

Optimization using Adjoint Technique Applied to Problems in Aerodynamics, Electromagnetics and Bio Fluid Mechanics

by

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Outline

- Aerodynamic Shape Optimisation
- Electromagnetic shape optimization for reduction of radar cross section
- Data assimilation in Bio Fluid Mechanics



Aerodynamic Shape Optimisation

Background

- The aerodynamic shape optimization system **cadsos** has been developed at SAAB during the last 5-10 years. Part of the work was done within the European project **Aeroshape**.
- The optimization technique is based on gradient calculations using the continuous adjoint technique.
- **Cadsos** can handle nonlinear objective functions and multiple nonlinear physical and geometrical constraints.
- 2D and 3D geometry parametrization och modifications are done in MATLAB. Grid sensitivities are computed by finite difference approximations.



Optimization technique

Minimize the Drag:

$$C_D = \frac{F_1 \cos \alpha + F_2 \sin \alpha}{\rho E_{k \text{ inf}} A_{REF}}$$

Constant Lift:

$$C_L = \frac{-F_1 \sin \alpha + F_2 \cos \alpha}{\rho E_{k \text{ inf}} A_{REF}}$$

Constant pitching moment:

$$C_M = \frac{M_3}{\rho E_{k \text{ inf}} A_{REF} L_{REF}}$$

Euler flow equations

$$\frac{\partial f_i}{\partial x_i} = 0$$

$$f_i = \begin{pmatrix} \rho \\ \rho \bar{u} \\ \rho H \end{pmatrix} u_i + p I_i$$

$$w = \begin{pmatrix} \rho \\ \rho \bar{u} \\ \rho E \end{pmatrix}$$



Optimization technique

Pressure Force and Moment:

$$\bar{F} = \int_{B_W(a)} p d\bar{S} \quad \bar{M} = \int_{B_W(a)} p(\bar{x} - \bar{x}_0) \times d\bar{S}$$



Optimization technique

Gradient of the Force:

$$\frac{\partial F_n}{\partial a} = \int_{B_W(a)} \frac{\partial}{\partial x_i} (p n_i + \psi^t w_H u_i) \frac{\partial x_k}{\partial a} dS_k$$

$$(\psi^t I_i - n_i) dS_i = 0$$

Adjoint solid wall bc:

Gradient of the Moment:

$$\frac{\partial M_n}{\partial a} = \int_{B_W(a)} \frac{\partial}{\partial x_i} (p \varepsilon_{kji} x_k n_j + \psi^t w_H u_i) \frac{\partial x_k}{\partial a} dS_k$$

$$(\psi^t I_i - \varepsilon_{kji} x_k n_j) dS_i = 0$$

Adjoint solid wall bc:



Optimization technique

Linearized optimization problem:
$$\begin{cases} \min_c (c, g^0) \\ (c, g^m) = \Delta^m & m = 1, \dots, M \\ (c, h^n) = \Delta^n & n = 1, \dots, N \end{cases}$$

← Physical constraints
← Geometrical constraints

Modified optimization problem:
$$\begin{cases} \min_c \frac{1}{2} \|c\|^2 \\ (c, g^0) = \Delta^0 \\ (c, g^m) = \Delta^m & m = 1, \dots, M \\ (c, h^n) = \Delta^n & n = 1, \dots, N \end{cases}$$

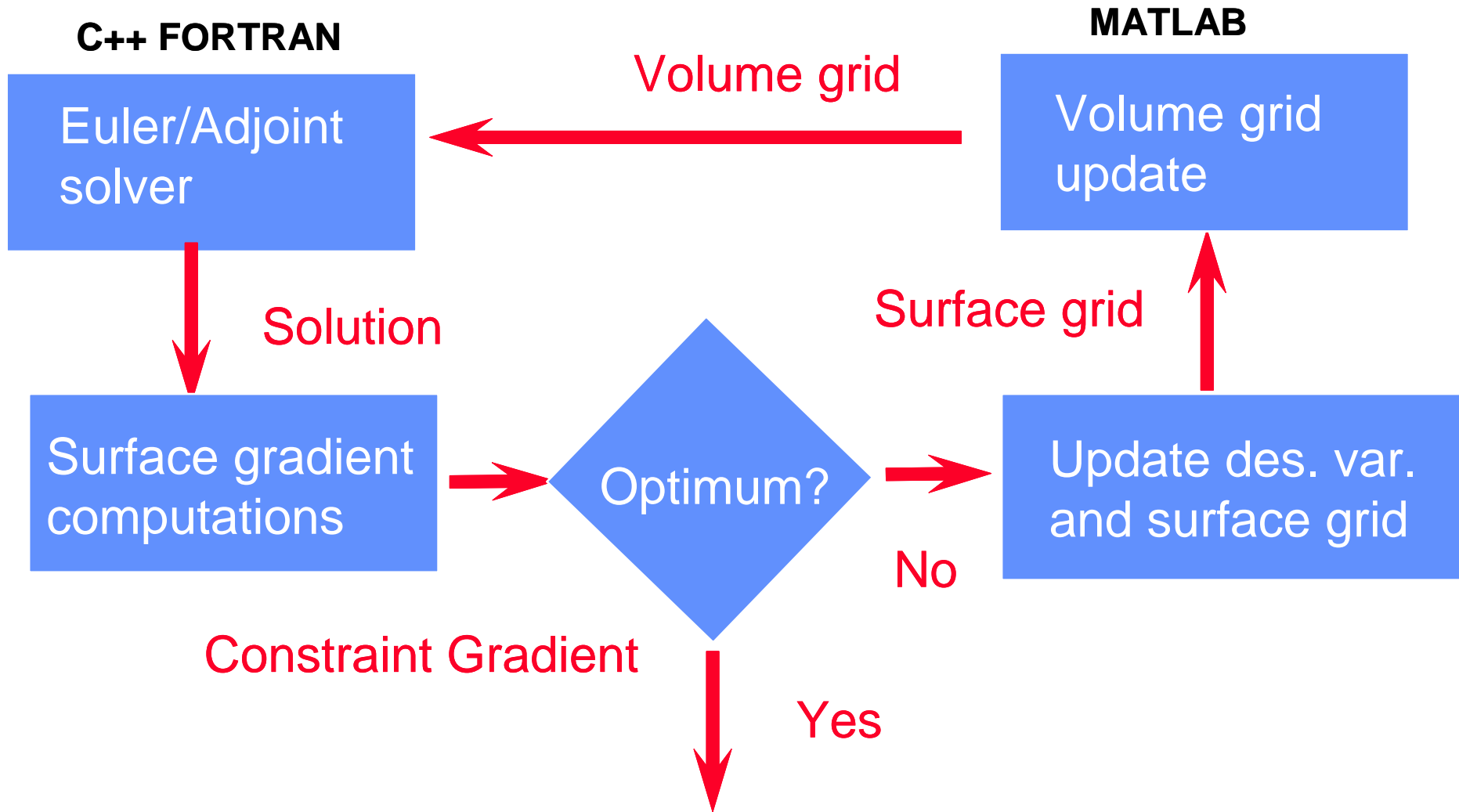
Lagrangian formulation:
$$L = \frac{1}{2} \|c\|^2 + \lambda_0 ((c, g^0) - \Delta^0) + \lambda_m ((c, g^m) - \Delta^m) + \lambda_n ((c, h^n) - \Delta^n)$$

$$\frac{\partial L}{\partial c_k} = c_k + \lambda_0 g_k^0 + \lambda_m g_k^m + \lambda_n h_k^n = 0, \quad \frac{\partial L}{\partial \lambda_0} = (c, g^0) - \Delta^0 = 0,$$

$$\frac{\partial L}{\partial \lambda_m} = (c, g^m) - \Delta^m = 0, \quad \frac{\partial L}{\partial \lambda_n} = (c, h^n) - \Delta^n = 0$$



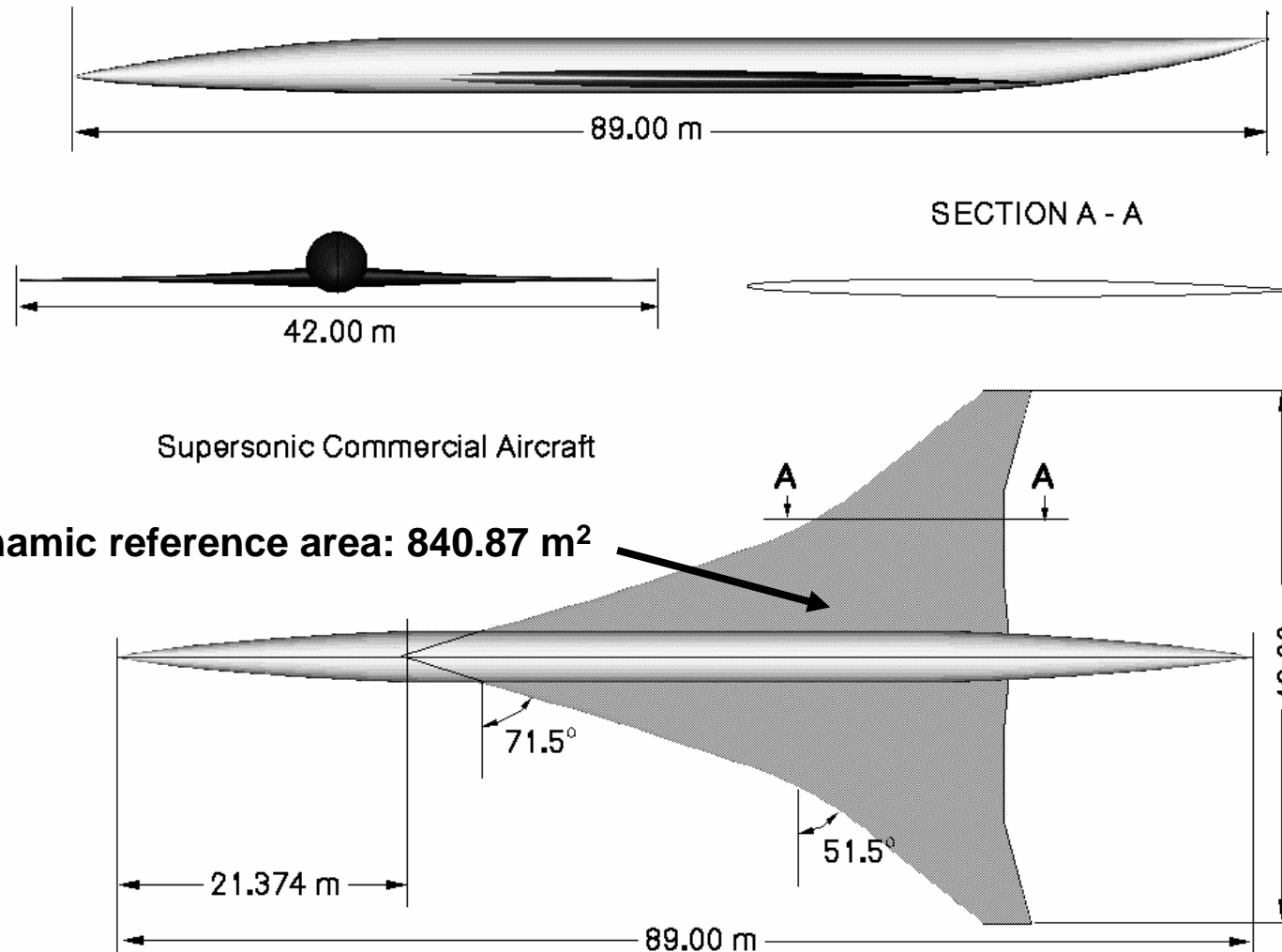
Optimization system **cadso** at SAAB



Example: Aerodynamic shape optimization of a Supersonic Commercial Transport Aircraft SCT



Description of the SCT geometry



Wing aerodynamic reference area: 840.87 m^2



Surface and volume grid generation

- The CFD grid around the SCT geometry consisted of 5 structured blocks and 196 000 cells.
- The mesh generation system MEGACADS, developed at DLR in Braunschweig, Germany, was used.
- The mesh generation procedure was executed in batch mode by means of script files.
- The multi block topology was kept fixed during the optimisation.



Formulation of the optimization problem

- Objective function: minimize drag
- Physical Constraint: constant lift
- Flow model: Euler equations (inviscid flow)
- Flow condition: $M=2.0$ and $C_L=0.12$
- Thickness constraints
- Design variables:
 - 9 spline functions describing the wing twist distribution in the spanwise direction
 - 36 spline functions describing the camber line distribution in the spanwise direction
 - 12 spline functions describing the radial shape of the body in the streamwise direction
 - 5 spline functions describing the camber line of the body



Gradient validation

For gradient validation, a comparison between gradient computations using adjoint technique and finite difference technique was performed.

