# Convergence guarantees for Newton type methods in tomographic problems via range invariance <br> <br> Barbara Kaltenbacher 

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Modeling - Analysis - Optimization
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## Motivation: PDE based tomographic imaging

- Some tomographic imaging techniques lead to coefficient identification in PDEs
- electrical impedance tomography EIT:

Identify conductivity $\sigma=\sigma(x)$ in

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-\nabla(\sigma \nabla \phi)=0 \text { in } \Omega
$$

from boundary observations of voltage/current $\left(\phi, \partial_{\nu} \phi\right)$ pairs.

- full waveform inversion FWI / ultrasound tomography: Identify wave speed $c=c(x)$ in an ibvp for

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A(q, u)=0 & \text { (model equation) } \\
C u=y & \text { (observation equation) }
\end{array}\right\} \quad \Leftrightarrow: \mathbb{F}(q, u)=(0, y)^{T}
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reduced formulation, with parameter-to-state operator $S: \mathcal{D}(\mathbf{F}) \rightarrow V$ defined by the first equation in

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A(q, S(q))=0 \text { and } C(S(q))=y \quad \Leftrightarrow: F(q)=y .
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$A: Q \times V \rightarrow W^{*} \ldots$ model operator, $\quad C \ldots$ observation op.
$Q \ldots$ parameter space, $V \ldots$ state space, $Y \ldots$ data space.

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- More generally, consider

$$
F(x)=y
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with $x=(q, u), F(x)=\mathbb{F}(q, u)$ or $x=q, F(x)=\mathbb{F}(q)$

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- regularize!
- convergence of iterative regularization:
$\rightsquigarrow$ restrictions on nonlinearity of $F$
- convergence of variational regularization: need local convexity of Tikhonov functional $\rightsquigarrow$ restrictions on nonlinearity of $F$


## The tangential cone condition and relatives

- tangential cone condition [Scherzer, 1995]

$$
\forall x, \tilde{x} \in U:\left\|F(x)-F(\tilde{x})-F^{\prime}(x)(x-\tilde{x})\right\|_{Y} \leq c_{\mathrm{tc}}\|F(x)-F(\tilde{x})\|_{Y}
$$

(in a neighborhood $U$ of the exact solution) for the convergence of Landweber iteration [Hanke \& Neubauer \& Scherzer, 1995] and Newton type methods [Hanke, 1997], [BK \& Previatti, 2018]

- weak nonlinearity condition [Chavent \& Kunisch, 1996] for local convexity of the Tikhonov functional
- Newton-Mysovskii condition

$$
\forall x, \tilde{x} \in U:\left\|\left(F^{\prime}(x)-F^{\prime}(\tilde{x})\right) F^{\prime}(x)^{\dagger}\right\|_{x} \leq C_{\mathrm{NM}}\|x-\tilde{x}\|_{x}
$$

[Deuflhardt \& Engl \& Scherzer, 1998] ${ }^{\dagger} . .$. generalized inverse

- some relaxed versions of convexity, see e.g., [Kindermann, 2017]


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- sufficient for this (and often used for its verification) is

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- Let's skip the $\star$ :

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that is, range invariance of the linearized forward operator

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- affine covariant Lipschitz condition

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\forall x, \tilde{x} \in U:\left\|F^{\prime}(x)^{\dagger}\left(F^{\prime}(x)-F^{\prime}(\tilde{x})\right)\right\|_{x} \leq C_{\mathrm{acL}}\|x-\tilde{x}\|_{x}
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(compare to Newton-Mysovskii) allows to prove convergence of Newton and quasi Newton methods, cf., e.g., [Burger \& BK 2006, Deuflhardt \& Engl \& Scherzer 1998, BK 1997, 1998].

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- a relaxed "difference instead of differential" version is

$$
\exists x_{0} \in U, K \in L(X, Y) \forall x \in U \exists r(x) \in X: F(x)-F\left(x_{0}\right)=K r(x)
$$

[BK 2022]

## Why should $F^{\prime}()$ invariance be easier to verify than $F^{\prime}()^{\star}$ invariance?

Reduced setting: $\mathbf{F}(q)=C S(q)$ with (nonlinear) parameter-to-state operator $S$ and linear observation operator $C$ :

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Similarly for all-at-once formulation

## An example: FWI/ ultrasound tomography in all-at-once

 form$$
\mathbb{F}(q, u)=\binom{q(x) u_{t t}(x, t)-\triangle u(x, t)}{C u}=\binom{0}{y}
$$

PDE will actually be considered in a variational form with inital and boundary conditions
$C \in L(V, Y) \ldots$ boundary observations
$c$. . . wave speed / sound speed / (velocity)
$q=\frac{1}{c^{2}} \ldots$ squared slowness
u. . . pressure

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Thus, $\mathbb{F}(q, u)-\mathbb{F}\left(q_{0}, u_{0}\right)=\operatorname{Kr}(q, u)$ holds (for arbitrary $C \in L(V, Y)$ ) with

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r(q, u)=\left(\frac{d q}{\frac{d q}{d u}}\right)=\binom{\left(q-q_{0}\right)\left(1+\frac{\left(u-u_{0}\right) t t}{u_{0, t}}\right)}{u-u_{0}}
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No. We can choose $u_{0} \neq S\left(q_{0}\right)$

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No. All-at-once allows to choose parameter and state space freely "independent of PDE theory".

