



# An Adaptive Finite Element Trust-Region Method for Regularized PDE-Constrained Optimization

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**Goal:** Develop efficient algorithms to solve the regularized nonsmooth optimization problem,

$$\min_{z \in \mathcal{Z}} F(z) := f(z) + \phi(z). \quad (1)$$

- ▶  $\mathcal{Z}$  is a Hilbert space with  $\langle \cdot, \cdot \rangle$  and  $\|\cdot\|$ ;
- ▶  $\phi : \mathcal{Z} \rightarrow [-\infty, \infty]$  is proper, closed, and convex, but may be nonsmooth;
- ▶  $f : \mathcal{Z} \rightarrow \mathbb{R}$  has Lipschitz continuous gradients on an open set containing  $\text{dom } \phi$ ;
- ▶  $F > -\infty$ , bounded below on  $\text{dom } \phi$ .

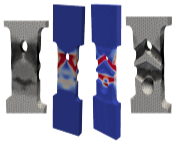
### Key Requirements

1. **Large-scale Problems:** Rapid convergence, mesh independence, and matrix free;
2. **Leverage Inexactness:** Converges even for inexact computations.

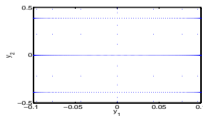
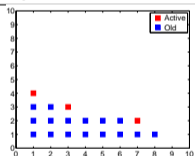
$f(z)$  may be nonconvex and often **impossible** to compute **exactly**.

- Stems from discretization, iterative procedures, adaptive model reduction, surrogate models, iterative linear and nonlinear solves, etc.

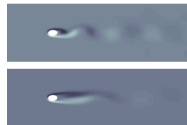
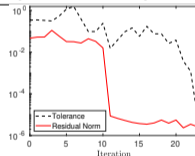
### Adaptive Finite Elements



### Adaptive Quadrature



### Adaptive Compression





$\phi(z)$  are typically sparsity-inducing and temper model complexity.

- ▶ **Sparse regularization:**  $\mathcal{Z} \hookrightarrow L^1(\Omega)$ ,  $\beta \in L^\infty(\Omega)$ ,  $\beta \geq 0$  a.e., and

$$\phi(z) = \int_{\Omega} \beta(\omega) |z(\omega)| d\omega.$$

**Applications:** Optimal control, data-science, learning, basis-pursuit.

- ▶ **Total Variation:**  $\mathcal{Z} \hookrightarrow BV(\Omega)$ ,  $\beta \in L^\infty(\Omega)$ ,  $\beta \geq 0$  a.e.,

$$\phi(z) = \int_{\Omega} \beta(\omega) |\nabla z(\omega)| d\omega.$$

**Applications:** Image processing, digital image correlation, topology optimization.

- ▶ **Convex Constraints:**  $C \subset \mathcal{Z}$  nonempty, closed and convex,

$$\phi(z) = \begin{cases} 0, & \text{if } z \in C \\ +\infty, & \text{otherwise.} \end{cases}$$

**Applications:** Optimal control, inverse problems, optimal design.



**Goal:** Incorporate adaptive mesh refinement into inexact trust-region framework [4]

- ▶ Trust Region Algorithm
  - ▶ Inexactness conditions
- ▶ Error Estimates for AFEM
- ▶ Numerical Example




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**Algorithm 1:** Nonsmooth Trust-Region Method
 

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**Data:**  $z_0 \in \text{dom } \phi$ ,  $\Delta_0 > 0$ ,  $0 < \eta_1 < \eta_2 < 1$ , and  $0 < \gamma_1 \leq \gamma_2 < 1 \leq \gamma_3$   
**for**  $k = 1, 2, \dots$  **do**

**Model Selection:** Select subproblem model  $f_k$  of  $f$  near  $z_k$ .

**Step Computation:** Compute  $z_{k+1} \in \mathcal{Z}$  that **approximately** solves

$$\min_{z \in \mathcal{Z}} \{m_k(z) := f_k(z) + \phi(z)\} \quad \text{subject to} \quad \|z - z_k\| \leq \Delta_k.$$

