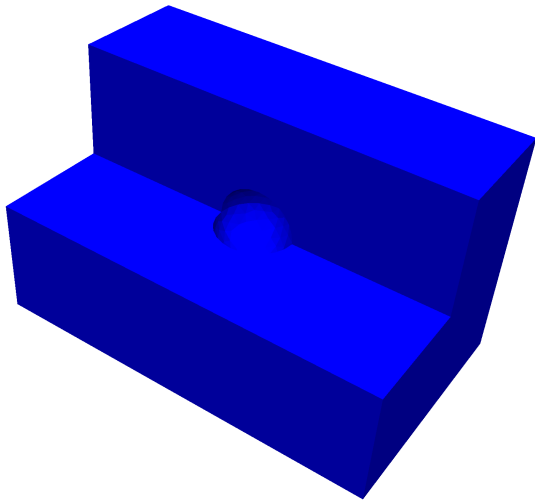


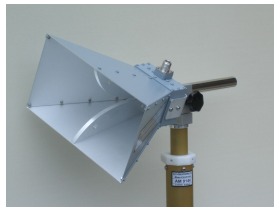
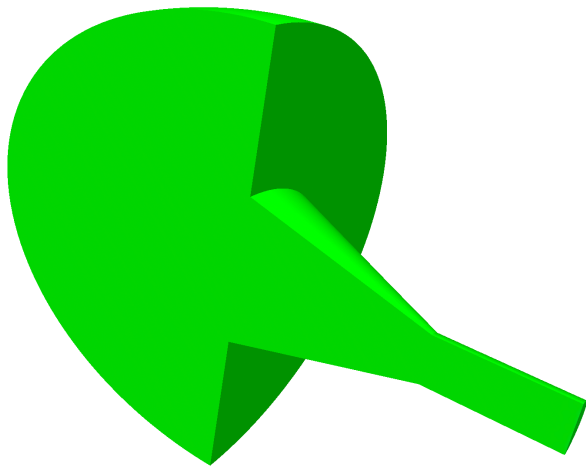
Non-Smooth Geometric Inverse Problems

Stephan Schmidt

25 June 2018

Maxwell Scattering Problem (joint with M. Schütte, O. Ebel, A. Walther)





- General problem formulation allows treatment of general problems
- Design of acoustic (linear wave) horn antenna, $3.5 \cdot 10^9$ unknowns!

Generalized Problem

$$\min_{(\varphi, \Gamma_{\text{inc}})} J(\varphi, \Omega) := \frac{1}{2} \int_0^T \int_{\Gamma_{i/o}} \|B(n)(\varphi - \varphi_{\text{meas}})\|_2^2 dt ds + \delta \int_{\Gamma_{\text{inc}}} 1 ds$$

subject to

$$\dot{\varphi} + \operatorname{div} F(\varphi) = 0 \quad \text{in } \Omega$$

$$\text{BCs} = g \quad \text{on } \Gamma$$

Acoustics:

$$\frac{\partial u}{\partial t} + \nabla p = 0 \quad \text{in } \Omega,$$

$$\frac{\partial p}{\partial t} + c^2 \operatorname{div} u = 0 \quad \text{in } \Omega,$$

$$\frac{1}{2}(p - c\langle u, n \rangle) = g \quad \text{on } \Gamma_{i/o}$$

Electromagnetism:

$$\mu \frac{\partial H}{\partial t} = -\nabla \times E \quad \text{in } \Omega,$$

$$\varepsilon \frac{\partial E}{\partial t} = \nabla \times H - \sigma E \quad \text{in } \Omega,$$

$$\text{BCs} = g \quad \text{on } \Gamma_{i/o}$$

Minimize Aerodynamic Drag

$$\min_{(U, \Omega)} J(U, \Omega) := \frac{1}{C_\infty} \int_{\Gamma_W} (\rho n - \tau n) \cdot \psi \, ds$$

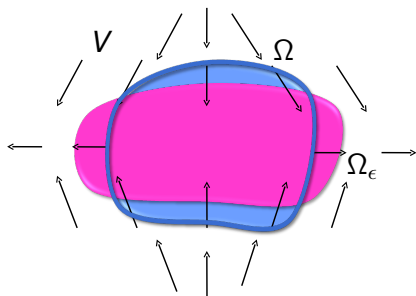
subject to

$$0 = -(\mathcal{F}^c(\mathbf{u}) - \mathcal{F}^v(\mathbf{u}, \nabla \mathbf{u}), \nabla \mathbf{v})_\Omega \\ + (n \cdot (\mathcal{F}^c(\mathbf{u}) - \mathcal{F}^v(\mathbf{u}, \nabla \mathbf{u})), \mathbf{v})_\Gamma \quad \forall \mathbf{v} \in \mathcal{H}$$

Additional essential boundary conditions (Sonntag, S., Gauger, 2015)

- Conserved variables: $\mathbf{u} = (\rho, \rho u_1, \rho u_2, \rho u_3, \rho E)^T$
- Primitive variables: $U = (\rho, u_1, u_2, u_3, p)^T$
- Perfect gas: $p = (\gamma - 1)\rho(E - \frac{1}{2}(u_1^2 + u_2^2 + u_3^2))$

Introduction to Shape Optimization



- Directional Derivative

$$dJ(\Omega)[V] := \lim_{\epsilon \rightarrow 0^+} \frac{J(\Omega_\epsilon) - J(\Omega)}{\epsilon}$$

- Shape is modeled by set Ω
- $\Omega_\epsilon := \{x + \epsilon V(x) : x \in \Omega\}$
- $J : \mathcal{P}(\Omega) \supseteq \mathcal{D} \rightarrow \mathbb{R}$: target function
- (Directional) derivative of J with respect to Ω ?

