

Regularization of the Cauchy problem for the Laplace equation by the conjugate gradient method

Ivan Cherlenyak

Universität Siegen
Department of Mathematics
D-57068 Siegen, Germany

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- 1 Operator formulation
- 2 Regularization by conjugate gradient method
- 3 Numerical experiments: Laplace equation

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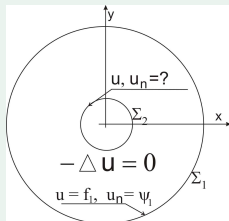
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Problem settings

Inverse problem (IP) and direct problem (DP) on annular domain:

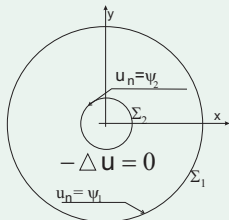
IP: Find $u|_{\Sigma_2}$, $u_n|_{\Sigma_2}$, where u is solution of the Cauchy Problem

$$\begin{cases} -\Delta u = 0 & \text{in } \Omega \\ u = f_1 & \text{auf } \Sigma_1 \\ \frac{\partial u}{\partial n} = \psi_1 & \text{auf } \Sigma_1 \end{cases}$$



DP: Find $u|_{\Sigma_1}$, where u is weak solution of the Neumann problem

$$\begin{cases} -\Delta u = 0 & \text{in } \Omega \\ \frac{\partial u}{\partial n} = \psi_1 & \text{auf } \Sigma_1 \\ \frac{\partial u}{\partial n} = \psi_2 & \text{auf } \Sigma_2 \end{cases}$$



Operator form of direct problem ($\psi_1 := 0$): $A : \psi_2 \mapsto u(\psi_2)|_{\Sigma_1}$

Compact operator formulation of the linear problem

$$T := R \circ Id_1 \circ A \in \mathcal{K}(L^2(\Sigma_2), L^2(\Sigma_1)),$$

$$Id_1 : H^{1/2}(\Sigma_1) \rightarrow L^2(\Sigma_1) \quad (\text{compact embedding})$$

$$R : L^2(\Sigma_1) \rightarrow L^2(\Sigma_1), \quad R : u \mapsto u - \frac{1}{|\Sigma_1|} \int_{\Sigma_1} u d\Sigma_1$$

$$A : L^2(\Sigma_2) \rightarrow H^{1/2}(\Sigma_1), \quad A : \psi_2 \mapsto u(\psi_2)|_{\Sigma_1}$$

where $u(\psi_2) \in V$ denotes the unique solution of variational equation

$$(\nabla u, \nabla \phi)_0 = \langle \psi_2, \phi \rangle_{L^2(\Sigma_2)} \quad \forall \phi \in V,$$

$$V = \{v \in H^1(\Omega) \mid \int_{\Omega} v dx = 0\}.$$

Lemma

A is linear and bounded: $\|A\psi_2\|_{H^{1/2}(\Sigma_1)} \leq c \|\psi_2\|_{L^2(\Sigma_2)}.$

Operator formulation of direct problem

Given $\psi_2 \in L^2(\Sigma_2)$, find \tilde{f}_1 :

$$T\psi_2 = \tilde{f}_1, \quad \tilde{f}_1 = Rf_1$$

Inverse Problem: Given f_1 , find ψ_2 ($:= u_n|_{\Sigma_2}$): $T\psi_2 = \tilde{f}_1$
is ill-posed, since $T = \mathbf{compact}$.

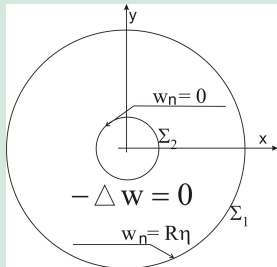
The adjoint operator:

$$T^*\eta := w|_{\Sigma_2}, \quad \eta \in L^2(\Sigma_1)$$

$$w \in V : (\nabla w, \nabla \phi)_0 = \langle R\eta, \phi \rangle_{L^2(\Sigma_1)} \quad \forall \phi \in V,$$

w is unique weak solution of

$$\begin{cases} -\Delta w = 0 \\ w_n|_{\Sigma_1} = R\eta \\ w_n|_{\Sigma_2} = 0. \end{cases}$$



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Discretization by projection

$$T \in \mathcal{K}(X, Y), X := L^2(\Sigma_2), Y := L^2(\Sigma_1), f := \tilde{f}_1$$