**Evaluate Objective:** Compute  $\text{cred}_k \approx \text{ared}_k$ .

**Step Acceptance:** Compute ratio of computed and predicted reduction

$$\rho_k := \frac{\text{cred}_k}{m_k(z_k) - m_k(z_{k+1})} < \eta_1 \quad \Rightarrow \quad z_{k+1} \leftarrow z_k.$$

**Update Trust-Region Radius:**  $\Delta_{k+1} \in \begin{cases} [\gamma_1 \Delta_k, \gamma_2 \Delta_k], & \text{if } \rho_k < \eta_1 \\ [\gamma_2 \Delta_k, \Delta_k], & \text{if } \rho_k \in [\eta_1, \eta_2) \\ [\Delta_k, \infty), & \text{if } \rho_k > \eta_2. \end{cases}$

**end**

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**Recall:** infinite-dimensional optimization function and gradient evaluations are often **impossible** to compute without discretization, leading to **inexactness**.

1. Ensure subproblem step yields decrease - existence of a Cauchy point ([1, 3, 2]);
2. Handle nonsmooth subproblems efficiently - subproblem solvers ([3]);
3. Ensure convergence with  $f_k, g_k$  inexact - adaptive FE.

- ▶ Assume approximations of objective  $f_k$  and gradient  $g_k$  have the form:

$$\begin{aligned} f_k(z, \tau) &: \mathcal{Z} \times [0, +\infty) \rightarrow \mathbb{R}, & f_k(z, 0) &= f(z) \\ g_k(z, \tau) &: \mathcal{Z} \times [0, +\infty) \rightarrow \mathcal{Z}, & g_k(z, 0) &= \nabla f(z). \end{aligned}$$

- ▶ Trust-region algorithm will 1) **controls** error in evaluations via satisfying 2) **computable error** estimates.
- ▶ **Algorithm selects tolerance**, and we must find grid whose error estimates are below given tolerance.



**Objective** function approximates the decrease

$$\text{cred}_k \approx \text{ared}_k := (f(z_k) + \phi(z_k) - (f(z_{k+1}) + \phi(z_{k+1})))$$

so for  $\text{pred}_k$  predicted model decrease, the objective bound (with  $\lim_{k \rightarrow +\infty} \theta_k = 0$ ) is

$$|\text{ared}_k - \text{cred}_k| \leq \kappa_{\text{obj}} [\eta \min\{\text{pred}_k, \theta_k\}]^\zeta, \quad (2)$$

The **gradient** bound is, for  $\kappa_{\text{grad}} > 0$  and  $h_k := t_0^{-1} \|\text{Prox}_{t_0\phi}(z_k - t_0 g_k) - z_k\|_{\mathcal{Z}}$ :

$$\|g_k - \nabla f(z_k)\| \leq \kappa_{\text{grad}} \min\{\Delta_k, h_k\} \quad \forall k. \quad (3)$$

**Conclusion:** There exists iterative procedures that satisfy (2) & (3) in finite time.

## 9 Computable A Posteriori Error Estimates



Consider full space (for a moment):

$$\min_{u \in \mathcal{U}, z \in \mathcal{Z}} F(u, z) := f(u, z) + \phi(z) \quad \text{subject to} \quad c(u, z) = 0. \quad (4)$$

with Lagrangian

$$L(u, z, \lambda) = f(u, z) + \langle \lambda, c(u, z) \rangle_{\mathcal{U}, \mathcal{U}^*}.$$

