

Low-rank response surface with application in numerical aerodynamic

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Outline

Overview

Modelling of free stream turbulence

Numerics

Uncertainties in geometry

Post-processing in low-rank data format

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Problem setup

Stationar Navier-Stokes equation:

$$\boldsymbol{v} \cdot \nabla \boldsymbol{v} - \frac{1}{Re} \nabla^2 \boldsymbol{v} + \nabla p = \boldsymbol{g}, \quad \text{and } \nabla \cdot \boldsymbol{v} = 0.$$

+ b.c. and Wilcox-k-w turbulence model
domain: RAE-2822 airfoil

TAU-solver has more than 300 parameters!
Many of them are or can be uncertain!
What does it mean for the solution ?

Overview of uncertainties

Uncertain Input:

1. Parameters and variables (α , Ma , Re , ...)
2. Geometry of airfoil
3. Parameters of a turbulence model

Uncertain solution:

1. statistical moments of $(v, p)^T$
2. exceedance probabilities $P(v > v^*)$ in each point x
3. probability density functions of u
4. position of shock.

Our Aims

1. Sparse representation of the input data (random fields)
2. Computing process in a reasonable time
3. Use the deterministic solver as a black box
4. A low-rank tensor data format for the solution
5. Efficient postprocessing in the low-rank tensor format

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Overview

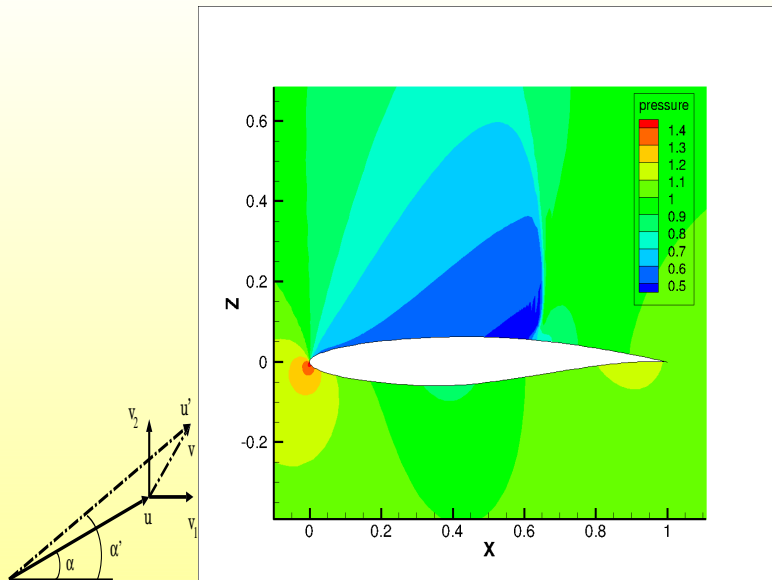
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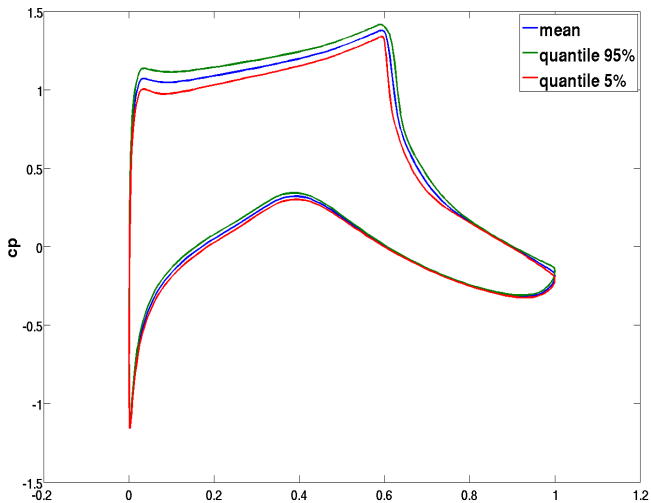
Modelling of uncertainties in free stream turbulence



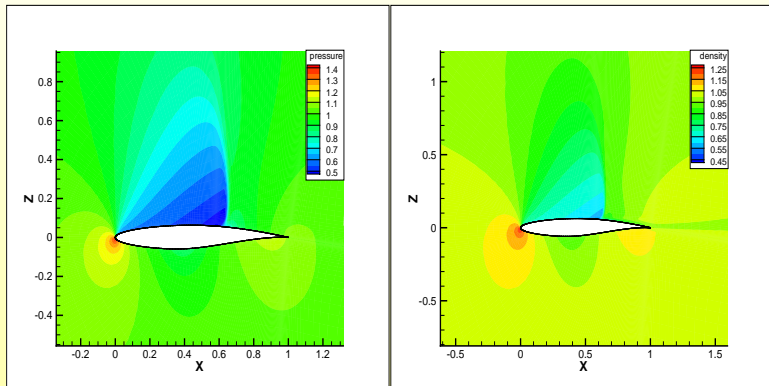
Random vectors $\mathbf{v}_1(\theta)$ and $\mathbf{v}_2(\theta)$ model free stream turbulence