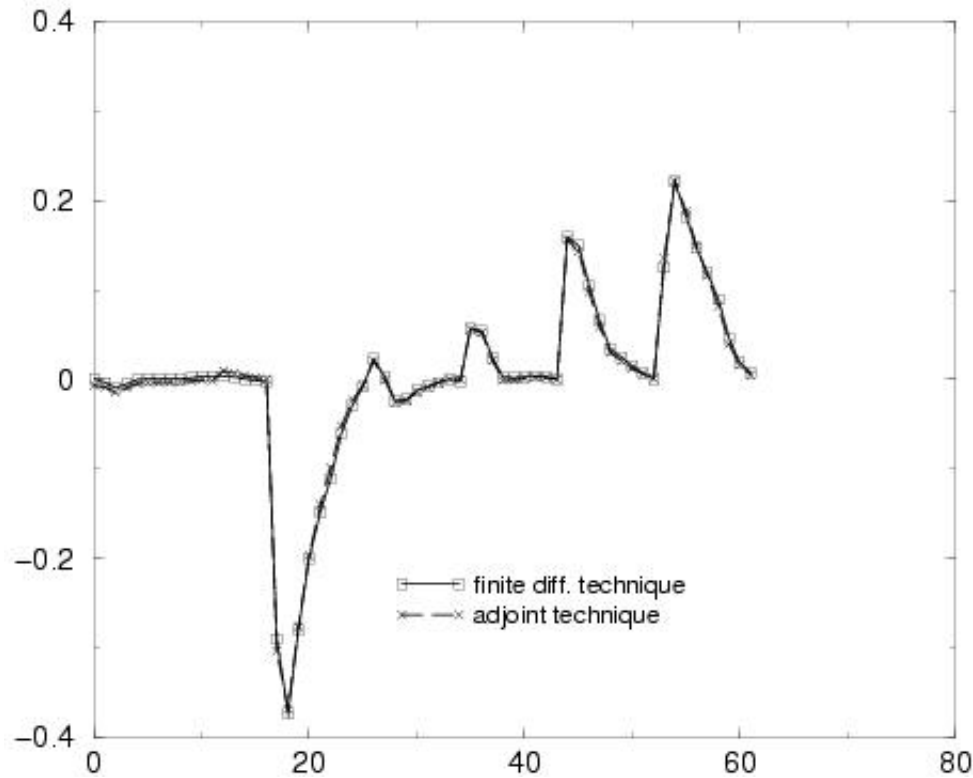
Test case: Inviscid flow over the SCT geometry, at free stream conditions $M=2.0$ and $C_L=0.12$. Disturbance parameter $\varepsilon=0.005$.
The geometry was modified by means of 62 design parameters.



Gradient validation

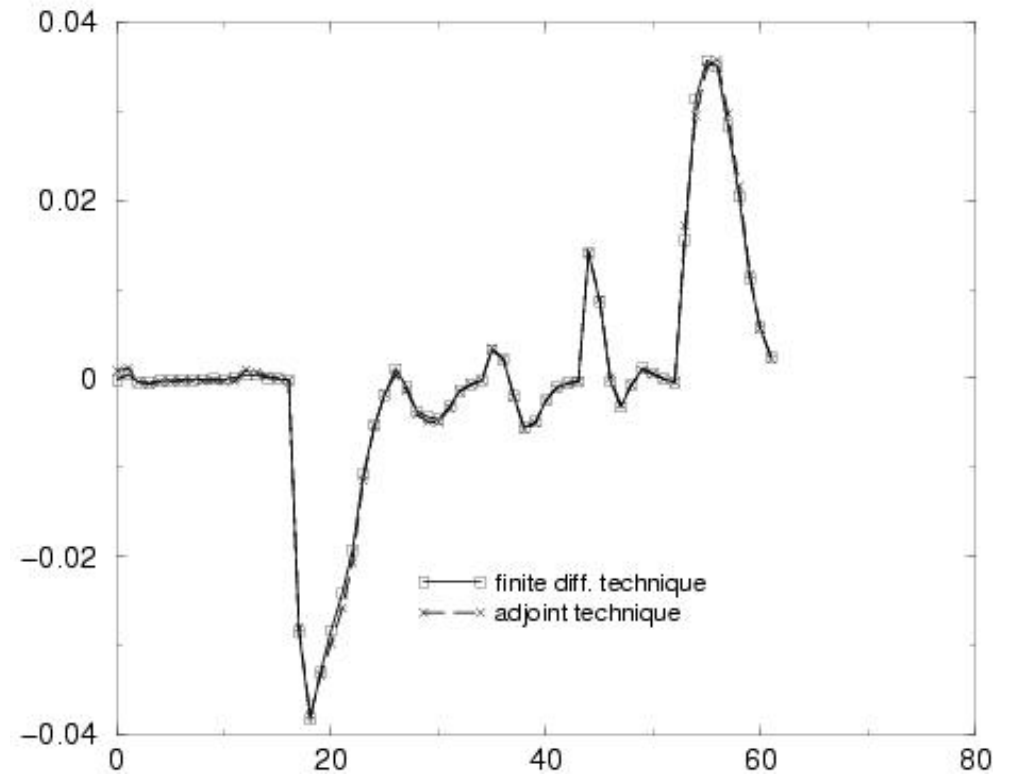
Lift

Lift gradient comparison finite diff. – adjoint technique

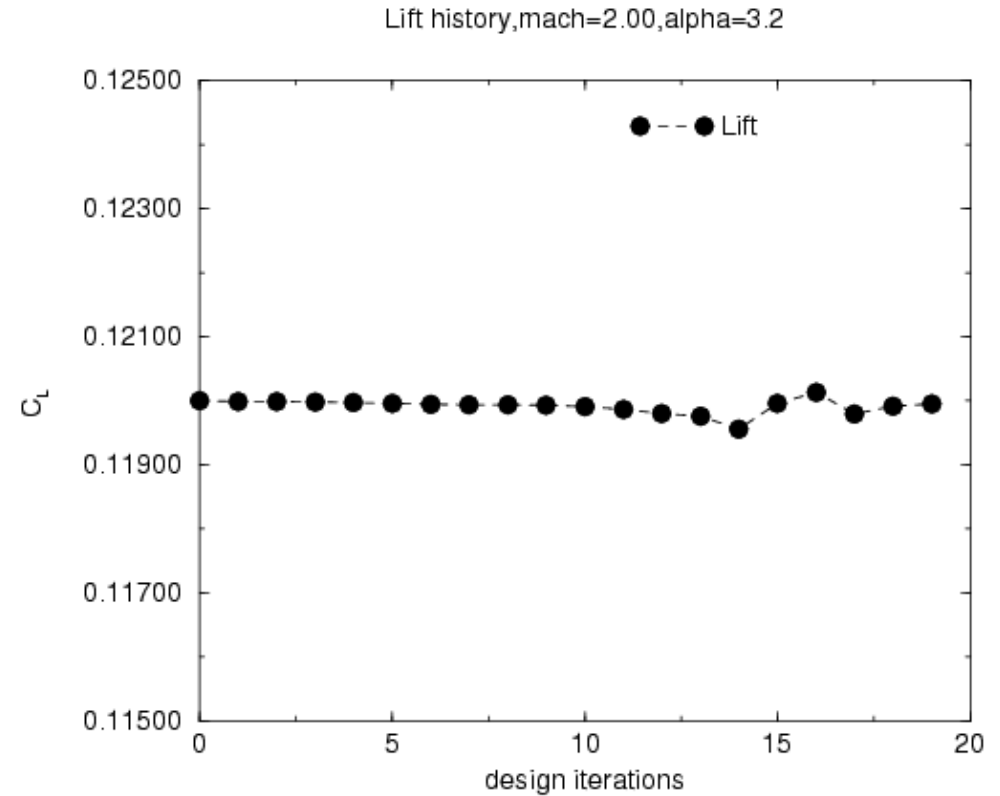
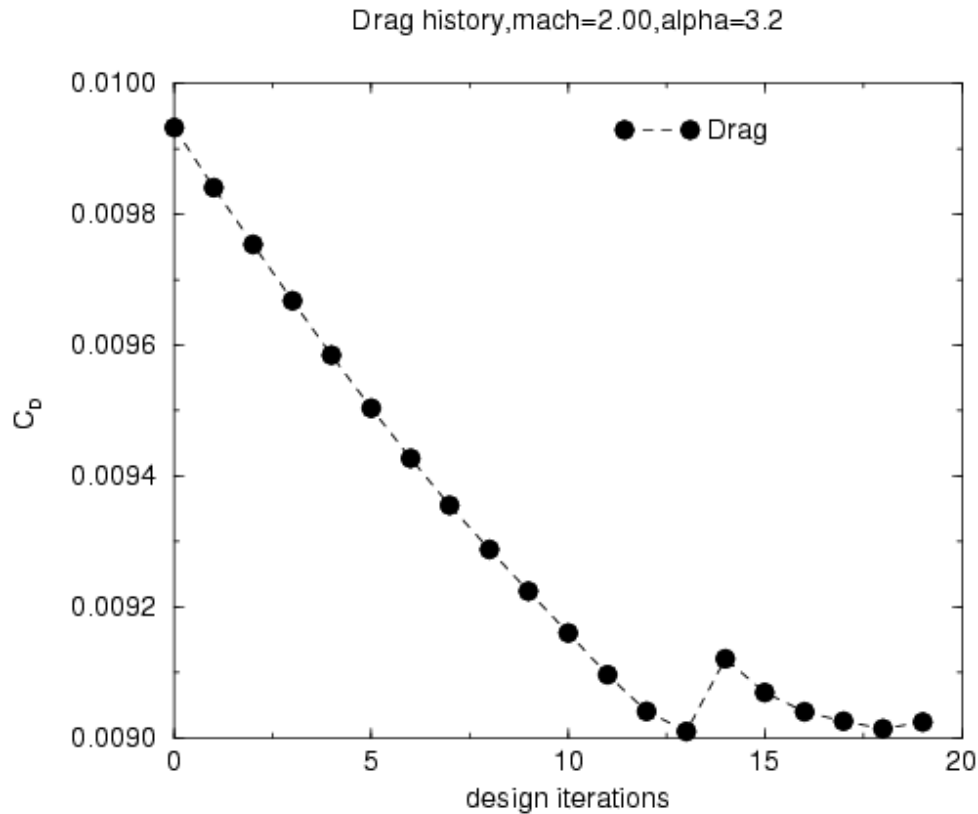