For given mesh parameter  $h > 0$ , let  $\eta_h^k := (\eta_h^{c,k}, \eta_h^{L_u,k}, \eta_h^{L_z,k})$  with  $\eta_h^{i,k} \rightarrow 0$  as  $h \rightarrow 0$  where  $i \in \{c, L_u, L_z\}$  such that

$$\|L_z(u_h^k, z_h^k, \lambda_h^k)\|_{\mathcal{Z}^*} \lesssim \underbrace{\|\mathbf{g}_{k,h}\|_{\mathcal{Z}_h^*} + \|c_h(u_h, z_h)\|_{\mathcal{U}_h^*}}_{\eta_h^{L_z,k}} + \|L_z(u_h^k, z_h^k, \lambda_h^k)\|_{\mathcal{Z}_h^*},$$

$$\|L_u(u_h^k, z_h^k, \lambda_h^k)\|_{\mathcal{U}^*} \lesssim \underbrace{\|\mathbf{g}_{k,h}\|_{\mathcal{Z}_h^*} + \|c_h(u_h, z_h)\|_{\mathcal{U}_h^*}}_{\eta_h^{L_u,k}} + \|L_u(u_h^k, z_h^k, \lambda_h^k)\|_{\mathcal{U}_h^*},$$

$$\|c(u_h^k, z_h^k)\|_{\mathcal{U}^*} \lesssim \underbrace{\|\mathbf{g}_{k,h}\|_{\mathcal{Z}_h^*}}_{\eta_h^{c,k}} + \|c_h(u_h^k, z_h^k)\|_{\mathcal{U}_h^*}.$$



**Goals:** Use inexact state/adjoint estimates to adaptively refine finite element mesh.

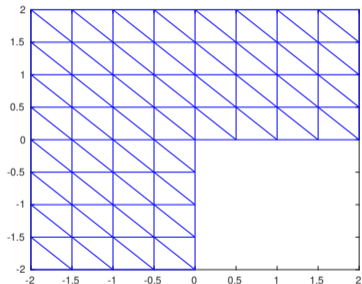
Our cost function is the usual regularized data misfit with  $L^1$  penalty

$$\min_{z \in \mathcal{Z}} \int_{\Omega} \left\{ \frac{1}{2} \|u(z) - u_d\|_{L^2(\Omega)}^2 + \dots \right. \\ \left. \dots \frac{\alpha}{2} \|z\|_{L^2(\Omega)}^2 + \frac{\beta}{2} \|z\|_{L^1(\Omega)} \right\} dx$$

for  $\mathcal{U} \equiv H_0^1(\Omega)$ ,  $\mathcal{Z} \equiv L^2(\Omega)$  and

$$-\Delta u = z, \quad x \in \Omega \subset \mathbb{R}^2 \\ u = 0, \quad x \in \partial\Omega$$

$\alpha = 10^{-4}$ ,  $\beta = 10^{-2}$ , Q2 discretization for states and P0 for controls; stopping tolerance  $10^{-6}$ .



Initial mesh for nonconvex domain in Poisson problem.



We introduce the following the computable error estimators:

$$\eta_h^{c,k} := \sum_{T \in \mathcal{T}_h} h_T^2 \| -\Delta u_h^k - z_h \|_{L^2(T)}^2 + \frac{1}{2} \sum_{e \in \mathcal{E}_h} \left\| \left[ \frac{\partial u_h^k}{\partial n} \right] \right\|_{L_2(e)}^2,$$

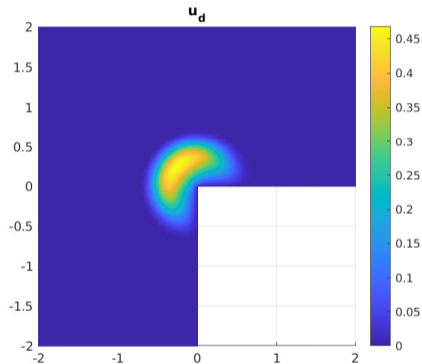
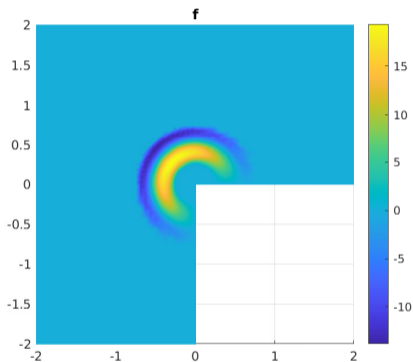
$$\eta_h^{L_u,k} := \sum_{T \in \mathcal{T}_h} h_T^2 \| u_h^k - u_d - \Delta \lambda_h^k \|_{L^2(T)}^2 + \frac{1}{2} \sum_{e \in \mathcal{E}_h} \left\| \left[ \frac{\partial \lambda_h^k}{\partial n} \right] \right\|_{L_2(e)}^2,$$

