

# Discrete and continuous adjoint method for compressible CFD

## J. Peter ONERA

J. Peter<sup>1</sup>

<sup>1</sup>ONERA DMFN

October 2, 2014



# Outline

- 1 Introduction
- 2 Discrete adjoint method
- 3 Continuous adjoint method
- 4 Discrete vs Continuous adjoint
- 5 Conclusions

# Introduction (1/4)

- Well-known aerodynamic optimization problems of the utmost importance
  - Aircraft drag reduction
  - Reduction of total pressure losses of a blade row.
- Strongly constrained problems (from aerodynamics, structure...)
- Several approaches for researches and studies in external aerodynamics
  - Flight tests
  - Wind tunnel experiments (with flight  $Re$ /lower than flight  $Re$ )
  - Numerical simulation
- Numerical simulation most adapted

# Introduction (2/4)

- (Non solvable) pde  $\rightarrow$  numerical simulation. Finite-volume simulation in this talk.
  - Infinite dimension possible deformation  $\rightarrow$  parametrization
  - Finite dimensional maths
- 
- Which type of optimization method ?
  - Local or global optimization ?

# Introduction (3/4)

- Global optimization
  - genetic/evolutionary algorithms, particle swarm, ant colony, CMA-ES...
  - large number of function evaluations required
  - combined with surrogate models
  - in particular used for design space exploration with low fidelity models
- Local optimization
  - very valuable when starting from pre-optimized shapes
  - pattern methods. e.g. simplex method
  - gradient-based methods. e.g. steepest descent, conjugate gradient
- Popular and efficient descent methods require objective and constraint sensitivities w.r.t. design parameters

# Introduction (4/4)

- Needed sensitivities w.r.t. design parameters
- ...not a trivial task in numerical simulation as state variables change with shape via the equations of the mechanical problem
- Sensitivity calculation
  - 70's 80's finite differences. Scaling with number of shape parameters
  - Control theory [Lions 71, Pironneau 73,74] aerodynamics shape optimization [Jameson 88] adjoint method. Scaling with the number of functions to be differentiated
- Other applications of adjoint method: understanding zones of influence for function value, goal-oriented mesh refinement

# Outline

- 1 Introduction
- 2 Discrete adjoint method**
- 3 Continuous adjoint method
- 4 Discrete vs Continuous adjoint
- 5 Conclusions

# Discrete adjoint method

- Framework: compressible flow simulation using finite volume method.  
Discrete approach for sensitivity analysis
- Notations
  - Volume mesh  $X$ , flowfield  $W$  (size  $n_a$ )
  - Wall surface mesh  $S$
  - Residual  $R$ ,  $C^1$  regular w.r.t.  $X$  and  $W$  – steady state:  $R(W, X) = 0$
  - Vector of design parameters  $\alpha$  (size  $n_d$ ),  $X(\alpha)$   $S(\alpha)$   $C^1$  regular
- Assumption of implicit function theorem
  - $\forall (W_i, X_i) / R(W_i, X_i) = 0 \quad (\partial R / \partial W)(W_i, X_i) \neq 0$
  - Unique steady flow corresponding to a mesh



# Introduction

## Discrete gradient calculation methods

- Functions of interest
  - $\mathcal{J}_k(\alpha) = J_k(W(\alpha), X(\alpha))$   $k \in [1, n_f]$
  - Flowfield and volume mesh linked by flow equations  $R(W(\alpha), X(\alpha)) = 0$
- Sensitivities  $d\mathcal{J}_k/d\alpha_i$   $k \in [1, n_f]$   $i \in [1, n_d]$  to be computed
- Discrete gradient computation methods
  - Finite differences –  $2n_d$  flow computations (non linear problems, size  $n_a$ )
  - Direct differentiation method –  $n_d$  linear systems (size  $n_a$ )
  - Adjoint vector method –  $n_f$  linear systems (size  $n_a$ )

# Finite difference method

- Choose steps  $\delta\alpha_i$ . Get shifted meshes  $X(\alpha + \delta\alpha_i)$ ,  $X(\alpha - \delta\alpha_i)$
- Solve flows

$$R(W(\alpha + \delta\alpha_i), X(\alpha + \delta\alpha_i)) = 0 \quad R(W(\alpha - \delta\alpha_i), X(\alpha - \delta\alpha_i)) = 0$$

$$\frac{dW}{d\alpha_i (FD)} = \frac{W(\alpha + \delta\alpha_i) - W(\alpha - \delta\alpha_i)}{2\delta\alpha_i}$$

- Compute outputs sensitivities

$$\frac{d\mathcal{J}_k}{d\alpha_i (FD)} = \frac{J_k(W(\alpha + \delta\alpha_i), X(\alpha + \delta\alpha_i)) - J_k(W(\alpha - \delta\alpha_i), X(\alpha + \delta\alpha_i))}{2\delta\alpha_i}$$

- Two issues: definition of  $\delta\alpha_i$ , cost of shifted flow solves

# Direct differentiation method (1/2)

- Discrete equations for mechanics (set of  $n_a$  non-linear equations )

$$R(W(\alpha), X(\alpha)) = 0$$

- Differentiation with respect to  $\alpha_i$   $i \in [1, n_d]$ . Derivation of  $n_d$  linear system of size  $n_a$

$$\frac{\partial R}{\partial W} \frac{dW}{d\alpha_i} = - \left( \frac{\partial R}{\partial X} \frac{dX}{d\alpha_i} \right)$$

- Calculation of derivatives

$$\frac{d\mathcal{J}_k}{d\alpha_i} = \frac{\partial J_k}{\partial X} \frac{dX}{d\alpha_i} + \frac{\partial J_k}{\partial W} \frac{dW}{d\alpha_i}$$

# Direct differentiation method (2/2)

- Gradient vectors

$$\nabla_{\alpha} \mathcal{J}_k(\alpha) = \frac{\partial J_k}{\partial X} \frac{dX}{d\alpha} + \frac{\partial J_k}{\partial W} \frac{dW}{d\alpha}$$

- Check the flow sensitivities using finite differences

$$R(W(\alpha + \delta\alpha_i), X(\alpha + \delta\alpha_i)) = 0 \quad R(W(\alpha - \delta\alpha_i), X(\alpha - \delta\alpha_i)) = 0$$

$$\frac{dW}{d\alpha_i} \simeq \frac{W(\alpha + \delta\alpha_i) - W(\alpha - \delta\alpha_i)}{2\delta\alpha_i}$$

- Check the outputs sensitivities

$$\frac{d\mathcal{J}_k}{d\alpha_i} \simeq \frac{J_k(W(\alpha + \delta\alpha_i), X(\alpha + \delta\alpha_i)) - J_k(W(\alpha - \delta\alpha_i), X(\alpha + \delta\alpha_i))}{2\delta\alpha_i}$$

# Mathematical game (1/4)

- Mathematical game in  $\mathbb{R}^n$  to understand adjoint method
- given  $(f, b_i) \in \mathbb{R}^n$  ( $i \in \{1, n_d\}$ ), given  $A \in \mathcal{M}(\mathbb{R}^n)$

Calculate the values of  $x_i.f$        $A x_i = b_i \quad i \in \{1, n_d\}$

- Solution solving one linear system instead of  $n_d$  linear systems ???

