Sparse Variational PAT Inversion

We need to solve \( f = G A p_0 \), with \( G \) sub-sampling and \( A \) forward operator. As conventional approaches fail when used on sub-sampled data (cf. Fig. 7), we employ sparse variational regularization (e.g., total variation, TV),

\[
\tilde{p}^k = \underset{p \geq 0}{\text{argmin}} \frac{1}{2} \| f - G A p \|^2 + \lambda J(p) \quad (1)
\]

enhanced by Bregman iterations (see Osher et al., 2005),

\[
p^{k+1} = \underset{p \geq 0}{\text{argmin}} \frac{1}{2} \| f + b^k - G A p \|^2 + \lambda J(p)
\]

\[
b^{k+1} = b^k + f - G A p^{k+1} \quad \text{and} \quad b_1 = 0
\]

to compensate the systematic bias of (1) (cf. Fig. 6).

Implementation & Preliminary Results

To solve (1) by first order optimization such as proximal gradient or (preconditioned) ADMM schemes (cf. Burger et al., 2014), we need to evaluate \( A \) and \( A^T \). Our implementation relies on a \( k \)-space pseudo-spectral method for 3D acoustic wave propagation (Treeby & Cox, 2010). We have formulated and tested an analytical and an explicit numerical representation of the adjoint \( A^T \) and utilized GPU computing to cope with the immense computational challenges.

Fig. 5, 6 & 7 show the evaluation of our methods with simulated data and demonstrate the potential of sparsity-based reconstructions from heavily sub-sampled data. Fig. 8 & 9 show their application to experimental data of a dynamic phantom. Various non-trivial difficulties such as developing pre-processing routines and improved forward models will have to be overcome to realize similar compression factors as in the simulations.

Spatio-Temporal Inversion

PAT data is continuously acquired. While using sparsity-based inversion on each short, sub-sampled stream of data (frame) individually can already significantly enhance the dynamic frame rate, full spatio-temporal schemes can also take advantage of the temporal redundancies of the data and lead to a better trade-off between spatial and temporal resolution. Dependend on the underlying dynamics, different dynamic models will be implemented and tested in the future:

- **Low-rank** (sparse) models for functional imaging with static anatomy.
- Tracer uptake/kinetic models for tracer-based imaging.
- Perfusion models for bolus tracking
- Optical flow constraints for joint image reconstruction and motion estimation.

Simultaneously, numerical and experimental phantoms will be developed to evaluate our results.

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