yields the following adaptive mesh refinement criteria:

$$\eta_h^{c,k} \lesssim \min \{ \| \nabla f_h^k \|_{\mathcal{Z}_h^*} + \| c_h(u_h^k, z_h^k) \|_{\mathcal{U}_h^*}, \tau \},$$

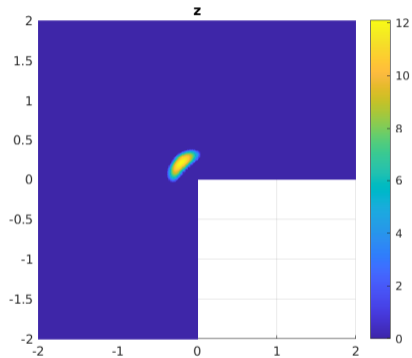
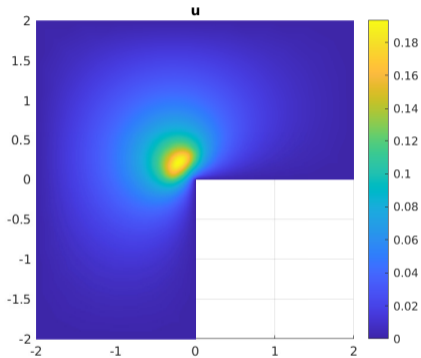
$$\eta_h^{L_u,k} \lesssim \min \{ \| \nabla f_h^k \|_{\mathcal{Z}_h^*} + \| c_h(u_h^k, z_h^k) \|_{\mathcal{U}_h^*} + \| L_u(u_h, z_h, \lambda_h) \|_{\mathcal{U}_h^*}, \tau \},$$

where  $\tau > 0$  is a given tolerance.



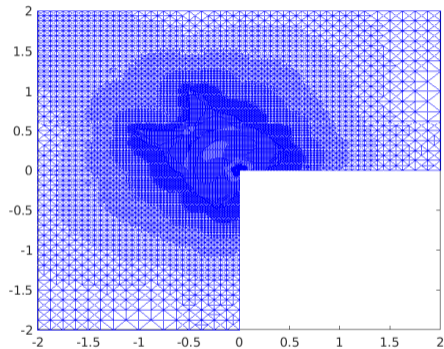
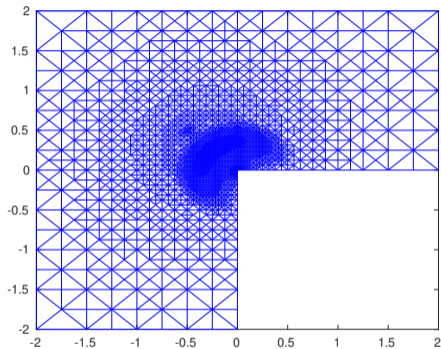
True solution:  $u_d(x) = (x_1 - x_1^2) \cdot (x_2 - x_2^2)$  and  $f(x) = 2(x_1 - x_1^2) + 2(x_2 - x_2^2)$

# Adaptive Finite Elements: $u(z)$ and $z$



Final state (left) and control (right).

# Adaptive Finite Elements: Grid Comparison



Q2 grid (left) and Q1 grid (right).



- ▶ Nonsmooth problems are extremely prevalent in the literature and require careful treatment.
- ▶ Moreover, numerical solutions require **expensive approximations**.
  - ▶ Objectives and gradients can only be compute **inexactly**.
- ▶ Nonsmooth trust-region is **provably convergent** even while **adaptively changing the FE grid**.
- ▶ Next: topology optimization problem.

# Acknowledgements



**Questions?**

**Thank you-**

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- ▶ Collaborators: H.A., D.K., Rohit Khandelwal.