# Mathematical game (2/4)

- Linear algebra reminder: the inverse of the transpose is the transpose of the inverse

$$M^T (M^{-1})^T = (M^{-1} M)^T = I^T = I$$

$$(M^{-1})^T M^T = (M M^{-1})^T = I^T = I$$

- The notation  $M^{-T}$  is suitable for  $(M^T)^{-1} / (M^{-1})^T$

# Mathematical game (3/4)

- Mathematical game in  $\mathbb{R}^n$  to understand adjoint method
- given  $(f, b_i) \in \mathbb{R}^n$  ( $i \in \{1, n_d\}$ ), given  $A \in \mathcal{M}(\mathbb{R}^n)$

Calculate the values of  $f.x_i$        $A x_i = b_i$      $i \in \{1, n_d\}$

- $f.x_i = f.(A^{-1}b_i) = ((A^{-1})^T f).b_i = (A^{-T} f).b_i$  efficient solution

Solve  $A^T \lambda = f$     Calculate  $\lambda.b_i$      $i \in \{1, n_d\}$

# Mathematical game (4/4)

- Mathematical game in  $\mathbb{R}^n$  to understand adjoint method
- given  $(f_j, b_i) \in \mathbb{R}^n$  ( $i \in \{1, n_d\}$   $j \in \{1, n_f\}$ ), given  $A \in \mathcal{M}(\mathbb{R}^n)$

Calculate the values of  $x_i.f_j$        $A x_i = b_i$      $i \in \{1, n_d\}$

- Solution solving  $n_d$  linear systems
- Solution solving  $n_f$  linear systems



# Discrete adjoint parameter method (1/5)

- Several ways of deriving the equations of discrete adjoint method. The following also helps understanding continuous adjoint
- Following equalities hold  $\forall \lambda_k \in \mathbb{R}^{n_a}$

$$\lambda_k^T \frac{\partial R}{\partial W} \frac{dW}{d\alpha_i} + \lambda_k^T \left( \frac{\partial R}{\partial X} \frac{dX}{d\alpha_i} \right) = 0$$

$$\frac{d\mathcal{J}_k(\alpha)}{d\alpha_i} = \frac{\partial J_k}{\partial X} \frac{dX}{d\alpha_i} + \frac{\partial J_k}{\partial W} \frac{dW}{d\alpha_i} + \lambda_k^T \frac{\partial R}{\partial W} \frac{dW}{d\alpha_i} + \lambda_k^T \left( \frac{\partial R}{\partial X} \frac{dX}{d\alpha_i} \right)$$

$$\frac{d\mathcal{J}_k(\alpha)}{d\alpha_i} = \left( \frac{\partial J_k}{\partial W} + \lambda_k^T \frac{\partial R}{\partial W} \right) \frac{dW}{d\alpha_i} + \frac{\partial J_k}{\partial X} \frac{dX}{d\alpha_i} + \lambda_k^T \left( \frac{\partial R}{\partial X} \frac{dX}{d\alpha_i} \right)$$

# Discrete adjoint parameter method (2/5)

- Vector  $\lambda_k$  defined in order to cancel the factor of the flow sensitivity  $\frac{dW}{d\alpha_i}$  ... the adjoint equation.  $\lambda_k$  actually appears to be linked to functions  $J_k$

$$\frac{\partial J_k}{\partial W} + \lambda_k^T \frac{\partial R}{\partial W} = 0$$

- Calculation of derivatives

$$\forall i \in [1, n_d] \quad \frac{dJ_k(\alpha)}{d\alpha_i} = \frac{\partial J_k}{\partial X} \frac{dX}{d\alpha_i} + \lambda_k^T \left( \frac{\partial R}{\partial X} \frac{dX}{d\alpha_i} \right)$$

$$\nabla_{\alpha} J_k(\alpha) = \frac{\partial J_k}{\partial X} \frac{dX}{d\alpha} + \lambda_k^T \left( \frac{\partial R}{\partial X} \frac{dX}{d\alpha} \right)$$

- Method with  $n_f$  and not  $n_d$  linear systems to solve

# Discrete adjoint parameter method (3/5)

- Other ways to derive the discrete adjoint equation
  - Introduce a Lagrangian
  - Manipulate direct differentiation gradient expression (like in the mathematical game)
- From direct method gradient expression

$$\nabla_{\alpha} \mathcal{J}_k(\alpha) = \frac{\partial J_k}{\partial X} \frac{dX}{d\alpha} + \frac{\partial J_k}{\partial W} \frac{dW}{d\alpha}$$

$$\nabla_{\alpha} \mathcal{J}_k(\alpha) = \frac{\partial J_k}{\partial X} \frac{dX}{d\alpha} - \frac{\partial J_k}{\partial W} \left( \frac{dR}{dW} \right)^{-1} \frac{dR}{dX} \frac{dX}{d\alpha}$$

$$\nabla_{\alpha} \mathcal{J}_k(\alpha) = \frac{\partial J_k}{\partial X} \frac{dX}{d\alpha} - \left( \frac{\partial J_k}{\partial W} \left( \frac{dR}{dW} \right)^{-1} \right) \frac{dR}{dX} \frac{dX}{d\alpha}$$

- Define  $\lambda_k$  column vector

# Discrete adjoint parameter method (4/5)

- From direct method gradient expression

$$\nabla_{\alpha} \mathcal{J}_k(\alpha) = \frac{\partial J_k}{\partial X} \frac{dX}{d\alpha} - \left( \frac{\partial J_k}{\partial W} \left( \frac{dR}{dW} \right)^{-1} \right) \frac{dR}{dX} \frac{dX}{d\alpha}$$