The Shape Derivative

- Objective function:

$$J_1(\epsilon, \Omega) := \int_{\Omega(\epsilon)} f(\epsilon, x_\epsilon) \, dx_\epsilon \quad \text{or} \quad J_2(\epsilon, \Omega) := \int_{\Gamma(\epsilon)} g(\epsilon, s_\epsilon) \, ds_\epsilon$$

- Take Limit:

$$dJ_1(\Omega)[V] = \left. \frac{d}{d\epsilon} \right|_{\epsilon=0} \int_{\Omega(\epsilon)} f(\epsilon, x_\epsilon) \, dx_\epsilon \quad \text{or} \quad dJ_2(\Omega)[V] = \left. \frac{d}{d\epsilon} \right|_{\epsilon=0} \int_{\Gamma(\epsilon)} g(\epsilon, s_\epsilon) \, ds_\epsilon$$

- Change of Variables = Change in Domain

$$dJ_1(\Omega)[V] = \int_{\Omega} \left. \frac{d}{d\epsilon} \right|_{\epsilon=0} \left[f(T_\epsilon(x)) \cdot |\det DT_\epsilon(x)| \right] + f'(x)[V] \, dx$$

$$dJ_2(\Omega)[V] = \int_{\Gamma} \left. \frac{d}{d\epsilon} \right|_{\epsilon=0} \left[g(T_\epsilon(s)) \cdot |\det DT_\epsilon(s)| \| (DT_\epsilon(s))^{-T} n(s) \|_2 \right] + g'(s)[V] \, ds$$

- Local / Shape Derivative: $f'(x)[V] := \frac{\partial}{\partial \epsilon} f(0, x)$

The Shape Derivative (Weak vs Strong)

- Differentiate

$$\begin{aligned}dJ_1(\Omega)[V] &= \int_{\Omega} \operatorname{div}(fV) + f'[V] \, dx \\ &= \int_{\Gamma} \langle V, n \rangle f \, ds + \int_{\Omega} f'[V] \, dx \\ &= \int_{\Omega} f \operatorname{div} V + df[V] \, dx \quad (\text{Berggren, 2010}) \\ dJ_2(\Omega)[V] &= \int_{\Gamma} (\nabla g, V) + g \operatorname{div}_{\Gamma} V(s) + g'[V] \, ds = \int_{\Gamma} \operatorname{div}_{\Gamma}(gV) + g'[V] \, ds \\ &= \int_{\Gamma} \langle V, n \rangle \left[\frac{\partial g}{\partial n} + \kappa g \right] + g'[V] \, ds \\ &= \int_{\Gamma} g \operatorname{div}_{\Gamma} V + dg[V] \, ds\end{aligned}$$

- Material Derivative: $df = \langle \nabla f, V \rangle + f'[V]$

Dido's Problem

Find shape of maximum volume for given surface:

$$\max_{\Omega} J(\Omega) := \int_{\Omega} 1 \, dx$$

s.t.

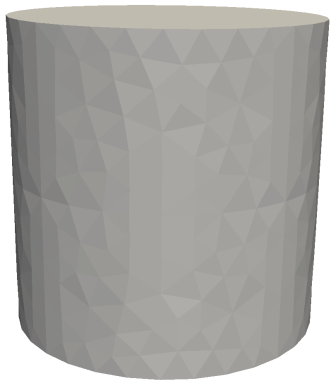
$$\int_{\Gamma} 1 \, ds = A_0$$

Lagrangian:

$$F(\Omega, \lambda) = \int_{\Omega} -1 \, dx + \lambda \left(\int_{\Gamma} 1 \, ds - A_0 \right)$$
$$dF(\Omega, \lambda)[V] = \int_{\Gamma} \langle V, n \rangle [-1 + \lambda \kappa] \, ds \stackrel{!}{=} 0 \quad \forall V$$

Because $\lambda \in \mathbb{R}$: $\kappa = \frac{1}{\lambda} \in \mathbb{R}$. Thus, curvature constant!
Optimality fulfilled by sphere!!