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$d q$ depends on $x$ and $t\left(\right.$ via $\left.u, u_{0}\right)$
but $q$ is supposed to be a function of $x$ only!

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Yes. To cope with this, we extend $q$ to be a function of $(x, t)$.

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Yes. To cope with this, we penalize time dependence by a term $\|P(q, u)\|^{2}:=\left\|q_{t}\right\|^{2}$ in the methods below.

## Structure exploiting regularization methods

back to $x=(q, u)$ or $x=q \ldots$

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Then (IP) is equivalent to
(see also Rem 2.2 [Deuflhardt \& Engl \& Scherzer, 1998])

$$
\begin{array}{ll}
K \hat{r}=y-F\left(x_{0}\right) & \text { linear ill-posed } \\
r(x)=\hat{r} & \text { nonlinear well-posed } \\
\mathcal{P}(x):=\|P(x)\|=0 &
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## Variational Regularization

$$
\begin{aligned}
& \left(\begin{array}{rl}
\left(r_{\alpha, \beta}^{\delta}, x_{\alpha, \beta}^{\delta}\right) \in \operatorname{argmin}_{(\hat{r}, x) \in X \times U} J_{\alpha, \beta}^{\delta}(\hat{r}, x) \\
\text { where } J_{\alpha, \beta}^{\delta}(\hat{r}, x):=\| K \hat{r}+ & +F\left(x_{0}\right)-y^{\delta} \|_{Y}^{p}+\alpha \mathcal{R}(\hat{r}) \\
& +\beta\|r(x)-\hat{r}\|_{X}^{b}+\mathcal{P}(x)
\end{array}\right.
\end{aligned}
$$

under some continuity/regularity conditions

- $r\left(x_{n}\right) \xrightarrow{\mathcal{T}} \hat{r} \Rightarrow \exists\left(x_{n_{k}}\right)_{k \in \mathbb{N}} \subseteq U, x \in U:\left(x_{n_{k}} \xrightarrow{\mathcal{T}} x\right.$ and $\left.r(x)=\hat{r}\right)$
- sublevel sets of $\mathcal{R}$ are $\mathcal{T}$ compact; $\mathcal{P}$ is $\mathcal{T}$ lower semicontinuous
- $K$ is $\mathcal{T}$-to- $\mathcal{T}_{Y}$ continuous and $\|\cdot\|$ is $\mathcal{T}_{Y}$ lower semicontinuous


## Structure exploiting regularization methods

（IP）is equivalent to

$$
\begin{array}{ll}
K \hat{r}=y-F\left(x_{0}\right) & \text { linear ill-posed } \\
r(x)=\hat{r} & \text { nonlinear well-posed } \\
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## Frozen Newton

$x_{n+1}^{\delta} \in \operatorname{argmin}_{x \in U}\left\|K\left(x-x_{n}^{\delta}\right)+F\left(x_{n}^{\delta}\right)-y^{\delta}\right\|_{Y}^{p}+\alpha_{n} \mathcal{R}(x)+\mathcal{P}(x)$. under the condition
$\exists c \in(0,1) \forall x \in U:\left\|\left(r\left(x^{\dagger}\right)-r(x)\right)-\left(x^{\dagger}-x\right)\right\| x \leq c\left\|x^{\dagger}-x\right\|_{X}$

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## Newton

$\left(\hat{r}_{n+1}^{\delta}, x_{n+1}^{\delta}\right) \in \operatorname{argmin}_{(\hat{r}, x) \in X \times U} J_{n}^{\delta}(\hat{r}, x)$
where $J_{n}^{\delta}(\hat{r}, x):=\left\|K \hat{r}+F\left(x_{0}\right)-y^{\delta}\right\|_{Y}^{p}+\alpha_{n} \mathcal{R}(\hat{r})$

$$
+\beta_{n}\left\|r\left(x_{n}^{\delta}\right)+r^{\prime}\left(x_{n}^{\delta}\right)\left(x-x_{n}^{\delta}\right)-\hat{r}\right\|_{x}^{b}+\mathcal{P}(x)
$$

under the condition

$$
\begin{aligned}
& r^{\prime}\left(x_{0}\right)^{-1} \in L(X, X) \text { and } \\
& \exists L_{r}>0 \forall x \in U:\left\|r^{\prime}\left(x^{\dagger}\right)-r^{\prime}(x)\right\|_{L(X, X)} \leq L_{r}\left\|x^{\dagger}-x\right\|_{x}<1,
\end{aligned}
$$

