$$

$$- (A^T(u) \nabla^h v)_i + (\nabla^h p^*)_i = \int_{\Omega} S^* + \tilde{p}^* \omega - A^T(u) v^* N_i - \int_{\Omega} \frac{\partial \mathcal{I}}{\partial u_k^*} + \int_{\Omega} \frac{\partial S}{\partial u_k^*} v^*$$

$$\mathcal{R}_{v^*}^* = \mathcal{R}_{v^*, \alpha}^* + \delta \mathcal{R}_{v^*}^*$$

$$\delta \mathcal{R}_{v^*}^* = \frac{\partial}{\partial v_i^*} \left[\sum_k \left(\frac{\partial}{\partial u_k^*} \left[\frac{\partial}{\partial u_k^*} (u_k^* \nu_k, \phi_k) - g(u_k^*, \phi_k) + g(u_k^*, \phi_k) \right] u_k^* \right) \right]$$

$$+ \frac{\partial}{\partial v_i^*} \left[\sum_k \left(\frac{\partial}{\partial u_k^*} \left[\frac{\partial}{\partial u_k^*} (u_k^* \nu_k, \phi_k) - g(u_k^*, \phi_k) + g(u_k^*, \phi_k) \right] u_k^* \right) \right]$$

$$- (\nabla^h \frac{\partial \mathcal{I}}{\partial u_k^*} \nabla^h v^*)$$

$$- \frac{1}{2} \sum_{k, l} \frac{\partial \mathcal{I}_k}{\partial v_i^*} \frac{\partial \mathcal{I}_l}{\partial v_i^*} (p_{kl} - p_k) (p_{kl} - p_l)$$

$$- (\nabla^h v^*)_i + \sum \lambda_{ij}^* (v_i, p) (p_j^* - p_i^*) + (\delta \mathcal{R}_{p^*})_i = - \int_{\Omega} v^* \nu - \int_{\Omega} \frac{\partial \mathcal{I}}{\partial p_i^*}$$

$$\left(\frac{\partial \mathcal{R}_{p^*}}{\partial p_i^*} \right)^T p_i^* = - \sum_k \lambda_{kp} (v, p) f^*$$

$$\left(\frac{\partial \mathcal{R}_{p^*}}{\partial p_i^*} \right)^T p_i^* = + \sum_{k, p} \lambda_{kp} (v, p) \frac{\partial p_{kp} - p_k^*}{\partial p_i^*} (p_k^* - p_i^*) + \sum_{k, p} \frac{\partial \lambda_{kp}}{\partial p_i^*} (p_{kp} - p_k) (p_k^* - p_i^*)$$

$$p_{kl} - p_k = \frac{\partial p_{kl}}{\partial p_k} (p_{kl} - p_k) + \frac{\partial p_{kl}}{\partial p_l} (p_{kl} - p_l)$$

$$\text{Lemme: } \frac{\partial p_{kl}}{\partial p_i} = \sum_{k, l} \lambda_{kl} \left(\frac{\partial p_{kl}}{\partial p_i} \right) \frac{\partial \mathcal{I}_k}{\partial p_i}$$

$$\mathcal{R}_{i^*}^* = - \nabla^h \otimes S + \int_{\Omega} \nu \otimes S N_i$$

$$\mathcal{R}_{i^*}^* = \sum_j \lambda_{ij}^* \frac{(v_i - v_j)}{2}$$

$$\sum_{k, l} \lambda_{kl} \frac{\partial v_k^* \otimes q}{\partial q_i}$$

$$\sum_{k, l} (\sum_{k, l} \lambda_{kl}) \frac{\partial v_k^* \otimes q}{\partial q_i}$$

$$\left(\frac{\partial \mathcal{R}_{p^*}}{\partial p_i^*} \right)^T p_i^* = \sum_{k, l} \lambda_{kl} \frac{\partial p_{kl}}{\partial p_i^*} \frac{\partial p_{kl}}{\partial p_i^*} \frac{(p_{kl} - p_k)}{2} \frac{\partial p_{kl}}{\partial p_i^*} + \sum_{k, l} \lambda_{kl} \frac{\partial p_{kl}}{\partial p_i^*} \frac{\partial p_{kl}}{\partial p_i^*} \frac{(p_{kl} - p_l)}{2}$$