Dido's Problem (Gradient Descent + Newton)



Non-Smoothness and Discretizations

Elongate Unit Cube by Stretching: $V = (0, 0, x_3)^T$

- The Naive Way:

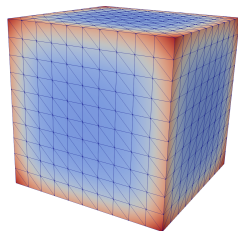
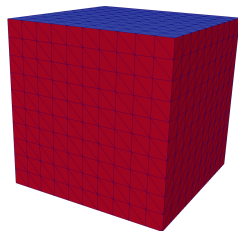
$$A(V) = 4(1(1 + v_3)) + 2 = 6 + 4v_3$$
$$\Rightarrow \frac{\partial A(V)}{\partial v_3} = 4$$

- The Weak Way:

$$dA[V] = \int_{\Gamma} \operatorname{div}_{\Gamma} V \, dS = \int_{\bigcup_{i=1}^4 S_i} 1 \, dS = 4$$

- The Strong Way:

$$dA[V] = \int_{\Gamma} \langle V, n \rangle_{\kappa} \, dS = 4.133872$$



Shape Linearization of General Conservation Law

Find $\varphi'[V]$ such that

$$\begin{aligned} 0 &= \int_0^T \int_{\Gamma} \langle V, n \rangle [\langle \lambda, \dot{\varphi} \rangle - \langle F(\varphi), \nabla \lambda \rangle] \, d s \, d t \\ &+ \int_0^T \int_{\Gamma} \langle V, n \rangle [\langle \nabla(\lambda \cdot F_b^*(\varphi, n)), n \rangle \\ &\quad + \kappa (\lambda \cdot F_b^*(\varphi, n) - D_n(\lambda \cdot F_b^*(\varphi, n)) \cdot n) + \operatorname{div}_{\Gamma} (D_n^T(\lambda \cdot F_b^*(\varphi, n)))] \, d s \, d t \\ &+ \int_0^T \int_{\Omega} \langle \lambda, \dot{\varphi}'[V] \rangle - \langle DF(\varphi)\varphi'[V], \nabla \lambda \rangle \, d x \, d t \\ &+ \int_0^T \int_{\Gamma} \langle \lambda, D_{\varphi} F_b^*(\varphi, n)\varphi'[V] \rangle \, d s \, d t \end{aligned}$$

Adjoint Equation

Adjoint equation can be read from the shape-linearized equation: Find λ such that

$$\begin{aligned} 0 &= \int_0^T \int_{\Omega} \langle -\dot{\lambda}, \varphi'[V] \rangle - \langle \varphi'[V], D^T F(\varphi) \nabla \lambda \rangle \, dx \, dt \\ &+ \int_0^T \int_{\Gamma} \langle \varphi'[V], D_{\varphi}^T F_b^*(\varphi, n) \cdot \lambda \rangle \, ds \, dt \\ &+ \int_0^T \int_{\Gamma_{i/o}} \langle B^T(n) B(n) \cdot (\varphi - \varphi_{\text{meas}}), \varphi'[V] \rangle \, ds \, dt \end{aligned}$$

\Rightarrow Flux for adjoint can be read: $D_{\varphi}^T F^*(\varphi, n) \cdot \lambda$

Shape Derivative for Tomography Problems

Maxwell (Existence Results: Cagnol/ Eller/Marmorat/Zolésio):

$$\begin{aligned} & dJ(H, E, \Omega)[V] \\ &= \int_0^T \int_{\Gamma_{\text{inc}}} \langle V, n \rangle \left[\langle \lambda_H, \dot{H} \rangle + \frac{1}{\mu} \langle E, \text{curl } \lambda_H \rangle + \langle \lambda_E, \dot{E} \rangle - \frac{1}{\epsilon} \langle H, \text{curl } \lambda_E \rangle + \frac{\sigma}{\epsilon} \langle \lambda_E, E \rangle \right] ds dt \\ &+ \int_0^T \int_{\Gamma_{\text{inc}}} \langle V, n \rangle \text{div} (Zc(H \times \lambda_E)) ds dt \end{aligned}$$

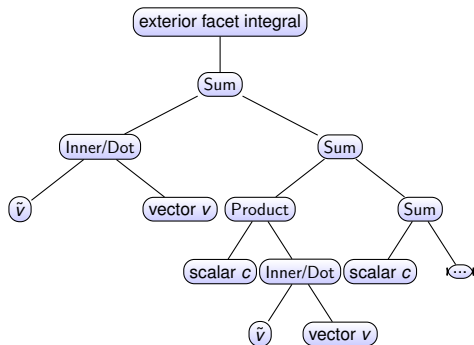
Horn/Linear Wave:

$$\begin{aligned} dJ(u, p, \Omega)[V] &= \int_0^T \int_{\Gamma_{\text{horn}}} \langle V, n \rangle \left[\langle \lambda_u, \dot{u} \rangle - p \text{div } \lambda_u + \lambda_p \dot{p} - c^2 \langle u, \nabla \lambda_p \rangle \right] ds dt \\ &+ \int_0^T \int_{\Gamma_{\text{horn}}} \langle V, n \rangle \text{div} (c^2 \lambda_p \cdot u) ds dt \end{aligned}$$

“Backwards in time” Adjoint Equations for (λ_H, λ_E) and (λ_u, λ_p)

