

Filtering techniques for efficient inversion of two-dimensional NMR data

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PROBLEM DESCRIPTION

► **NMR data model:** The distribution of amplitudes $F(T_1, T_2)$ of longitudinal and transversal relaxation times T_1, T_2 is related to the NMR data $S(t_1, t_2)$ by the first-kind Fredholm integral equation:

$$S(t_1, t_2) = \int_0^\infty \int_0^\infty k_1(t_1, T_1) k_2(t_2, T_2) F(T_1, T_2) dT_1 dT_2 + e(t_1, t_2), \quad k_1(t_1, T_1) = 1 - 2 \exp(-t_1/T_1), \quad k_2(t_2, T_2) = \exp(-t_2/T_2) \quad (1)$$

where t_1 and t_2 are two independent evolution time variables and $e(t_1, t_2)$ is additive Gaussian noise

► **Reconstruction model:**
$$\min_{\mathbf{f}} \|(\mathbf{K}_2 \otimes \mathbf{K}_1)\mathbf{f} - \mathbf{s}\|_2^2 + \sum_{i=1}^N \lambda_i (\mathbf{L}\mathbf{f})_i^2 \quad \text{s.t.} \quad \mathbf{f} \geq 0 \quad (2)$$

- $\mathbf{s} \in \mathbb{R}^M$ vector ordering of $S \in \mathbb{R}^{M_1 \times M_2}$ measured noisy signal
- $\mathbf{f} \in \mathbb{R}^N$ vector ordering of $F \in \mathbb{R}^{N_1 \times N_2}$, unknown distribution
- $\mathbf{K}_1 \in \mathbb{R}^{M_1 \times N_1}$, $\mathbf{K}_2 \in \mathbb{R}^{M_2 \times N_2}$
- λ_i local spatially adapted regularization parameters
- $\mathbf{L} \in \mathbb{R}^{N \times N}$ discrete Laplacian operator
- $(\mathbf{L}\mathbf{f})_i$ i -th element $\mathbf{L}\mathbf{f}$

CONTRIBUTION

- **2DUPEN** is an *iterative algorithm* that computes the λ_i 's by imposing that all the non-null products $\lambda_i (\mathbf{L}\mathbf{f})_i^2$ have the same constant value (UPEN principle [Inv. Problems, 33(1), 2016]) and an approximated distribution by solving a problem of the form (2) with the Newton Projection method
- 2DUPEN is able to achieve *high quality reconstructions* but requires a *high computational cost*
- The **Mean Windowing (MW)** and **Singular Value Decomposition (SVD)** filters can be used in order to reduce the computational cost of 2DUPEN when applied to *real 2D NMR data*
- The purpose of this work is to analyze the separate and combined effects of these filtering techniques on *synthetic 2D NMR data*.

FILTERING TECHNIQUES

THE MEAN WINDOWING-LIKE FILTER

- Windowing the 2D IR-CPMG data reduces the points in the CPMG blocks: $\bar{\mathbf{s}} \in \mathbb{R}^{\bar{M}_1 \cdot \bar{M}_2}$ with $\bar{M}_2 \ll M_2$
- Consider the *diagonal weighting matrix* $(\mathbf{B} \otimes \mathbf{I})$ where $\mathbf{B} \in \mathbb{R}^{\bar{M}_2 \times \bar{M}_2}$ contains the numbers of points of each CPMG windowed block and $\mathbf{I} \in \mathbb{R}^{\bar{M}_1 \times \bar{M}_1}$ is the identity matrix
- **Weighted least squares problem:**

$$\min_{\mathbf{f} \geq 0} \left\{ \|(\tilde{\mathbf{K}}_2 \otimes \mathbf{K}_1)\mathbf{f} - \tilde{\mathbf{s}}\|_2^2 + \sum_{i=1}^N \lambda_i (\mathbf{L}\mathbf{f})_i^2 \right\}$$

where $\tilde{\mathbf{K}}_2 = \mathbf{B}\bar{\mathbf{K}}_2$, $\bar{\mathbf{K}}_2 \in \mathbb{R}^{\bar{M}_2 \times N_2}$ and $\tilde{\mathbf{s}} = (\mathbf{B} \otimes \mathbf{I})\bar{\mathbf{s}}$,

