The BART Toolbox
for Computational Magnetic Resonance Imaging

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***Abstract*—We present our BART Toolbox for computational Magnetic Resonance Imaging (MRI). The main motivation for the development of this toolbox was the simultaneous need for rapid prototyping of new computational imaging methods for MRI and for highly efficient implementations. The main philosophy is the use of generic numerical algorithms and re-usable and highly configurable software components. The BART toolbox consists of programming libraries and flexible command-line tools. It contains tools for simulation, pre-processing, calibration, and image reconstruction.**

I. Compressed Sensing and Parallel Imaging

Compressed sensing is based on the idea that a sparse signal can be recovered using iterative denoising from undersampled data if the aliasing is incoherent. This idea can be applied to MRI and also combined with parallel imaging [1], [2]. In parallel imaging, the signal can be modelled as samples of the Fourier transform of the magnetization image ρ modulated by the receive-coil sensitivities c_j along a given k-space trajectory $k(t)$:

$$y_j(t) = \int \mathrm{d}\vec{r}\, \rho(\vec{r}) c_j(\vec{r}) e^{-2\pi i \vec{k}(t)\cdot\vec{r}}$$

If the coil sensitivities c_j are known, image reconstruction can be formulated as a linear inverse problem [3]. For autocalibrating parallel imaging the sensitivities must be estimated from the data. This yields a bilinear problem which is similar to blind multi-channel deconvolution. Three different reconstruction approaches are implemented in BART: non-linear inversion (NLINV) [4], structured low-rank matrix completion (SAKE) [5], and ESPIRiT [6] which is based on identification of the signal subspace.

II. Generalized Reconstruction

Many recent methods are based on high-dimensional reconstruction problems which include additional time and parametric dimensions (see Fig. 1 for examples). To facilitate experimentation, BART implements a generic framework based on the following optimization problem [7]:

$$\operatorname*{arg\,min}_x \sum_j \| W (P \mathcal{F} \sum_k S_j{}^k x^k - y_j) \|_2^2 + \sum_i^N \lambda_i f_i(B_i x)$$

Here, $\mathcal{F}$ is a multi-dimensional Fourier transform, P is a sampling operator, S the multiplication with the sensitivities, W a weighting matrix, the B_i are linear operators, f_i convex functions, λ_i regularization parameters. For arbitrary combinations of certain regularization terms and transforms along arbitrary dimensions, this problem can be solved using ADMM and a library of proximity functions using the following BART command:

> bart pics -Rf:B:C:λ -R ... [-t P] -p W y S x

III. Conclusion

BART provides a flexible and efficient framework for rapid prototyping of advanced computational methods in MRI.

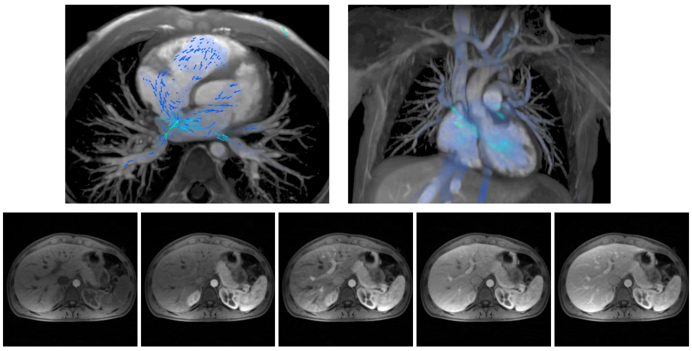

Fig. 1. Reconstruction of high-dimensional data using BART. **Top:** Highly accelerated 4D-flow [9]. **Bottom:** Dynamic contrast-enhanced MRI using GRASP [10]. Data courtesy of Joseph Y. Cheng and Tobias Block.

References

[1] M. Lustig, D. Donoho, and J. M. Pauly, “Sparse MRI: The application of compressed sensing for rapid MR imaging.” *Magn. Reson. Med.*, vol. 58, pp. 1182–1195, 2007.

[2] K. T. Block, M. Uecker, and J. Frahm, “Undersampled radial MRI with multiple coils. iterative image reconstruction using a total variation constraint,” *Magn. Reson. Med.*, vol. 57, pp. 1086–1098, 2007.

[3] K. P. Pruessmann, M. Weiger, P. Börnert, and P. Boesiger, “Advances in sensitivity encoding with arbitrary k-space trajectories.” *Magn. Reson. Med.*, vol. 46, pp. 638–651, 2001.

[4] M. Uecker, T. Hohage, K. T. Block, and J. Frahm, “Image reconstruction by regularized nonlinear inversion - joint estimation of coil sensitivities and image content,” *Magn. Reson. Med.*, vol. 60, pp. 674–682, 2008.

[5] P. J. Shin, P. E. Z. Larson, M. A. Ohliger, M. Elad, J. M. Pauly, D. B. Vigneron, and M. Lustig, “Calibrationless parallel imaging reconstruction based on structured low-rank matrix completion.” *Magn. Reson. Med.*, vol. 72, pp. 959–970, 2014.

[6] M. Uecker, P. Lai, M. J. Murphy, P. Virtue, M. Elad, J. M. Pauly, S. S. Vasanawala, and M. Lustig, “ESPIRiT - an eigenvalue approach to autocalibrating parallel MRI: Where SENSE meets GRAPPA.” *Magn. Reson. Med.*, vol. 71, pp. 990–1001, 2014.

[7] J. I. Tamir, F. Ong, J. Y. Cheng, M. Uecker, and M. Lustig, “Generalized magnetic resonance image reconstruction using the berkeley advanced reconstruction toolbox,” in *ISMRM Workshop on Data Sampling and Image Reconstruction*, 2016.

[8] M. Uecker, F. Ong, J. I. Tamir, D. Bahri, P. Virtue, J. Y. Cheng, T. Zhang, and M. Lustig, “Berkeley advanced reconstruction toolbox,” in *Proc. Intl. Soc. Mag. Reson. Med*, vol. 23, 2015, p. 2486.

[9] J. Y. Cheng, K. Hanneman, T. Zhang, M. T. Alley, P. Lai, J. I. Tamir, M. Uecker, J. M. Pauly, M. Lustig, and S. S. Vasanawala, “Comprehensive motion-compensated highly-accelerated 4D flow MRI with ferumoxytol enhancement for pediatric congenital heart disease,” *Journal of Magnetic Resonance Imaging*, vol. 43, pp. 1355–1368, 2016.

[10] L. Feng, R. Grimm, K. T. Block, H. Chandarana, S. Kim, J. Xu, L. Axel, D. K. Sodickson, and R. Otazo, “Golden-angle radial sparse parallel MRI: Combination of compressed sensing, parallel imaging, and golden-angle radial sampling for fast and flexible dynamic volumetric MRI,” *Magn. Reson. Med.*, vol. 72, pp. 707–717, 2014.