privat

$$\left(\frac{\partial \mathcal{R}_k^v}{\partial u_k^*} \right)^T u_k^*$$

$$= - \nabla \mu \nabla u_k^* + \int_{\Omega} S_k u_k^* - \int_{\Omega} \frac{\partial S_k}{\partial u_k^*} u_k^*$$

$$- (\nabla^h v)_i \nabla_i^h u_k^* + \dots$$

$$+ \int_{\Omega} S_k u_k^* A^T(u) v^*$$

$$\left(\frac{\partial \mathcal{R}_k^p}{\partial p_k^*} \right)^T p_k^* = + \nabla^h v + \sum_{j \neq i} R_{ij}(v, p) (p_j - p_i)$$

$$\left(\frac{\partial \mathcal{R}_k^p}{\partial u_k^*} \right)^T p_k^* = - \nabla^h p_k^* + \int_{\Omega} p_k^* \nu + \dots$$

$$- (\nabla \mu \nabla^h v)_i + \delta R_{i, \alpha}^*$$

$$- (A^T(u) \nabla^h v)_i + (\nabla^h p^*)_i = \int_{\Omega} S^* + \tilde{p}^* \omega - A^T(u) v^* N_i - \int_{\Omega} \frac{\partial \mathcal{I}}{\partial u_k^*} + \int_{\Omega} \frac{\partial S}{\partial u_k^*} v^*$$

$$\mathcal{R}_{v^*}^* = \mathcal{R}_{v^*, \alpha}^* + \delta \mathcal{R}_{v^*}^*$$

$$\delta \mathcal{R}_{v^*}^* = \frac{\partial}{\partial v_i^*} \left[\sum_k \left(\frac{\partial}{\partial u_k^*} \left[\frac{\partial}{\partial u_k^*} (u_k^* \nu_k, \phi_k) - g(u_k^*, \phi_k) + g(u_k^*, \phi_k) \right] u_k^* \right) \right]$$

$$+ \frac{\partial}{\partial v_i^*} \left[\sum_k \left(\frac{\partial}{\partial u_k^*} \left[\frac{\partial}{\partial u_k^*} (u_k^* \nu_k, \phi_k) - g(u_k^*, \phi_k) + g(u_k^*, \phi_k) \right] u_k^* \right) \right]$$

$$- (\nabla^h \frac{\partial \mathcal{I}}{\partial u_k^*} \nabla^h v^*)$$

$$- \frac{1}{2} \sum_{k, l} \frac{\partial \mathcal{I}_k}{\partial v_i^*} \frac{\partial \mathcal{I}_l}{\partial v_i^*} (p_{kl} - p_k) (p_{kl} - p_l)$$

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Discrete adjoint solver

- **By Algorithmic Differentiation:**

- *The source code itself is differentiated*
- *2 modes: direct / reverse*
- *2 approaches: source transformation / operator overloading*