Drag

Drag gradient comparison finite diff. – adjoint technique



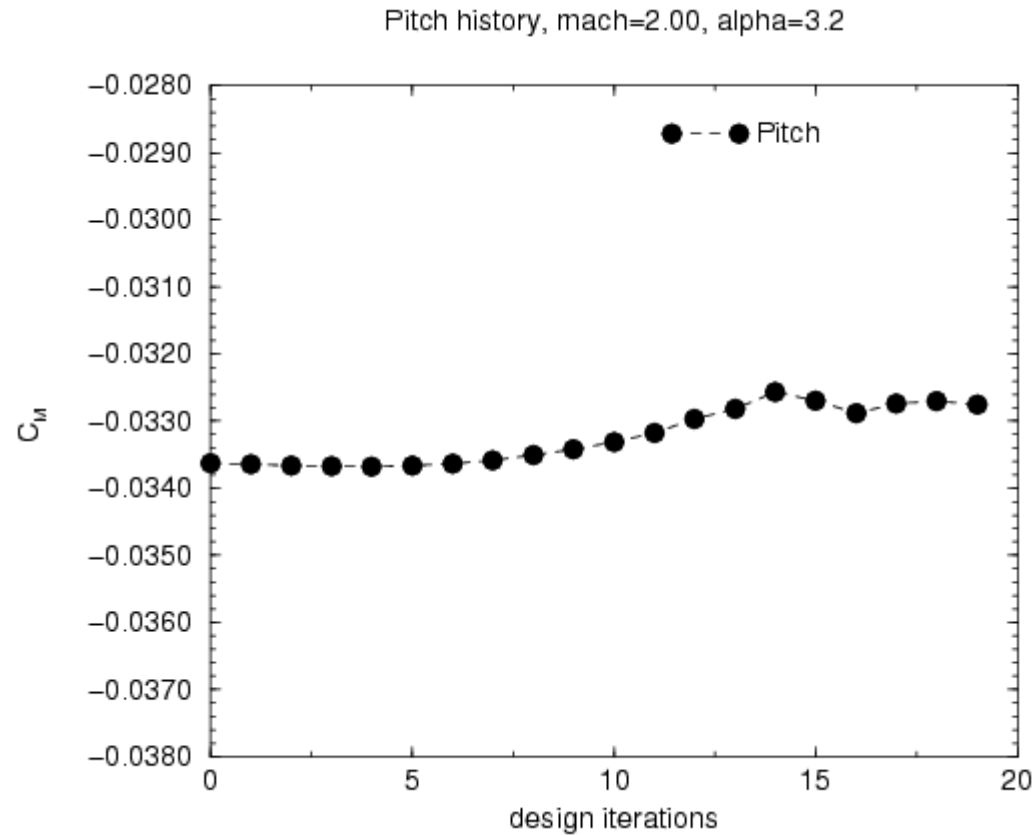
Optimization results



9.6 % drag reduction



Optimization results



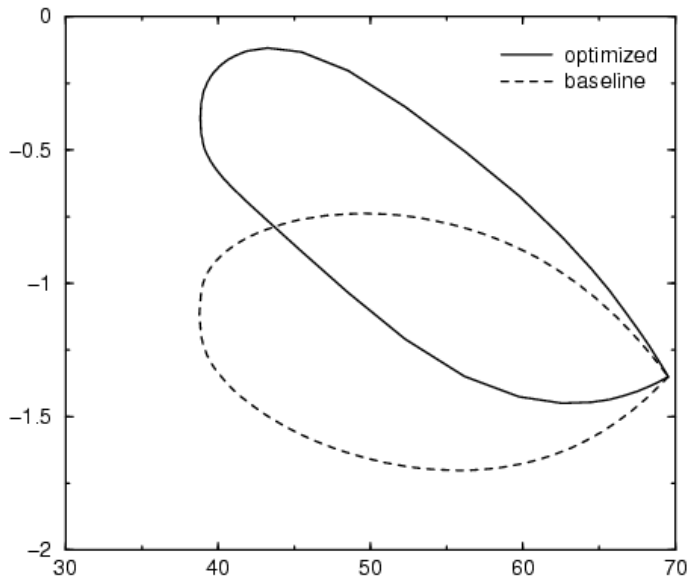
Pitch history during the optimization



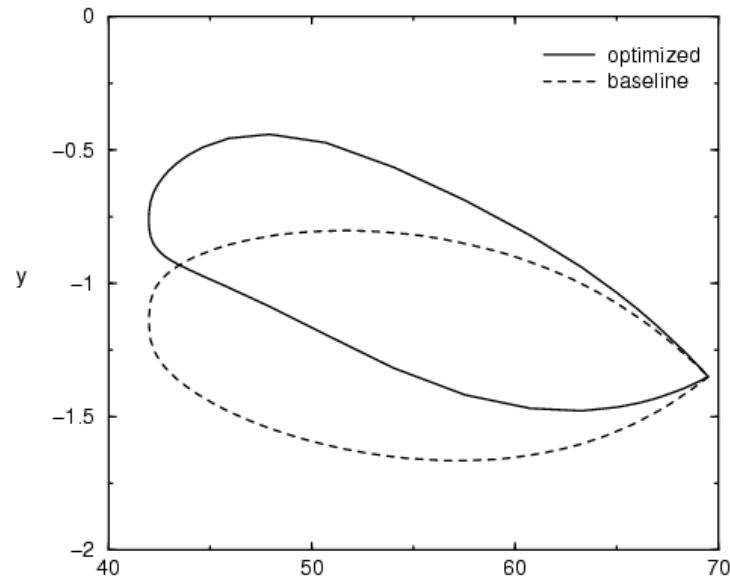
Optimization results

Wing profiles in the wing span direction

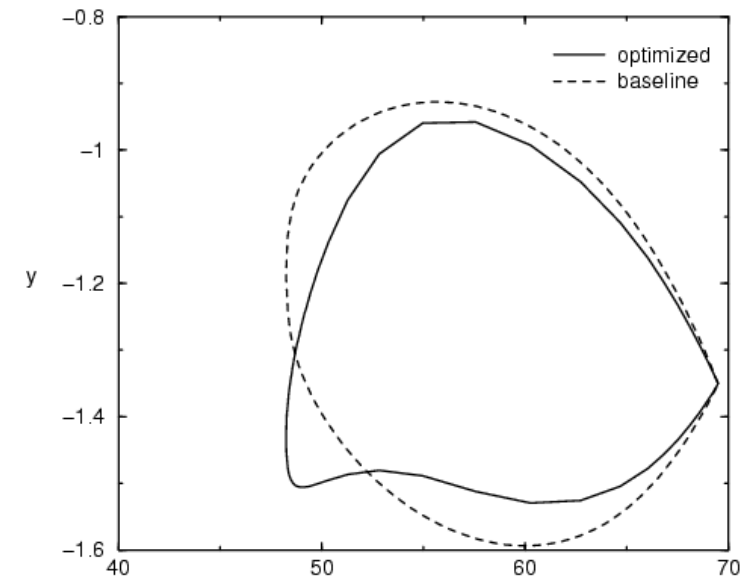
geom. profile at $\eta=0.24$



geom. profile at $\eta=0.29$



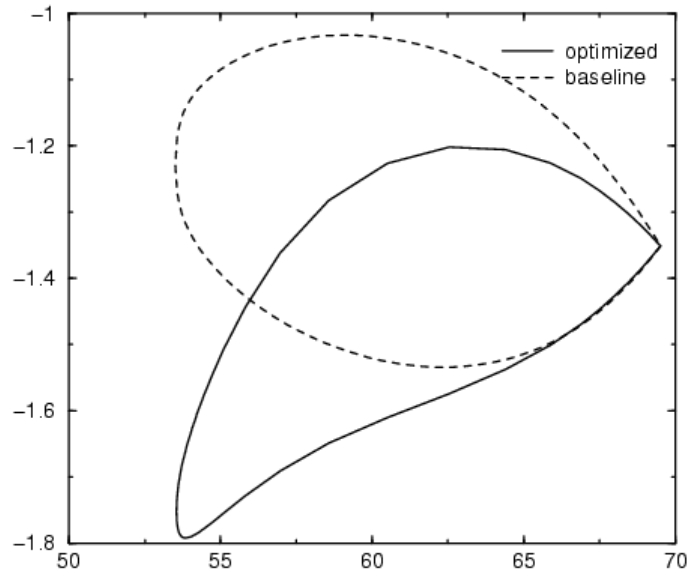
geom. profile at $\eta=0.39$



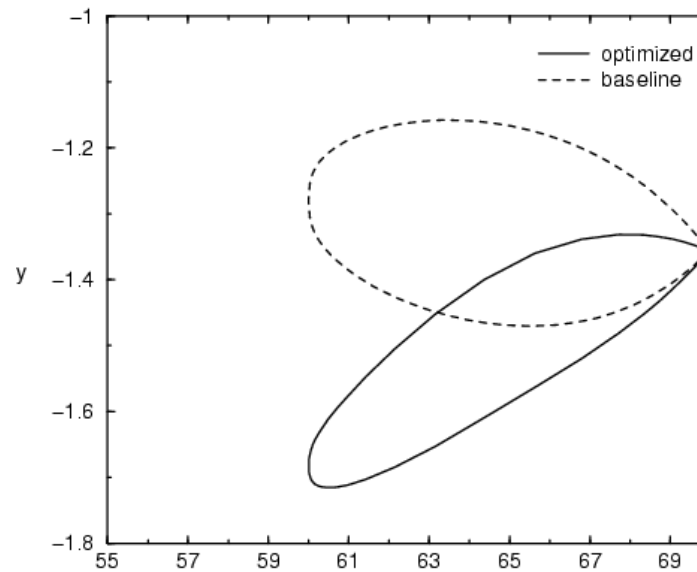
Optimization results

Wing profiles in the wing span direction

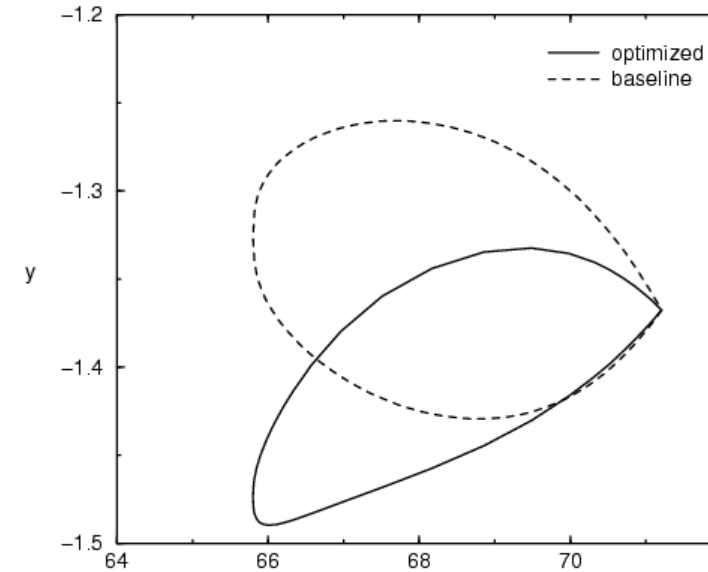
geom. profile at $\eta=0.49$



geom. profile at $\eta=0.70$



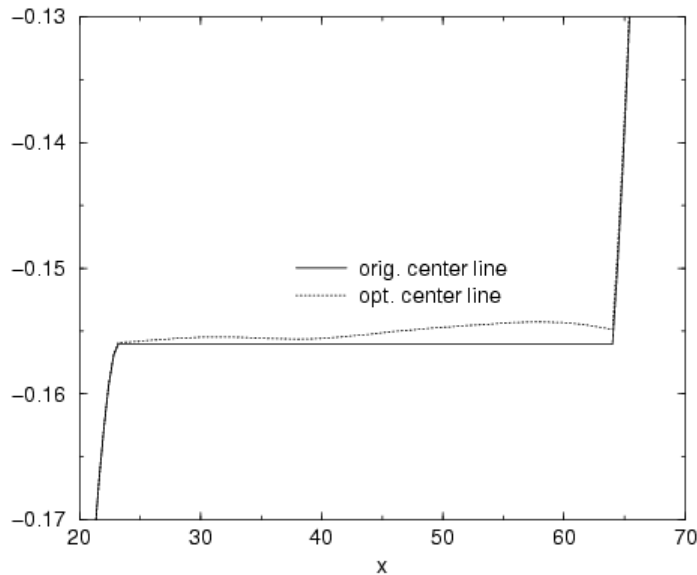
geom. profile at $\eta=0.92$



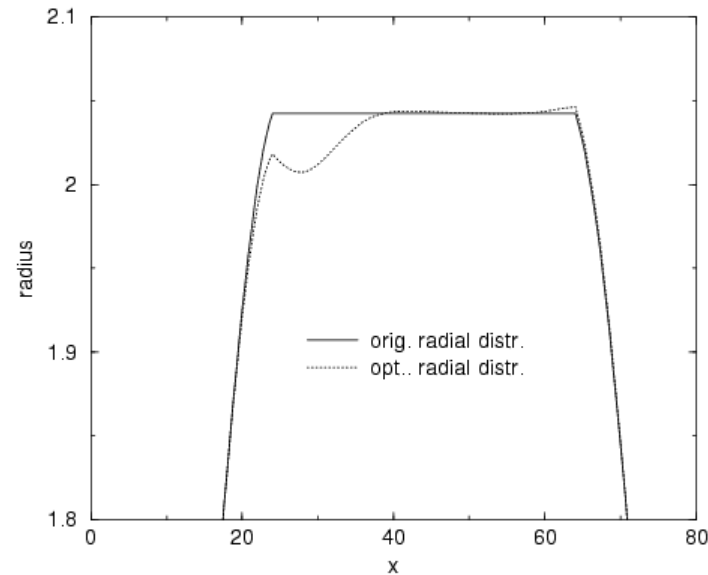
Optimization results

Centreline. Radius and thickness distribution

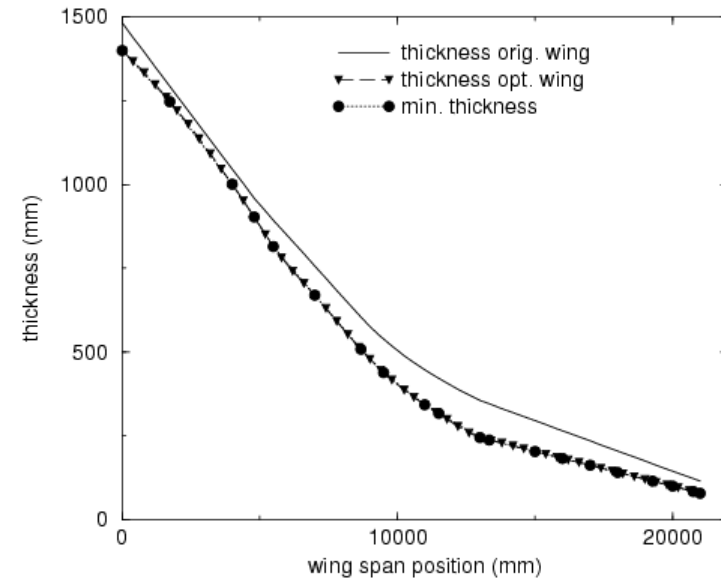
SCT body, center line



SCT body, radial distribution in the span wise direction



SCT wing thickness



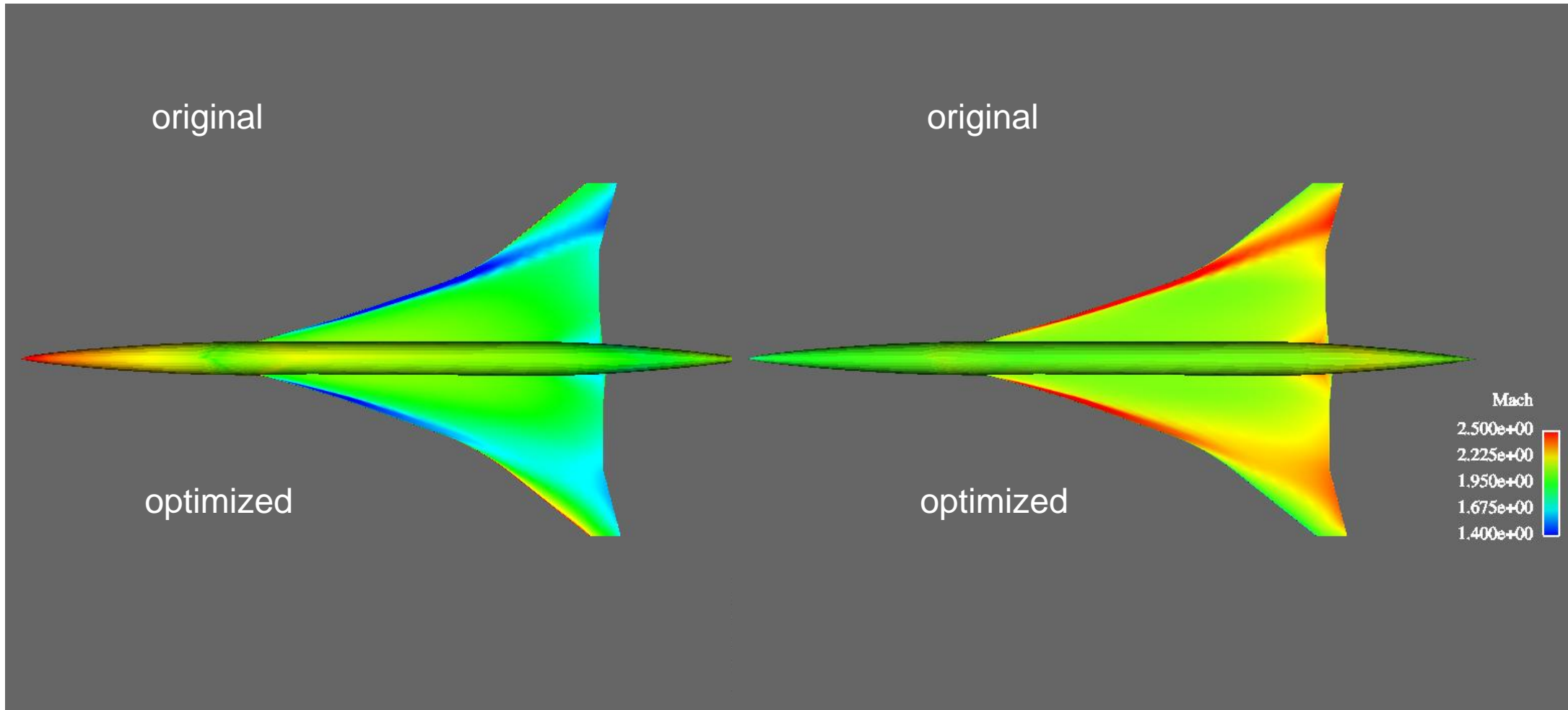
Drag reduction from decreased thickness: 6.4%
Total drag reduction: 16%



