PySAP-MRI: a Python Package for MR Image Reconstruction

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Target audience: It is expected that the audience has preliminary knowledge of classical MRI acquisition and reconstruction techniques. Pysap-mri is aimed at researchers who need fast MR image reconstruction algorithms for under-sampled k-space data. It has been fully tested on Linux Ubuntu 16.04/18.04 LTS and Mac OS operating systems.

Purpose: We present the open-source MRI plugin, called pysap-mri, of the software package PySAP (Python Sparse data Analysis Package). PySAP offers a large set of fast wavelet transforms and a range of integrated optimization algorithms in Python. The plugin pysap-mri provides methods, tools and examples for MR image reconstruction in various acquisition setups (2D and 3D imaging, Cartesian and non-Cartesian readout, parallel imaging, etc.) in the context of accelerated acquisitions using compressed sensing. This plugin is available on Pypi as `pysap-mri 0.1.1`. Test data are available in pysap-data.

Methods: We address the problem of compressed sensing parallel imaging (CS-PI) reconstruction using a Sensitivity Encoding (SENSE) formulation. Let L be the number of coils used to acquire the NMR signal, N be the number of pixels of the complex-valued image $\boldsymbol{x}$ to be reconstructed and M the number of samples collected per channel during acquisition. We denote by $\boldsymbol{y}_\ell \in \mathbb{C}^M$ the complex-valued data recorded by the ℓ^{th} channel, $\boldsymbol{S}_\ell \in \mathbb{C}^{N\times N}$ the corresponding diagonal sensitivity matrix. Let $\boldsymbol{F}$ be the Fourier operator and $\Omega \in \{1, \dots, N\}$ the sampling pattern in k-space, with $|\Omega| = M \ll N$, the forward model reads: $\boldsymbol{y}_\ell = \boldsymbol{F}_\Omega \boldsymbol{S}_\ell \boldsymbol{x} + \boldsymbol{n}_\ell$, $\forall \ell = 1, \dots, L$. In pysap-mri, two different approaches have been proposed and implemented for solving the CS-PI reconstruction problem, namely *self-calibrating* [El Gueddari et al, IEEE SAM 2018] and *calibrationless* [El Gueddari et al, IEEE ISBI, 2019] approaches. The self-calibrating approach means that we first extracted the sensitivity maps $(\boldsymbol{S})_{1\leq\ell\leq L}$ from the k-space center and then we compute the following minimizer: $\widehat{\boldsymbol{x}} = \arg\min_{\boldsymbol{x}\in\mathbb{C}^N} \left[\mathcal{J}(\boldsymbol{x}) = \sum_{\ell=1}^{L} \frac{1}{2\sigma_\ell^2} \|\boldsymbol{y}_\ell - \boldsymbol{F}_\Omega \boldsymbol{S}_\ell \boldsymbol{x}\|_2^2 + \lambda \|\boldsymbol{\Psi}\boldsymbol{x}\|_1\right]$ where parameter $\lambda > 0$ refers to the regularization parameter and $\boldsymbol{\Psi} \in \mathbb{C}^{N_\Psi \times N}$ to the wavelet decomposition operator as the MR image is assumed to be sparse (at least compressible) in the wavelet basis. In PySAP, we have a large set of candidates for $\boldsymbol{\Psi}$. Here, we used a orthogonal wavelet basis (Symmlet 8) but the presented work extends to redundant transforms such as curvelets or tight frames. In the calibrationless framework, instead of extracting matrices $\boldsymbol{S}_\ell$, we directly reconstruct a set of L MR images stacked in $\boldsymbol{X} = [\boldsymbol{x}_1 \dots, \boldsymbol{x}_L] \in \mathbb{C}^{N\times L}$ and in the end we used the sum of square to recombine all of them into a single image. In that case, we compute the following solution: $\widehat{\boldsymbol{X}} = \underset{\boldsymbol{X}\in\mathbb{C}^{N\times L}}{\arg\min} \left\{\sum_{\ell=1}^{L} \frac{1}{2\sigma_\ell^2} \|\boldsymbol{y}_\ell - \boldsymbol{F}_\Omega \boldsymbol{x}_\ell\|_2^2 + g(\boldsymbol{\Psi}\boldsymbol{X})\right\}$ where $g \in \Gamma_0(\mathbb{C}^{N_\Psi \times L})$ is a regularization function composed with $\boldsymbol{\Psi}$, with the aim to enforce structured sparsity across channels (e.g. group-LASSO or OSCAR penalty) [El Gueddari et al, ISBI 2019]. For optimization purposes, we implemented both proximal gradient methods (e.g. FISTA, greedy FISTA, POGM) [Ramzi et al, SPARS 2019] or primal-dual splitting methods (e.g. [Condat, JOTA 2013; Vũ, ACM 2013]).

