Adaptive Wavelet Frame Methods for Operator Equations: Sparse Grids, Vector-Valued Spaces and Applications to Nonlinear Inverse Parabolic Problems II





Stephan Dahlke, Peter Maass, Rob Stevenson

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Scope

Parameter identification related to nonlinear parabolic equations

(1)

SPP

University of Amsterdam

DFG

 $g' - \operatorname{div}(D\operatorname{grad} g) + \lambda g = R\Phi(Wg),$

on bounded Lipschitz domains $U \subset \mathbb{R}^d$ with nonlinear signal response function Φ

Goals

- Reconstruction of reaction parameters $p = (D, \lambda, R, W)$ from noisy data g^{δ}
- Application to embryogenesis of Drosophila [10]

Ansatz

III-posed problem > regularization needed > minimization problem

• Tikhonov regularization with Besov penality term

 δ $\delta \|^2$ $\delta \|^2$

Parameter identification problem

I. Parameter-to-state map

- Parameters $p = (D, \lambda, R, W)$
- $\circ D \in L_{\infty}([0,T], L_{\infty}(U, \mathbb{R}^d)) \quad \circ \lambda, R \in L_r([0,T], L_r(U, \mathbb{R}^d)), W \in L_r([0,T], L_r(U, \mathbb{R}^{d \times d}))$
- \circ pointwise global bounds, $r \in (2,\infty)$ chosen respectively for $\lambda, R, W >$ admissible sets are non-complete metric spaces
- In practice: noisy data measurements $g_{\mathbf{t}}^{\delta} \in L(\mathbf{t}, L_2(U, \mathbb{R}^d))$ at discrete time points $\mathbf{t} = \{t_i\}_{i=1}^k \subset [0, T]^k$ \rhd need sampling operator $\mathscr{P} : L_2([0, T], L_2(U, \mathbb{R}^d)) \to L_2(\mathbf{t}, L_2(U, \mathbb{R}^d))$
- Resulting parameter identification problem

(4)

$$\mathscr{P}\mathscr{S}(p) = g_{\mathbf{t}}^{\delta}$$

Theorem. The parameter-to-state map \mathscr{S} is continuously differentiable with Hölder continuous

$$p_{\alpha}^{o} = \operatorname*{argmin}_{p=(D,\lambda,R,W)} \left\| \mathscr{S}(p) - g^{o} \right\| + \alpha |p|_{s},$$

with $p \mapsto \mathscr{S}(p) :=$ solution to (1) with parameters p

Besov penality term promotes sparse solutions

Tasks

- Efficient solver for the forward problem with optimal convergence rates for prescribed tolerance
- Efficient mimimization strategy for (2)

Numerical treatment of the forward problem

I. Parabolic problem

• Solution space for PDE (1)

 $\mathscr{W} = \{ u \in L_q(0, T, V_1) : u' \in L_q(0, T, V_2) \},\$

where $V_1=W_q^1(U,\mathbb{R}^d)$, $V_2=(W_{q'}^1(U,\mathbb{R}^d))'$

Implicit discretization by Rothes method:
 first in time, then in space
 system of elliptic equations
 per time step:

(3)

$$g(t_{n+1}) \approx g^{(n+1)} = g^{(n)} + m_1 g_1$$

$$(\frac{1}{h\gamma_{11}} I - J)g_1 = \operatorname{div}(D \operatorname{grad} g^{(n)}) - \lambda g^{(n)} + R \Phi(W g^{(n)})$$

• Strategy: employ adaptive methods (in time/space) to increase efficiency

II. Elliptic problems

Ansatz: adaptive algorithms based on tensor wavelets > dimension-independent convergence rates

• Construction of generalized anisotropic tensor wavelets

Theorem. Let U be decomposable into cubes \Box_i . Let Ψ_i be an anisotropic tensor wavelet basis

derivative \mathscr{S}' on convex, bounded, admissible sets.