Optimization results

Pressure on the upper surface

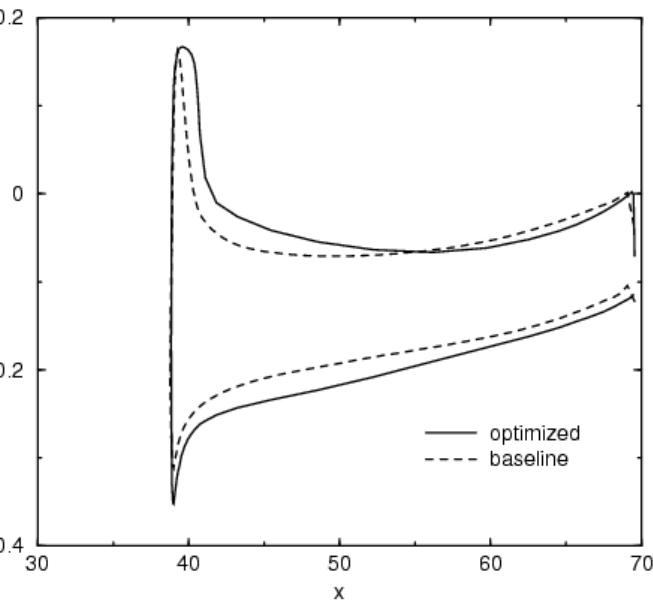
Mach number distr. on the upper surface



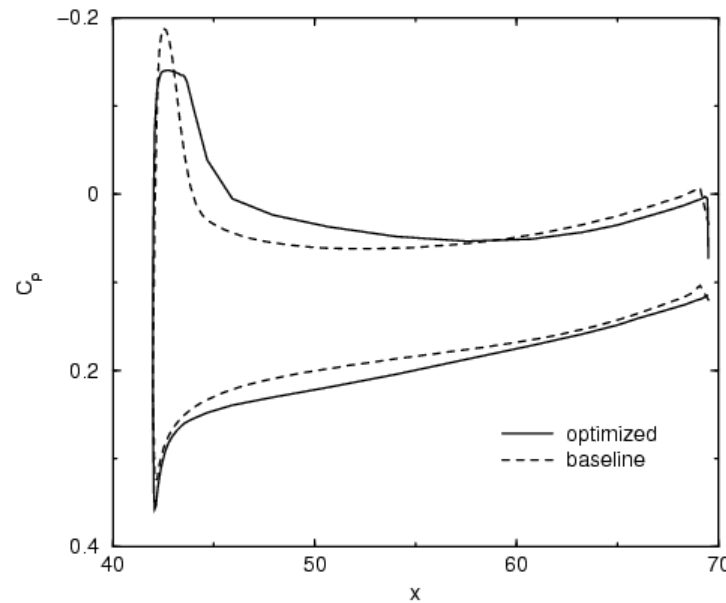
Optimization results

C_p distribution in the wing span direction

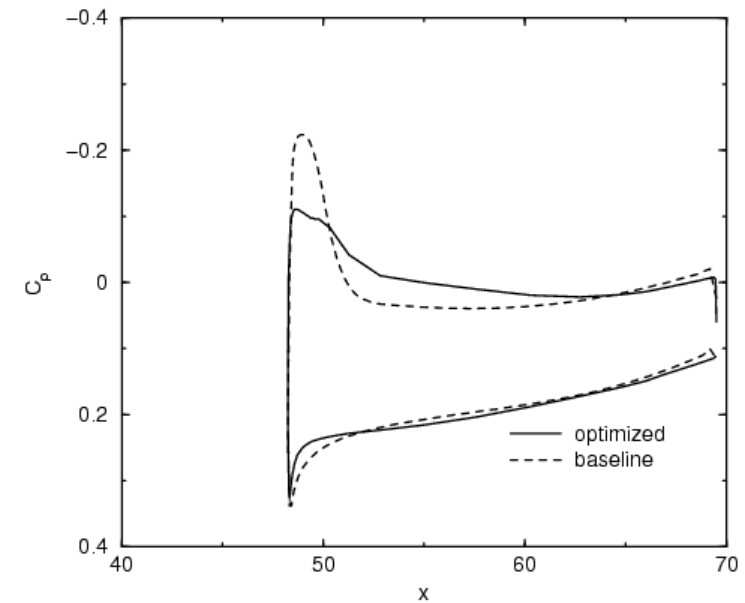
pressure distr. at $\eta=0.24$



pressure distr. at $\eta=0.29$



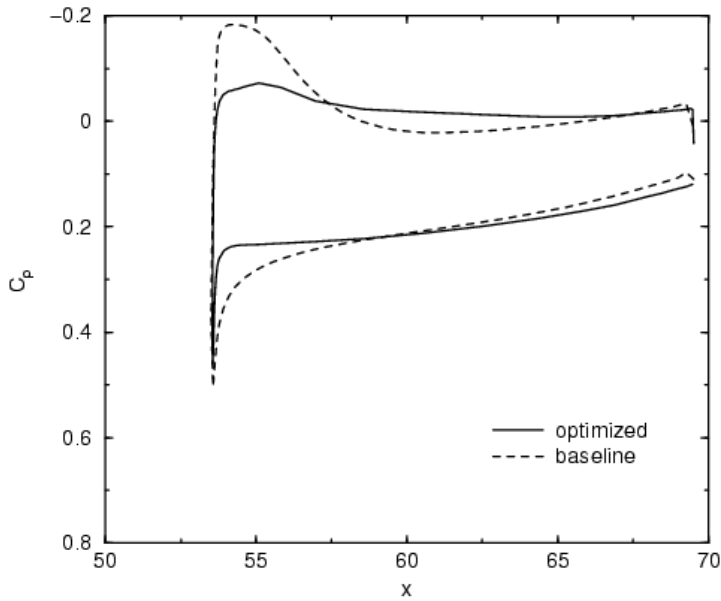
pressure distr. at $\eta=0.39$



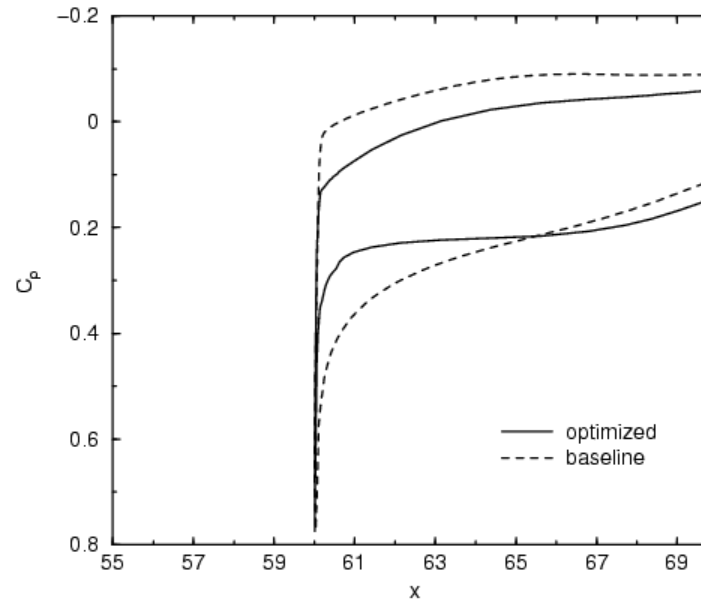
Optimization results

C_p distribution in the wing span direction

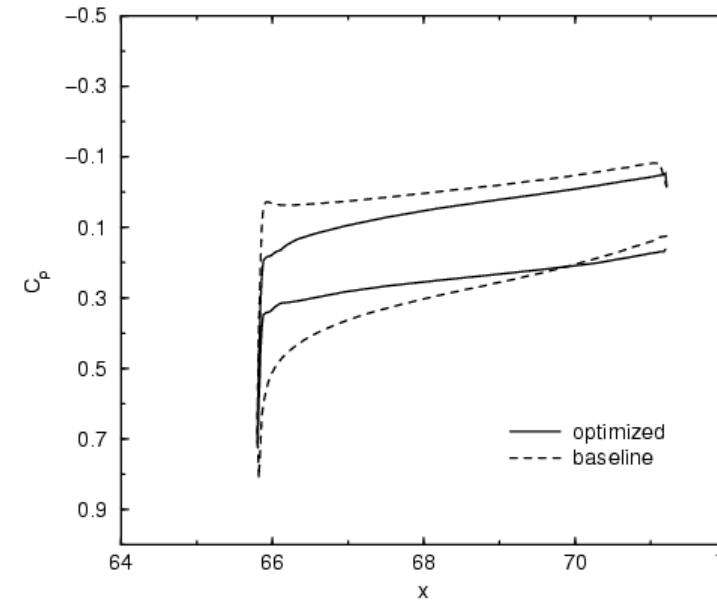
pressure distr. at $\eta=0.49$



pressure distr. at $\eta=0.70$



pressure distr. at $\eta=0.92$



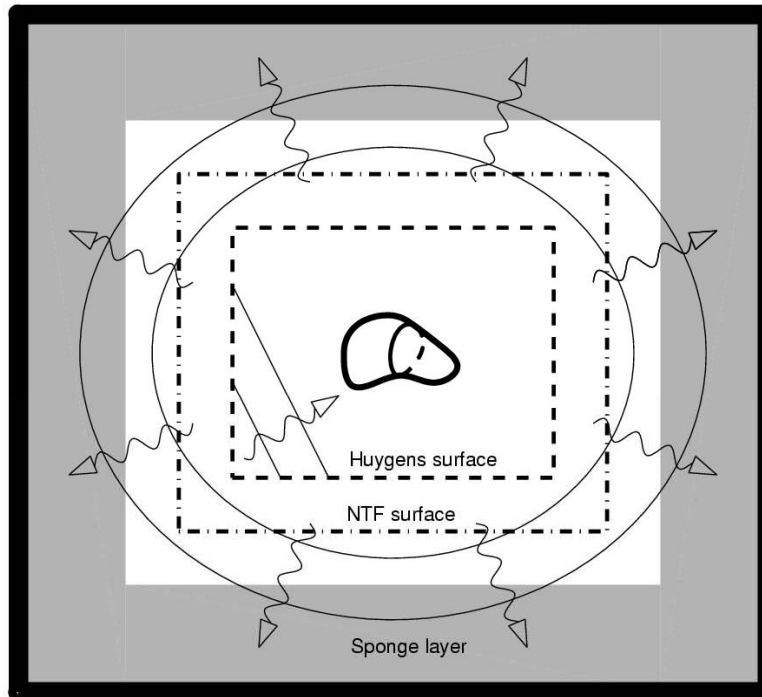
Electromagnetic shape optimization for reduction of radar cross section

joint work with

A. Bondesson and Y. Yang
Chalmers University of Technology



Scattering problem



- Incident wave on Huygens surface
- Near-to-Far Field Transformation
- Absorbing boundary condition
- Differential equation formulation used for derivation only
- In reality: solve scattering problem with integral equation to compute surface currents.

Scattering problem

- Incident plane wave $\vec{E}_i = \vec{E}_0 \exp(-j\vec{k}_0 \cdot \vec{r})$

- Monostatic RCS $\sigma = \frac{4\pi|A_{\perp}|^2}{E_0^2 k_0^2}$

- Scattering amplitude

$$\vec{A} = \vec{a}(\vec{E}) = \frac{k_0}{4\pi} \oint_{NTF} \left[\hat{n} \times (\nabla \times \vec{E}) - j\vec{k}_0 \times (\vec{E} \times \hat{n}) \right] \exp(-j\vec{k}_0 \cdot \vec{r}) dS$$

- Scattering problem in total field/scattered field form $\vec{E} = \vec{E}_s + \sigma(u)\vec{E}_i$

$$\nabla \times \mu_r^{-1} \nabla \times \vec{E} - k_0^2 \epsilon_r \vec{E} = -\nabla \times [\hat{n} \times \vec{E}_i \delta(u)] - \delta(u) \hat{n} \times \nabla \times \vec{E}_i$$

u surface label, positive inside Huygens surface, $dv = dudS$

- ϵ_r and μ_r can be complex



Weak form and adjoint problem

$$\mathcal{L}(\vec{w}, \vec{E}) = \mathcal{L}_0(\vec{w}, \vec{E}) - (4\pi/k_0)\vec{E}_0 \cdot \vec{a}(\vec{w}) = 0, \quad \forall \vec{w} \in H(\text{curl}, \Omega).$$

$$\mathcal{L}_0(\vec{w}, \vec{E}) = \int_{\Omega} \left(\mu_r^{-1} \nabla \times \vec{w} \cdot \nabla \times \vec{E} - k_0^2 \epsilon_r \vec{w} \cdot \vec{E} \right) dv + \oint_{\partial\Omega} (\hat{n} \times \vec{w}) \cdot (jk_0 \hat{r} \times \vec{E}) dS$$

\mathcal{L}_0 symmetric if $\partial\Omega$ is a large sphere $\hat{n} = \hat{r}$.

