

## COST, COMPLEXITY AND UNCERTAINTY IN AERODYNAMIC SHAPE OPTIMISATION: A NEW OPPORTUNITY FOR HPC

**H Telib**, R Arpa, A Scardigli A Torluccio E Minisci, A Ricardi I Spisso

OPTIMAD engineering, Turin, Italy Automobili Lamborghini, Sant'Agata Bolognese, Italy University of Strathclyde, Glasgow, Scotland CINECA, Casalecchio di Reno, Italy

HPC enabling of OF @CINECA, 26/03/2015



# Outline



- 1. Practical problems in shape optimization
- 2. Enabling of large scale aerodynamic shape optimization
  - Shape morphing based on FFD and Level-Sets
  - ROM based on POD and domain decomposition
- 3. The Fortissimo SOUTH experiment

## Motivation

2 major burdens to aerodynamic shape optimization

### 1. Difficult to set-up (Integration)

- identification of parameters, parameterization itself etc
- totally automatized (geometry creation, pre-processing)
- especially critical if at advanced design

# 2. Expensive (Availability)

- computing resources sized for analysis
- licenses CAD, CFD



### The optimization context – Information provided by solver





### The optimization context – Time & Costs

cost of real life RANS approx.	С <sub>нғм</sub> =2000 сриһ
# of design variables	O(10)
cost of computing	0.1€/cpuh
cost of licenses	0

### 2 Level multi-fidelity approach using response surface (neglectable cost) + HFM

global optimization run O(100) - O(1000)	2.e5 – 2.e6 cpuh
computing resources O(10) – O(1000)	2. e2 – 2.e4 h

1week – 2years -> stop we you have to

20K€ - 200K€ -> convince your management !!

### 3 Level multi-fidelity approach using response surface (neglectable cost) + ROM + HFM

cost of Reduced Order Model	$C_{ROM} = \sigma C_{HFM}$
global optimization run O(1000) ROM + O(10) HFM	2.e6 σ + 2.e4 cpuh
necessary saving factor σ O(1month), O(10K€)	1-1/100



### 1. simulation

- calibration of models
- hope in "systematic errors" or "conservation of trends"
- what if your new prototype(!!) performs worse than original??
- 2. optimal strategy
  - should I use Krigging or ANN?
  - optimal number of initial samples??
  - when should I stop my optimization??
  - best answer we can give today "depends from case to case"



- Uncertainty nowadays is mastered by empirical knowledge. Limited basin of validity
- it takes specialized technical staff (like Joel!!)
  - i. to build an automatic workflow (geometry??, mesh??, 1month)
  - ii. and to do some preliminary investigations (sensitivity, uncertainty) (1.5 month)
  - iii. which help you to set up the optimization run (0.5 month)
- very costly (factor 10-100 wrt analysis)
- Automatic shape optimization is used only if strategic







**Free-Form Deformation using Level-Sets** 



### **Requirements to geometrical engine**

### Geometry represented as surface triangulation (CAD neutral)

### 1.parameterization of complex geometries

Free-Form Deformation developed by Desideri et al @INRIA adaptive parameterization (multi-level etc)

### 2.constraints handling

C<sup>0</sup>, C<sup>1</sup>, C<sup>2</sup> conditions on arbitrary boundaries no-penetration condition

### 3.features & curvature based surface mesh adaptation

if deformed geometry needs finer surface mesh than original geometry



## **Constraints via Level-Set information**

Free-Form Deformation applies a displacement vector  $N_i = S_i + D(S_i)$ 

difficult to impose regularity conditions on an arbitrary shaped boundary **Г** 



our approach introduces a weight function  $N_i = S_i + w[\phi(S_i | \mathbf{\Gamma})] D(S_i)$ 

withw(0) = 0for  $C^0$  conditionwithw(0) = 0, w'(0) = 0for  $C^1$  conditionwithw(0) = 0, w'(0) = 0, w''(0) = 0for  $C^2$  condition

Constraint control Free condition C0 condition C1 condition C2 condition 1.2 0.1 Filter value 0.6 0.4 0.2 0.2 0.4 0.6 0.8 Normalized distance function



 $φ(S_i|\Gamma)$  must provide topological information but it is requires that  $φ(S_i|\Gamma)$  is C<sup>0</sup>, C<sup>1</sup> and C<sup>2</sup> respectively

### **Geodesic distance from boundary**



resulting function is only C<sup>0</sup>, cannot impose higher regularity



### Geodesics based on heat kernel proposed by Crane et al.



- resovle heat equation  $u_{,t} = -u_{,xx}$  for a given time (parameter for smoothing) calculate X = -grad u / |grad u|1.
- 2.
- solve lap Φ = div grad X 3.