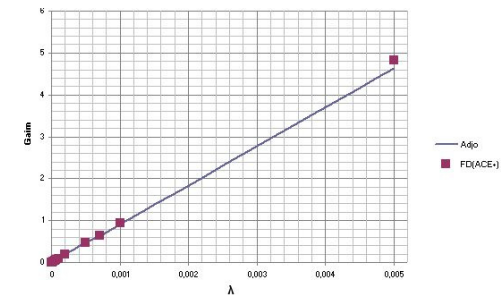
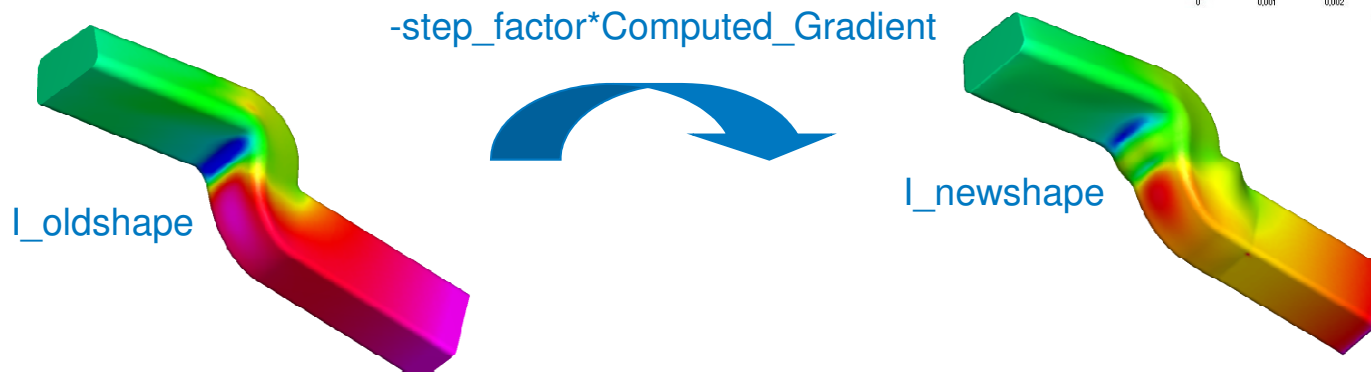
- **Pros & cons:**

- *Low cost maintenance: the code is differentiated once and for all (no further effort for accommodating newly developed models in the primal solver)*
- *But each application solver adjoint derivation has to be addressed mostly independently*
- *May turn to be tedious and time consuming depending on the code structure and programming language*
- *Very invasive: requires full access to the source code*
- *Severe CPU efficiency and memory consumption challenges*

Discrete adjoint solver

- **Academic validation against FD**
- **Dynamic library interfaced with CFD-ACE+**
- **Any mesh topology**
- **Enriched with converters so that it can accomodate results of alternative CFD codes**
 - the CFD may be run using OpenFOAM or Star-CCM+ and the adjoint using PAM-FLOW
- **Limitations:**
 - **Not yet parallelized**

- A word on rigorous validation:



