

Ivanov regularization for parameter identification in PDEs

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joint work with
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Inverse Problems for PDEs, Bremen, March 29, 2016



Outline

- Motivation: parameter identification in PDEs
- Tikhonov, Ivanov, Morozov regularization
- a counterexample for the equivalence of Tikhonov and Ivanov
- convergence analysis
- application to inverse problems for PDEs

motivation and problem setting

Parameter Identification in Differential Equations: Some Examples

- Identify spatially varying coefficients/source a, b, c in elliptic boundary value problem

$$-\nabla(a\nabla u) + cu = b \text{ in } \Omega,$$

$\Omega \subseteq \mathbb{R}^d$, $d \in \{1, 2, 3\}$, from boundary or (restricted) interior observations of u .

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- Identify parameter ϑ in

$$\dot{u}(t) = f(t, u(t), \vartheta) \quad t \in (0, T), \quad u(0) = u_0(\vartheta)$$

from discrete or continuous observations of u .

$$y_i = g_i(u(t_i), \vartheta), \quad i \in \{1, \dots, m\} \text{ or } y(t) = g(t, u(t), \vartheta), \quad t \in (0, T)$$

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bound constraints arise naturally

\rightsquigarrow use them for regularizing the inverse problem

Problem Setting

nonlinear inverse problem

$$F(x) = y$$

$F : X \rightarrow Y$, X, Y Banach spaces,

forward operator = observation operator \circ parameter-to-state map

F not continuously invertible, noisy data

$$\mathcal{S}(y, y^\delta) \leq \delta$$

$\mathcal{S} : Y \times Y \rightarrow \mathbb{R}$ data misfit functional

Tikhonov, Ivanov, Morozov regularization

Tikhonov Regularization

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$\mathcal{R} : X \rightarrow \overline{\mathbb{R}}$ regularization functional

Tikhonov regularization: x_{α}^{δ} solves

$$\min_{x \in \mathcal{D}(F)} \mathcal{S}(F(x), y^{\delta}) + \alpha \mathcal{R}(x).$$

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or

α such that minimizer x_α^δ exists and $\delta < \mathcal{S}(F(x_\alpha^\delta), y^\delta) \leq \tau \delta$
where $\tau \geq 1$ is a fixed constant independent of δ .

- Morozov regularization (method of the residual): x_{Mo}^δ solves

$$\min_{x \in \mathcal{D}(F)} \mathcal{R}(x) \text{ s.t. } S(F(x), y^\delta) \leq \tau \delta$$

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- Ivanov regularization (method of quasi solutions): x_ρ^δ solves

$$\min_{x \in \mathcal{D}(F)} \mathcal{S}(F(x), y^\delta) \text{ s.t. } \mathcal{R}(x) \leq \rho$$

where $\rho \in \{\rho_*^I, \rho_*^{II}, \rho_*^{III}\}$ (regularization parameter):

$$\rho_*^I = \rho^\dagger = \mathcal{R}(x^\dagger)$$

$$\rho_*^{II} \in \operatorname{argmin} \{ \rho \geq 0 : \text{minimizer } x_\rho^\delta \text{ exists and } \mathcal{S}(F(x_\rho^\delta), y^\delta) \leq \tau\delta \}$$

$$\rho_*^{III} \text{ such that minimizer } x_{\rho_*^{III}}^\delta \text{ exists and } \delta < \mathcal{S}(F(x_{\rho_*^{III}}^\delta), y^\delta) \leq \tau\delta$$

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[Lorenz& Worliczek'13, Ivanov'62,'63, Dombrovskaja& Ivanov'65,
Seidman& Vogel'89, Ivanov& Vasin& Tanana'02, Neubauer& Ramlau'14]

a counterexample for the equivalence of
Tikhonov and Ivanov

very similar to counterexample in [Lorenz& Worliczek'13] in 1-d:
 $X=Y=\mathbb{R}$, $f(x) = (x - x_0)^3 + y$, $y^\delta = y + \delta$, $r(x) = |x|$.