Actual Code in FEniCS/Python

```
U = VectorFunctionSpace(mesh, "CG", 1)
P = FunctionSpace(mesh, "CG", 1)
H = U*P
(u,p) = TrialFunction(H)
(v,q) = TestFunction(H)
u_old = project(Constant((0.0,0.0,0.0)), U)
p_old = project(Constant(0.0), P)
DeltaT = 0.1; c = 345.0
t = 0.0
a = inner(v, (u-u_old)/DeltaT) + p*div(v))*dx
a += inner(q*(p-p_old)/DeltaT - c*c*inner(u, grad(q)))*dx
...
q = Function(H)
while t < 60:
    solve(lhs(a) == rhs(a), q)
    (u,p) = split(q)
    t = t + DeltaT
J=Functional(((p+c*dot(u,n))**2)*0.5*ds(3)*dt)
for (adj,var) in compute_adjoint(J, forget=False):
    ...
```



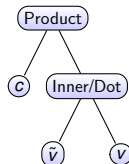
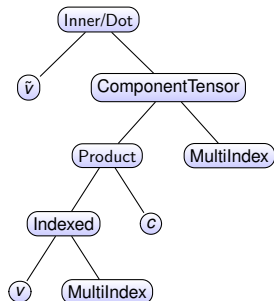
- Change expression into “maximally expanded form”
- Sort all sums closest to integral
- Apply rules to each sub-branch
- Pattern Recognition Problems
- Argument UFL derivatives in dolfin-adjoint/pyadjoint with release 2018.1

Freely Available: www.bitbucket.org/Epoxid/femorph

Pattern Recognition Problems

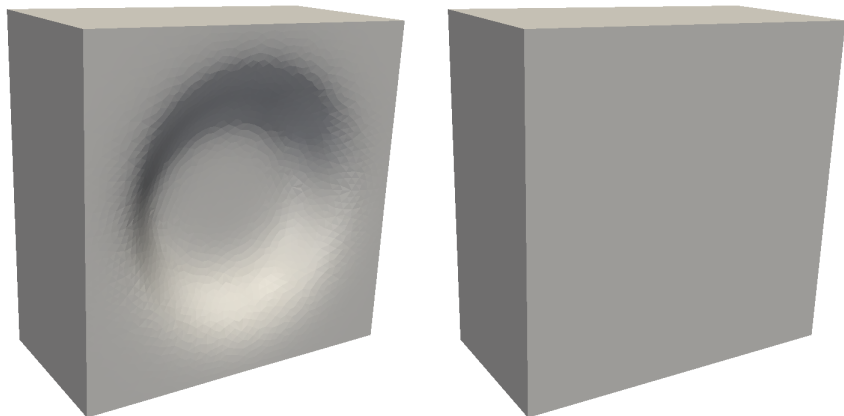
$$\langle c \cdot v, \tilde{v} \rangle = c \langle v, \tilde{v} \rangle,$$

$$\langle v, A\tilde{v} \rangle = \langle A^T v, \tilde{v} \rangle$$



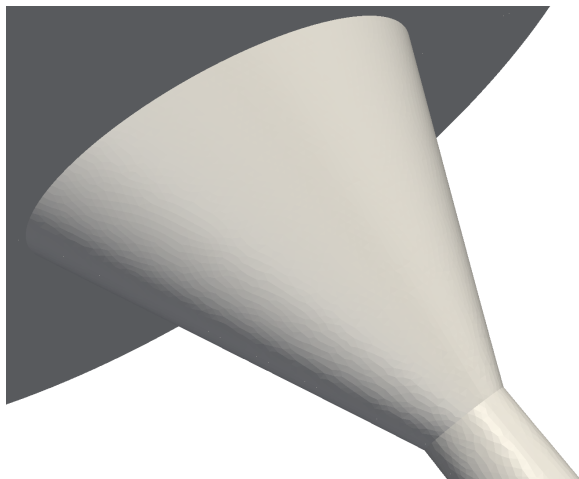
- Two UFL-Representations of the same expression
- Apply Shape Differentiation Rules on either:
 - Left: Ideal for Div-Theorem
 - Right: Human readability, $(DV)^T W = 0$, etc...

Obstacle Without Antenna



- 4.1 – 12.3 Ghz SINC-puls
- 2.4 – 7.3 cm waves, 3.65 cm obstacle
- (time with dolfin-adjoint/pyadjoint integration soon, 2018.1)

Optimal Emitter for Acoustics

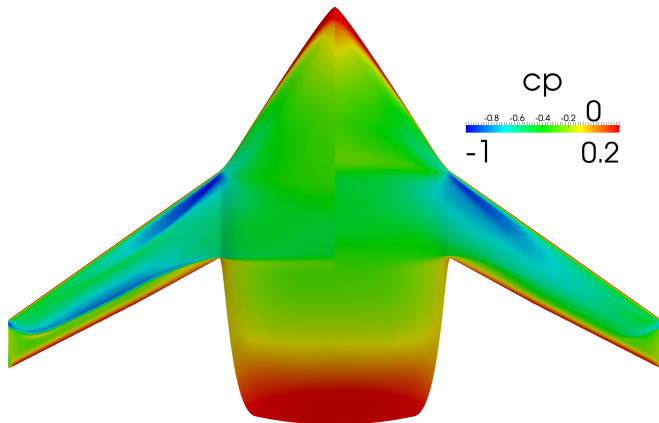


Boundary Data Compression:

$3.5 \cdot 10^9$ unknowns: 26 TB to 3.26 GB, 3 Months on 48 CPUs

(S., Wadbro, Berggren, 2016)