- [1] R. J. Baraldi and D. P. Kouri. A proximal trust-region method for nonsmooth optimization with inexact function and gradient evaluations. *Mathematical Programming*, 1(201):559–598, 2023.
- [2] R. J. Baraldi and D. P. Kouri. Local convergence analysis of an inexact trust-region method for nonsmooth optimization. *Optimization Letters*, 18:663–680, 2024.
- [3] R. J. Baraldi and D. P. Kouri. Efficient subproblem solvers for a nonsmooth trust-region method. *Computational Optimization and Applications*, 90:193–226, 2025.
- [4] R. J. Baraldi, R. Kandelwahl, D. P. Kouri, and H. Antil. An adaptive finite element method for nonsmooth optimal control. *in preparation*, 2025.



Assume that we have an approximation  $\bar{g} : \mathcal{Z} \times [0, +\infty) \rightarrow \mathcal{Z}$  that satisfies  $C_{\text{grad}} \geq 0$  such that

$$\bar{g}(z, 0) = \nabla f(z) \quad \text{and} \quad \|\nabla f(z) - \bar{g}(z, \tau)\| \leq C_{\text{grad}}\tau \quad \forall \tau \in \mathbb{R}_+. \quad (6)$$

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**Algorithm 2:** Inexact Gradient Computation
 

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**Require:** Constant  $\bar{\kappa}_{\text{grad}} > 0$ , a tolerance  $\mu_{\text{grad}} > 1$ , current iterate  $z_k \in \mathcal{Z}$ , and  $\Delta_k$ .

Set  $\tau_k^- \leftarrow \bar{\kappa}_{\text{grad}}\Delta_k$

Compute  $h_k \leftarrow r_0^{-1} \|\text{Prox}_{r_0\phi}(z_k - r_0\bar{g}(z_k, \tau_k^-)) - z_k\|$

Set  $\tau_k^+ \leftarrow \bar{\kappa}_{\text{grad}} \min\{h_k, \Delta_k\}$

**while**  $\mu_{\text{grad}}\tau_k^+ < \tau_k^-$  **do**

    Compute  $h_k \leftarrow r_0^{-1} \|\text{Prox}_{r_0\phi}(z_k - r_0\bar{g}(z_k, \tau_k^+)) - z_k\|$

    Set  $\tau_k^- \leftarrow \tau_k^+$  and  $\tau_k^+ \leftarrow \bar{\kappa}_{\text{grad}} \min\{h_k, \Delta_k\}$

**end while**

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If  $h(z_k) > 0$ , Algorithm 2 terminates finitely and (3) holds with  $\kappa_{\text{grad}} = \mu_{\text{grad}}\bar{\kappa}_{\text{grad}}C_{\text{grad}}$ .



Assume  $\tau_k^{\text{obj}} \leq \mu_{\text{obj}} \tau_{k+1}^{\text{obj}}$ , then  $\kappa_{\text{obj}} = (1 + \mu_{\text{obj}}) \bar{\kappa}_{\text{obj}} C_{\text{obj}}$  since

$$|\text{ared}_k - \text{cred}_k| \leq (1 + \mu_{\text{obj}}) \bar{\kappa}_{\text{obj}} C_{\text{obj}} [\eta \min\{\text{pred}_k, \theta_k\}]^\zeta.$$

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### Algorithm 3: Inexact Objective Function Computation

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**Require:** Constants  $\bar{\kappa}_{\text{obj}} > 0$  and  $\mu_{\text{obj}} \geq 1$ , the current objective function tolerance  $\tau_k$ , the current iterate  $x_k \in X$  and approximate objective value  $v_k = \bar{f}(x_k, \tau_k)$ , the new iterate  $z_{k+1} \in X$ , and the predicted reduction  $\text{pred}_k$ .