Examples

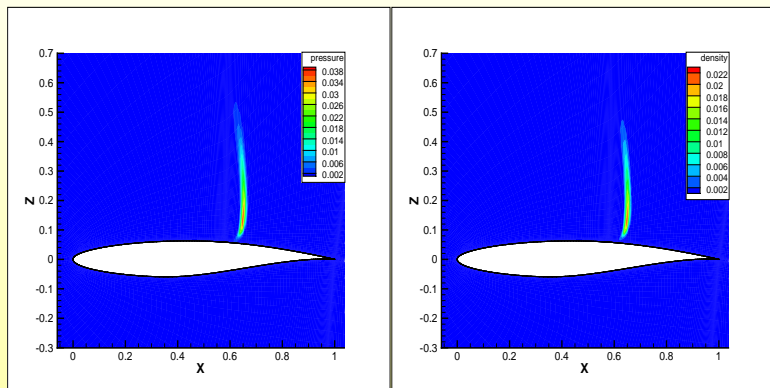
5% and 95% quantiles for cp from 500 MC realisations.



Mean of the pressure and density (from MC)



Variance of the pressure and density (from MC)



Polynomial Chaos Expansion of $p(\mathbf{x}, \boldsymbol{\theta})$

Represent $p(\mathbf{x}_\ell, \boldsymbol{\theta})$, $\mathbf{x}_\ell \in \mathcal{G}$, $\ell = 1..n$, in a Hermitian basis $H_\beta(\boldsymbol{\theta})$, $\beta \in \mathcal{J}$:

$$\rho(\mathbf{x}_\ell, \boldsymbol{\theta}) \approx \sum_{\beta \in \mathcal{J}_{M,p}} H_\beta(\boldsymbol{\theta}) \rho_\beta(\mathbf{x}_\ell), \quad (1)$$

$$\rho_\beta(\mathbf{x}_\ell) = \frac{1}{\beta!} \int_{\Theta} H_\beta(\boldsymbol{\theta}) \rho(\mathbf{x}_\ell, \boldsymbol{\theta}) \mathbb{P}(d\boldsymbol{\theta}) \approx \frac{1}{\beta!} \sum_{i=1}^{n_q} H_\beta(\boldsymbol{\theta}_i) \rho(\mathbf{x}_\ell, \boldsymbol{\theta}_i) w_i,$$

Further compression

$$\rho_\beta(\mathbf{x}_\ell) \approx \sum_{k=1}^r \bigotimes_{j=1}^M \rho_k^{(\beta_j)}(\mathbf{x}_\ell)$$

Sparse Gauss-Hermite Quadratures

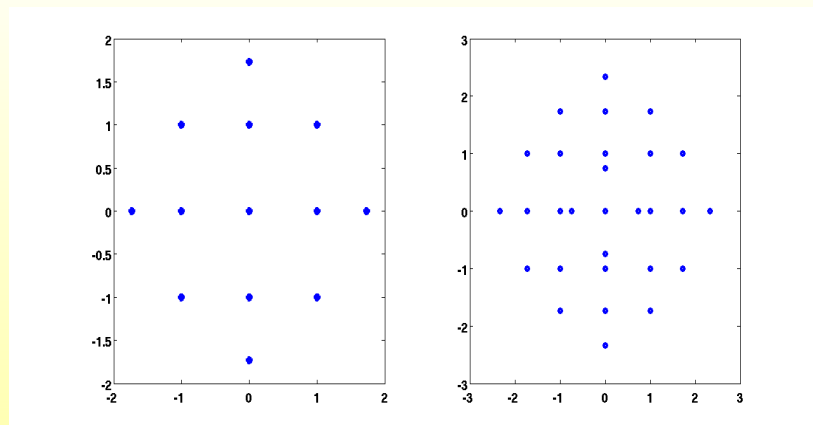


Figure: Sparse Gauss-Hermite grids of order 2 (13 points) and 3 (29 points).