3D Euler Flow: VELA



Shape	C_D	%	C_L	%
460,517	$3.342 \cdot 10^{-3}$	-30.06%	$1.775 \cdot 10^{-1}$	-0.67%

(S., Ilic, Schulz, Gauger 2013)

Model Problem: Incompressible Navier–Stokes

$$\min_{(u,p,\Omega)} E_{NS}(u,p,\Omega) := \frac{1}{2} \int_{\Omega} \mu \sum_{j,k=1}^3 \left(\frac{\partial u_k}{\partial x_j} \right)^2 dA$$

subject to

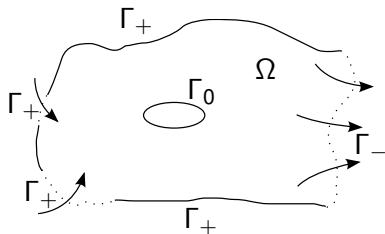
$$-\mu \Delta u + \rho u \nabla u + \nabla p = 0 \quad \text{in } \Omega$$

$$\operatorname{div} u = 0$$

$$u = u_+ \quad \text{on } \Gamma_+$$

$$u = 0 \quad \text{on } \Gamma_0$$

$$\rho n - \mu \frac{\partial u}{\partial n} = 0 \quad \text{on } \Gamma_-$$



Weak/Volume/Material form of Shape Derivative:

$$dJ_1[V] = \int_{\Omega} f \operatorname{div} V + \langle \nabla f, V \rangle + f'[V] \, dx = \int_{\Omega} f \operatorname{div} V + df[V] \, dx$$

Material derivative $df[V]$ does not commute with differentiation:

- Jacobian / Gradient:

$$d(Df)[V] = Ddf[V] - DfDV$$

- Divergence:

$$d(\operatorname{div} u)[V] = \operatorname{div} du[V] - \operatorname{tr}(Du \cdot DV)$$

- Tangent-Divergence:

$$\operatorname{div}_{\Gamma} u = \operatorname{div} u - \langle DVn, n \rangle, \quad dn[V] \text{ as above}$$

Weak Shape Hessians

Strategy:

Use adjoint approach to eliminate material derivatives du , not u'

Result:

$$d^2 J_1[V, W] = \int_{\Omega} f \operatorname{div} V \operatorname{div} W + df[V] \operatorname{div} W + df[W] \operatorname{div} V - f \operatorname{tr}(DVDW) + d^2 f[V, W] \, dx$$

$$\begin{aligned} & d^2 J_2[V, W] \\ = & \int_{\Gamma} g \operatorname{div}_{\Gamma} V \operatorname{div}_{\Gamma} W + df[V] \operatorname{div}_{\Gamma} W + df[W] \operatorname{div}_{\Gamma} V - f \operatorname{tr}(DVDW) + d^2 g[V, W] \\ & + g \left(\langle (DV)^T n, DWn \rangle + \langle DVn, (DW)^T n \rangle + \langle (DW)^T n, (DV)^T n \rangle - 2 \langle DVn, n \rangle \langle DWn, n \rangle \right) \end{aligned}$$

↪ Excessively long expressions with normal, curvature or PDEs

↪ Automatic generation!!

Regularization, Approximate Newton, H^1 -Descent

So far: No consideration of the regularization term $R(\Gamma)$.

Standard Choice:

$$R(\Gamma) = \int_{\Gamma} 1 \, d\mathbf{s}$$

Then:

$$dR(\Gamma)[V] = \int_{\Gamma} \langle V, n \rangle \kappa \, d\mathbf{s}$$

$$d^2R(\Gamma)[V, W] = \int_{\Gamma} \langle \nabla_{\Gamma} \langle V, n \rangle, \nabla_{\Gamma} \langle W, n \rangle \rangle + \langle V, n \rangle \langle W, n \rangle \kappa^2 \, d\mathbf{s}$$

Shape-descent in H^1 / Sobolev Gradient Method / Approximate Newton can all be motivated by surface area penalization!

Descent Direction:

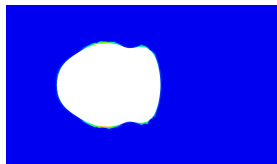
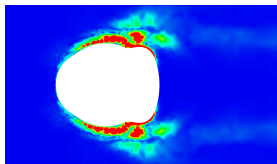
- Volume Hessian has large Kernel!
- Solve during each optimization step: Find W , such that