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 $X=Y=\mathbb{R}$, $f(x) = (x - x_0)^3 + y$, $y^\delta = y + \delta$, $r(x) = |x|$.
 $x^\dagger = x_0$ solves $f(x) = y$

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$$x^\dagger = x_0 \text{ solves Ivanov } \min_{x \in \mathbb{R}} |f(x) - y^\delta| \text{ s.t. } r(x) \leq \rho \text{ with } \rho = r(x^\dagger)$$

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However, for any $\alpha > 0$, a Tikonov minimizer

$$x_\alpha^\delta \in \operatorname{argmin} \left\{ \frac{1}{2} |f(x) - y^\delta|^2 + \alpha r(x) \right\} \text{ differs from } x_0:$$

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$x^\dagger = x_0$ solves Morozov $\min_{x \in \mathbb{R}} r(x)$ s.t. $|f(x) - y^\delta| \leq \delta$

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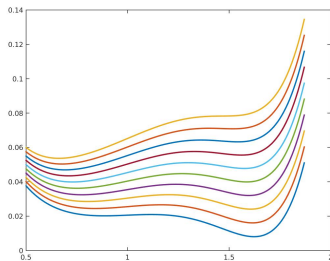
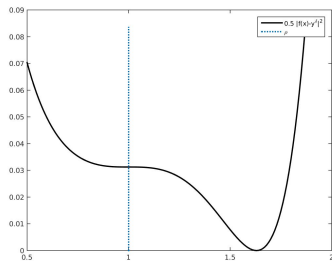


Figure : Ivanov (left) and Tikhonov (right; for different values of α)
 $\delta = 0.25$

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Can be lifted to an ill-posed function space setting

$$X = L^\infty(\Omega), \quad Y = L^2(\Omega), \quad \mathcal{S}(y_1, y_2) = \frac{1}{2} \|y_1 - y_2\|_{L^2}^2, \quad \mathcal{R}(x) = \frac{1}{2} \|x\|_{L^\infty}^2$$

$$F(x)(t) = \int_{\Omega} \Phi(t-s) f(x(s)) \, ds, \quad t \in \Omega$$

with $\Phi : \Omega - \Omega \rightarrow [0, \infty)$ with $\int_{\Omega} \Phi(t-s) \, ds = 1$ for all $t \in \Omega$.

If Φ is weakly singular then F is compact.

If Φ is the Green's function of a differential operator D then

$F(x) = y$ is equivalent to

$$Dy = f(x)$$

(a nonlinear inverse source problem for a PDE)

convergence analysis

Assumptions

Assumption

There exist topologies $\mathcal{T}_X, \mathcal{T}_Y$ on X, Y such that

- ❶ F is \mathcal{T}_X - \mathcal{T}_Y -sequentially closed
- ❷ $\mathcal{R}, \mathcal{S}(\cdot, y^\delta)$ are lower semicontinuous wrt. \mathcal{T}_X and \mathcal{T}_Y .
- ❸ $\forall C > 0: M_C^{\mathcal{R}} = \{x \in \mathcal{D}(F) : \mathcal{R}(x) \leq C\}$ is \mathcal{T}_X -compact.
- ❹ $\forall C > 0, y^\delta \in Y: M_C^{\mathcal{S}} = \{y \in F(\mathcal{D}(F)) : \mathcal{S}(y, y^\delta) \leq C\}$ \mathcal{T}_Y -comp.
- ❺ There exists a solution x^\dagger of $Fx = y$ such that $\mathcal{R}(x^\dagger) < \infty$.
- ❻ $\delta < \mathcal{S}(F(x_{\rho_0}^\delta), y^\delta)$.
- ❼ $\mathcal{S}(\tilde{y}, y) = 0$ implies $\tilde{y} = y$
- ❽ There exists a constant $C_S > 0$ such that for all $y_1, y_2, y_3 \in Y$

$$\mathcal{S}(y_1, y_3) \leq C_S(\mathcal{S}(y_1, y_2) + \mathcal{S}(y_3, y_2))$$

Assumptions

...like for Tikhonov regularization

Well-posedness

Theorem (Clason & Bock & Klassen '16)

Let $y^\delta \in Y_-$, $\tau \geq 1$, $\delta > 0$ be fixed and let for the two functionals $\mathcal{R} : X \rightarrow R_0^+$, $\mathcal{S} : Y \times Y \rightarrow R_0^+$, conditions 1.–5. of Assumption 1 hold, with x^\dagger an \mathcal{R} -minimizing solution of $Fx = y$.