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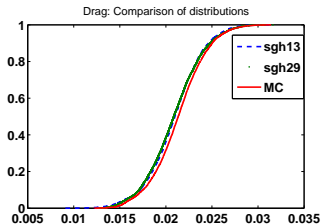
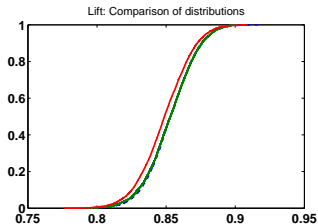
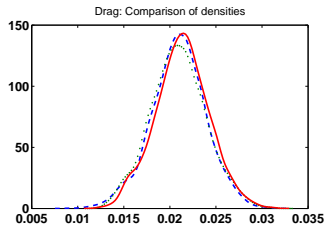
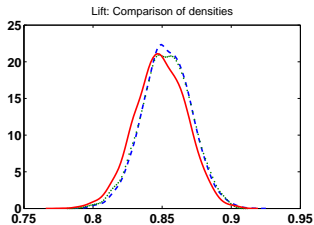
Sparse Gauss-Hermite grid, 13 points.

Assume that RVs α and Ma are Gaussian with

	mean	st. dev.	σ/mean
α	2.79	0.1	0.036
Ma	0.734	0.005	0.007

Then uncertainties in the solution lift CL and drag CD are

CL	0.853	0.0174	0.02
CD	0.0206	0.003	0.146



Density functions and distribution functions of CL and CD . PCE is of order 1 and depends on two RVs. Comparison is done with 6360 MC simulations.

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Uncertainties in geometry

Random boundary perturbations:

$$\partial D_\varepsilon(\omega) = \{\mathbf{x} + \varepsilon\kappa(\mathbf{x}, \omega)\mathbf{n}(\mathbf{x}) : \mathbf{x} \in \partial D\}.$$

where $\kappa(\mathbf{x}, \omega)$ is a random field.

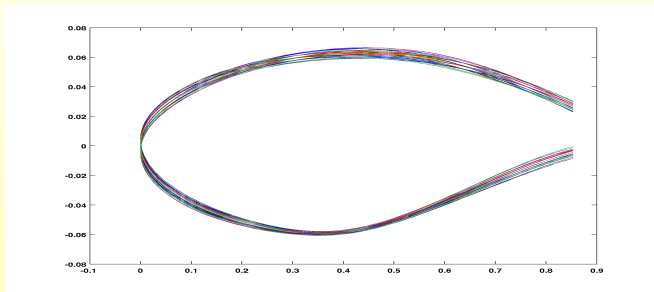
How to generate geometry with uncertainties ?

Algorithm:

1. Assume cov. function $\text{cov}(\mathbf{x}, \mathbf{y})$ for random field $\kappa(\mathbf{x}, \omega)$ given
2. Compute $C_{ij} := \text{cov}(x_i, x_j)$ for all grid points (in a sparse format!)
3. Solve eigenproblem $C\phi_i = \lambda_i\phi_i$
4. Then $\kappa(\mathbf{x}, \omega) \approx \sum_{i=1}^m \sqrt{\lambda_i}\phi_i\xi_i(\omega)$, where $\xi_i(\omega)$ are uncorrelated random variables.

Sparse approximation of dense matrix C is done in [Khoromskij, Litvinenko, Matthies, 2009]

21 realisations of RAE-2822 airfoil (expanded along y)



Covariance function is of Gaussian type

$$\text{cov}(\rho) = 10^{-5} \exp\left(-\sum_{i=1}^2 (x_i - y_i)^2 / \ell_i^2\right).$$

For each airfoil solve the deterministic problem.

Uncertainties in geometry

	mean	st. dev. σ	σ/mean
<i>CL</i>	0.8552	0.0049	0.0058
<i>CD</i>	0.0183	0.00012	0.0065

PCE of order 1 with 3 random variables and sparse Gauss-Hermite grid with 21 points were used.

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Low-rank approximation of the solution

Let $\mathbf{W} := [\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_Z]$, where \mathbf{v}_i are solution vectors.

Given tSVD $\mathbf{W}_k = \mathbf{U}_k \Sigma_k \mathbf{V}_k^T \approx \mathbf{W} \in \mathbb{R}^{n \times Z}$.

How to compute tSVD of $[\mathbf{W}_k, \mathbf{v}_{Z+1}, \dots, \mathbf{v}_{Z+R}]$ with a linear complexity? (M. Brand, 2006)

$$\bar{\mathbf{v}} = \frac{1}{Z} \sum_{i=1}^Z v_i = \frac{1}{Z} \sum_{i=1}^Z \mathbf{A} \cdot b_i = \mathbf{A} \bar{b}, \quad (2)$$

$$\mathbf{C} = \frac{1}{Z-1} \mathbf{W}_c \mathbf{W}_c^T = \frac{1}{Z-1} \mathbf{U} \Sigma \mathbf{V}^T \mathbf{V} \Sigma^T \mathbf{U}^T = \frac{1}{Z-1} \mathbf{U} \Sigma \Sigma^T \mathbf{U}^T. \quad (3)$$

Diagonal of \mathbf{C} can be computed with the complexity $\mathcal{O}(k^2(Z+n))$.