Set  $\tau_{k+1} \leftarrow \bar{\kappa}_{\text{obj}} [\eta \min\{\text{pred}_k, \theta_k\}]^\zeta$

**if**  $\mu_{\text{obj}} \tau_{k+1} < \tau_k$  **then**

    Compute  $v_k \leftarrow \bar{f}(x_k, \tau_{k+1})$

**end if**

Compute  $v_{k+1} \leftarrow \bar{f}(z_{k+1}, \tau_{k+1})$  and set  $\text{cred}_k = (v_k + \phi(z_k)) - (v_{k+1} + \phi(z_{k+1}))$

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**Recall:**  $h_k := r_0^{-1} \|\text{Prox}_\phi(z_k - r_0 g_k) - z_k\|_{\mathcal{Z}}$

### Theorem (Algorithm Convergence)

Let  $\{z_k\}$  be the sequence of iterates generated

$$\liminf_{k \rightarrow \infty} h_k = 0 \quad \Rightarrow \quad \liminf_{k \rightarrow \infty} r_0^{-1} \|\text{Prox}_\phi(z_k - r_0 \nabla f(z_k)) - z_k\|_{\mathcal{Z}} = 0. \quad (7)$$

**Note:** Permits unbounded model curvature.

Given  $\varepsilon > 0$  and bounded model curvature, then Trust-Region Algorithm satisfies  $h_k \leq \min\{\varepsilon, 1\}$  in at most  $\mathcal{O}(\varepsilon^{-2})$  iterations.

**Note:** This is a **worst-case bound**; we find much better performance in practice.



### Definition (Moreau-Yosida Envelope)

For a proper, lower semicontinuous function  $\phi : \mathcal{Z} \rightarrow \overline{\mathbb{R}}$  and a parameter  $t > 0$ , the *Moreau envelope*  $e_{t\phi} : \mathcal{Z} \rightarrow \mathbb{R}$  and the *proximal operator*  $\text{Prox}_{t\phi} : \mathcal{Z} \rightarrow \mathcal{Z}$  are defined by

$$e_{t\phi}(y) := \inf_{z \in \mathcal{Z}} \left\{ \frac{1}{2t} \|z - y\|^2 + \phi(z) \right\}, \quad (8a)$$

$$\text{Prox}_{t\phi}(y) := \operatorname{argmin}_{z \in \mathcal{Z}} \left\{ \frac{1}{2t} \|z - y\|^2 + \phi(z) \right\}. \quad (8b)$$

- ▶ Interpretation: extension of cost function to minimizing  $\phi$  and near  $y$ .
- ▶ Utility: many proximal operators have **analytic** solutions (can be relaxed somewhat);
  - ▶  **$L^1$ -Norm**:  $\mathcal{Z} = L^2(\Omega)$ ,  $\phi(z) = \beta \|z\|_{L^1(\Omega)} \Rightarrow \text{Prox}_{t\phi} = \text{sign}(z) \odot (|z| - t\beta)_+$ .
  - ▶ **ReLU**:  $\mathcal{Z} = \mathbb{R}$ ,  $\phi(z) = \max\{0, z\} \Rightarrow \text{Prox}_{t\phi} = \max\{z - t, \min\{0, z\}\}$ .



Background on Nonsmoothness

## Definition (Local Minimizer)

$\bar{z} \in \mathcal{Z}$  is a **local minimizer** of  $(f + \phi)$  if there exists a neighborhood  $U$  of  $\bar{z}$  on which  $(f + \phi)(\bar{z}) \leq (f + \phi)(z) \quad \forall z \in U$ . Additionally,  $\bar{z}$  satisfies

$$-\nabla f(\bar{z}) \in \partial\phi(\bar{z}) \quad \Leftrightarrow \quad \bar{z} = \text{Prox}_{t\phi}(\bar{z} - t\nabla f(\bar{z})) \quad \forall t > 0. \quad (9)$$

## Lemma (Generalized Gradient & Stationary Point)

If  $\bar{z} \in \mathcal{Z}$  is a stationary point of  $(f + \phi)$ , then  $h(\bar{z}) = 0$  where

$$h(z) := t^{-1} \|\text{Prox}_{t\phi}(z - t\nabla f(z)) - z\|$$

for arbitrary fixed  $t > 0$ .