IP (operator formulation): $T\psi_2 = f, f \in \mathcal{R}(T)$

$P_I : X \rightarrow X_I$ and $Q_I : Y \rightarrow Y_I$ orthoprojectors with $\dim(X_I) = n_I, \dim(Y_I) = m_I$

Projected equation: $T_I \psi_{2,I} = Q_I f, T_I := Q_I T P_I$ and $\psi_{2,I} \in \mathcal{R}(P_I)$

We assume only an approximation f^ε for f is available: $f^\varepsilon \in Y, \|f^\varepsilon - f\|_Y \leq \varepsilon$

Projected normal equation: $T_I^* T_I \psi_{2,I} = T_I^* Q_I f$

Remark: The projected problems are ill-conditioned and we regularize it using CGNE with an appropriated stopping rule.

CGNE for projected equation

$\psi_{2,l}^{(0)} := 0$ and $\psi_{2,l}^{(1)}, \psi_{2,l}^{(2)}, \dots$, determines by

$$\psi_{2,l}^{(m)} \in \mathcal{K}_m(T_l^* T_l, T_l^* Q_l), \quad \mathcal{K}_m(A^* A, r) := \text{span}\{r, (A^* A)r, \dots, (A^* A)^{m-1}r\}$$

$$\|T_l \psi_{2,l}^{(m)} - Q_l f\|_Y = \min_{\psi \in \mathcal{K}_m(T_l^* T_l, T_l^* Q_l)} \|T_l \psi - Q_l f\|_Y$$

projected CGNE algorithm:

$$r^0 := g - T_l \psi_{2,l}^{(0)}; \quad p^1 := d^0 := T_l^* r^0; \quad m := 1;$$

while ($d^{m-1} \neq 0$)

$$\{q^m := T_l p^m;$$

$$\alpha_m := \|d^{m-1}\|_X^2 / \|q^m\|_Y^2$$

$$\psi_{2,l}^{(m)} := \psi_{2,l}^{(m-1)} + \alpha_m p^m;$$

$$r^m := r^{m-1} - \alpha_m q^m;$$

$$d^m := T_l^* r^m;$$

$$\beta_m := \|d^m\|_X^2 / \|d^{m-1}\|_X^2;$$

$$p^{m+1} := d^m + \beta_m p^m;$$

$$m := m + 1; \}$$

- CGNE breaks down at step $m_* := m \leq \dim(X_l)$ if $T_l r^m = 0$
- **Representation:** $\psi_{2,l}^{(m)} = q_{m-1}(T_l^* T_l, Q_l f) Q_l f$ with $q_{m-1} \in \Pi_{m-1}$
- $q_{m-1}(0)$, $m = 1, 2, \dots$ can be easily computed by three term recursion

A stopping criterion for projected CGNE

Stopping rule 1 Plato 90 ($\zeta_l \in \mathbb{R}$ with $\|A(I - P_l)\| \leq \zeta_l < 1$ and $\tau > 1$)

Stop the iteration at step $\bar{m} = m$, if one of the following conditions is satisfied

$$\|T_l \psi_{2,l}^{(m)} - Q_l f^\varepsilon\|_Y \leq \tau \varepsilon \quad \text{or} \quad q_{m-1}(0, Q_l f^\varepsilon) \geq \zeta_l^{-2} \quad \text{or} \quad m = m_*.$$

Then define

$$\bar{\psi}_2(l, \varepsilon, \tau, f^\varepsilon) = \begin{cases} \psi_{2,l}^{\bar{m}-1} & q_{\bar{m}-1}(0) \geq \zeta_l^{-2} \\ \psi_{2,l}^{\bar{m}} & q_{\bar{m}-1}(0) < \zeta_l^{-2}. \end{cases}$$