Idea of proof for frozen Newton in Hilbert space

$$
\begin{aligned}
& x_{n+1}^{\delta}-x^{\dagger}=\left(K^{\star} K+P^{\star} P+\alpha_{n} I\right)^{-1} \\
& \left(K^{\star}\left(y^{\delta}-y\right)+K^{\star} K\left(\left(r\left(x^{\dagger}\right)-r\left(x_{n}^{\delta}\right)\right)-\left(x^{\dagger}-x_{n}^{\delta}\right)\right)\right. \\
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$$
\left\|x_{n+1}^{\delta}-x^{\dagger}\right\| x \leq \frac{\delta}{\sqrt{\alpha_{n}}}+c\left\|x_{n}^{\delta}-x^{\dagger}\right\|_{x}+a_{n}
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with $a_{n}=\alpha_{n}\left\|\left(K^{\star} K+P^{\star} P+\alpha_{n} I\right)^{-1}\left(x_{0}-x^{\dagger}\right)\right\| x \rightarrow 0$ as $n \rightarrow \infty$ provided $x_{0}-x^{\dagger} \in(\operatorname{nsp}(K) \cap \operatorname{nsp}(P))^{\perp} \subseteq \operatorname{nsp}(A)^{\perp}$.

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$\rightsquigarrow$ verify this in applications by (existing) linearized uniqueness proofs.
some further examples

## Combined diffusion and absorption identification

Identify $a(x)$ and $c(x)$ (that is, $q=(a, c))$ in

$$
\begin{equation*}
-\nabla \cdot(a \nabla u)+c u=0 \text { in } \Omega \tag{1}
\end{equation*}
$$

from the $\mathrm{N}-\mathrm{t}-\mathrm{D}$ maps $\Lambda_{\lambda} \in L\left(H^{-1 / 2}(\partial \Omega), H^{1 / 2}(\partial \Omega)\right)$ for all $\lambda \geq 0$; that is, $\left(\operatorname{tr}_{\partial \Omega} u_{\lambda, n}\right)_{\lambda \geq 0, n \in \mathbb{N}}$ where $u^{\lambda, n}$ solves
$-\nabla \cdot(a \nabla u)+(c-\lambda) u=0$ with $\partial_{\nu} u^{n}=\varphi^{n}$ on $\partial \Omega$ for a basis of boundary currents $\varphi_{n} \in H^{-1 / 2}(\partial \Omega)$.

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steady-state diffuse optical tomography
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Convergence of frozen Newton with $a=a(x), c=c(x) \rightarrow c(x, \lambda, n)$.

## Reconstruction of a boundary coefficient

Identify the Robin coefficient $q=q(x)$ in the elliptic boundary value problem

$$
\begin{align*}
-\Delta u & =\ell \text { in } \Omega \\
\partial_{\nu} u+q \cdot \Phi(u) & =h \text { on } \Gamma_{R} \subseteq \partial \Omega  \tag{2}\\
\partial_{\nu} u & =h \text { on } \Gamma_{N} \subseteq \partial \Omega \backslash \Gamma_{R} \\
u & =0 \text { on } \Gamma_{D}:=\partial \Omega \backslash\left(\Gamma_{R} \cup \Gamma_{N}\right)
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from boundary observations $y=\operatorname{tr}_{\partial \Omega} u$.
Note the nonlinearity wrt $u$.

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Convergence of frozen Newton
without any extension/penalization of $q$ being needed.

## Nonlinearity coefficient imaging

Identify the squared slowness $s=s(x)$ and the nonlinearity coefficient $\eta=\eta(x)$ in the fractionally damped Westervelt equation

$$
\begin{gathered}
\left(s u-\eta u^{2}\right)_{t t}-\triangle u+\tilde{D} u=\tilde{r} \quad \text { in } \Omega \times(0, T) \\
\partial_{\nu} u+\gamma u=0 \text { on } \partial \Omega \times(0, T), \quad u(0)=0, \quad u_{t}(0)=0 \quad \text { in } \Omega .
\end{gathered}
$$

from two boundary observations

$$
\begin{equation*}
h_{i}(t)=u_{i}\left(x_{0}, t\right), \quad t \in(0, T), \quad \text { for } r=r_{i}, \quad i=1,2 \tag{3}
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see [BK \& Rundell IPI 2021, Math.Comp. 2021] uniqueness of $\eta=\eta(x)$ from N-t-D map: [Acosta \& Uhlmann \& Zhai 2022]

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Convergence of frozen Newton with $\eta=\eta(x), s=s(x) \rightarrow\left(s_{1}(x, t), s_{2}(x, t)\right)$ [BK \& Rundell, 2022]

Thank you for your attention!