Expected Improvement := step_factor*Computed_Gradient_Norm**2

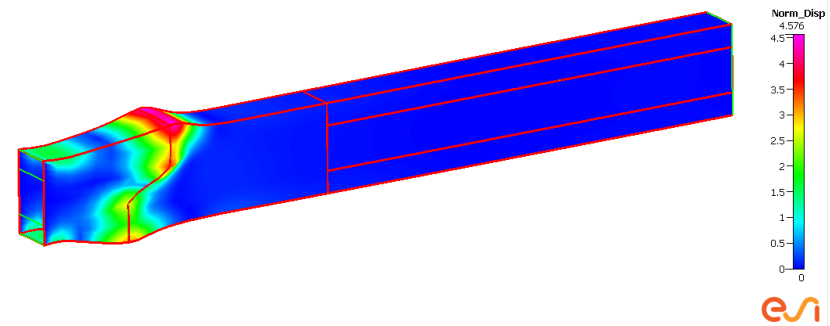
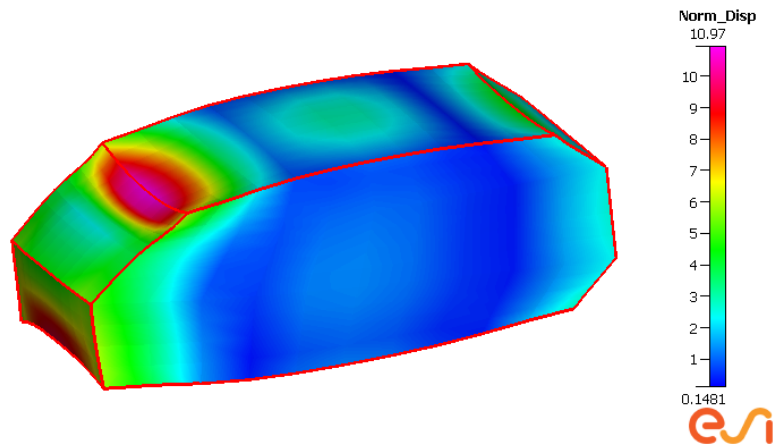
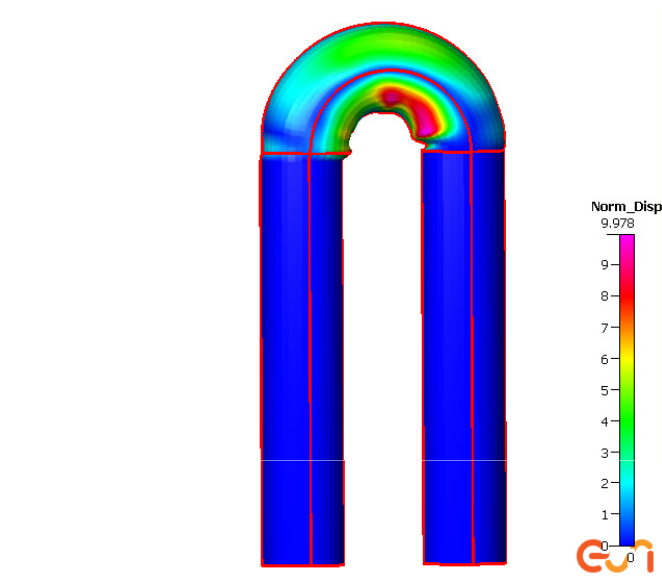
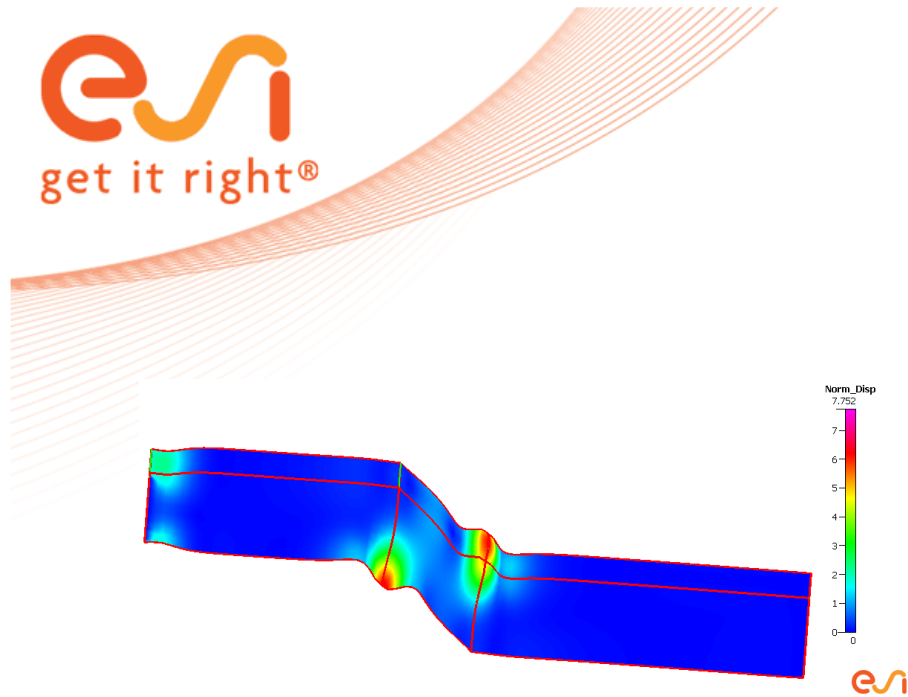
Effective Improvement := I_oldshape-I_newshape

Relative error := 100* ABS(Expected_Improvement-Effective_Improvement)
/Effective_Improvement

Discrete adjoint solver

	Airfoil Tet	Airfoil Hex	Aifoil Hex	S-Bend (Viscart)	Ahmed Body (Viscart)
Physics	Laminar	Laminar	Frozen Turbulent	Frozen Turbulent	Frozen Turbulent
Relative error (%)	0,07	0,14	0,37	5,15	0,11