- Define  $\lambda_k$

$$\lambda_k^T = -\frac{\partial J_k}{\partial W} \left( \frac{dR}{dW} \right)^{-1} \quad \text{or} \quad \lambda_k^T \left( \frac{dR}{dW} \right) = -\frac{\partial J_k}{\partial W} \quad \text{or} \quad \left( \frac{dR}{dW} \right)^T \lambda_k = -\frac{\partial J_k}{\partial W}^T$$

- Expresion of sensitivity

$$\nabla_{\alpha} \mathcal{J}_k(\alpha) = \frac{\partial J_k}{\partial X} \frac{dX}{d\alpha} + \lambda_k^T \frac{dR}{dX} \frac{dX}{d\alpha}$$

# Iterative solution of direct and adjoint equation (1/3)

- CFD teams tend to mimic the solution of steady state flow although flow equations are non-linear whereas direct/adjoint equation are linear
- Storing the jacobian of the scheme and sending to direct solver has been done but is rare and is not tractable for large cases
- Iterative resolution is much more common. Newton/relaxation algorithm

$$\left(\frac{\partial R}{\partial W}\right)^{(APP) T} \left(\lambda_k^{(l+1)} - \lambda_k^{(l)}\right) = - \left( \left(\frac{\partial R}{\partial W}\right)^T \lambda_k^{(l)} + \left(\frac{\partial J_k}{\partial W}\right)^T \right)$$

# Iterative solution of direct and adjoint equation (2/3)

- Common Newton/relaxation algorithm for adjoint

$$\left( \frac{\partial R}{\partial W} \right)^{(APP) T} \left( \lambda_k^{(l+1)} - \lambda_k^{(l)} \right) = - \left( \left( \frac{\partial R}{\partial W} \right)^T \lambda_k^{(l)} + \frac{\partial J_k}{\partial W} \right)^T$$

- Common Newton/relaxation algorithm for direct

$$\left( \frac{\partial R}{\partial W} \right)^{(APP)} \left( \left( \frac{dW}{d\alpha_i} \right)^{(l+1)} - \left( \frac{dW}{d\alpha_i} \right)^{(l)} \right) = - \left( \left( \frac{\partial R}{\partial W} \right) \frac{dW}{d\alpha_i} + \frac{\partial R}{\partial X} \frac{dX}{d\alpha_i} \right)$$

- Defining an approximate Jacobians  $\left( \frac{\partial R}{\partial W} \right)^{(APP)}$  is an old subject in compressible CFD (definition of implicit stages for backward-Euler schemes...)
  - upwind approximate linearization of convective flux
  - neglecting cross derivatives in linearization of viscous fluxes...
- Possibly adapting implicit stages and multigrid algorithm (flow solver to adjoint solver)

# Iterative solution of direct and adjoint equation (3/3)

- Common Newton/relaxation algorithm for adjoint

$$\left(\frac{\partial R}{\partial W}\right)^{(APP)T} \left(\lambda_k^{(l+1)} - \lambda_k^{(l)}\right) = - \left(\left(\frac{\partial R}{\partial W}\right)^T \lambda_k^{(l)} + \frac{\partial J_k}{\partial W}\right)^T$$

- Accuracy of adjoint vector only depends on  $\left(\frac{\partial R}{\partial W}\right)$ . Only minor simplifications are allowed at this stage to preserve an acceptable accuracy
- Convergence towards solution of the linear system depends on  $\left(\frac{\partial R}{\partial W}\right)$ ,  $\left(\frac{\partial R}{\partial W}\right)^{(APP)}$ , multigrid (if active), other operations like smoothing (if active)

# Discrete adjoint parameter method (5/5)

- Checking adjoint method... much more difficult than checking direct differentiation method. If

$$\frac{d\mathcal{J}_k}{d\alpha_i} \approx \frac{J_k(W(\alpha + \delta\alpha_i), X(\alpha + \delta\alpha_i)) - J_k(W(\alpha - \delta\alpha_i), X(\alpha - \delta\alpha_i))}{2\delta\alpha_i}$$

no easy checking procedure

- In the iterative resolution method, the gradient accuracy depends on the  $(\frac{\partial R}{\partial W})^T \lambda_k^{(l)}$  operation
- If direct mode is coded, duality checks between direct and adjoint code are useful.  $(U, V)$  two column vectors of  $\mathbb{R}^{n_a}$

$$U^T \left( \frac{\partial R}{\partial W} \right) V = \left( U^T \left( \frac{\partial R}{\partial W} \right) \right)_{adj-code} \cdot V = U^T \cdot \left( \left( \frac{\partial R}{\partial W} \right) V \right)_{lin-code}$$

- Valid for individual fluxes routine. Valid for part of the interfaces (border, joins...)



# Discrete adjoint mesh method (1/3)

- Vector  $\lambda_k$  defined by

$$\frac{\partial J_k}{\partial W} + \lambda_k^T \frac{\partial R}{\partial W} = 0$$

- Calculation of derivatives

$$\forall i \in [1, n_f] \quad \frac{d\mathcal{J}_k(\alpha)}{d\alpha_i} = \frac{\partial J_k}{\partial X} \frac{dX}{d\alpha_i} + \lambda_k^T \left( \frac{\partial R}{\partial X} \frac{dX}{d\alpha_i} \right)$$

$$\forall i \in [1, n_f] \quad \frac{d\mathcal{J}_k(\alpha)}{d\alpha_i} = \left( \frac{\partial J_k}{\partial X} + \lambda_k^T \frac{\partial R}{\partial X} \right) \frac{dX}{d\alpha_i}$$

- Obvious mathematical factorization. Huge practical importance.

# Discrete adjoint mesh method (2/3)

- Solve for adjoint vectors
- CFD gradient computation code computes “only”

$$\frac{dJ_k}{dX} = \frac{\partial J_k}{\partial X} + \lambda_k^T \frac{\partial R}{\partial X}$$

The functional outputs sensitivities  $d\mathcal{J}_k(\alpha)/d\alpha_i$  are calculated later by a mesh/geometrical tool

- Pros : CFD has no knowledge of parametrization. Huge memory savings [Nielsen, Park 2005] Try several parametrization. Check  $(dJ_k/dS)$  with engineers
- Cons : Matrix  $(\partial R/\partial X)$  has to be explicitly computed (instead of  $\frac{\partial R}{\partial X} \frac{dX}{d\alpha_i}$  computable by finite differences) Hard work...