As similar as possible to geodesic distance, but imposes smoothness



# Geodesics based on heat kernel proposed by Crane et al.



# Deformation using C<sup>0</sup> constraint



# **Deformation using C<sup>1</sup> constraint**



# Deformation using C<sup>2</sup> constraint



## **Control of penetration**

1. User may indicate no-penetration surfaces:

- surface id
- distance to be maintained

2. Ray-tracing algorithm will calculate maximum displacement for each vertex

3. Two different types of rescaling algorithms available.



CM2: global rescale









## **Volume constraints**

# **Multi-level parameterization**

Spin-Off del Politecnico di Torino



Goal: Successively refine optimization run by introducing local shape parameters











podFOAM: ROM based on POD and Domain decomposition

### Sustainable CFD: Domain Decomposition

inner zone: use non-linear CFD outer zone: use simplified model to impose BC to inner zone

Far Field BC



### Sustainable CFD: Re-Use your data

Our assumptions are that

- in the outer zone, the perturbation becomes linear
- the **information needed** for describing the flow field of outer zone, is **already available** in the data stored on your HD

### If fulfilled then

- that the new flow field will can be represented as a linear combination of the ones on your HD
- no need to compute



### Sustainable CFD: Re-Use your data: But how?

### Represent the green zone by Proper Orthogonal Decomposition

- representation of a solution as  $u_i^j(x) = \Sigma a_i^j \Phi_i(x)$  for i= 0...N
- $\Phi_i(x)$  are orthogonal POD basis, which can be found by solving the eigen-problem of the **snapshot correlation matrix**
- no series converges faster than POD; identification of coherent structures; very few modes to capture 99% of the energy

### Couple to CFD in blue zone

- through a Least-Squares Problem on the data at the interface
- through a Least-Squares Problem on the residuals at the interface or domain





### Validation of POD: case 1 mirror

RANS calculations k-omega TM







# Reproduction of a case included in the database



white isolines: ROM, colormap: CFD



# Performance of POD: optimization of rear diffusor





Velocity Mode 0





Velocity Mode 1







### **Reproduction of case NOT included in database: velocity**

U Magnitude





white isolines: ROM, colormap: CFD

### **Reproduction of case NOT included in database: pressure**



white isolines: ROM, colormap: CFD

## **TC2: Performance Summary**

	original	hybrid
cost		
# of grid points	40M - 120M	4M – 9M
iterations	10K	2К
cpuh	1.5K – 2.5K	45 – 75
cost reduction	1	O(50)
accuracy		
drag	1.	1.005
lift	1.	0.93*
loss of accuracy	<1% drag, <10%lift	

\*dependency on grid





An outlook: SOUTH experiment within FORTISSIMO



## The SOUTH experiment

### Shape Optimization under Uncertainty through HPC cloudS

- Enable easy setup of optimization runs to SMEs through massive usage of HPC resources.
- Target: Expert user in analysis, un-experienced in optimization
- User provides intuitive information:
  - 1. time and budget
  - 2. simulation templates
  - 3. indication of uncertain and tuneable parameters reference data if available (e.g. wind tunnel)
- automatic setup the optimization run, by exploiting the simulation parameter space through HPC
- Accessible via web using HTML5 protocol, Software-as-a-Service paradigm
- Compatibility with any CAE solution (testing using OpenFOAM)



### The SOUTH platform



### **Contribution per partner**

geometrical

engine

multi level,&

fidelity optimization

engine

simulation

bus & interface

specifications

& testing