Results: For validation purposes, we used anatomical brain MRI data collected at 7T (Magnetom Siemens scanner, Erlangen, Germany) using the 32-channel (Nova Medical Inc., Washington, MA, USA) coil (i.e., $L = 32$). A modified 2D T2*-weighted GRE sequence was implemented to perform prospective CS based on the multi-shot Sparkling trajectories [Lazarus et al, MRM 2019] The acquisition parameters were set as follows: TR = 550 ms, TE = 30 ms and FA = 25° with in-plane resolution of 400 μm corresponding to an image matrix size of $N = 512 \times 512$. Slice thickness was 3mm. Scan time was 35 s per slice for 8-fold accelerated Sparkling acquisition as compared to Cartesian reference. Extraction of sensitivity maps took about 1 min using the proposed self-calibrating methods, compared to 10 min in the ESPIRiT framework (see [El Gueddari et al, IEEE SAM 2018] for details). The corresponding self-calibrating and calibrationless *magnitude* images are shown in Fig. 1 and match very well the Cartesian reference, as well as the slower ℓ_1-ESPIRiT approach [Uecker et al, MRM 2014]. In terms of computation time, self-calibrating and OSCAR-based calibrationless MR image reconstruction took respectively 3 and 8 min for a single slice on a computer equipped with a 8-core (2.40 GHz) Intel Xeon Silver 4112 2.6 GHz Processor and 128 GB of RAM. The increase in computing load for calibrationless reconstruction is due to both the larger number of unknowns to be estimated and the higher complexity associated with the proximity operator of OSCAR-norm regularization [Bondell and Reich, Biom. 2008].

Discussion: All methods recover approximately the same magnitude image. However, some differences may appear in the phase image (results not shown). Although the calibrationless approach is more computationally expensive, it is more flexible for *online* CS MR image reconstruction as it no longer requires the extraction of sensitivity maps. Hence, this formulation allows one to interleave data acquisition and image reconstruction by segmenting the acquisition in mini-batches and performing partial image reconstruction. By doing so one can deliver a decent MR image by the end of acquisition [El Gueddari et al, SPIE 2019].

Conclusion: We have presented pysap-mri, a new open source, well documented and continuously integrated software package for 2D and 3D CS MR image reconstruction that will be progressively enriched with contributions on deep learning.

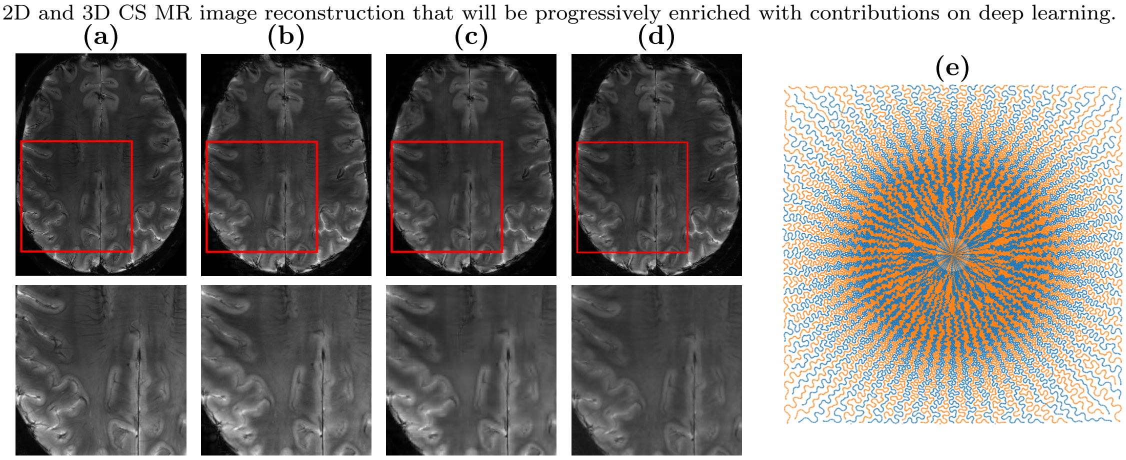

Figure 1: **Top:** **(a)** Cartesian reference; **(b)**: our self-calibrating approach; **(c)**:ℓ_1-ESPIRiT and **(d)**: OSCAR-based calibrationless reconstruction from 8-fold accelerated prospective Sparkling acquisition shown in **(e)**. **Bottom:** respective zooms in the red frames.