# Discrete adjoint mesh method (3/3)

- Solve for adjoint vectors. Compute “only”

$$\frac{dJ_k}{dX} = \frac{\partial J_k}{\partial X} + \lambda_k^T \frac{\partial R}{\partial X}$$

- Cons : Matrix  $(\partial R / \partial X)$  has to be explicitly computed (instead of  $\frac{\partial R}{\partial X} \frac{dX}{d\alpha_i}$  computable by finite differences) Hard work...
- How to calculate  $(dJ_k / dS)$  ?
  - Explicit link between  $X$  and  $S$

$$\frac{dJ_k}{d\alpha_i} = \left[ \frac{dJ_k}{dX} \frac{dX}{dS} \right] \frac{dS}{d\alpha_i}$$

- Implicit link between  $X$  and  $S$  [Nielsen, Park 2005]

# Outline

- 1 Introduction
- 2 Discrete adjoint method
- 3 Continuous adjoint method**
- 4 Discrete vs Continuous adjoint
- 5 Conclusions

# Bibliography

- Mathematical references [Pironneau 73,74]
- Mathematical aeronautical reference [Jameson 88]
- Simplest introduction [Giles, Pierce 99]  
*An introduction to the adjoint approach to design* ERCOFTAC Workshop on Adjoint Methods, Toulouse 1999.

# Continuous Adjoint for toy problems (1/6)

- From [Giles, Pierce 99] section (3.2)
- Toy problems without design parameters

- Solve

$$\frac{du}{dx} - \epsilon \frac{d^2 u}{dx^2} = f \text{ on } [0, 1] \quad u(0) = u(1) = 0$$

before calculating

$$J = (u, g) = \int_0^1 u g \, dx$$

- Adjoint problem ? Define (if it exists)

$$L^* \lambda = g \text{ on } [0, 1] \text{ plus boundary conditions}$$

such that

$$J = (\lambda, f) = \int_0^1 \lambda f \, dx$$

# Continuous Adjoint for toy problems (2/6)

- Direct: solve

$$\frac{du}{dx} - \epsilon \frac{d^2 u}{dx^2} = f \text{ on } [0, 1] \quad u(0) = u(1) = 0$$

before calculating

$$J = (u, g) = \int_0^1 u g dx$$

- Adjoint problem (if it exists):

$$L^* \lambda = g \text{ on } [0, 1]$$

plus boundary conditions such that

$$J = (\lambda, f) = \int_0^1 \lambda f dx$$

- Defining equation  $L^*$

# Continuous Adjoint for toy problems (3/6)

- Defining equation  $L^*$

$$(\lambda, f) = \int_0^1 \lambda f dx = \int_0^1 \lambda \left( \frac{du}{dx} - \epsilon \frac{d^2 u}{dx^2} \right) dx$$

$$(\lambda, f) = - \int_0^1 \frac{d\lambda}{dx} u dx + [\lambda u]_0^1 + \epsilon \int_0^1 \frac{d\lambda}{dx} \frac{du}{dx} dx - \epsilon \left[ \lambda \frac{du}{dx} \right]_0^1$$

$$(\lambda, f) = - \int_0^1 \frac{d\lambda}{dx} u dx + [\lambda u]_0^1 - \epsilon \int_0^1 \frac{d^2 \lambda}{dx^2} du dx - \epsilon \left[ \lambda \frac{du}{dx} \right]_0^1 - \epsilon \left[ \frac{d\lambda}{dx} u \right]_0^1$$

- Finally

$$(\lambda, f) = \int_0^1 \left( \frac{d\lambda}{dx} - \epsilon \frac{d^2 \lambda}{dx^2} \right) u dx + [\lambda u]_0^1 + \epsilon \left[ \frac{d\lambda}{dx} u \right]_0^1 - \epsilon \left[ \lambda \frac{du}{dx} \right]_0^1$$

- Suitable adjoint equation. Solving

$$-\frac{d\lambda}{dx} - \epsilon \frac{d^2 \lambda}{dx^2} = g \text{ on } [0, 1] \quad \lambda(0) = \lambda(1) = 0$$

ensures  $(\lambda, f) = (u, g)$



# Continuous Adjoint for toy problems (4/6)

- In order to calculate  $J = (u, g) = \int_{\Omega} u g \, d\Omega$ , solve for  $u$

$$\operatorname{div}(k \operatorname{grad}(u)) = f \quad \text{on } \Omega \quad u = 0 \quad \text{on } \partial\Omega$$

- In order to calculate  $J$  as  $(\lambda, f) = \int_{\Omega} \lambda f \, d\Omega$ , solve for  $\lambda$

$$\operatorname{div}(k \operatorname{grad}(\lambda)) = g \quad \text{on } \Omega \quad \lambda = 0 \quad \text{on } \partial\Omega$$

- Definition of adjoint operator comes from

$$(\lambda, f) = \int_{\Omega} u \operatorname{div}(k \operatorname{grad}(\lambda)) d\Omega - \int_{\partial\Omega} k u (\operatorname{grad}(\lambda) \cdot n) dS + \int_{\partial\Omega} k \lambda (\operatorname{grad}(u) \cdot n) dS$$

# Continuous Adjoint for toy problems (5/6)

- Direct: solve

$$\frac{\partial u}{\partial t} - \frac{\partial^2 u}{\partial x^2} = f \text{ on } [0, L] \times [0, T] \quad u(0, \cdot) = u(L, \cdot) = 0 \quad u(\cdot, 0) = 0$$

before calculating

$$J = (u, g) = \int_0^L \int_0^T u g \, dx dt$$

- Adjoint: solve

$$-\frac{\partial \lambda}{\partial t} - \frac{\partial^2 \lambda}{\partial x^2} = g \text{ on } [0, L] \times [0, T] \quad \lambda(0, \cdot) = \lambda(L, \cdot) = 0 \quad \lambda(\cdot, T) = 0$$

before calculating  $J$  as

$$(\lambda, f) = \int_0^L \int_0^T \lambda f \, dx dt$$

# Continuous Adjoint for toy problems (6/6)

- Time derivative  $\frac{\partial u}{\partial t}$  gets  $-\frac{\partial \lambda}{\partial t}$   
Backward time integration for unsteady adjoint
- Convection term  $\frac{\partial u}{\partial x}$  gets  $-\frac{\partial \lambda}{\partial x}$   
“Backward propagation” in adjoint steady state solutions
- Diffusion term  $\frac{\partial^2 u}{\partial x^2}$  gets  $\frac{\partial^2 \lambda}{\partial x^2}$