THE SINGULAR VALUE FILTER FILTER

- SVD of $\mathbf{K}_1 = \mathbf{U}_1 \Sigma_1 \mathbf{V}_1^T$ and $\mathbf{K}_2 = \mathbf{U}_2 \Sigma_2 \mathbf{V}_2^T$ where $\mathbf{U}_i, \mathbf{V}_i$, are orthogonal matrices and Σ_i are the diagonal matrices of the singular values ($i = 1, 2$)
- $\|(\mathbf{K}_2 \otimes \mathbf{K}_1)\mathbf{f} - \mathbf{s}\|_2^2 = \|(\Sigma_2 \mathbf{V}_2^T \otimes \Sigma_1 \mathbf{V}_1^T)\mathbf{f} - (\mathbf{U}_2^T \otimes \mathbf{U}_1^T)\mathbf{s}\|_2^2$
- ρ_i ($i = 1, 2$) is the number of singular values of Σ_i greater than the threshold τ
- **SVD compressed problem:**

$$\min_{\mathbf{f} \geq 0} \left\{ \|(\hat{\mathbf{K}}_2 \otimes \hat{\mathbf{K}}_1)\mathbf{f} - \hat{\mathbf{s}}\|_2^2 + \sum_{i=1}^N \lambda_i (\mathbf{L}\mathbf{f})_i^2 \right\}$$

where: $\hat{\mathbf{K}}_1 = \hat{\Sigma}_1 \hat{\mathbf{V}}_1^T$, $\hat{\mathbf{K}}_2 = \hat{\Sigma}_2 \hat{\mathbf{V}}_2^T$, $\hat{\mathbf{s}} = (\hat{\mathbf{U}}_2^T \otimes \hat{\mathbf{U}}_1^T)\mathbf{s}$, $\hat{\Sigma}_i$ has the first ρ_i diagonal elements of Σ_i and $\hat{\mathbf{U}}_i, \hat{\mathbf{V}}_i$ are made by the first ρ_i columns of $\mathbf{U}_i, \mathbf{V}_i$

ALGORITHM

FILTERED 2DUPEN METHODS

- 2DUPEN_{m1}: SVD filter without MW data reduction
- 2DUPEN_{m2}: SVD filter, MW data reduction without weighting matrix $(\mathbf{B} \otimes \mathbf{I})$
- 2DUPEN_{m3}: MW data reduction, weighting matrix $(\mathbf{B} \otimes \mathbf{I})$ without SVD
- Improved 2DUPEN: SVD filter, MW data reduction, weighting matrix $(\mathbf{B} \otimes \mathbf{I})$

NOTATION

- p_μ, c_μ are the local slope and curvature values of the 2D distribution
- I_i are the indices subset related to the neighborhood of the distribution point i
- $\beta_0, \beta_p, \beta_c$ are parameters depending on the nature of the measured data

DATA PREPROCESSING

- Compute $\tilde{\mathbf{K}}_2 = \mathbf{B}\bar{\mathbf{K}}_2$
- Compute $\tilde{\mathbf{s}} = (\mathbf{B} \otimes \mathbf{I})\bar{\mathbf{s}}$
- Compute the TSVD of \mathbf{K}_1 and $\tilde{\mathbf{K}}_2$ and set $\hat{\mathbf{K}}_1 = \hat{\Sigma}_1 \hat{\mathbf{V}}_1^T$, $\hat{\mathbf{K}}_2 = \hat{\Sigma}_2 \hat{\mathbf{V}}_2^T$
- Compute $\hat{\mathbf{s}} = (\hat{\mathbf{U}}_2^T \otimes \hat{\mathbf{U}}_1^T)\tilde{\mathbf{s}}$

IMPROVED 2DUPEN (I2DUPEN) ALGORITHM

Set $\mathbf{k} = \mathbf{0}$ and compute an over smoothed solution $\mathbf{f}^{(k)}$ of the problem

$$\min_{\mathbf{f} \geq 0} \|(\hat{\mathbf{K}}_2 \otimes \hat{\mathbf{K}}_1)\mathbf{f} - \hat{\mathbf{s}}\|_2^2$$

by applying a few iterations of the **Gradient Projection method**

repeat

1. Compute $\lambda_i^{(k)}$, $i = 1, \dots, N$

$$\lambda_i^{(k)} = \frac{\|(\hat{\mathbf{K}}_2 \otimes \hat{\mathbf{K}}_1)\mathbf{f}^{(k)} - \hat{\mathbf{s}}\|_2^2}{N \left(\beta_0 + \beta_p \max_{\mu \in I_i} (p_\mu^{(k)})^2 + \beta_c \max_{\mu \in I_i} (c_\mu^{(k)})^2 \right)}$$