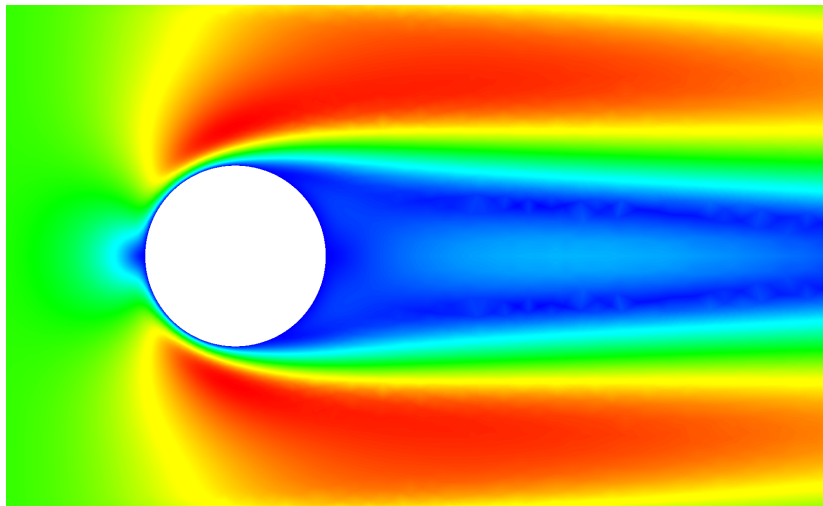
$$KKT(V, W, \dots) + \langle V, W \rangle_{\Omega} + 0.1 \langle \nabla V, \nabla W \rangle_{\Omega} = dL(V, \dots)$$

- UFL-Testfunction: V , UFL-Trialfunction W
- KKT and dL generated automatically

Mesh Defo:

- Boundary trace of W as Dirichlet BC in Laplace mesh deformation
- Inexact PDE \Rightarrow Spurious volume movement (One Shot)





The Regularization Term

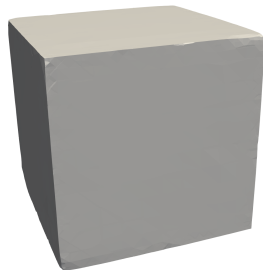
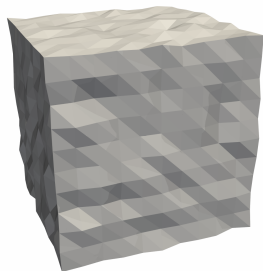
Geometric Inverse Problems:

$$\min_{(\varphi, \Gamma_{\text{inc}})} \frac{1}{2} \int_{\Gamma_{\text{in}}} \int_{t_0}^{t_f} \|(\varphi - f)\|^2 dt dS + \beta R(\Gamma)$$

subject to

$$\begin{aligned} \dot{\varphi} + \operatorname{div} F(\varphi) &= 0 & \text{in } \Omega \\ \text{BCs} &= g & \text{on } \Gamma \end{aligned}$$

- Scanning pulse g
- f given measurement data
- Previously:
 - R surface area = Laplace Smoothing
- **Idea:** Regularization to favor kinks
- **Idea:** Total Variation of Normal!



- Let's start with functions on surfaces:

$$\min_{u \in BV(S)} \frac{1}{2} \int_S |Ku - f|^2 ds + \frac{\alpha}{2} \int_S |u|^2 ds + \beta \int_S |\nabla u|$$

- Denoising: $K = Id$, Noisy Texture: f , Denoised Texture: u
- $S \subset \mathbb{R}^3$ is a smooth, compact, orientable and connected surface without boundary
- A function $u \in L^1(S)$ belongs to $BV(S)$ if the TV-seminorm defined by

$$\int_S |\nabla u| = \sup \left\{ \int_S u \operatorname{div} \eta ds : \eta \in \mathbf{V} \right\}$$

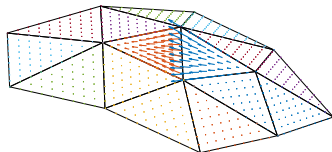
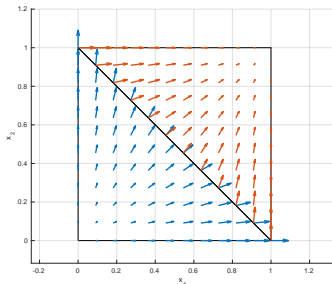
is finite, where $\mathbf{V} = \{ \eta \in \mathbf{C}_c^\infty(\operatorname{int} S, TS) : |\eta(p)|_2 \leq 1 \ \forall p \in S \}$ with TS as the *tangent bundle* of S . Note that $BV(S) \hookrightarrow L^2(S)$

- Fenchel Predual Problem:

$$\min_{\mathbf{p} \in \mathbf{H}(\operatorname{div}; S)} \frac{1}{2} \|\operatorname{div} \mathbf{p} + K^* f\|_{B^{-1}}^2$$

subject to $|\mathbf{p}|_2 \leq \beta$ a.e. on S

- $\mathbf{H}(\operatorname{div}; S) := \{\mathbf{v} \in \mathbf{L}^2(S; T(S)) : \operatorname{div} \mathbf{v} \in L^2(S)\}$
- $\|w\|_{B^{-1}}^2 = (w, B^{-1} w)_{L^2(S)} = (w, w)_{B^{-1}}$
with $B := \alpha \operatorname{id} + K^* K \in \mathcal{L}(L^2(S))$
- Connection: $\bar{u} = B^{-1} (\operatorname{div} \bar{\mathbf{p}} + K^* f)$
- Transforms non-Differentiability into Box/Ball Constraints



Logarithmic barrier method to deal with the non-linear inequality constraints:

$$\min_{\mathbf{p} \in \mathbf{H}(\text{div}; S)} \frac{1}{2} \|\text{div } \mathbf{p} + K^* f\|_{B^{-1}}^2 - \mu \int_S \ln(\beta^2 - |\mathbf{p}|_2^2) ds$$

