

CHT problems and computing coupled discrete adjoints using AD

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September 17, 2018

1 Introductory example

2 Computing accurate (discrete) adjoints in SU2

3 Coupled problems and validations

Problem characteristics:

- ▶ multiple physical zones that exchange heat at some interfaces
- ▶ different governing equation systems, conductivities, timesteps, ...

Why to start developments in SU2?

- ▶ approach from a Bosch research department working on pin-fin cooler optimizations
- ▶ joint project with them since 2017

Can SU2 give accurate sensitivities?

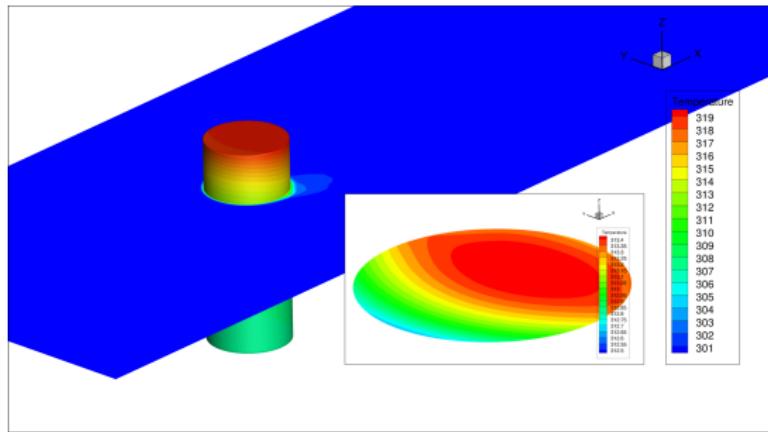


Required ...

- ▶ A heat solver (cf. `CHeatSolverFVM`) that can be run in solid zones and coupled to `CIIncNSSolver`
- ▶ Transfer routines to communicate energies (cf. `CTransfer_ConjugateHeatVars-class`)
- ▶ A new driver to iterate the solvers with this kind of coupling (ended up in a much more general approach to handle arbitrary ones, cf. `CMultiphysicsZonalDriver`)

3D test case

Heated aluminium cylinder in (coolant) water flow (at $0,25 \frac{m}{s}$, 300K at inlet, 4W heat load at pin's top).

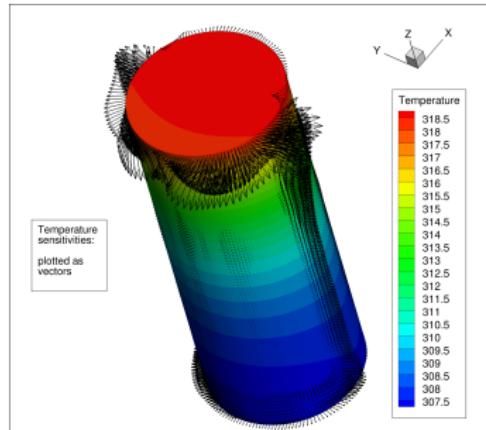


Pin's height/diameter: 5mm/2mm. **Reaches 319K** in average at its top in good agreement to FLUENT.

Optimization with shape gradients

Define

- ▶ X be the vector of mesh node *coordinates* determining the pin's surface
- ▶ an objective function $J(X)$, e.g. the average temperature at a pin's tip



$\nabla J(X^*)$ suggests the geometry update for minimization of J . It should be passed

- ▶ to an appropriate shape update function (FFD, filtering, ...)
- ▶ and an optimizer.

How to obtain such sensitivities?

$J(X)$ depends – more precisely – on a state vector U holding pressure, momentum and temperature solutions at each node,

$$J(X) = \tilde{J}(X, U(X)).$$

Denote by \mathcal{G} a CFD solver iterating the vectors U_k , that is

$$U_{k+1} = \mathcal{G}_{(X)}(U_k).$$

The solution $U(X)$ is given by the first iterate solution fulfilling

$$\|\mathcal{G}_{(X)}(U) - U\| < \varepsilon.$$

The computation cost of $\nabla J(X)$ crucially depends on the complexity of \mathcal{G} .