Accuracy of the mean value

Let $\mathbf{1} = (1, \dots, 1)^T$.

Lemma

Let $\|\mathbf{W} - \mathbf{W}_k\| \leq \varepsilon$. Let $\bar{\mathbf{v}}_k$ be a rank- k approximation of the mean $\bar{\mathbf{v}}$, then $\|\bar{\mathbf{v}} - \bar{\mathbf{v}}_k\| \leq \varepsilon$.

Proof: Since $\bar{\mathbf{v}} = \frac{1}{n}\mathbf{W}\mathbf{1}$ and $\bar{\mathbf{v}}_k = \frac{1}{n}\mathbf{W}_k\mathbf{1}$, then

$$\|\bar{\mathbf{v}} - \bar{\mathbf{v}}_k\| = \frac{1}{n}\|(\mathbf{W} - \mathbf{W}_k)\mathbf{1}\| \leq \frac{1}{n}\|(\mathbf{W} - \mathbf{W}_k)\| \cdot \|\mathbf{1}\| \leq \varepsilon.$$

i.e. the mean can be computed in rank- k data format with ε accuracy.

Accuracy of the variance value

Lemma

Let $\|\mathbf{W} - \mathbf{W}_k\| \leq \varepsilon$, then $\|\mathbf{W}_c - (\mathbf{W}_c)_k\| \leq \varepsilon$.

Proof:

$$\|\mathbf{W}_c - (\mathbf{W}_c)_k\| \leq \|\mathbf{W} - \mathbf{W}_k\| \cdot \left\| \mathbf{I} - \frac{1}{n} \cdot \mathbf{1} \cdot \mathbf{1}^T \right\| \leq \|\mathbf{W} - \mathbf{W}_k\| \cdot 1 \leq \varepsilon,$$

Lemma

Let $\|\mathbf{W}_c - (\mathbf{W}_c)_k\| \leq \varepsilon$, then $\|\mathbf{C} - \mathbf{C}_k\| \leq \frac{1}{Z-1} \varepsilon^2$.

Proof:

$$\|\mathbf{C} - \mathbf{C}_k\| \leq \frac{1}{Z-1} \|\mathbf{W}_c \mathbf{W}_c^T - (\mathbf{W}_c)_k (\mathbf{W}_c)_k^T\| \quad (4)$$

$$= \frac{1}{Z-1} \|\mathbf{U} \Sigma \mathbf{V}^T \mathbf{V} \Sigma^T \mathbf{U}^T - \mathbf{U}_k \Sigma_k \mathbf{V}_k^T \mathbf{V}_k \Sigma_k^T \mathbf{U}_k^T\| \quad (5)$$

$$= \|\mathbf{U} \Sigma \Sigma^T \mathbf{U}^T - \mathbf{U}_k \Sigma_k \Sigma_k^T \mathbf{U}_k^T\| \leq \frac{1}{Z-1} \varepsilon^2. \quad (6)$$

Relative errors of rank- k approximations

k	press.	density	tke	ev	xv	zv	memory, MB
10	1.9e-2	1.9e-2	4.0e-3	1.4e-3	1.1e-2	1.3e-2	21
20	1.4e-2	1.3e-2	5.9e-3	4.1e-4	9.7e-3	1.1e-2	42
50	5.3e-3	5.1e-3	1.5e-4	7.7e-5	3.4e-3	4.8e-3	104

Table: each matrix $\in \mathbb{R}^{260000 \times 600}$. Dense matrix format costs 1.25 GB.

Conclusion: already with a small rank a good accuracy can be achieved. Why?

Comparison of computing times

rank k	Update time, sec.	SVD time, sec.
10	107	1537
20	150	2084
50	228	8236

Table: Computing times of rank- k approximations of $W \in \mathbb{R}^{260000 \times 600}$.

Literature

1. A.Litvinenko, H. G. Matthies, *Sparse Data Representation of Random Fields*, PAMM, 2009.
2. B.N. Khoromskij, A.Litvinenko, H. G. Matthies, *Application of hierarchical matrices for computing the Karhunen-Loève expansion*, Springer, Computing, 84:49-67, 2009.
3. B.N. Khoromskij, A.Litvinenko, *Data Sparse Computation of the Karhunen-Loève Expansion*, AIP Conference Proceedings, 1048-1, pp. 311-314, 2008.
4. H. G. Matthies, *Uncertainty Quantification with Stochastic Finite Elements*, Encyclopedia of Computational Mechanics, Wiley, 2007.

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Elmar Zander:

A Matlab/Octave toolbox for stochastic Galerkin methods (KLE, PCE, sparse grids, tensors, many examples etc)

<http://ezander.github.com/sglib/>