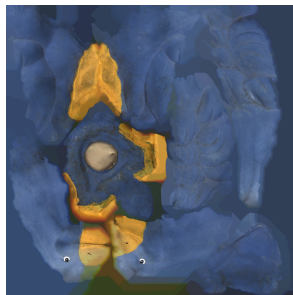
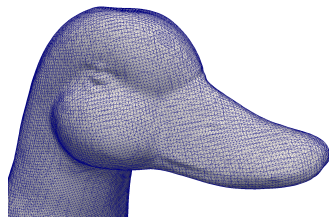
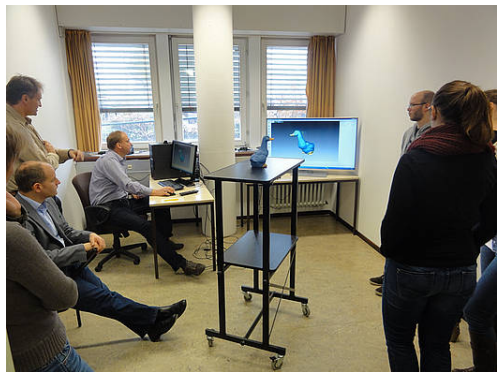
Theorem: Existence and Uniqueness

For every $\mu > 0$, this problem possesses a unique solution $\mathbf{p} \in \mathbf{H}(\text{div}; S)$. It is characterized by

$$(\text{div } \mathbf{p} + K^* f, \text{div } \delta \mathbf{p})_{B^{-1}} + \mu \int_S \frac{2(\mathbf{p}, \delta \mathbf{p})_2}{\beta^2 - |\mathbf{p}|_2^2} ds = 0$$

Proof: By construction, extends (Prüfert, Tröltzsch, Weiser, 2008) and (Ulbrich, Ulbrich, 2009) to surfaces

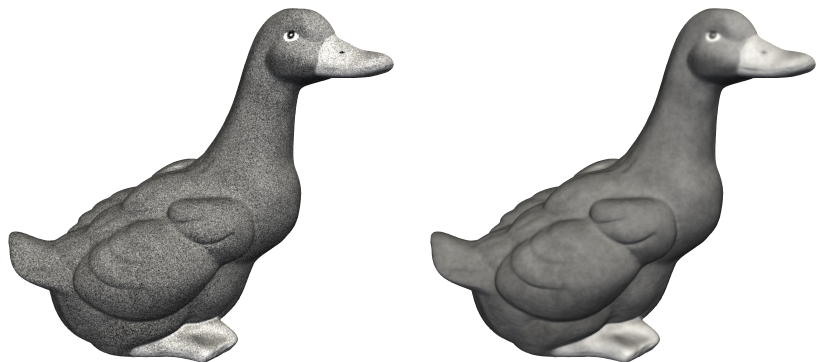
Fully integrated DG-Suite



3D Scan \Rightarrow FEM/DG/Optimization
(FEniCS) \Rightarrow 3D Print

Edge-Preserving TV-Denoising of 3D Scan Data

Interface with 3D Scanner (354,330 Polygons, 177,167 Vertices)



- Convert Geometry + Texture (Bitmap) to DG-Space on Surface
- Predual Approach in RT/DG-Space, interior point method

Color Unerazing / Color Inpainting

Simulation of missed scan sweep, 3% signal missing

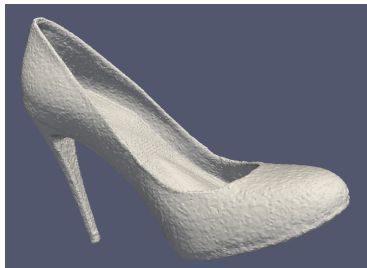


- K : “Identity with Zeros”
- Exactly 100,000 triangles and 50,002 vertices
- DG3, RT4

Denoising of Geometries?

How to carry over insights from pictures on surfaces?

- Surface is represented by signed distance function (SDF)
- Normal is gradient of SDF
- Primal approach: gradient of CG1 SDF = Edge Jump
- Split-Bregman Algorithm necessitates “DG0 Skeleton Space” \Rightarrow “HDivTrace”



Mesh Denoising Formulation

$$\begin{aligned} \min_{\ell \in \mathcal{CG}_1(D)} \quad & \|\ell\|_{L^2(\Gamma_0)}^2 + \beta |\nabla \ell|_{DTV_2(\Gamma(\ell=0))} \\ \text{s.t.} \quad & \ell(x) < 0 \Leftrightarrow x \text{ is 'inside' } \Gamma \\ & \|\nabla \ell\|_2 = 1 \quad \forall x \in D \end{aligned}$$

Discrete Total Variation

$$|\nabla \ell|_{DTV_2(\Gamma(\ell=0))} := \sum_{f \in \mathcal{F}_\Gamma} c_{f,\Gamma} \|(\nabla \ell|^+ - \nabla \ell|^-)_f\|_2$$

where $c_{f,\Gamma}$ is the length of the intersection between Γ and the facet f

Primal Non-Smooth Optimization Algorithm

Split-Bregman Algorithm: Solve non-smooth problem by introducing new variables: $q = \nabla \ell \in \mathcal{DG}_0^3(D)$ and $p = (q|^{+} - q|^{-}) \in \mathcal{DG}_0^3(\mathcal{F})$