Rewriting $J(X)$ as a Lagrangian

Regard J and \mathcal{G} as functions of *two* vectors X, U and set up the **Lagrangian**

$$L(X, U) = \tilde{J}(X, U) + (\tilde{\mathcal{G}}(X, U) - U)^T \cdot \lambda.$$

Along actual flow solutions, L equals \tilde{J} , independent of the choice of λ .

By λ we denote the factor („Lagrange multiplier“) such that

$$\nabla_U \tilde{J}(X, U) = (D_U \tilde{\mathcal{G}}^T(X, U) - \text{Id}) \cdot \lambda.$$

This condition ensures that at flow solutions we have

$$\nabla J(X) = \nabla_X L(X, U)$$

which is cheap to compute as it **does not involve the flow solver anymore**.

To obtain λ , we carry out the fixed point iteration

$$\lambda \stackrel{!}{=} \nabla_U \tilde{J}(X, U) + D_U \tilde{\mathcal{G}}^T(X, U) \cdot \lambda$$

Note that so far we didn't make any assumptions on \mathcal{G} except for being able to carry out the derivative

$$D_U \tilde{\mathcal{G}}^T(X, U) \cdot \lambda$$

subject to an arbitrary vector λ to compute $\nabla J(X)$.

Use of AD (in reverse mode)

For an arbitrary implementation of a function $f : \mathbb{R}^n \rightarrow \mathbb{R}^n$ and an arbitrary vector $y \in \mathbb{R}^n$, automatic differentiation in reverse mode computes

$$Df^T(\tilde{x}) \cdot \lambda$$

by the following steps:

- ▶ registering the input variables x of the computer program f
- ▶ recording a tape while running f at a given point \tilde{x} , that is storing $Df(\tilde{x})$
- ▶ setting the values λ
- ▶ evaluating $Df^T(\tilde{x}) \cdot \lambda$

How to use this generality for multiphysics?

Let our iterator \mathcal{G} actually consist of two **coupled iterators**, $\begin{pmatrix} \mathcal{G}^A \\ \mathcal{G}^B \end{pmatrix}$, with two sets of meshes X, Y and variables U^A, U^B being iterated like

$$\begin{aligned} U_k^A &\mapsto \mathcal{G}^A(X, U_k^B, U_k^A) = U_{k+1}^A \\ U_k^B &\mapsto \mathcal{G}^B(Y, U_k^A, U_k^B) = U_{k+1}^B. \end{aligned}$$

We then compute $\nabla J(X, Y)$ by simply computing both λ^A and λ^B in the corresponding Lagrangian

$$\tilde{J}(X, Y, U^A, U^B) + \begin{pmatrix} \mathcal{G}^A(X, U^B, U^A) - U^A \\ \mathcal{G}^B(Y, U^A, U^B) - U^B \end{pmatrix} \cdot \begin{pmatrix} \lambda^A \\ \lambda^B \end{pmatrix}.$$

The fixed point iteration for obtaining $\begin{pmatrix} \lambda^A \\ \lambda^B \end{pmatrix}$ now contains cross derivatives:

$$\begin{pmatrix} \lambda_{k+1}^A \\ \lambda_{k+1}^B \end{pmatrix} = \begin{pmatrix} \frac{\partial}{\partial U^A} \mathcal{G}^A & \frac{\partial}{\partial U^B} \mathcal{G}^B \\ \frac{\partial}{\partial U^B} \mathcal{G}^A & \frac{\partial}{\partial U^B} \mathcal{G}^B \end{pmatrix} \cdot \begin{pmatrix} \lambda_k^A \\ \lambda_k^B \end{pmatrix}$$

To keep the multizone discrete adjoint driver as **modular** as possible, the implementation allows for:

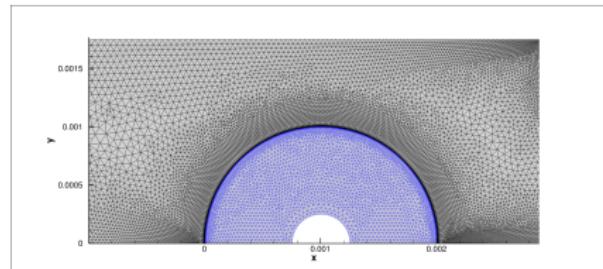
- ▶ initialising only parts of the right hand side adjoint vector
- ▶ evaluating with respect to arbitrary variable vectors
- ▶ restricting the evaluation to parts of the computational graph.

