3D-Dictionary-Learning-CS Reconstruction of Radial ^{23}Na-MRI-data

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Intruduction

The increasing availability of ultra-high field MR-systems within the last years has enabled in-vivo sodium MRI at resolutions of a few millimeters within measurement times of 10-20 minutes. However, the major drawbacks of sodium MRI are still its low NMR sensitivity (9.2% of proton sensitivity) and the low in-vivo concentration that result in poor SNR[1]. Several attempts that utilize compressed sensing[2], iterative imagine reconstruction techniques and the incorporation of prior knowledge from proton MRI have been made to improve the image quality of non-proton data[3,4,5]. Whereas first implementations of compressed sensing in MRI used analytical transforms such as wavelets or total variation to enforce sparsity, adaptive patch-based dictionaries recently made their appearance in MRI[6,7]. In this work we propose the application of 3-dimensional block dictionaries learnt directly on the noisy high-resolution ^{23}Na-images reconstructed with gridding, using the K-SVD algorithm described by Aharon et al[8]. These dictionaries are then used as the sparsifying transform in a compressed sensing framework. The performance of this method is evaluated on simulated data showing multiple sclerosis (MS)-lesions, a resolution phantom and in-vivo ^{23}Na-data of a healthy volunteer.

Methods

For 3D-dictionary-learning-CS the following minimization problem has to be solved iteratively:

$$\{\hat{\boldsymbol{\alpha}}_{\mathbf{ijk}}, \hat{\mathbf{X}}\} = \mathbf{arg}\min_{\boldsymbol{\alpha}_{\mathbf{ijk}},\mathbf{X}} \boldsymbol{\lambda}\|\mathbf{FX}-\mathbf{Y}\|_2^2 + \sum_{\mathbf{ijk}} \mu_{\mathbf{ijk}}\|\boldsymbol{\alpha}_{\mathbf{ijk}}\|_0 + \sum_{\mathbf{ijk}} \|\mathbf{D}\boldsymbol{\alpha}_{\mathbf{ijk}} - \mathbf{R}_{\mathbf{ijk}}\mathbf{X}\|_2^2$$

X is the reconstructed image, **FX** is its gridding reconstruction, **Y** is the measured raw data, $\boldsymbol{\alpha}_{\mathbf{ijk}}$ is the sparse representation in the dictionary **D** and $\mathbf{R}_{\mathbf{ijk}}$ is a diagonal matrix that extracts a block of interest from the image. The cost function combines self-consistency of the reconstructed image, sparsity of the dictionary coefficients and block wise consistency of the reconstructed image and its dictionary representation. The minimization of the cost function is achieved by alternately solving $\hat{\boldsymbol{\alpha}}_{\mathbf{ijk}} = \mathbf{arg}\min_{\boldsymbol{\alpha}_{\mathbf{ijk}}} \mu_{\mathbf{ijk}}\|\boldsymbol{\alpha}_{\mathbf{ijk}}\|_0 + \|\mathbf{D}\boldsymbol{\alpha}_{\mathbf{ijk}} - \mathbf{x}_{ijk}\|_2^2$ using the K-SVD algorithm and $\hat{\mathbf{X}} = \mathbf{arg}\min_{\mathbf{X}} \boldsymbol{\lambda}\|\mathbf{FX}-\mathbf{Y}\|_2^2 + \|\mathbf{D}\boldsymbol{\alpha}_{\mathbf{ijk}} - \mathbf{x}_{ijk}\|_2^2$ with a conjugate gradient algorithm. The algorithm was initialized with the gridding reconstruction of the image with zero-filling to a matrix size of 256x256x256 (original size: 128x128x128). The applied dictionary consists of 1024 blocks (block-size: 8x8x8) and is learnt on 40000 samples from the image obtained by gridding. The reconstruction algorithm was tested on simulated data with MS-lesions from the BrainWeb database (1mm isotropic). Radial k-space data was simulated with a nominal resolution of 2mm isotropic. 10000 projections were used, which corresponds to ≈ 20% of the Nyquist sampling rate.