Discrete adjoint solver

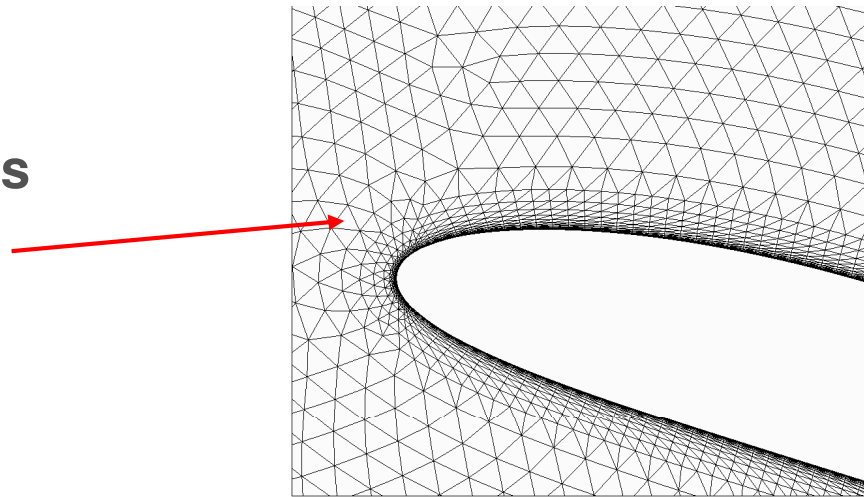


- At first bound interior node displacement to surface nodes one thanks to harmonic mapping (ALE-like):
 - Minimizes mesh isotropic distortion

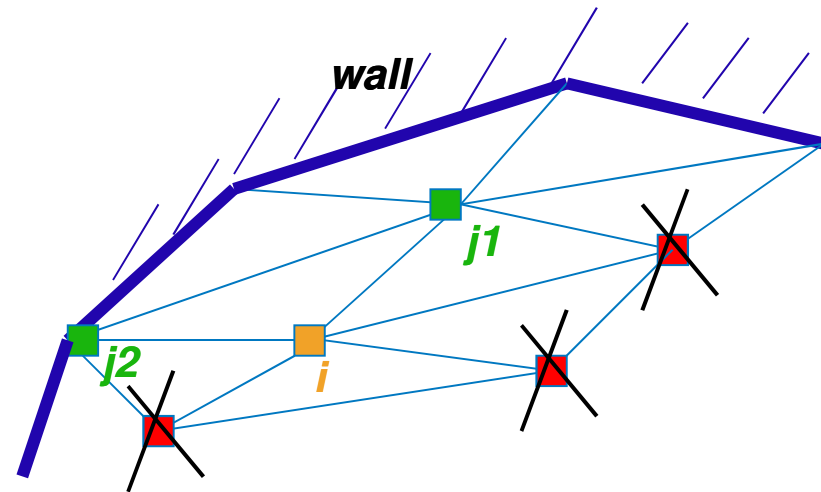
$$\left\{ \begin{array}{l} -\Delta \delta x = 0 \\ \delta x = \delta x_{surf} \quad \text{on } \Gamma_{wall} \\ \delta x = 0 \quad \text{on } \partial\Omega \setminus \Gamma_{wall} \end{array} \right. \quad \longrightarrow \quad \delta x_{int} = K \delta x_{surf}$$

- Not good for boundary layers (anisotropic mesh)

- Use rigidification instead :



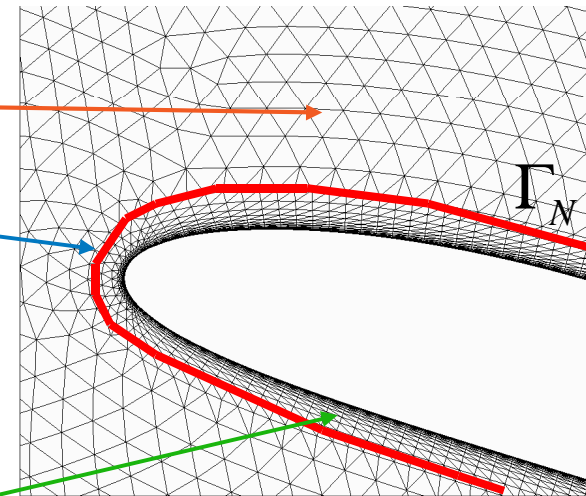
$$\delta x_{i \in bl(n)} = \frac{\sum_{j \in N_i \cap bl(n-1)} (1 / \|x_j - x_i\|) \delta x_j}{\sum_{j \in N_i \cap bl(n-1)} (1 / \|x_j - x_i\|)}$$