Then x_{Mo}^δ and x_ρ^δ with $\rho = \rho_*^I$ or with $\rho = \rho_*^{II}$ or, if additionally Assumption 1.6. holds, with $\rho = \rho_*^{III}$, **are well defined** and

$$\mathcal{R}(\hat{x}^\delta) \leq \mathcal{R}(x^\dagger) \quad \mathcal{S}(F(\hat{x}^\delta), y^\delta) \leq \tau \delta.$$

holds for $\hat{x}^\delta \in \{x_{Mo}^\delta, x_{\rho_*^I}^\delta, x_{\rho_*^{II}}^\delta, x_{\rho_*^{III}}^\delta\}$.

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For any $\rho_1, \rho_2 \geq \rho_*^{II}$ and any two minimizers $x_{\rho_i}^\delta$, $i \in \{1, 2\}$

$$\rho_1 \leq \rho_2 \Rightarrow \mathcal{S}(F(x_{\rho_1}^\delta), y^\delta) \geq \mathcal{S}(F(x_{\rho_2}^\delta), y^\delta)$$

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If F is linear, $\mathcal{R} = \|\cdot\|$, and $y^\delta \in \overline{F(X)} \subseteq Y$, then for any $\rho \in (0, \rho(y^\delta) := \inf \{\rho > 0 : y^\delta \in Q_\rho\} \in [0, \infty])$, any Ivanov minimizer lies on the boundary of the feasible set, i.e., $\|x_\rho^\delta\| = \rho$

Convergence

Theorem (Clason& BK& Klassen'16)

Let $y \in F(\mathcal{D}(F))$ and let $(y^\delta)_{\delta>0}$ be a family of noisy data satisfying $\mathcal{S}(y, y^\delta) \leq \delta$ such that (with $y^0 := y$) for all $\delta \geq 0$, and for two functionals $\mathcal{R} : X \rightarrow \bar{R}_0^+$, $\mathcal{S} : Y \times Y \rightarrow \bar{R}_0^+$, Assumption 1.1.–1.5. and 1.7., 1.8. hold with x^\dagger an \mathcal{R} -minimizing solution of $Fx = y$.

Then we have \mathcal{T}_X -subsequential convergence as $\delta \rightarrow 0$ to x^\dagger for x_{Mo}^δ and for x_ρ^δ with $\rho \in \{\rho_*^I, \rho_*^{II}, \rho_*^{III}\}$ (imposing Assumption 1.6. for the latter).

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Under a variational source condition for $\phi : \mathbb{R}^+ \rightarrow \mathbb{R}^+$

$$\forall \tilde{x} \in \left\{ x \in \mathcal{D}(F) : \mathcal{R}(\tilde{x}) \leq \mathcal{R}(x^\dagger) \right\} : E(\tilde{x}, x^\dagger) \leq \phi(\mathcal{S}(F(\tilde{x}), F(x^\dagger)))$$

$$\hat{x}^\delta \in \{x_{Mo}^\delta, x_{\rho_*^I}^\delta, x_{\rho_*^{II}}^\delta, x_{\rho_*^{III}}^\delta\} \text{ satisfy the rates}$$

$$E(\hat{x}^\delta, x^\dagger) = O(\phi(\delta))$$

application to inverse problems for PDEs

Parameter Identification in Elliptic PDEs

$$\mathcal{S}(y_1, y_2) = \|y_1 - y_2\|_Y = \|y_1 - y_2\|_{L^p(\Omega)}, \quad p \in [1, \infty], \quad \mathcal{R} = \|\cdot\|_X$$

- Identify the diffusion coefficient $a = a(x)$ in

$$-\nabla(a\nabla u) = f \text{ in } \Omega$$

from measurements of u , given f , $u|_{\partial\Omega} = g$. $X = BV(\Omega)$

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- Identify the potential c in

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Hence $\hat{a}^\delta, \hat{b}^\delta, \hat{c}^\delta \in \{x_{Mo}^\delta, x_{\rho_*^I}^\delta, x_{\rho_*^{II}}^\delta, x_{\rho_*^{III}}^\delta\}$ are well-defined and converge weakly* in X to $a^\dagger, b^\dagger, c^\dagger$ as $\delta \rightarrow 0$.