Variation of \vec{E} gives variation of RCS:
$$\delta\sigma = \frac{8\pi \text{Re}[\vec{A}_{\perp}^* \cdot \vec{a}(\delta\vec{E})]}{E_0^2 k_0^2}$$

The **adjoint field** \vec{E}_a satisfies

$$\mathcal{L}(\vec{w}, \vec{E}_a) = \mathcal{L}_0(\vec{w}, \vec{E}_a) - \frac{4\pi}{k_0} \vec{A}_{\perp}^* \cdot \vec{a}(\vec{w}) = 0$$

Same scattering problem, but the incident wave is $\vec{E}_{a,i} = \vec{A}_{\perp}^* \exp(-j\vec{k}_0 \cdot \vec{r})$.

Choose $\vec{w} = \delta\vec{E}$ in the weak form of the adjoint equation

$$\delta\sigma = \frac{8\pi \text{Re}[\vec{A}_{\perp}^* \cdot \vec{a}(\delta\vec{E})]}{E_0^2 k_0^2} = \frac{2\text{Re}[\mathcal{L}_0(\vec{E}_a, \delta\vec{E})]}{E_0^2 k_0}$$



Displace PEC scatterer

Evaluate $\mathcal{L}_0(\vec{w}, \delta\vec{E})$ by requiring $(\mathcal{L} + \delta\mathcal{L})(\vec{w}, \vec{E} + \delta\vec{E}) = 0$

$\delta\vec{E}$ from a normal displacement ξ of PEC boundary Γ satisfies

$$\mathcal{L}_0(\vec{w}, \delta\vec{E}) = -\delta\mathcal{L}_0(\vec{w}, \vec{E}) = \oint_{\Gamma} \left(\nabla \times \vec{w} \cdot \nabla \times \vec{E} - k_0^2 \vec{w} \cdot \vec{E} \right) \xi dS.$$

Akel and Webb (IEEE Trans. Magn. 2000) derive discretized design sensitivity, which corresponds to a surface integral.

Analytic form

$$\delta\sigma = \frac{2}{E_0^2 k_0} \oint_{\Gamma} \operatorname{Re} \left(\nabla \times \vec{E}_a \cdot \nabla \times \vec{E} - k_0^2 \vec{E}_a \cdot \vec{E} \right) \xi dS$$

In terms of surface quantities:

$$\delta\sigma = -\frac{2k_0 Z_0^2}{E_0^2} \oint_{\Gamma} \operatorname{Re} \left(\vec{J}_{\text{adj}} \cdot \vec{J}_{\text{orig}} + c^2 \rho_{\text{adj}} \rho_{\text{orig}} \right) \xi dS$$



2D - TM polarization

TM RCS (a length) $L = \frac{4|A|^2}{k_0|E_0^2|}$ where

$$A = -\frac{1}{4} \oint_{NTF} \left(j\vec{k}_0 E + \nabla E \right) \cdot \hat{n} \exp(-j\vec{k}_0 \cdot \vec{r}) dl,$$

Adjoint solution $E_a = \frac{A^*}{E_0} E$.

Variation of RCS

$$\delta L = \frac{8\text{Re}(A^* \delta A)}{k_0|E_0^2|} = \frac{2}{k_0|E_0^2|} \oint_{\Gamma} \text{Re}(\nabla E_a \cdot \nabla E - k_0^2 E_a E) \xi dl$$

In terms of surface quantities

$$\delta L = -\frac{2Z_0^2 k_0}{|E_0^2|} \oint_{\Gamma} \text{Re}(J_{\text{adj}} J_{\text{orig}}) \xi dl$$



2D - TE polarization

$$\text{RCS } L = \frac{4|G|^2}{k_0|H_0^2|} \text{ where}$$

$$G = -\frac{1}{4} \oint_{NTF} \left(j\vec{k}_0 H + \nabla H \right) \cdot \hat{n} \exp(-j\vec{k}_0 \cdot \vec{r}) dl$$

Adjoint solution $H_a = (G^*/H_0)H$.

Variation of the RCS

$$\delta L = \frac{8\text{Re}(G^*\delta G)}{k_0|H_0^2|} = -\frac{2k_0}{|H_0^2|} \oint_{\Gamma} \text{Re} \left(J_{\text{adj}} J_{\text{orig}} + c^2 \rho_{\text{adj}} \rho_{\text{orig}} \right) \xi dl$$



Optimization

- **Compute shape derivative on all surface nodes.**
- **Introduce reduced parametrization $\xi = \xi(\vec{r}, p_1, p_2, \dots, p_n)$**
- **Find derivatives wrt parameters by the chain rule $\frac{\partial \sigma}{\partial p_k} = \sum_i \frac{\partial \sigma}{\partial \xi_i} \frac{\partial \xi_i}{\partial p_k}$**
- **Allows a clear separation of the geometry description (shape parameters), from the RCS calculation (nodes on grid), which fits with CFD optimization developed at Saab.**
- **Use “black-box” optimizer, e.g., Levenberg-Marquardt least square.**
- **Solve scattering problem by Complex Field Integral Equation.**
Need many angles: $\Delta\theta < \lambda/(8d)$ for sufficient sampling



2D test problem - shape optimization

Reduce average σ in $[-\theta_m, \theta_m]$ and $[180^\circ - \theta_m, 180^\circ + \theta_m]$.

PEC boundary parametrized as a Fourier expansion for $r(\Theta)$:

$$r(\Theta) = 1 + \sum_{n=1}^{n_{\max}/2} \frac{c_{2n}}{(2n)^\alpha} \cos 2n\Theta.$$

EM solver uses integral formulation (Method of Moments).

α influences gradients in parameter space.

There are several local optima, i.e., **optimization problem is ill posed.**

Tikhonov regularization: add penalty term νR to goal function

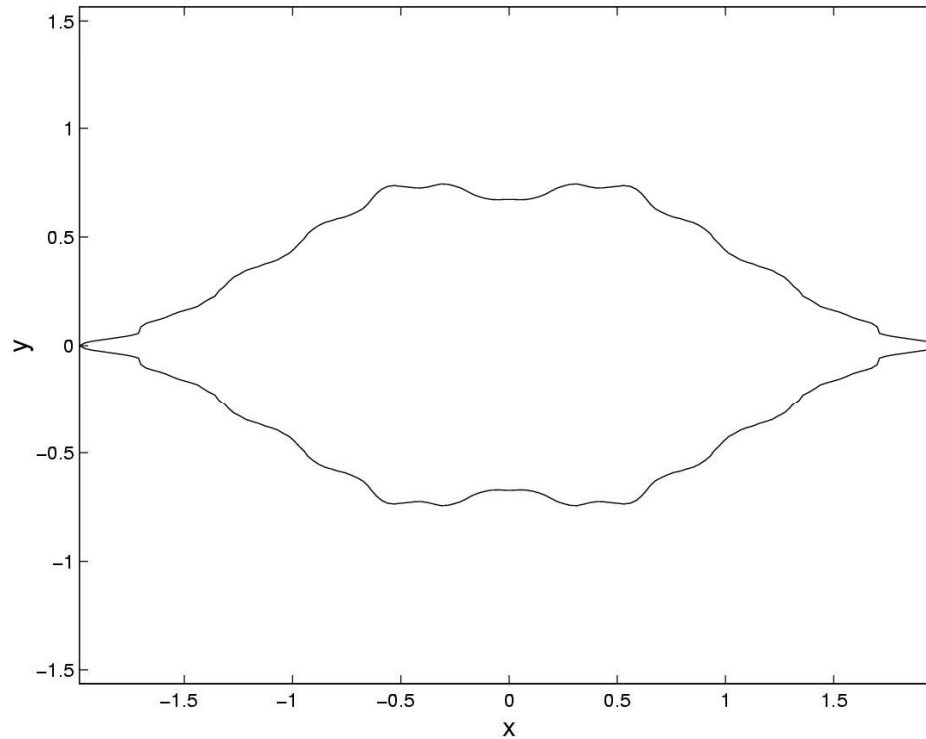
$$R = \frac{1}{\pi} \int_0^{2\pi} \left(\frac{\partial^2 r}{\partial \Theta^2} \right)^2 w_P(l) d\Theta$$

Regularized problem converges well to “nice” shapes for $\alpha \sim 0.5$

but the optimization problem is ill posed.



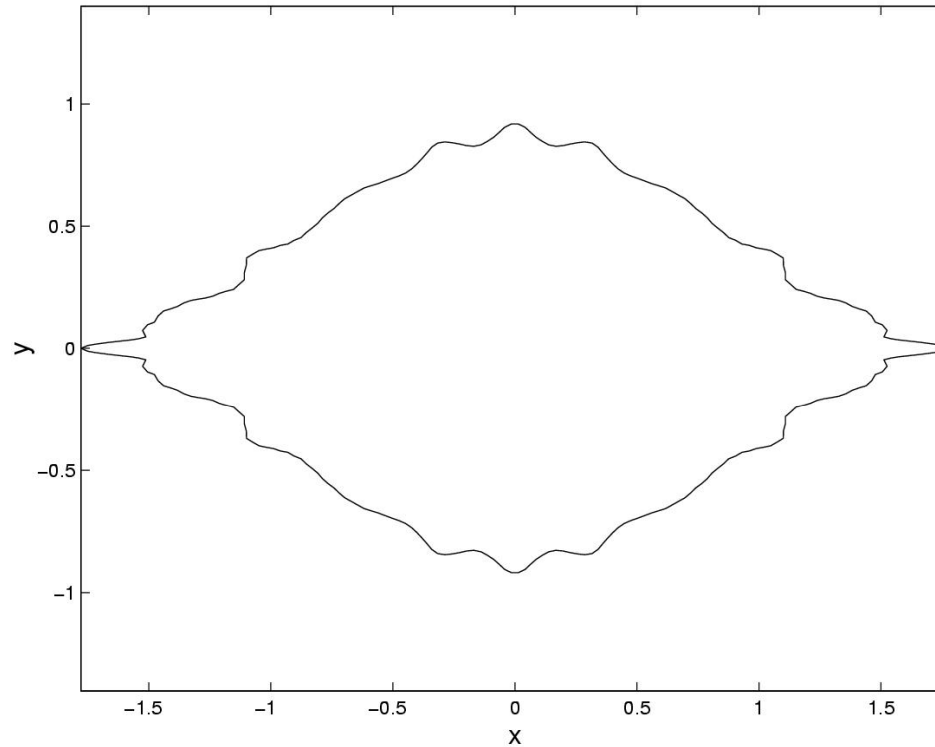
TE only, no penalty, $\theta_m = 45^\circ$



Optimized shape for TE without penalty has **corrugations**. The RCS in $[-45^\circ, 45^\circ]$ is reduced 400 times from a circle to $I_2^{\text{TE}}(\pi/4) = 0.00823$ and $I_2^{\text{TM}} = 0.213$.



TE + TM, no penalty, $\theta_m = 45^\circ$



Final shape of the combined TE and TM optimization without penalty.

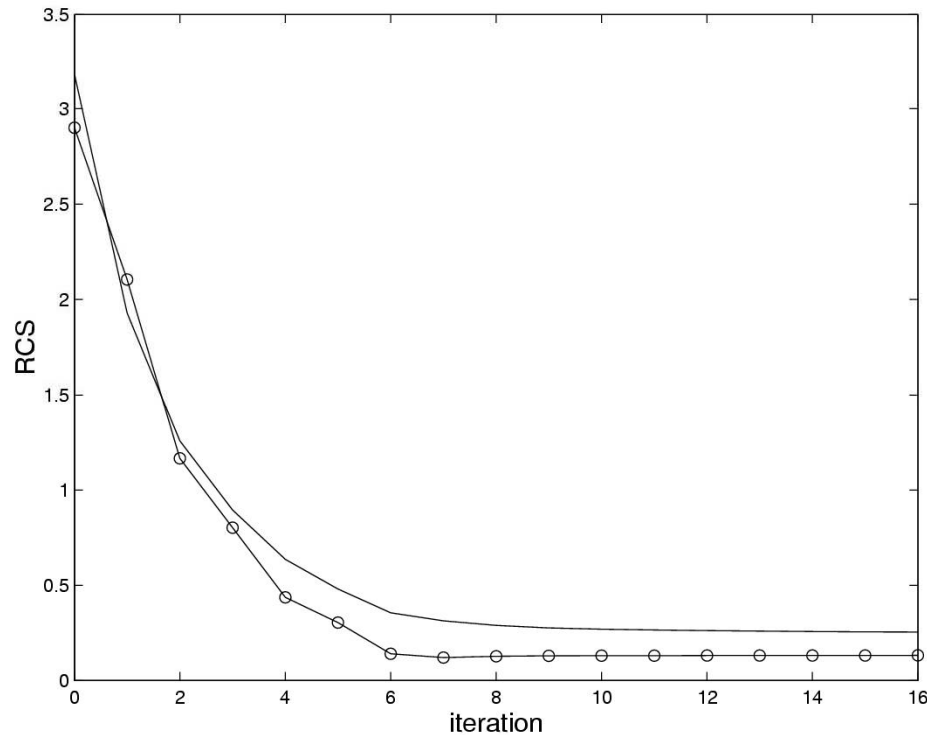
$$I_2^{\text{TE}} = 0.118$$

and $I_2^{\text{TM}} = 0.179$.