2. Compute $\mathbf{f}^{(k+1)}$ by solving

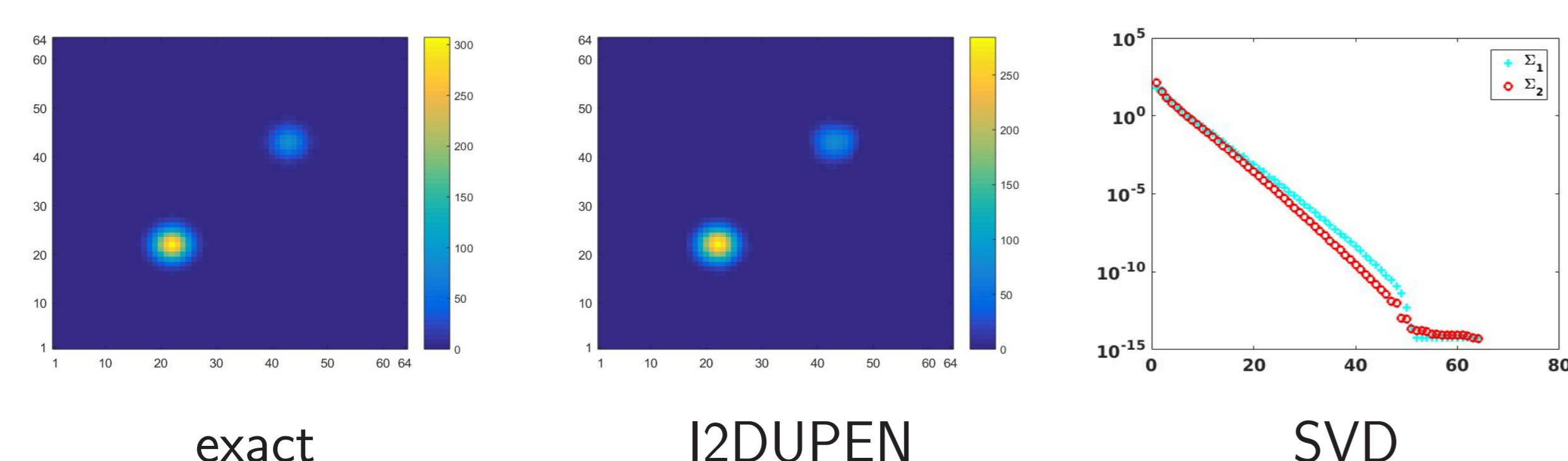
$$\min_{\mathbf{f} \geq 0} \|(\hat{\mathbf{K}}_2 \otimes \hat{\mathbf{K}}_1)\mathbf{f} - \hat{\mathbf{s}}\|_2^2 + \sum_{i=1}^N \lambda_i^{(k)} (\mathbf{L}\mathbf{f})_i^2$$

using the **Newton Projection method**

until $\|\mathbf{f}^{(k+1)} - \mathbf{f}^{(k)}\| \leq \text{tol} \|\mathbf{f}^{(k)}\|$

Tests on Synthetic NMR relaxation data

- Synthetic data: $M_1 = 128$, $M_2 = 2048$, $\bar{M}_2 = 118$, $N_1 = N_2 = 64$
- Gaussian random noise added with variance 10^{-2} .
- 2DUPEN parameters: $\beta_0 = 10^{-6}$, $\beta_p = \beta_c = 1$, $\text{tol} = 0.001$.



τ	2DUPEN _{m1}				2DUPEN _{m2}				I2DUPEN			
	ρ_1, ρ_2	Err	Time(s)		ρ_1, ρ_2	Err	Time(s)	ρ_1, ρ_2	Err	Time(s)		
0	64 64	2.749e-02	1352.93		64 64	3.717e-02	2444.87	64 64	7.402e-02	925.04		
10^{-6}	32 29	2.620e-02	1455.08		32 28	3.768e-02	1598.35	32 29	5.571e-02	884.07		
10^{-4}	24 22	2.731e-02	1252.22		24 21	3.827e-02	1362.99	24 22	6.124e-02	840.35		
10^{-3}	20 18	2.841e-02	907.54		20 17	3.878e-02	1409.33	20 18	5.655e-02	915.50		
10^{-2}	16 15	3.245e-02	839.48		16 14	3.914e-02	1295.50	16 15	5.833e-02	826.31		
10^{-1}	12 11	4.459e-02	738.53		12 10	5.214e-02	778.53	12 11	6.706e-02	720.71		