Inverse Source Problem

Identify the source term $b = b(x)$ in

$$-\Delta u = b \text{ in } \Omega$$

from measurements of u , given $u|_{\partial\Omega} = g$, $\Omega \subseteq \mathbb{R}^d$.

$$\mathcal{S}(y_1, y_2) = \|y_1 - y_2\|_{L^p(\Omega)}, \quad p \in [1, \infty], \quad \mathcal{R}(b) = \|b\|_{L^\infty}$$

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Variational source condition

$$\forall \tilde{b} \in \left\{ b \in X : \mathcal{R}(\tilde{b}) \leq \mathcal{R}(b^\dagger) \right\} : E(\tilde{b}, b^\dagger) \leq \phi(\mathcal{S}(F(\tilde{b}), F(b^\dagger)))$$

holds with

$$E(b_1, b_2) = \|b_1 - b_2\|_{W^{-1,p}(\Omega)}, \quad \phi(t) = \sqrt{t} \quad \text{or}$$

$$E(b_1, b_2) = \|b_1 - b_2\|_{BV(\Omega)^*}, \quad \phi(t) = t^{(1-\frac{d}{p}-\epsilon)/2}, \quad p > d, \quad \epsilon \in (0, 1 - \frac{d}{p}]$$

Inverse Source Problem

Identify the source term $b = b(x)$ in

$$-\Delta u = b \text{ in } \Omega$$

from measurements of u , given $u|_{\partial\Omega} = g$, $\Omega \subseteq \mathbb{R}^d$.

$$\mathcal{S}(y_1, y_2) = \|y_1 - y_2\|_{L^p(\Omega)}, \quad p \in [1, \infty], \quad \mathcal{R}(b) = \|b\|_{L^\infty}$$

$\hat{b}^\delta \in \{x_{Mo}^\delta, x_{\rho_*^I}^\delta, x_{\rho_*^{II}}^\delta, x_{\rho_*^{III}}^\delta\}$ converges weakly* in $L^\infty(\Omega)$ to b^\dagger as $\delta \rightarrow 0$.

Variational source condition

$$\forall \tilde{b} \in \left\{ b \in X : \mathcal{R}(\tilde{b}) \leq \mathcal{R}(b^\dagger) \right\} : E(\tilde{b}, b^\dagger) \leq \phi(\mathcal{S}(F(\tilde{b}), F(b^\dagger)))$$

holds with

$$E(b_1, b_2) = \|b_1 - b_2\|_{W^{-1,p}(\Omega)}, \quad \phi(t) = \sqrt{t} \quad \text{or}$$

$$E(b_1, b_2) = \|b_1 - b_2\|_{BV(\Omega)^*}, \quad \phi(t) = t^{(1-\frac{d}{p}-\epsilon)/2}, \quad p > d, \quad \epsilon \in (0, 1 - \frac{d}{p}]$$

Hence $\hat{b}^\delta \in \{x_{Mo}^\delta, x_{\rho_*^I}^\delta, x_{\rho_*^{II}}^\delta, x_{\rho_*^{III}}^\delta\}$ satisfy the rates

$$\|\hat{b}^\delta - b^\dagger\|_{W^{-1,p}(\Omega)} = O(\sqrt{\delta}), \quad \|\hat{b}^\delta - b^\dagger\|_{BV(\Omega)^*} = O(\delta^{(1-\frac{d}{p}-\epsilon)/2})$$

Numerical Experiments

$$X = L^\infty(\Omega), Y = L^2(\Omega), g = 0, \Delta : H_0^1(\Omega) \rightarrow H^{-1}(\Omega) \rightsquigarrow$$

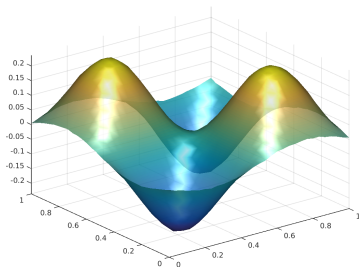
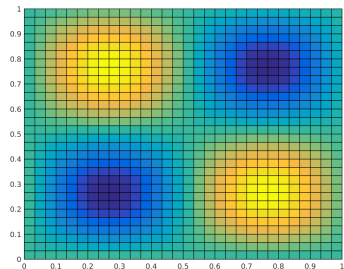
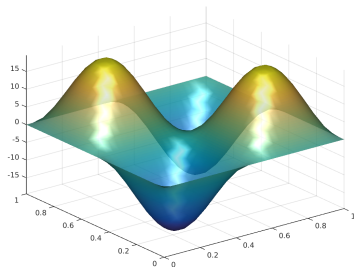
Consider Tikhonov, Morozov, Ivanov as PDE constrained optimization problems with pointwise control bounds:

$$\min \frac{1}{2} \|u - y^\delta\|_{L^2(\Omega)}^2 + \alpha r \quad \text{s.t.} \quad -\Delta u = b, \quad |b(x)| \leq r, \quad x \in \Omega$$

$$\min r \quad \text{s.t.} \quad -\Delta u = b, \quad \frac{1}{2} \|u - y^\delta\|_{L^2(\Omega)}^2 \leq \tau \delta, \quad |b(x)| \leq r, \quad x \in \Omega$$

$$\min \frac{1}{2} \|u - y^\delta\|_{L^2(\Omega)}^2 \quad \text{s.t.} \quad -\Delta u = b, \quad |b(x)| \leq \rho, \quad x \in \Omega$$

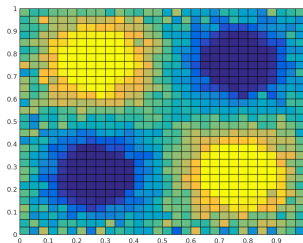
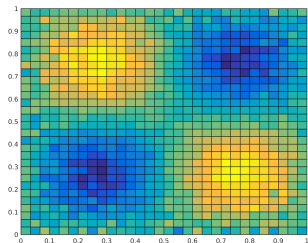
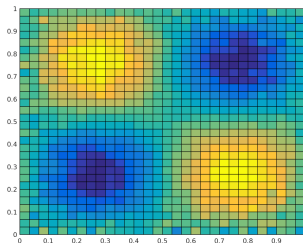
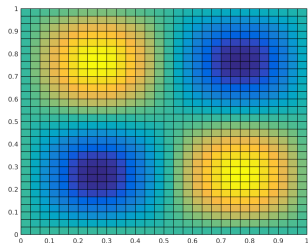
Numerical Experiments: Smooth Source



Numerical Experiments: Smooth Source; $\delta = 1\%$

exact

$$\rho = \|x^\dagger\|$$



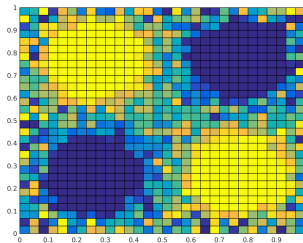
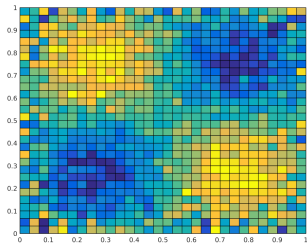
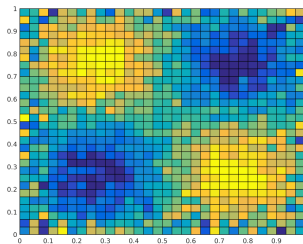
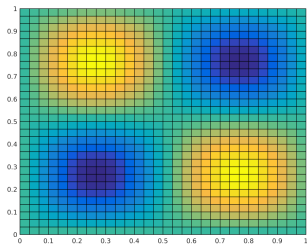
$$\rho = 1.1\|x^\dagger\|$$

$$\rho \text{ by discr.princ.} < \|x^\dagger\|$$

Numerical Experiments: Smooth Source; $\delta = 3\%$

exact

$$\rho = \|x^\dagger\|$$



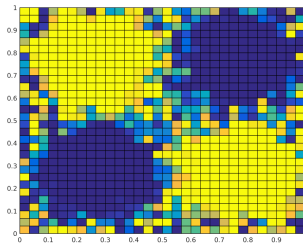
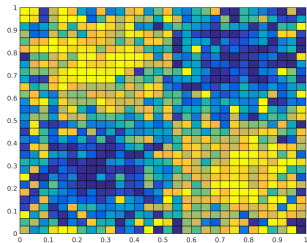
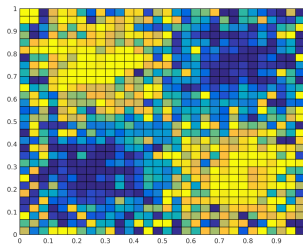
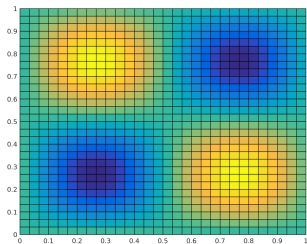
$$\rho = 1.1 \|x^\dagger\|$$