# Continuous Adjoint for 2D Euler equations (1/11)

- 2D Euler equations

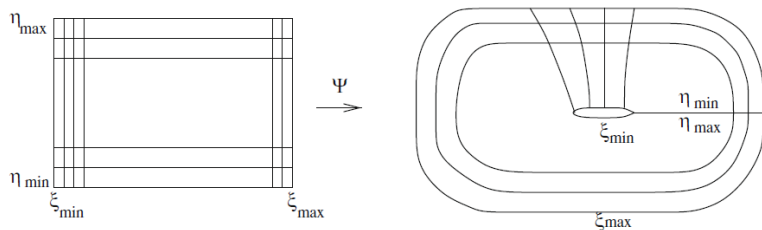
$$\frac{\partial w}{\partial t} + \frac{\partial f(w)}{\partial x} + \frac{\partial g(w)}{\partial y} = 0$$

avec

$$w = \begin{pmatrix} \rho \\ \rho u \\ \rho v \\ \rho E \end{pmatrix} \quad f(w) = \begin{pmatrix} \rho u \\ \rho u^2 + p \\ \rho uv \\ \rho Hu \end{pmatrix} \quad g(w) = \begin{pmatrix} \rho v \\ \rho uv \\ \rho v^2 + p \\ \rho Hv \end{pmatrix}$$

$$p = (\gamma - 1)\rho\left(E - \frac{u^2 + v^2}{2}\right), \quad \rho H = \rho E + p$$

# Continuous Adjoint for 2D Euler equations (2/11)



**Figure:** Coordinate transformation for airfoil-fitted structured mesh

- Coordinate transformation  $\Gamma$ ,  $C^1$  diffeomorphism  $D_{\xi\eta} = [\xi_{min}, \xi_{max}] \times [\eta_{min}, \eta_{max}]$  en  $D_w$ .

$$\Gamma \left\{ \begin{array}{l} D_{\xi\eta} \\ (\xi, \eta) \end{array} \right\} \rightarrow \begin{array}{l} D_{xy} \\ (x, y) \end{array}$$

# Continuous Adjoint for 2D Euler equations (3/11)

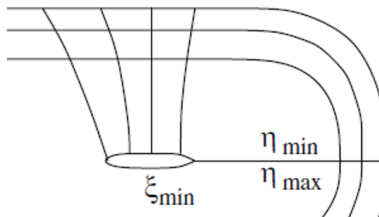


Figure: Normal surface vectors

# Continuous Adjoint for 2D Euler equations (4/11)

- 2D Euler equations generalized coordinates

$$K = \left( \frac{\partial x}{\partial \xi} \frac{\partial y}{\partial \eta} - \frac{\partial y}{\partial \xi} \frac{\partial x}{\partial \eta} \right)$$

$$\begin{pmatrix} U \\ V \end{pmatrix} = \frac{1}{K} \begin{pmatrix} \frac{\partial y}{\partial \eta} & -\frac{\partial x}{\partial \eta} \\ -\frac{\partial y}{\partial \xi} & \frac{\partial x}{\partial \xi} \end{pmatrix} \begin{pmatrix} u \\ v \end{pmatrix}$$

$$W = K \begin{pmatrix} \rho \\ \rho u \\ \rho v \\ \rho E \end{pmatrix} \quad F(W) = K \begin{pmatrix} \rho U \\ \rho U u + p \frac{\partial \xi}{\partial x} \\ \rho U v + p \frac{\partial \xi}{\partial y} \\ \rho U H \end{pmatrix} \quad G(W) = K \begin{pmatrix} \rho V \\ \rho V u + p \frac{\partial \eta}{\partial x} \\ \rho V v + p \frac{\partial \eta}{\partial y} \\ \rho V H \end{pmatrix}$$

$$\frac{\partial W}{\partial t} + \frac{\partial F(W)}{\partial \xi} + \frac{\partial G(W)}{\partial \eta} = 0$$

# Continuous Adjoint for 2D Euler equations (5/11)

- Steady state equation can also be rewritten as

$$\frac{\partial}{\partial \xi} \left( f \frac{\partial y}{\partial \eta} - g \frac{\partial x}{\partial \eta} \right) + \frac{\partial}{\partial \eta} \left( -f \frac{\partial y}{\partial \xi} + g \frac{\partial x}{\partial \xi} \right) = 0 \quad \text{sur} \quad D_{\xi\eta}$$

- Jacobians per mesh directions :

$$a(w) = \frac{df(w)}{dw} \quad b(w) = \frac{dg(w)}{dw}$$

$$a_1(w, \xi, \eta) = \left( a(w) \frac{\partial y}{\partial \eta} - b(w) \frac{\partial x}{\partial \eta} \right) \quad a_2(w, \xi, \eta) = \left( -a(w) \frac{\partial y}{\partial \xi} + b(w) \frac{\partial x}{\partial \xi} \right)$$



# Continuous Adjoint for 2D Euler equations (6/11)

- Coordinate transformation now depending on a design parameter  $\alpha$  (for the sake of simplicity scalar)

$$\Gamma \begin{cases} D_{\xi\eta} D_{\alpha} & \rightarrow D_w \\ (\xi, \eta)(\alpha) & \rightarrow (x(\xi, \eta, \alpha), y(\xi, \eta, \alpha)) \end{cases} \quad (1)$$

- $D_w$  changes with  $\alpha$  but not  $D_{\xi\eta}$
- Equation for  $dW/d\alpha_i$  ?

# Continuous Adjoint for 2D Euler equations (7/11)

- Variations induced by  $d_\alpha$  change

$$\begin{cases} f(w) & \rightarrow & f(w) + \frac{df}{dw} \frac{dw}{d\alpha_i} d_{\alpha_i} \\ \frac{\partial x}{\partial \eta} & \rightarrow & \frac{\partial x}{\partial \eta} + \frac{\partial^2 x}{\partial \eta \partial \alpha_i} d_{\alpha_i} \end{cases}$$

- Fluid dynamics equations on the fixed domain  $D_{\xi\eta}$

$$\forall \quad \alpha \in D_\alpha \quad \frac{\partial}{\partial \xi} \left( f \frac{\partial y}{\partial \eta} - g \frac{\partial x}{\partial \eta} \right) + \frac{\partial}{\partial \eta} \left( -f \frac{\partial y}{\partial \xi} + g \frac{\partial x}{\partial \xi} \right) = 0 \quad \text{on} \quad D_{\xi\eta}$$