This provides a fair functionality for further **stable and efficient** developments.

Cylinder test case

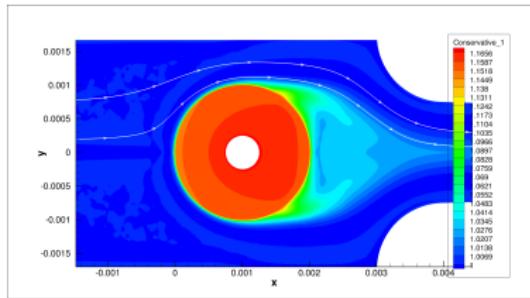
Let \mathcal{G}^A be a **RANS solver** (with coupled heat equation) and \mathcal{G}^B a **heat solver**, both coupled by transferring temperature and heat flux data.

The test geometry (denoted by X^*) is a cylinder, heated from the inside and surrounded by a fluid flow:



- ▶ Water, $300K / 0,25 \frac{m}{s}$ at inlet
- ▶ Fixed conductivity ($Pr = 7$)
- ▶ Aluminium
- ▶ Heat load at inner wall: $4 \frac{kW}{m}$

Primal solve and objective function



- ▶ Obtained flow solution U^*
- ▶ Using averaged temperature at interface as objective function
- ▶ $\tilde{J}(X^*, U^*) = 415K$

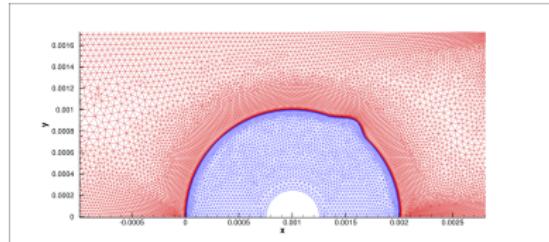
We easily compute the value

$$\nabla J(X) = \nabla_X \tilde{J}(X^*, U^*) + D_X \mathcal{G}^T(X^*, U^*) \cdot \lambda.$$

with the help of λ . **To validate ...**

Geometry change to validate $\nabla J(X)$

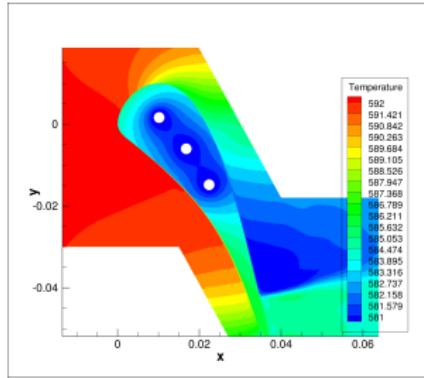
- ▶ we suggest a new geometry
 $Y_h = X + h\delta$
- ▶ $J(Y) \approx J(X) + h\nabla J(X) \cdot \delta$
- ▶ check $\lim_{h \rightarrow 0} \frac{J(Y_h) - J(X)}{h} \stackrel{?}{=} \nabla J(X) \cdot \delta$



Changing the value of h , we obtain the following data:

h (in mm)	$J(Y)$ (in K)	$\frac{J(Y) - J(X)}{h}$ (in $\frac{K}{m}$)	rel. error to $\nabla J(X) \cdot \delta$
$1.0e^{-1}$	417,873795	-65,89	8,68%
$5.0e^{-2}$	417,877298	-61,74	1,83%
$1.0e^{-3}$	417,879767	-60,7	1,15%
$5.0e^{-3}$	417,880081	-60,6	0,05%

- ▶ Uniting the CHT and turbomachinery functionalities for cooled turbine blade optimizations



- ▶ Speed up existing coupled simulations
- ▶ Trying out vertex-morphing optimizers, especially for internal flow applications