Optimized shape has corrugations and sharp tips.



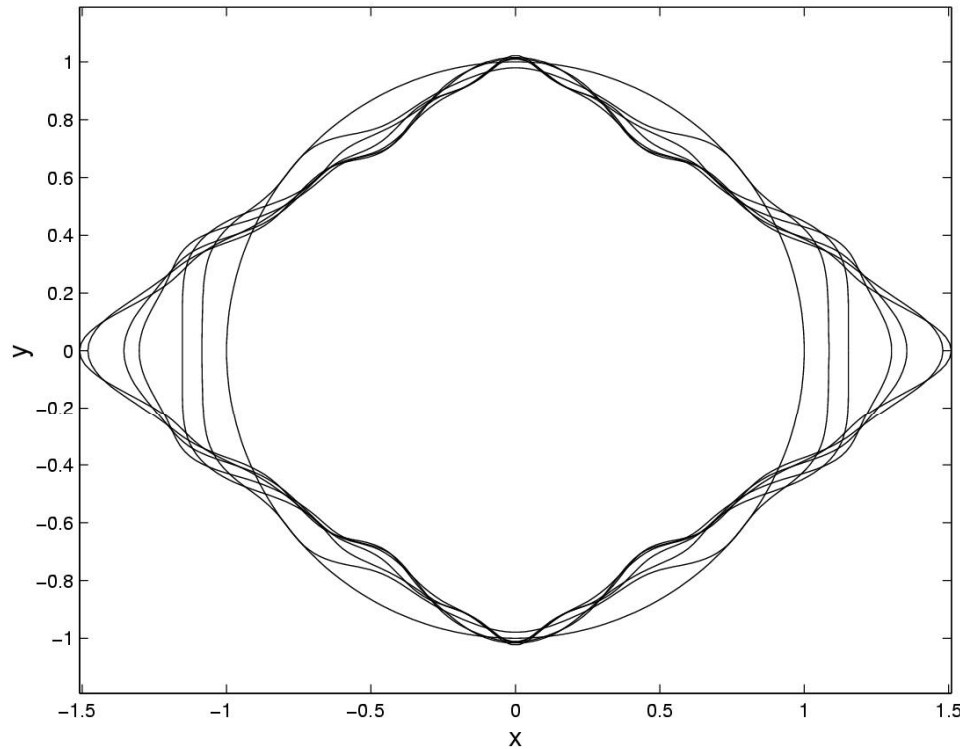
TE + TM, penalty except at the tips, $\theta_m = 45^\circ$



Evolution of the average RCS for TE (-o-) and TM (-) polarization in $|\theta| < 45^\circ$ when the optimized quantity is $I_1^{\text{TE}} + I_1^{\text{TM}} + 0.02R_2$, $\alpha = 0.5$, and the penalty is removed in regions of length 0.15λ from the tips. Convergence in ~ 6 iterations.



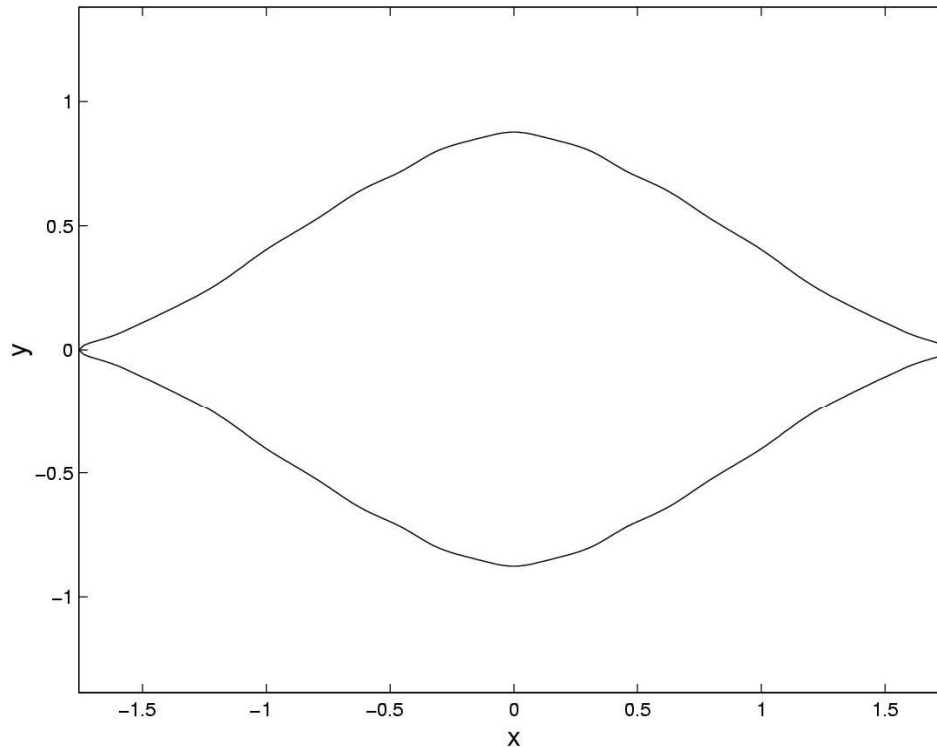
TE + TM, penalty except at the tips, $\theta_m = 45^\circ$



Six first shapes for combined TE and TM optimization with penalty. Radius of circle is two wavelengths



TE + TM, penalty except at the tips, $\theta_m = 45^\circ$



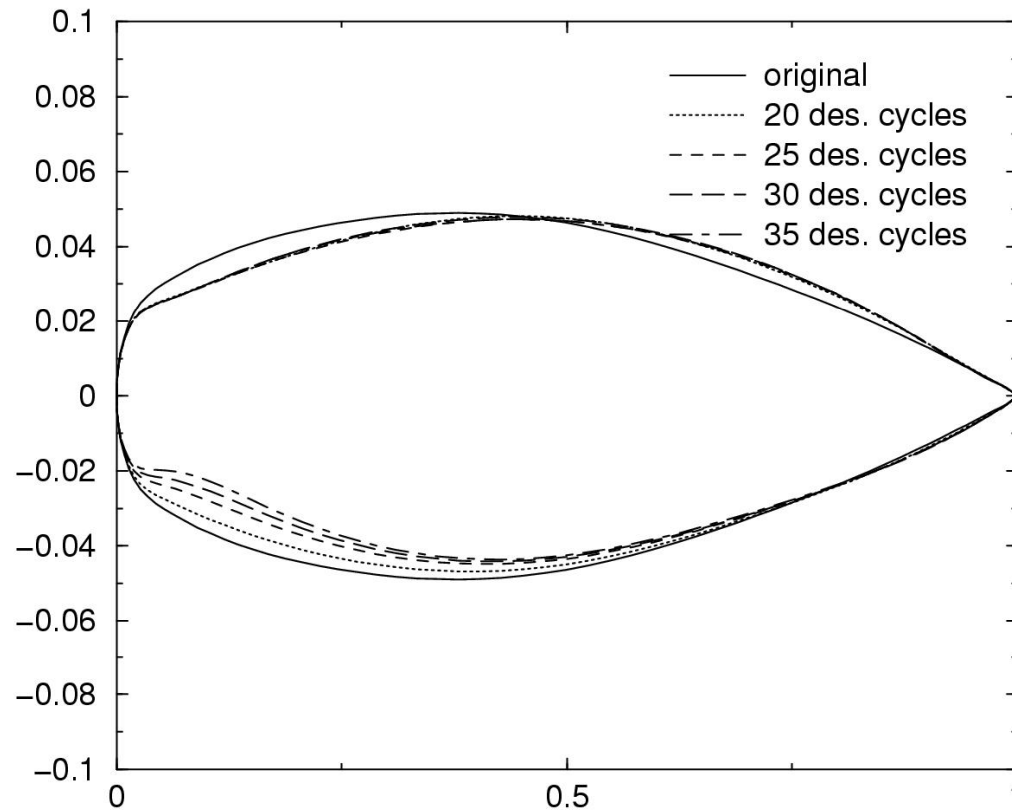
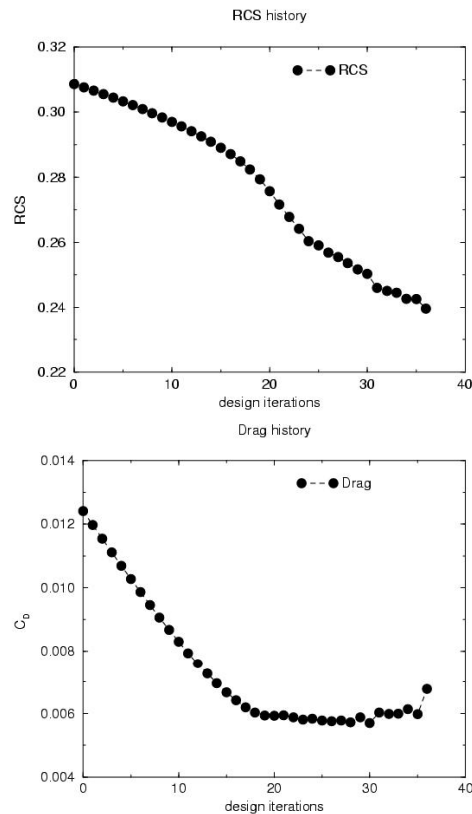
Shape optimized for TE and TM polarization with a penalty $0.02R_2$ with zero weighting within 0.15λ of the tips. $I_2^{\text{TE}} = 0.135$, $I_2^{\text{TM}} = 0.245$. Penalty has practically removed the corrugations.



Combined RCS + CFD optimization

Steepest descent. Lift fixed as a constraint. $y(x)$ modified with “bump functions”.

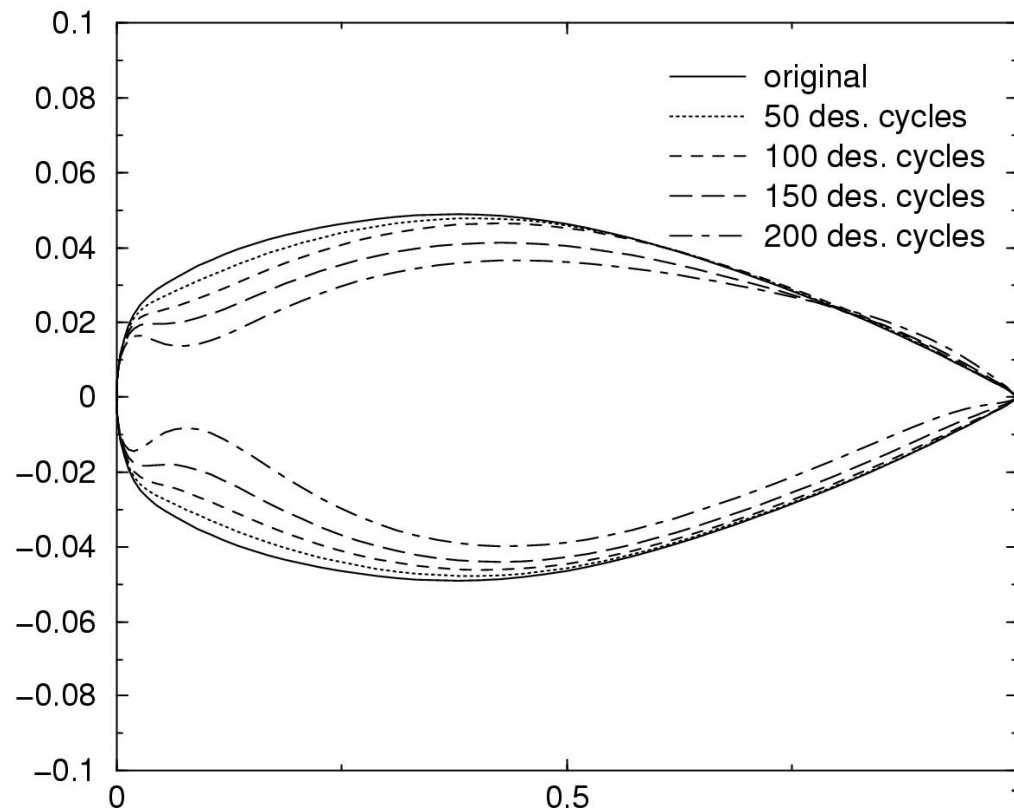
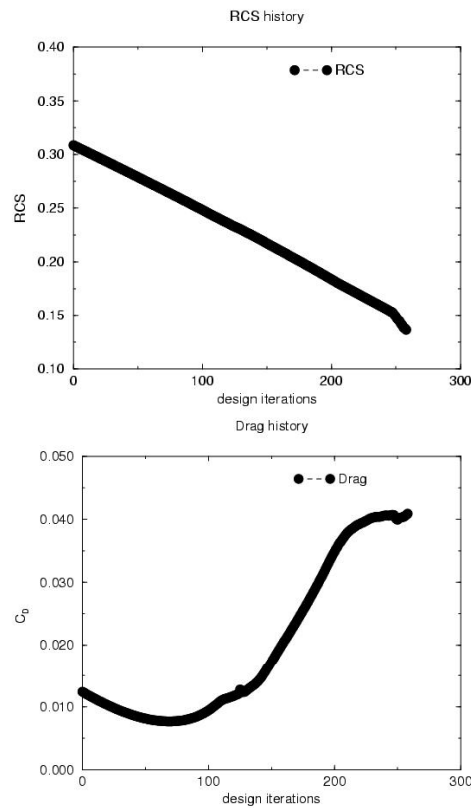
Goal function $0.1 \times \text{RCS} + 0.9 \times \text{drag}$.