- Differentiate w.r.t.  $\alpha$

# Continuous Adjoint for 2D Euler equations (8/11)

- Continuous direct differentiation equation

$$\frac{\partial}{\partial \xi} \left( a_1(w, \xi, \eta) \frac{dw}{d\alpha} \right) + \frac{\partial}{\partial \eta} \left( a_2(w, \xi, \eta) \frac{dw}{d\alpha} \right) + \frac{\partial}{\partial \xi} \left( f(w) \frac{\partial^2 y}{\partial \eta \partial \alpha} - g(w) \frac{\partial^2 x}{\partial \eta \partial \alpha} \right) + \frac{\partial}{\partial \eta} \left( -f(w) \frac{\partial^2 y}{\partial \xi \partial \alpha} + g(w) \frac{\partial^2 x}{\partial \xi \partial \alpha} \right) = 0$$

- Objective function (fixed domain  $D_{\xi\eta}$ )

$$\mathcal{J}(\alpha) = \int_{\xi_{min}} J_1(w) d\eta + \int_{D_{\xi\eta}} J_2(w) d\xi d\eta$$

- derivative of the objective function (fixed domain  $D_{\xi\eta}$ )

$$\frac{d\mathcal{J}(\alpha)}{d\alpha} = \int_{\xi_{min}} \frac{dJ_1(w)}{dw} \frac{dw}{d\alpha} d\eta + \int_{D_{\xi\eta}} \frac{dJ_2(w)}{dw} \frac{dw}{d\alpha} d\xi d\eta$$

# Continuous Adjoint for 2D Euler equations (9/11)

- continuous direct differentiation equation is multiplied by  $\psi$ ,  $C^1$ , periodic in  $\eta_{min}, \eta_{max}$

$$\forall \psi \in C^1(D_{\xi\eta})^4 \quad \int_{D_{\xi\eta}} \psi^T \left( \frac{\partial}{\partial \xi} \left( a_1(w, \xi, \eta) \frac{dw}{d\alpha} \right) + \frac{\partial}{\partial \eta} \left( a_2(w, \xi, \eta) \frac{dw}{d\alpha} \right) \right) d\xi d\eta +$$

$$\int_{D_{\xi\eta}} \psi^T \left( \frac{\partial}{\partial \xi} \left( f(w) \frac{\partial^2 y}{\partial \eta \partial \alpha} - g(w) \frac{\partial^2 x}{\partial \eta \partial \alpha} \right) + \frac{\partial}{\partial \eta} \left( -f(w) \frac{\partial^2 y}{\partial \xi \partial \alpha} + g(w) \frac{\partial^2 x}{\partial \xi \partial \alpha} \right) \right) d\xi d\eta = 0$$

- Integration by parts

$$\begin{aligned} & - \int_{D_{\xi\eta}} \frac{\partial \psi^T}{\partial \xi} a_1(w, \xi, \eta) \frac{dw}{d\alpha} d\xi d\eta - \int_{D_{\xi\eta}} \frac{\partial \psi^T}{\partial \eta} a_2(w, \xi, \eta) \frac{dw}{d\alpha} d\xi d\eta + \\ & - \int_{D_{\xi\eta}} \frac{\partial \psi^T}{\partial \xi} \left( f(w) \frac{\partial^2 y}{\partial \eta \partial \alpha} - g(w) \frac{\partial^2 x}{\partial \eta \partial \alpha} \right) d\xi d\eta \\ & - \int_{D_{\xi\eta}} \frac{\partial \psi^T}{\partial \eta} \left( -f(w) \frac{\partial^2 y}{\partial \xi \partial \alpha} + g(w) \frac{\partial^2 x}{\partial \xi \partial \alpha} \right) d\xi d\eta \\ & + \int_{\xi_{min}} \psi^T a_1(w, \xi, \eta) \frac{dw}{d\alpha} d\eta + \int_{\xi_{min}} \psi^T \left( f(w) \frac{\partial^2 y}{\partial \eta \partial \alpha} - g(w) \frac{\partial^2 x}{\partial \eta \partial \alpha} \right) d\eta = 0. \end{aligned}$$

# Continuous Adjoint for 2D Euler equations (10/11)

- Gradient of objective function for all  $\psi$  function of  $C_{\eta}^1(D_{\xi\eta})^4$

$$\begin{aligned}
 \frac{d\mathcal{J}(\alpha)}{d\alpha} = & \int_{\xi_{\min}} \frac{dJ_1(w)}{dw} \frac{dw}{d\alpha} d\eta + \int_{D_{\xi\eta}} \frac{dJ_2(w)}{dw} \frac{dw}{d\alpha} d\xi d\eta \\
 & - \int_{D_{\xi\eta}} \frac{\partial \psi^T}{\partial \xi} a_1(w, \xi, \eta) \frac{dw}{d\alpha} d\xi d\eta - \int_{D_{\xi\eta}} \frac{\partial \psi^T}{\partial \eta} a_2(w, \xi, \eta) \frac{dw}{d\alpha} d\xi d\eta + \\
 & - \int_{D_{\xi\eta}} \frac{\partial \psi^T}{\partial \xi} \left( f(w) \frac{\partial^2 y}{\partial \eta \partial \alpha} - g(w) \frac{\partial^2 x}{\partial \eta \partial \alpha} \right) d\xi d\eta \\
 & - \int_{D_{\xi\eta}} \frac{\partial \psi^T}{\partial \eta} \left( -f(w) \frac{\partial^2 y}{\partial \xi \partial \alpha} + g(w) \frac{\partial^2 x}{\partial \xi \partial \alpha} \right) d\xi d\eta \\
 & + \int_{\xi_{\min}} \psi^T a_1(w, \xi, \eta) \frac{dw}{d\alpha} d\eta + \int_{\xi_{\min}} \psi^T \left( f(w) \frac{\partial^2 y}{\partial \eta \partial \alpha} - g(w) \frac{\partial^2 x}{\partial \eta \partial \alpha} \right) d\eta
 \end{aligned}$$

- $\psi$  chosen so as to cancel all flow sensitivity terms

$$\begin{cases} \frac{dJ_2(w)}{dw} - \frac{\partial \psi^T}{\partial \xi} a_1(w, \xi, \eta) - \frac{\partial \psi^T}{\partial \eta} a_2(w, \xi, \eta) = 0 & \text{over } D_{\xi, \eta} \\ \psi^T a_1(w, \xi, \eta) + \frac{dJ_1(w)}{dw} = 0 & \text{on } \xi_{\min} \end{cases}$$