$$\rho \text{ by discr.princ.} < \|x^\dagger\|$$

Numerical Experiments: Smooth Source; $\delta = 10\%$

exact

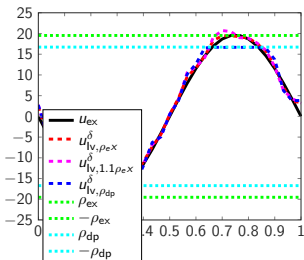
$$\rho = \|x^\dagger\|$$



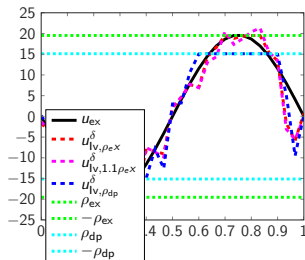
$$\rho = 1.1 \|x^\dagger\|$$

$$\rho \text{ by discr.princ.} < \|x^\dagger\|$$

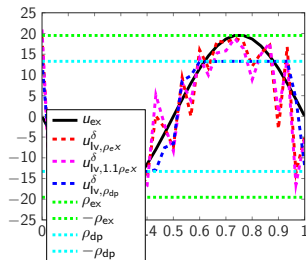
Numerical Experiments: Smooth Source; Cross Sections



$\delta = 1\%$

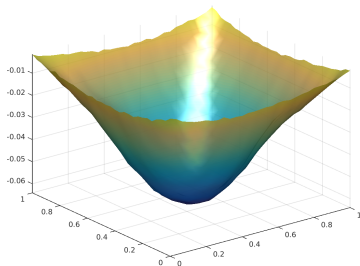
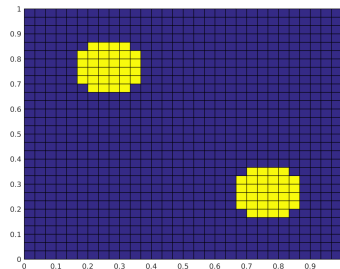
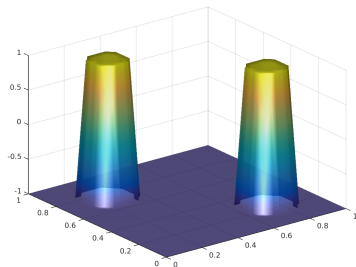


$\delta = 3\%$



$\delta = 10\%$

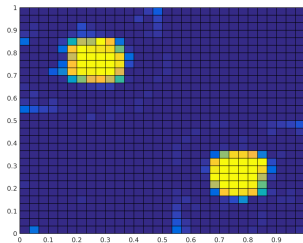
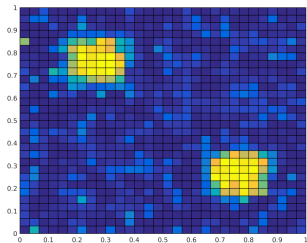
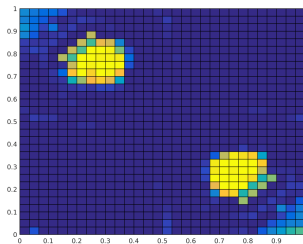
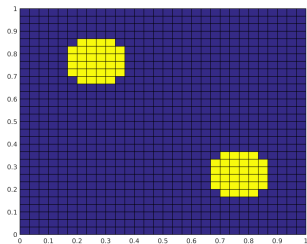
Numerical Experiments: Bang-Bang Source