“Augmented Lagrangian Problem”:

$$\min \|\ell\|_{L^2(\Gamma_0)}^2 + \beta \sum_{f \in \mathcal{F}_\Gamma} c_{f,\Gamma} \|p_f\|_2 + \frac{\lambda_1}{2} \|q - \nabla \ell - b_T\|_{L^2(D)}^2 + \frac{\lambda_2}{2} \|p - (q|^{+} - q|^{-}) - b_F\|_{L^2(\mathcal{F})}^2$$

s.t. $\ell(x) < 0 \Leftrightarrow x$ is ‘inside’ Γ

$$\|\nabla \ell\|_2 = 1 \quad \forall x \in D$$

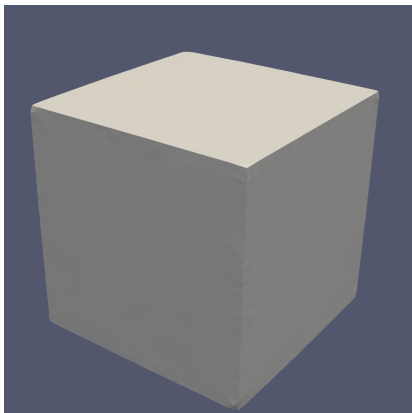
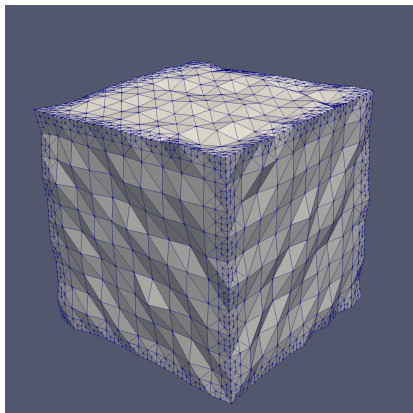
with $b_T \in \mathcal{DG}_0^3(D)$ and $b_F \in \mathcal{DG}_0^3(\mathcal{F})$

Splitting in Split-Bregman \Rightarrow “Mesh-Bregman”

Key optimization steps:

- $\hat{\ell}^{(n+1)} := \arg \min_{\ell \in \mathcal{CG}_1(D)} \|\ell\|_{L^2(\Gamma_0)}^2 + \frac{\lambda_1}{2} \|\mathbf{q}^{(n)} - \nabla \ell - \mathbf{b}_T^{(n)}\|_{L^2(D)}^2$
- a) $\ell^{(n+1)} := \hat{\ell}^{(n+1)}$ b) $\ell^{(n+1)} := \ell^{(n)} + \tau_n \left(\hat{\ell}^{(n+1)} - \ell^{(n)} \right)$
- Update: $\Gamma, \mathcal{F}_\Gamma, \mathbf{c}_{f,\Gamma}$
- $\mathbf{g}^{(n+1)} := \frac{\nabla \ell^{(n+1)}}{\|\nabla \ell^{(n+1)}\|_2}$
- $\mathbf{q}^{(n+1)} := \arg \min_{\mathbf{q} \in \mathcal{DG}_0^3(D)} \frac{\lambda_1}{2} \|\mathbf{q} - \mathbf{g}^{(n+1)} - \mathbf{b}_T^{(n)}\|_{L^2(D)}^2 + \frac{\lambda_2}{2} \|\mathbf{p}^{(n)} - (\mathbf{q}|^+ - \mathbf{q}|^-) - \mathbf{b}_F^{(n)}\|_{L^2(\mathcal{F})}^2$
- $\mathbf{j}^{(n+1)} := \left(\frac{\mathbf{q}^{(n+1)}}{\|\mathbf{q}^{(n+1)}\|_2} \Big|_+ - \frac{\mathbf{q}^{(n+1)}}{\|\mathbf{q}^{(n+1)}\|_2} \Big|_- \right)$
- $\mathbf{p}^{(n+1)} := \arg \min_{\mathbf{p} \in \mathcal{DG}_0^3(\mathcal{F})} \beta \sum_{f \in \mathcal{F}_\Gamma} \mathbf{c}_{f,\Gamma} \|\mathbf{p}_f\|_2 + \frac{\lambda_2}{2} \sum_{f \in \mathcal{F}} \mathbf{c}_f \|\mathbf{p}_f - \mathbf{j}_f^{(n+1)} - (\mathbf{b}_F^{(n)})_f\|_2^2$
- $\mathbf{b}_T^{(n+1)} := \mathbf{b}_T^{(n)} + \mathbf{g}^{(n+1)} - \mathbf{q}^{(n+1)}$
- $\mathbf{b}_F^{(n+1)} := \mathbf{b}_F^{(n)} + \mathbf{j}^{(n+1)} - \mathbf{p}^{(n+1)}$

Results



Conclusions and Outlook

- Inverse Problems and Surfaces with Kinks!
- Weak and Strong Shape Differentiation
- GPU Computing and Topology Optimization
- Shape SQP-Methods and Automatization