# Continuous Adjoint for 2D Euler equations (11/11)

- Final form of objective gradient ( $\psi$  being the solution of continuous adjoint equation)

$$\begin{aligned} \frac{d\mathcal{J}(\alpha)}{d\alpha_i} &= \int_{\xi_{min}} \psi^T \left( f(w) \frac{\partial^2 y}{\partial \eta \partial \alpha_i} - g(w) \frac{\partial^2 x}{\partial \eta \partial \alpha_i} \right) d\eta \\ &- \int_{D_{\xi\eta}} \frac{\partial \psi^T}{\partial \xi} \left( f(w) \frac{\partial^2 y}{\partial \eta \partial \alpha_i} - g(w) \frac{\partial^2 x}{\partial \eta \partial \alpha_i} \right) d\xi d\eta \\ &- \int_{D_{\xi\eta}} \frac{\partial \psi^T}{\partial \eta} \left( -f(w) \frac{\partial^2 y}{\partial \xi \partial \alpha_i} + g(w) \frac{\partial^2 x}{\partial \xi \partial \alpha_i} \right) d\xi d\eta \end{aligned} \quad (2)$$

- Just as for discrete adjoint, one adjoint field for one function of interest and design parameters
- Partial differential equation which derivation exceeds level of maths ordinarily used by engineers
- Equation to be discretized to get numerical values

# Some intuitions about adjoint vector ? (1/7)

- Could I get some intuition about adjoint vector ?

Try again with continuous adjoint !

- Rewrite flow equation locally, neglecting metric derivatives terms

$$\frac{\partial}{\partial \xi} \left( f \frac{\partial y}{\partial \eta} - g \frac{\partial x}{\partial \eta} \right) + \frac{\partial}{\partial \eta} \left( -f \frac{\partial y}{\partial \xi} + g \frac{\partial x}{\partial \xi} \right) = 0 \quad \text{sur} \quad D_{\xi\eta}$$

$$a(w) = \frac{df(w)}{dw} \quad b(w) = \frac{dg(w)}{dw}$$

$$a_1(w, \xi, \eta) = \left( a(w) \frac{\partial y}{\partial \eta} - b(w) \frac{\partial x}{\partial \eta} \right) \quad a_2(w, \xi, \eta) = \left( -a(w) \frac{\partial y}{\partial \xi} + b(w) \frac{\partial x}{\partial \xi} \right)$$

# Some intuitions about adjoint vector ? (1/7)

- Could I get some intuition about adjoint vector ?

**Try again with continuous adjoint !**

- Rewrite flow equation locally, neglecting metric derivatives terms

$$\frac{\partial}{\partial \xi} \left( f \frac{\partial y}{\partial \eta} - g \frac{\partial x}{\partial \eta} \right) + \frac{\partial}{\partial \eta} \left( -f \frac{\partial y}{\partial \xi} + g \frac{\partial x}{\partial \xi} \right) = 0 \quad \text{sur} \quad D_{\xi\eta}$$

$$a(w) = \frac{df(w)}{dw} \quad b(w) = \frac{dg(w)}{dw}$$

$$a_1(w, \xi, \eta) = \left( a(w) \frac{\partial y}{\partial \eta} - b(w) \frac{\partial x}{\partial \eta} \right) \quad a_2(w, \xi, \eta) = \left( -a(w) \frac{\partial y}{\partial \xi} + b(w) \frac{\partial x}{\partial \xi} \right)$$



# Some intuitions about adjoint vector ? (2/7)

- Could I get some intuition about adjoint vector ?  
Trying again based on continuous adjoint
- Rewrite flow equation locally, neglecting metric derivatives terms

$$a_1(w, \xi, \eta) \frac{\partial w}{\partial \xi} + a_2(w, \xi, \eta) \frac{\partial w}{\partial \eta} = 0$$

- Reminder adjoint equation

$$\frac{dJ_2(w)}{dw} - \frac{\partial \psi^T}{\partial \xi} a_1(w, \xi, \eta) - \frac{\partial \psi^T}{\partial \eta} a_2(w, \xi, \eta) = 0$$

- Change of sign, transposed jacobians, source term.
- Hyperbolic system. Same conditions for existence of simple wave solutions  $\psi(\xi, \eta) = \Psi(a\xi + b\eta)V$ , propagation par convection. Number of solutions for subsonic/supersonic flow...