Numerical Experiments: Bang-Bang Source; $\delta = 1\%$

exact

$$\rho = \|x^\dagger\|$$



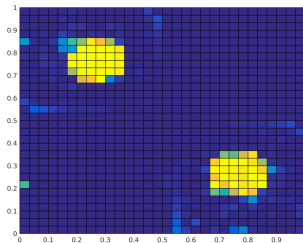
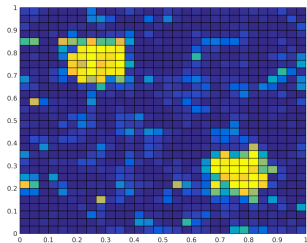
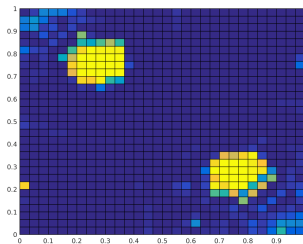
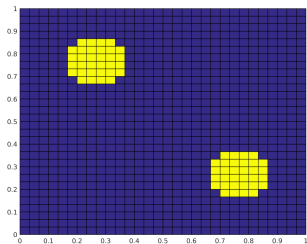
$$\rho = 1.1\|x^\dagger\|$$

$$\rho \text{ by discr.princ.} < \|x^\dagger\|$$

Numerical Experiments: Bang-Bang Source; $\delta = 2\%$

exact

$$\rho = \|x^\dagger\|$$



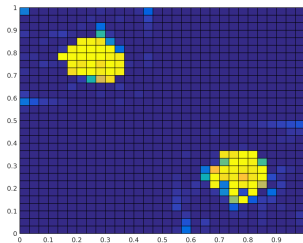
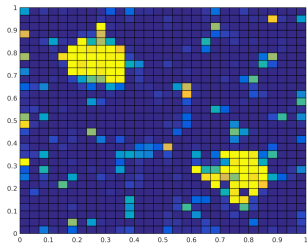
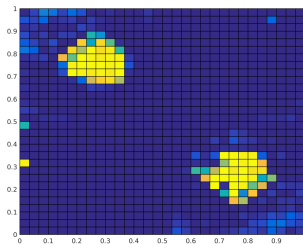
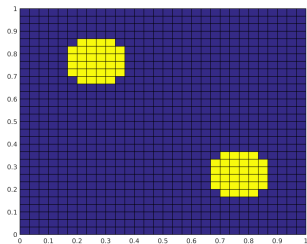
$$\rho = 1.1\|x^\dagger\|$$

$$\rho \text{ by discr.princ.} < \|x^\dagger\|$$

Numerical Experiments: Bang-Bang Source; $\delta = 4\%$

exact

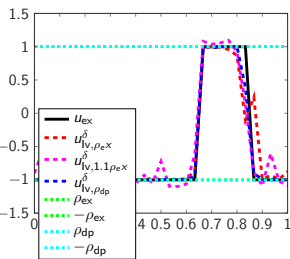
$$\rho = \|x^\dagger\|$$



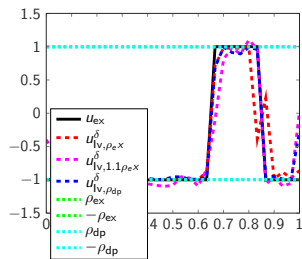
$$\rho = 1.1\|x^\dagger\|$$

$$\rho \text{ by discr.princ.} < \|x^\dagger\|$$

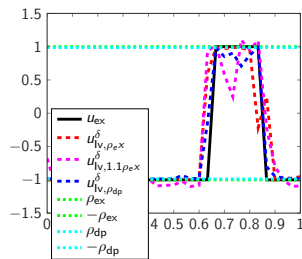
Numerical Experiments: Bang-Bang Source; Cross Sections



$\delta = 1\%$



$\delta = 2\%$



$\delta = 4\%$

Conclusions

- Ivanov regularization allows to naturally incorporate information on $\rho_*^I = \mathcal{R}(x^\dagger)$
- If ρ_*^I is known then optimal convergence rates are obtained without needing knowledge on δ and ϕ !
- underestimation of ρ_*^I still yields a stable solution, overestimation might be fatal

Conclusions

- Ivanov regularization allows to naturally incorporate information on $\rho_*^I = \mathcal{R}(x^\dagger)$
- If ρ_*^I is known then optimal convergence rates are obtained without needing knowledge on δ and ϕ !
- underestimation of ρ_*^I still yields a stable solution, overestimation might be fatal

Thank you for your attention!



tc7.2+4 workshop

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Offen im Denken

Optimal Control Meets Inverse Problems

University of Duisburg-Essen

September 5-9, 2016

Organizers:

Christian Clason

Arnd Rösch

Irwin Yousept

<https://www.uni-due.de/mathematik/agclason/ifip2016>