Theorem: Assume $T \in \mathcal{K}(X, Y)$, $\mathcal{N}(A)^\perp \subset \overline{\bigcup X_h}$, $\mathcal{R}(A) \subset \overline{\bigcup Y_h}$ and MNS-Solution $\psi_2^\dagger \in X_\mu$, $\mu > 0$ and $\|f^\dagger\|_\mu \leq \rho$. For projected CGNE with noisy data $f^\varepsilon \in Y$, $\|f^\varepsilon - f\|_Y \leq \varepsilon$ let the iteration be stopped according to the stopping rule 1 with corr. approximation $\bar{\psi}_2(l, \varepsilon, \tau, f^\varepsilon)$. Then ex. $c_{cg} > 0$

$$\|\bar{\psi}_2(l, \varepsilon, \tau, f^\varepsilon) - \psi_2^\dagger\|_X \leq c_{cg}(\varepsilon^{\frac{\mu}{\mu+1}} \rho^{\frac{1}{\mu+1}} + \rho(\zeta_l^{\min\{\mu, 1\}} + \|(I - Q_l)T\|^{\min\{\mu, 2\}})).$$

A modified stopping criterion for projected CGNE

Stopping rule 2 ($\zeta_l \in \mathbb{R}$ with $\|A(I - P_l)\| \leq \zeta_l < 1$ and $\tau > 1$)

Stop the iteration at step $\bar{m} = m$, if one of the following conditions is satisfied

$$\|T_l \psi_{2,l}^{(m)} - Q_l f^\varepsilon\|_Y \leq \tau \varepsilon \quad \text{or} \quad q_{m-1}(0, Q_l f^\varepsilon) \geq P(\varepsilon, \rho, \zeta_l) \quad \text{or} \quad m = m_*.$$

Then define $\bar{\psi}_2(l, \varepsilon, \tau, f^\varepsilon) = \begin{cases} \psi_{2,l}^{\bar{m}-1} & q_{\bar{m}-1}(0) \geq P(\varepsilon, \rho, \zeta_l) \\ \psi_{2,l}^{\bar{m}} & q_{\bar{m}-1}(0) < P(\varepsilon, \rho, \zeta_l) \end{cases}$,

$$\text{where } P(\varepsilon, \rho, \zeta_l) := \begin{cases} \zeta_l^{-2}, & \text{if } \left(\frac{\varepsilon}{\rho}\right)^{\frac{1}{\mu+1}} \leq \zeta_l \\ \left(\frac{\varepsilon}{\rho}\right)^{-\frac{2}{\mu+1}}, & \text{if } \left(\frac{\varepsilon}{\rho}\right)^{\frac{1}{\mu+1}} > \zeta_l. \end{cases}$$

Theorem: Assume $T \in \mathcal{K}(X, Y)$, $\mathcal{N}(A)^\perp \subset \overline{\bigcup X_h}$, $\mathcal{R}(A) \subset \overline{\bigcup Y_h}$ and MNS-Solution $\psi_2^\dagger \in X_\mu$, $\mu > 0$ and $\|f^\dagger\|_\mu \leq \rho$. For projected CGNE with noisy data $f^\varepsilon \in Y$, $\|f^\varepsilon - f\|_Y \leq \varepsilon$ let the iteration be stopped according to the stopping rule 2 with corr. approximation $\bar{\psi}_2(l, \varepsilon, \tau, f^\varepsilon)$. Then ex. $\hat{c}_{cg} > 0$

$$\|\bar{\psi}_2(l, \varepsilon, \tau, f^\varepsilon) - \psi_2^\dagger\|_X \leq \hat{c}_{cg} (\varepsilon^{\frac{\mu}{\mu+1}} \rho^{\frac{1}{\mu+1}} + \rho (\zeta_l^{\min\{\mu, 1\}} + \|(I - Q_l)T\|^{\min\{\mu, 2\}})).$$

Conclusions

- On the annular domain with $h_1 = \frac{2\pi R}{n_l}$ on $L^2(\Sigma_1)$ and $h_2 = \frac{2\pi r}{m_l}$ on $L^2(\Sigma_2)$ holds: $\zeta_l = \mathcal{O}(h_2)$, $\|(I - Q_l)T\| = \mathcal{O}(h_1)$
- CGNE with stopping rule 2 possibly breaks down earlier than with stop. rule 1
- If $(\frac{\varepsilon}{\rho})^{\frac{1}{\mu+1}} > \zeta_l$ we can formulate stopping rule 2 without the discrepancy constraint $\|T_l \psi_{2,l}^{(m)} - Q_l f^\varepsilon\|_Y < \tau \varepsilon$
- If $(\frac{\varepsilon}{\rho})^{\frac{1}{\mu+1}} > \zeta_l$ CGNE with stop. rule 2 provides more precise approximations