# Some intuitions about adjoint vector ? (3/7)

- Supersonic inviscid flow  $M_\infty = 1.5$   $AoA = 1^\circ$

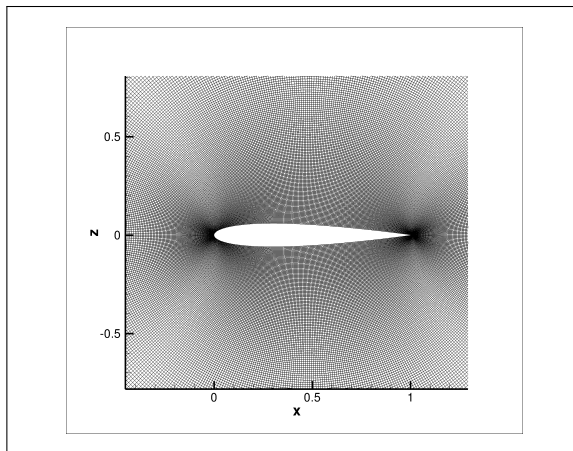


Figure:  $513 \times 513$  mesh

# Some intuitions about adjoint vector ? (5/7)

- Supersonic inviscid flow  $M_\infty = 1.5$   $AoA = 1^\circ$

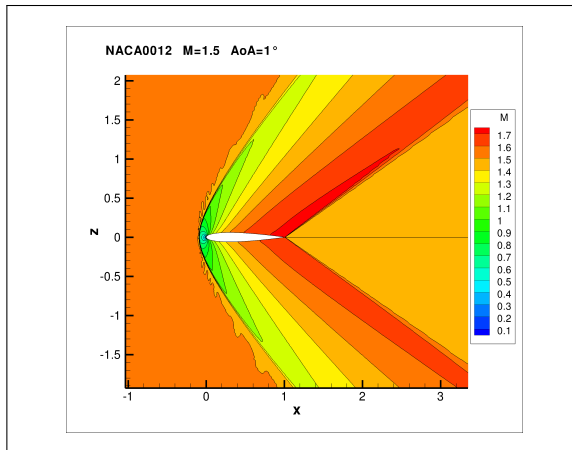


Figure: iso-lines of Mach number

# Some intuitions about adjoint vector ? (6/7)

- Supersonic inviscid flow  $M_\infty = 1.5$   $AoA = 1^\circ$

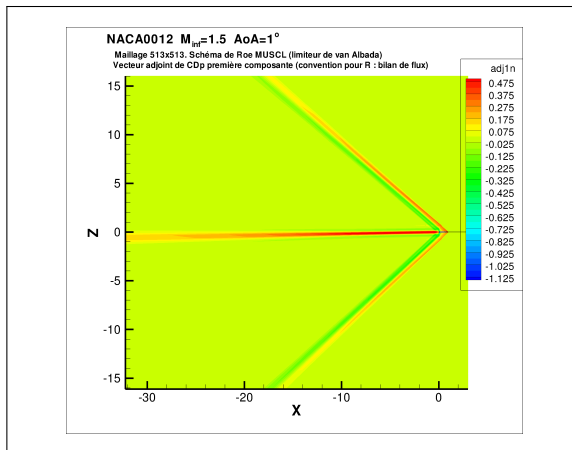


Figure: First component of adjoint vector for  $CDp$

# Some intuitions about adjoint vector ? (6/7)

- Supersonic inviscid flow  $M_\infty = 1.5$   $AoA = 1^\circ$

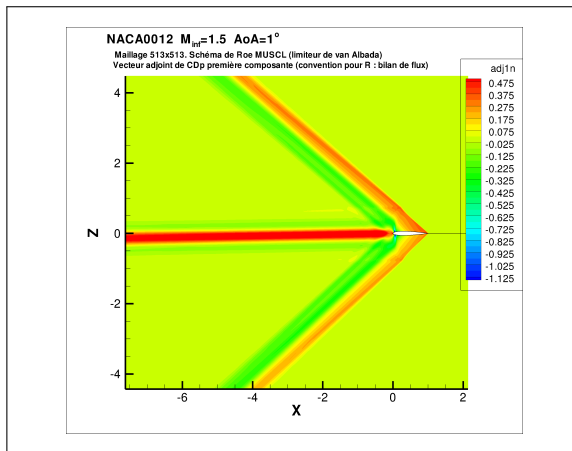


Figure: First component of adjoint vector for  $CD_p$  (close view)

# Some intuitions about adjoint vector ? (7/7)

- Supersonic inviscid flow  $M_\infty = 1.5$   $AoA = 1^\circ$

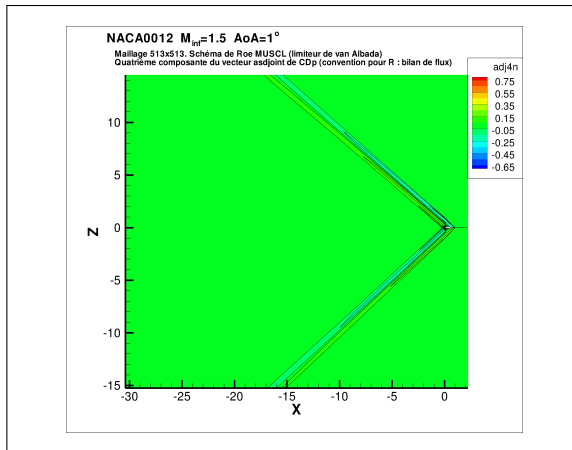


Figure: Fourth component of adjoint vector for  $CDp$

# Some intuitions about adjoint vector ? (7/7)

- Supersonic inviscid flow  $M_\infty = 1.5$   $AoA = 1^\circ$

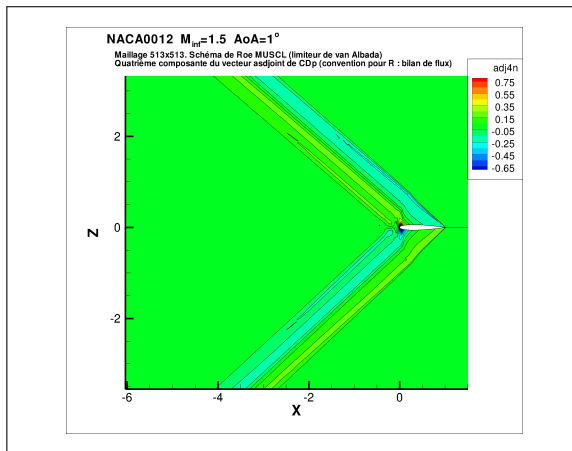


Figure: Fourth component of adjoint vector for  $CD_p$  (close view)

# Outline

- 1 Introduction
- 2 Discrete adjoint method
- 3 Continuous adjoint method
- 4 Discrete vs Continuous adjoint**
- 5 Conclusions



# Discrete adjoint

- Assets

- calculates what you want = sensitivity of your code
- can deal with all types of functions
- code can be partly built by AD (automatic differentiation)
- higher order derivatives simple (not too complex) in a discrete framework

- Drawbacks

- no understanding of underlying physics (Euler flows...)
- numerical consistency with a set of pde ? Dissipative scheme for this set of pde ?

# Discrete adjoint

- Assets

- get physical understanding of underlying equations (with all following restrictions)
- codes a dissipative discretization of underlying equation
- the code is shorter and simpler than the one of discrete adjoint

- Drawbacks

- does not calculate the sensitivity of your direct (steady state) code
- no reason that continuous adjoint equations would exist for all types of initial pde
- can not deal with far-field functions

# Coexistence of continuous and discrete adjoint

- Coexistence comes from the fact that their assets are balanced
- Continuous more suitable for theoretical mechanics
- Probably discrete more suitable for practical applications

# Outline

- 1 Introduction
- 2 Discrete adjoint method
- 3 Continuous adjoint method
- 4 Discrete vs Continuous adjoint
- 5 Conclusions**

# Conclusion

- More material can be found in *Numerical sensitivity analysis for aerodynamic optimization: A survey of approaches. Computers and Fluids 39* J.P. & RP Dwight 2010
  - Second order derivatives, frozen turbulence and other approximations, discretization of the continuous adjoint equation...
- Twenty-six years after [Jameson 88] famous article...
  - All large CFD code in aeronautics have an adjoint module
  - Some robustness issues to be solved
  - Compatibility with some complex options of direct code possibly missing
  - Integration in automated local shape optimization requires adjoint enhanced robustness and CAD/parametrization issue to be solved
  - Numerous successful adjoint-based local optimizations and goal-oriented adaptations