- Then combine Laplace and rigidification:

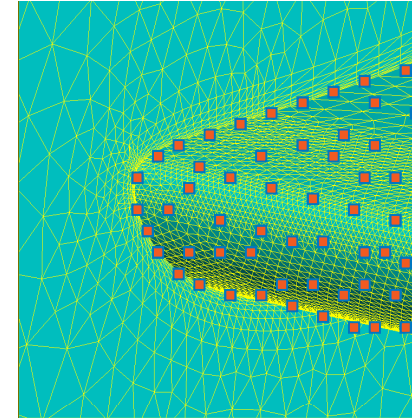
$$\begin{cases} -\Delta \delta x = 0 \\ \delta x = \delta x_{bl(N)} \quad \text{on } \Gamma_N \\ \delta x = 0 \quad \text{on } \partial\Omega \setminus \Gamma_{wall} \end{cases}$$

$$\delta x_{i \in bl(n \leq N)} = \frac{\sum_{j \in N_i \cap bl(n-1)} (1 / \|x_j - x_i\|) \delta x_j}{\sum_{j \in N_i \cap bl(n-1)} (1 / \|x_j - x_i\|)}$$



- For boundary nodes, apply LSQ morphing:

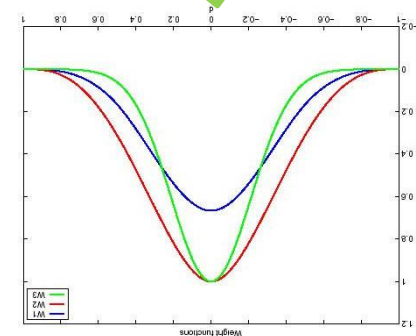
- Sample the surface nodes $(\delta x_{surf}^i) \rightarrow (\delta y_s^j)$
- Apply LSQ operator (exact for polynomial up to desired degree)



$$\delta x_{surf}(x) = \sum_{j \in S} \delta y_s^j \Phi_j(x)$$

$$(\Phi_i(x))_{1 \leq i \leq n} = \operatorname{argmin} \left(J(\lambda) = \sum_{i \in S} W_\varepsilon(x - x_i) \lambda_i^2 \right)$$

subject to $\sum_{i \text{ node}} \lambda_i p_k(x_i) = p_k(x) \quad \forall p_k$



- Finally, adapt the shape derivative accordingly via chain rule:

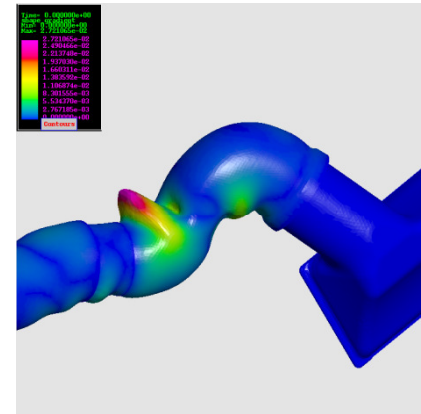
:

$$\frac{\partial \ell}{\partial y_s} = \left\{ \left(\frac{\partial \ell}{\partial x_{in}} \right) \left(\frac{\partial x_{in}}{\partial x_{surf}} \right) + \left(\frac{\partial \ell}{\partial x_{surf}} \right) \right\} \left(\frac{\partial x_{surf}}{\partial y_s} \right)$$

- Do not forget this step, otherwise the gradient is wrong !

:

- **Morphing option available both within PAM-FLOW Continuous Adjoint Solver and ACE+ Discrete one**
:
- **Limited to small displacements**
:
- **Additionally, the tool provides the value of the maximal step factor so that all volume remain positive**
:





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