Combined RCS + CFD optimization

Steepest descent. Lift fixed as a constraint. $y(x)$ modified with “bump functions”.

Goal function $0.8 \times \text{RCS} + 0.2 \times \text{drag}$.



Data assimilation in Bio Fluid Mechanics

joint work with

J. Lundvall, V. Kozlov and M. Karlsson
Linköping University



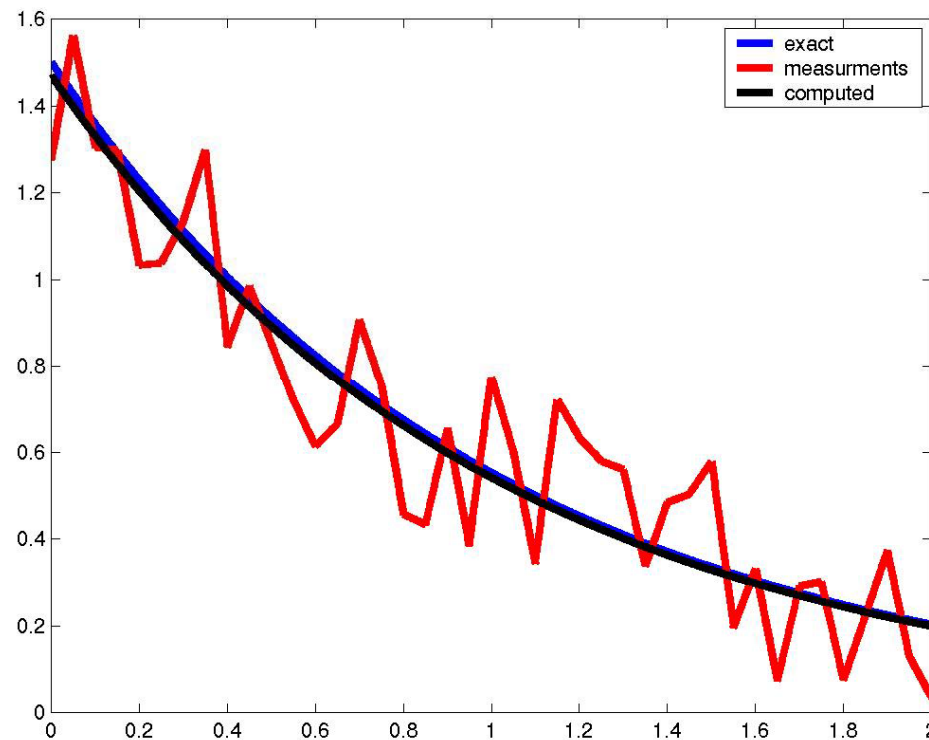
Data assimilation

Given: Sparse measured data in space and time including noise.

Objective: Compute data on a high resolution grid in space and time assuming that the physics is described by wellknown mathematical equations with an unknown initial condition.

Example:

$$y' + y = 0, y(0) = ?$$

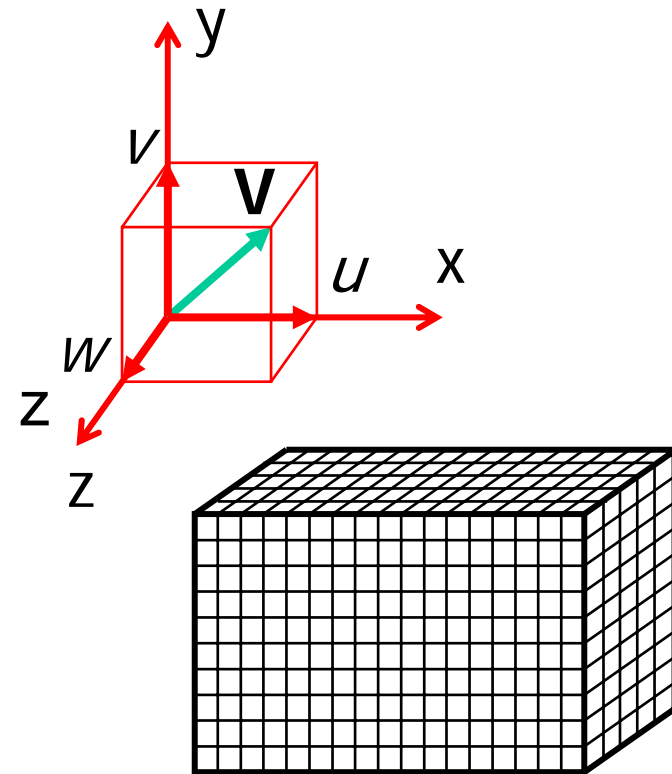


Example of application fields

- Meteorology, weather forecast
- **Medicine, MR measurements**
- Wind tunnel experiments



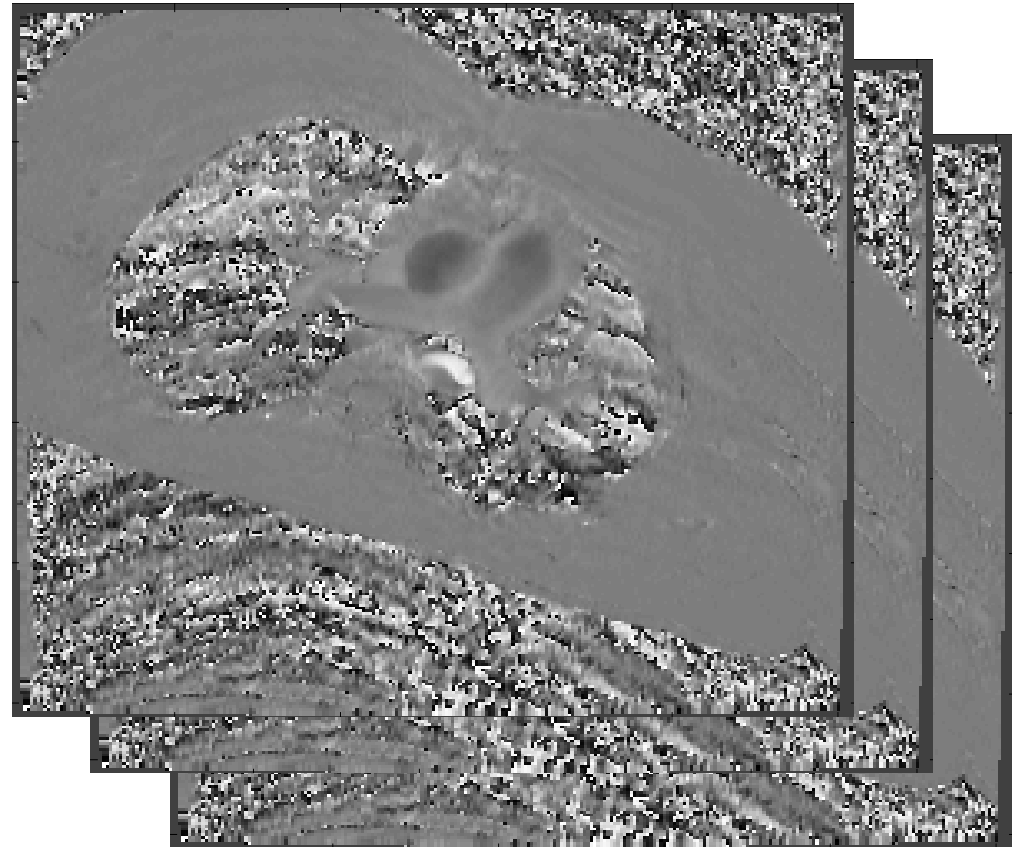
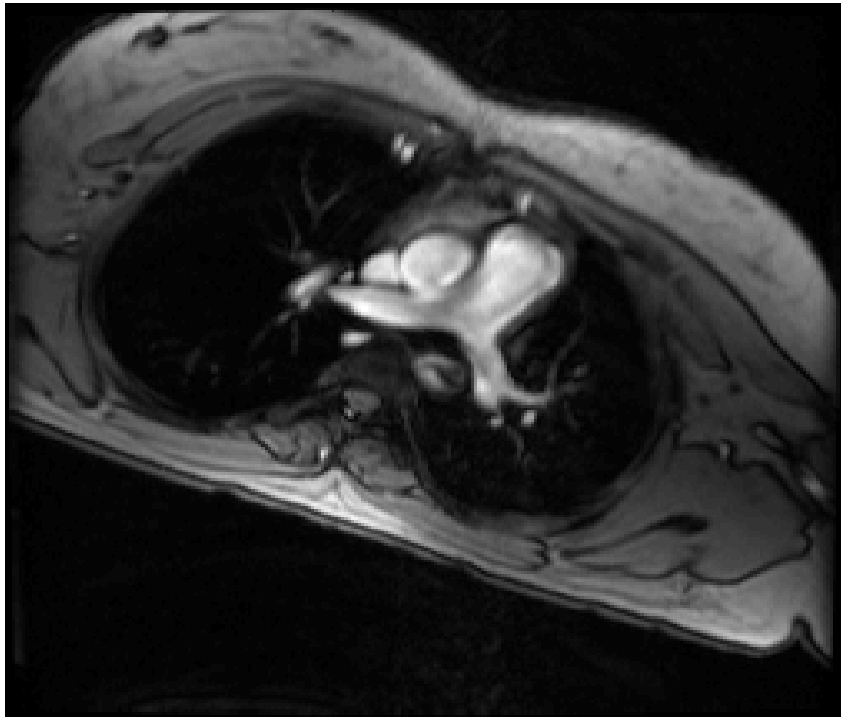
Velocity Measurement using MR camera



$$3D + T = 4D$$



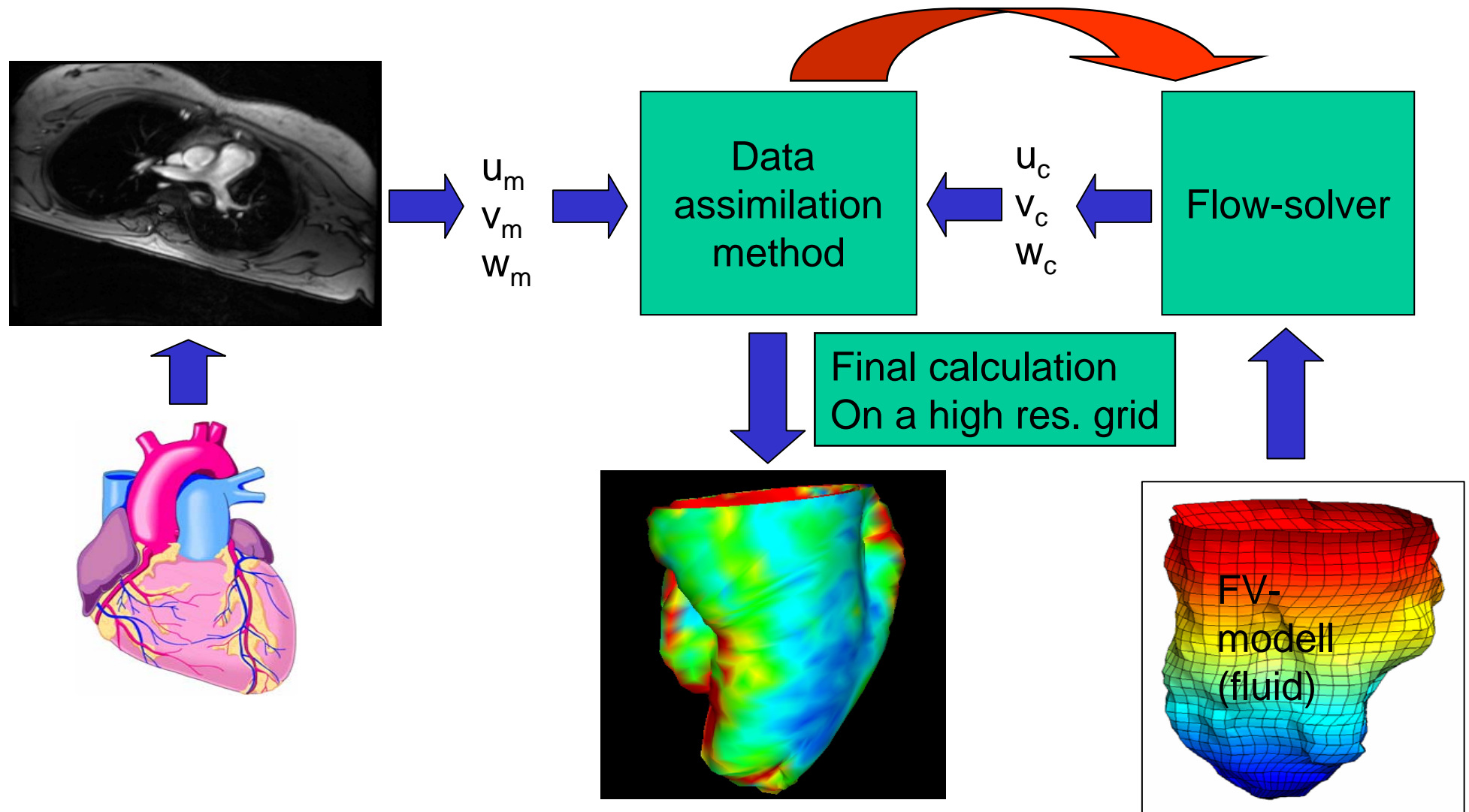
MR-data: Magnitude and Phase Images



MR Magnitude

Phase (velocity)

Reconstruction of velocity field from MR-data



Problem formulation

- measured data u^* is given
- assume that the physical model is known and described by a PDE
- the boundary conditions are given
- the initial condition is unknown and used as the control variable

$$Q_T = \Omega \times (0, T), \quad \min_{u_0} \|u - u^*\|_{L^2(Q_T)},$$

s.a. $P(u, \psi) = 0.$



Differential equation

$$\begin{aligned}\frac{\partial u}{\partial t} + \frac{\partial}{\partial x} F(u, u_x) &= 0, \\ u(x, t)|_{x \in \partial\Omega} &= 0, \\ u(x, 0) &= u_0(x).\end{aligned}$$

Weak formulation : $u \in X$ Is a weak solution if

$$-\int_{Q_T} (u\psi_t + F(u, u_x)\psi_x) dxdt + \int_{\Omega} (u(x, T)\psi(x, T) - u_0(x)\psi(x, 0)) dx = 0,$$

for all $\psi \in X'$.