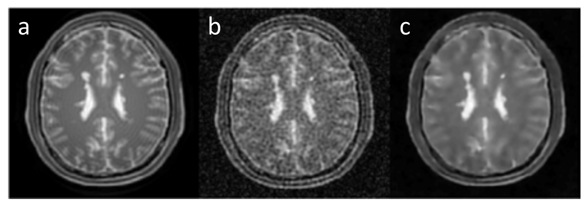

Fig. 1: Simulated radial data, a: fully sampled noiseless gridding reconstruction, b: undersampled gridding reconstruction, c: 3D-dictionary-learning-CS reconstruction

A density-adapted 3D radial projection pulse sequence[9] was applied to acquire ^{23}Na data on a 7 T whole body MR system (Magnetom 7 T, Siemens Healthcare, Erlangen, Germany). A double-resonant (^{1}H: 297.2 MHz; ^{23}Na: 78.6 MHz) quadrature birdcage coil (Rapid Biomed GmbH, Rimpar, Germany) was used. Both a resolution phantom (0.9% saline solution; the distances between the acrylic glass rods are identical to the diameters of the rods; acquisition parameters: 1.5mm isotropic, 20000 projections, TE/TR=0.35/30ms, α=51°, TA=10min) and a healthy volunteer (2mm isotropic, 40000 projections, TE/TR=0.35/30ms, α=51°, TA=20min) were measured and reconstructed with gridding and 3D-dictionary-learning-CS reconstruction.

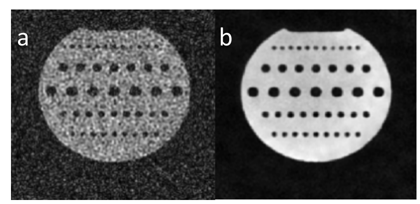

Fig. 2: Phantom ^{23}Na-data, a: gridding reconstruction, b: 3D-dictionary-learning-CS reconstruction; rod diameters are 3-10mm

Results

Figure 1 shows the fully sampled noiseless gridding reconstruction (figure 1a), the undersampled gridding reconstruction with additional noise (figure 1b) and the 3D-dictionary-learning reconstruction of the noisy undersampled simulated data (figure 1c). Compared to gridding, the 3D-dictionary-learning-CS reconstruction benefits from significantly reduced noise, 25% higher structural similarity (SSIM)[10] and 12.5% lower RMSE. Small lesions that cannot be distinguished from noise when using gridding are visible when using 3D-dictionary-learning-CS. The K-SVD converged after a maximum of 20 iterations, the conjugate gradient algorithm after 5 iterations. The total reconstruction time was 10 min on a standalone PC. The reconstructions of the phantom-data can be seen in figure 2. The image reconstructed with 3D-dictionary-learning benefits from significantly reduced noise while edges and small structures are well preserved. This is confirmed by the results achieved with in-vivo data (figure 3). While noise is clearly reduced, fine structures are well resolved without any visible loss of information. The reconstruction times were 60 min for the phantom data and 30 min for in-vivo data.

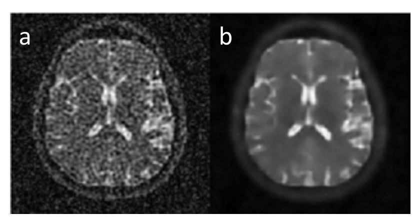

Fig. 3: In-vivo ^{23}Na-data, a: gridding reconstruction, b: 3D-dictionary-learning-CS reconstruction

Discussion & Conclusion

3D-dictionary-learning-CS was applied for the reconstruction of ^{23}Na-data. Compared to other algorithms no prior knowledge about the anatomy was included, which prevents bias. The applied algorithm enables sparse representations and therefore good performance in the reduction of noise and incoherent artifacts. The results obtained exhibit significant noise reduction compared to the gridding reconstructions without compromising the visibility of small structures or smearing edges.

References

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