Disadvantage:

- For stopping rule 2 we additionally need to know the source representation data ρ, μ

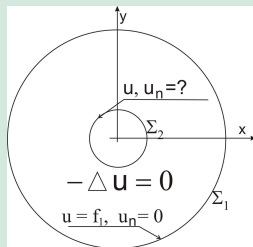
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$$f_1 := v_m(x, 0) = \frac{\cos(m\pi x)}{(m\pi)^2},$$

$$\psi_2^\dagger := \frac{\partial v_m}{\partial n}(x, 0.2) = \frac{\cos(m\pi x) \sinh(0.2m\pi)}{m\pi}.$$

$$\psi_2^\dagger \in R(T^*) = X_1 \text{ (source representation)}$$



Noisy data: $f_1^\varepsilon = \sum_i (f_1(x_i) + \delta(x_i)) \phi_i$ ($\varepsilon = \mathcal{O}(h^2 + \delta)$)

Reconstruction Error(Stopping rule 1+2):

$$\|\bar{\psi}_2 - \psi_2^\dagger\|_{L^2(\Sigma_2)} \leq C(\psi_2^\dagger)((h_1^2 + \delta)^{1/2} + h_1 + h_2),$$

With $h_1 = h_2 = h$ and $\delta = h^2$:

$$\|\bar{\psi}_2 - \psi_2^\dagger\|_{L^2(\Sigma_2)} = \mathcal{O}(h) \text{ for } (h \rightarrow 0)$$

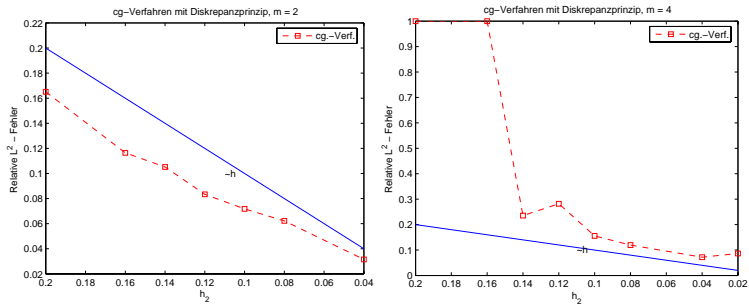


Figure: Order optimality of CGNE with stopping rule 2

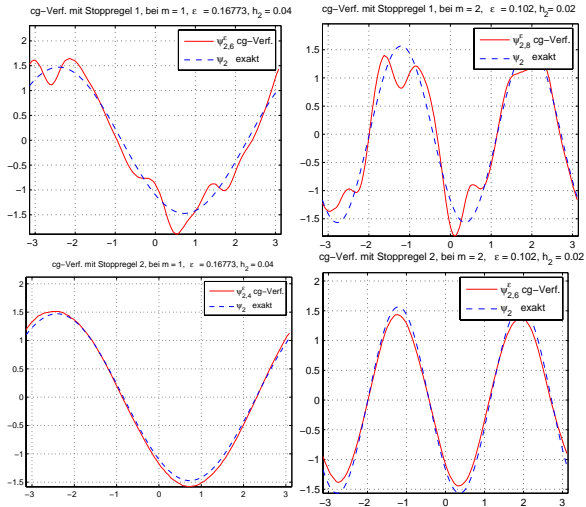


Figure: Top: CGNE with stop. rule 1, Bottom: CGNE with stop. rule 2 ($(\varepsilon/\rho)^{\frac{1}{\mu+1}} > \zeta_h$).

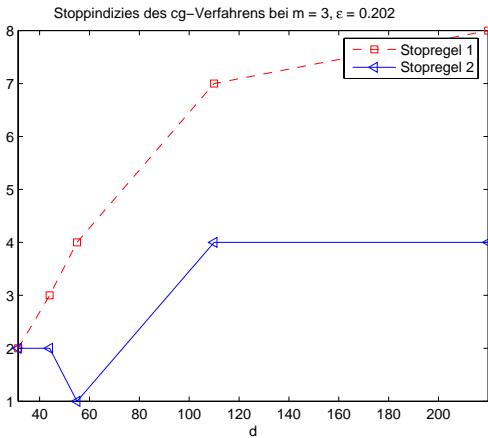







Figure: Stopping index: stopping rule 1 and 2.

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