↑
 $P(u, \psi) = 0$



Variational formulation

$$\begin{aligned} L(u) &= \frac{1}{2} \int_{Q_T} (u - u^*)^2 dx dt + P(u, \psi) \\ \delta L(u; \delta u_0) &= \int_{Q_T} (u - u^*) \delta u dx dt + \delta P(u, \psi) = \\ &= \int_{Q_T} \left(u - u^* - \frac{\partial \psi}{\partial t} - \frac{\partial F}{\partial u} \frac{\partial \psi}{\partial x} + \frac{\partial}{\partial x} \left(\frac{\partial F}{\partial u_x} \frac{\partial \psi}{\partial x} \right) \right) \delta u dx dt \\ &\quad + \int_{\Omega} (\psi(x, T) \delta u(x, T) - \psi(x, 0) \delta u_0(x)) dx \end{aligned}$$



Adjoint equations

$$\begin{aligned}\psi(x, T) &= 0, \\ \frac{\partial \psi}{\partial t} + \frac{\partial F}{\partial u} \frac{\partial \psi}{\partial x} - \frac{\partial}{\partial x} \left(\frac{\partial F}{\partial u_x} \frac{\partial \psi}{\partial x} \right) &= u - u^*, \\ \psi(x, t)|_{x \in \partial \Omega} &= 0\end{aligned}$$

$$\delta L = - \int_{\Omega} \psi(x, 0) \delta u_0 dx,$$

$$\delta u_0 = \alpha \psi(x, 0), \alpha > 0 \implies \delta L < 0.$$

Iteration: $u_0^{k+1} = u_0^k + \alpha \delta u_0^k.$



Existence of an optimal solution

- Ill posed problem
- No optimal solution exist in general
- Regularization necessary

$$u_0(x) = \sum_{m=1}^M c_m \phi_m(x).$$



Existence of an optimal solution

- $T : L^2(\Omega) \rightarrow L^2(Q_T), y = Tx.$
- Min. problem is equivalent to solving $\|y^\delta - Tx\| \leq \delta$, där $\|y^\delta - y\| \leq \delta.$
- T is a compact operator and the inverse problem is ill posed
- The previous iteration is equivalent to the Landweber regularization method for non linear inverse problems

$$x_{k+1}^\delta = x_k^\delta + T'(x_k^\delta)^*(y^\delta - Tx_k^\delta).$$

- The iteration converges to the true solution if $\delta \rightarrow 0$



Application: Viscous Burgers' equation

$$\frac{\partial u}{\partial t} + \frac{\partial}{\partial x} \left(\frac{1}{2} u^2 - \mu u_x \right) = 0, \quad \mu > 0.$$

- Adjoint equation

$$\frac{\partial \psi}{\partial t} + u \frac{\partial \psi}{\partial x} + \mu \frac{\partial^2 \psi}{\partial x^2} = u - u^*.$$

- Data voids: V denotes a void region in the (x,t) plane and m is def. according to

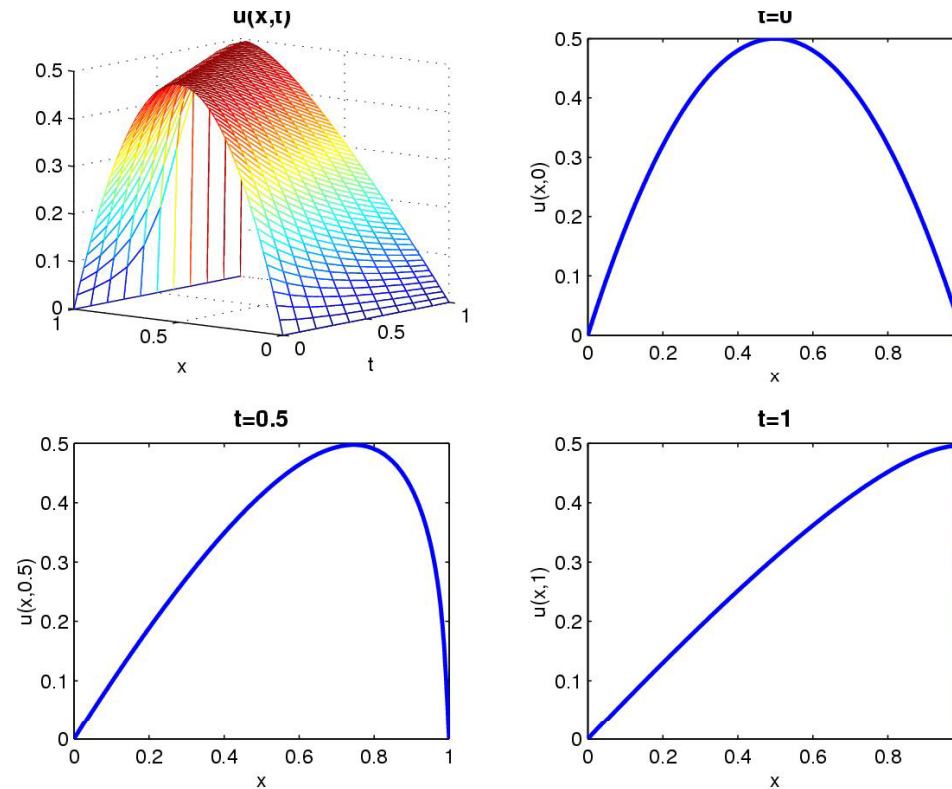
$$m(x, t) = \begin{cases} 0 & \text{om } (x, t) \in V, \\ 1 & \text{om } (x, t) \notin V. \end{cases}$$

- The adjoint equation

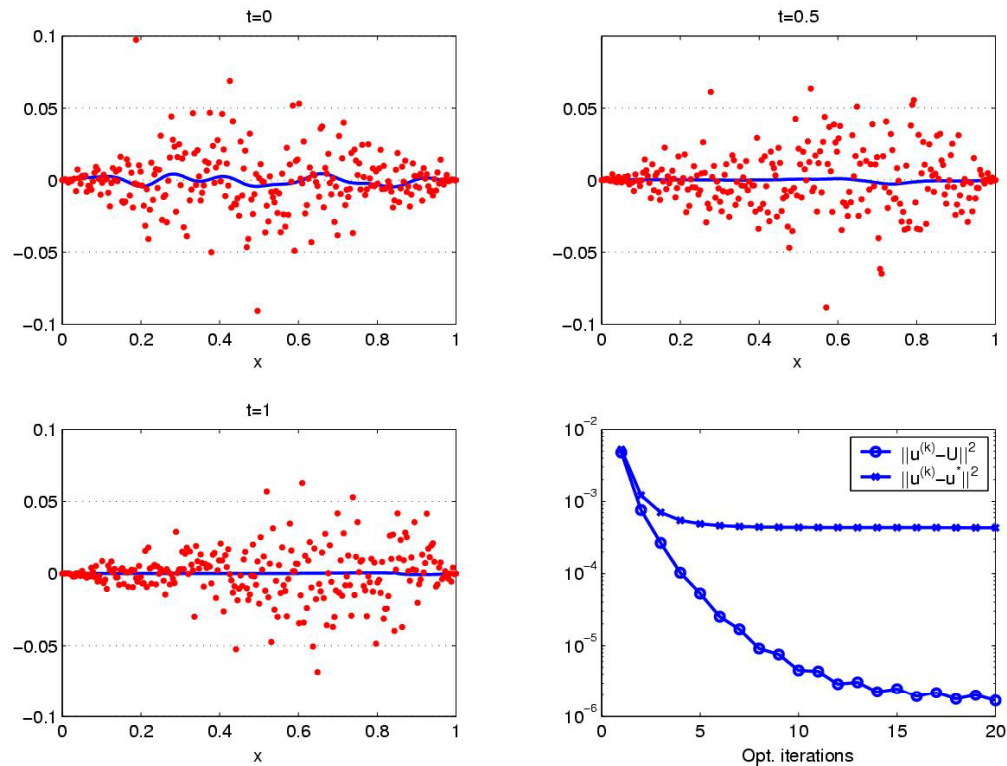
$$\frac{\partial \psi}{\partial t} + u \frac{\partial \psi}{\partial x} + \mu \frac{\partial^2 \psi}{\partial x^2} = m(x, t)(u - u^*).$$



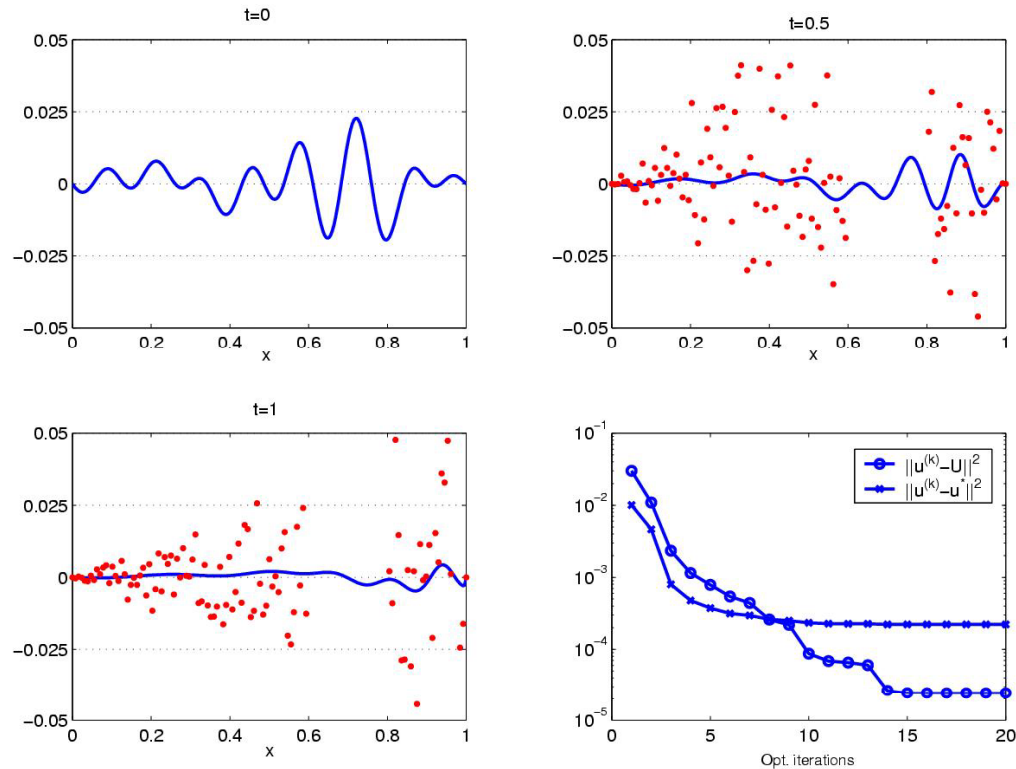
"Exact" solution



Example 1: Noise data



Example 2: Noise and void data



Summary and conclusions

- Optimization technique coupled to PDE:s have been presented.
- The optimization gradients are computed from the continuous governing equations and corresponding adjoint equations.
- The optimization technique has been successfully applied to three different problems:
 - Aerodynamic shape optimization
 - Electromagnetic RCS optimization
 - Data assimilation in Bio Fluid Dynamics







Summary and conclusions

- An efficient gradient based optimization technique which can handle large number of design variables.
- Gradients are computed from Euler and Adjoint Euler calc.
- Good agreement with finite difference gradient calculations.
- Applied to realistic 3D aircraft configurations such as the SCT.
- The drag was reduced by 9.5% without thickness modifications and by 16% with thickness modifications.
- Lift and pitching moment was not changed.



Conclusions

- **Gradient method with adjoint solution developed for RCS reduction.**
- **Both shape and materials optimization in 2D work well.**
- **Far more efficient than evolutionary methods.**
- **Optimization problems generally ill-posed, but can be regularized.**
- **Conflicting demands of RCS reduction and aerodynamics on PEC shape can be resolved by using absorbing materials.**
- **Gradient method will be tested on moderate-sized 3D problems solved with Multipole code developed at Uppsala University (Nilsson & Lötstedt).**
- **Method potentially useful in many microwave applications.**



Aerodynamic Shape Optimisation

- Background
- Optimization technique
- The optimization system **cadso**s at SAAB
- Example: Aerodynamic shape optimization of a SCT Aircraft
- Description of the SCT geometry and grid generation
- Aerodynamic shape optimization of the SCT geometry
- Formulation of the optimization problem
- Gradient validation
- Optimization results