II. Regularization

Tikhonov approach yields regularization scheme: p^δ_α → p for a suitable parameter choice rule for α
 Minimization problem (2) is solved by generalized conditional gradient method (iterative soft-shrinkage)

 $p_{n+1} = \operatorname{Shrink}_{\alpha}(p_n - (\mathscr{S}'(p_n))^* \mathscr{P}^*(\mathscr{P}\mathscr{S}(p_n) - g_{\mathbf{t}}^{\delta})) \to p_{\alpha}^{\delta}$

with Besov ℓ_s penality term on coefficients with respect to wavelet basis/frame

Numerical realization





 $\alpha = 1.8 \cdot 10^{-6}, \delta = 2 \cdot 10^{-4}$





 $lpha = 1.2 \cdot 10^{-6}, \delta = 10^{-7}$



 $\frac{-0.5}{-1} - \frac{1}{-1.5} - \frac{1}{-2.5} - \frac$

Objectives and work schedule

Linearized model problem, d = 1,2
Reconstruction of coupling parameter W(t,x)
Adaptive (tensor) wavelet approach
Based on Marburg software library

for $L_2(\Box_i)$, scaled: $W_2^s(\Box_i)$. Let *E* be a combination of univariate extension operators, bounded on $\prod_{i=1}^m L_2(\Box_i)$ and $\prod_{i=1}^m W_2^s(\Box_i)$. Then

 $\Psi_U := E\{\Psi_i\}_{i=1}^m, \tilde{\Psi}_U := E^{-*}\{\tilde{\Psi}_i\}_{i=1}^m$

defines a (biorthogonal) wavelet basis for $L_2(U)$, scaled: $W_2^s(U)$.

> advantages: constructions retains

- tensor structure
- global/local smoothness
- vanishing moments
 piecewise polynomiality

c> dimension-independent approximation rates

Theorem. Given $u \in W_2^m(U)$ there exists an *N*-term approximation $u_N = \sum_{i=1}^N c_\lambda \psi_\lambda$ from Ψ_U , such that

 $\|u - u_N\|_{W_2^m(U)} \lesssim N^{-(\tau - m)} \left(\prod_{\Box_i \subset U} \|u\|_{\mathscr{H}^{\tau}_{m,\theta}(\Box_i)}^2\right)^{\frac{1}{2}}$

whenever u is contained in the weighted Sobolev spaces $\mathscr{H}_{m,\theta}^{\tau}(\Box_i)$.

- Design of adaptive method
- \circ main building block of adaptive methods: approximation of biinfinite matrix/vector-multiplication **APPLY**[$\mathbf{A}, \mathbf{x}, \delta$] $\rightarrow v_{\delta}$ finitly supported with $||\mathbf{A}\mathbf{x} - v_{\delta}|| \leq \delta$
- design of APPLY possible if A is compressible

Theorem. Let **A** be the stiffness matrix according to (3) with respect to Ψ_U . Then there exist matrices \mathbf{A}^M with $\mathscr{O}(M^{\frac{1-\varepsilon}{2}}d)$ many entries per column, such that

 $\|\mathbf{A}-\mathbf{A}^M\| \lesssim 2^{-M}.$

Forward problem: adaptive tensor product wavelet schemes for elliptic/parabolic equations I. Finetuning of adaptive algorithms

- Vector-valued case
- Parallelization strategies
- II. Generalization to nonlinear problems
- Sparse evaluation of nonlinear functionals applied to tensor wavelet expansions
- Generalization to vector-valued case

III. Theoretical justification

- Investigate regularity of solution in generalized weighted Sobolev spaces
- Generalizations to nonlinear problems

Inverse problem: parameter identification with sparsity constraints I. Convergence aspects

- Convergence theory and rates in case of inexact solution of forward problem
- Exploration of different approaches encompassing positivity constraints

II. Accelaration strategies

- Speed-up for iterated soft shrinkage > decreasing thresholding
- Investigate alternative minimization procedures
- Numerical realization and application

I. Fully adaptive solver in time and space

- Efficient sparse evaluation of nonlinearity Φ Vector-valued case
- Adaptive discretization in time
 Parallelization
- Based on Marburg software library

II. Application to full embryogenesis model

Adaptive method converges with optimal order!

• Combination of new forward solver with iterated soft shrinkage • Complex geometry

• High-dimensional parameter space

University of An Rob Stevenson, N	abi Chegini Peter Maass, Rudolf Ressel	Philipps-Universität Marburg Stephan Dahlke, Ulrich Friedrich	
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