A comparison of 19F MRI recovery from compressive sensing

Sayuan Liang[1], Yipeng Liu[2], Tom Dresselaers[1], Sabine Van Huffel[2], and Uwe Himmelreich[1]
[1]*Department of Imaging & Pathology, KU Leuven, Leuven, Flemish Brabant, Belgium,* [2]*ESAT, KU Leuven, Leuven, Flemish Brabant, Belgium*

Introduction

Recently, compressed sensing (CS) has been considered as an effective method for reducing the acquisition time without degrading the image quality[1]. Essential to CS is that the data should be sparse, which is typically the case for ^{19}F images (in the original image domain). Though the feasibility of accelerating cellular ^{19}F MRI using CS has been demonstrated by Zhong *et al*[2], knowledge about the performances of different CS reconstruction techniques in ^{19}F applications, especially for newly developed non-convex methods, is still missing. In this study, we have implemented four non-convex algorithms along with one typical convex algorithm (SparseMRI software) provided by Lustig[1] as golden standard to compare and evaluate the features including speed and accuracy of different methods based on the CS simulation of fully sampled phantom data.

Method and Materials

A phantom was prepared by filling 0.25 mM/ml NaF solution into plastic tips and then moved to a pre-prepared plastic container filled with 2% agarose. MR imaging was performed on a 9.4T Bruker Biospec small animal MR scanner (Bruker Biospin, Ettlingen, Germany) using a home-built surface coil tuneable-matcheable to ^{19}F or ^{1}H resonances. Fully sampled 3D FLASH ^{19}F image were acquired using scan parameters: TE/TR = 4.4/100 ms, FA = 15, NA = 16, FOV = 4 * 4 *4 cm^3, matrix size = 64 * 64 * 64.
Four different non-convex based reconstruction algorithms including compressive sampling matching pursuit[3] (CoSaMP), orthogonal multimatching pursuit[4] (OMMP), two-level L1 minimization[5] and reweighted-L1 minimization[6] were evaluated in this study. Raw k-space data were under-sampled offline in both phase encoding directions. The under-sample patterns were generated by SparseMRI software using probability density function with different under-sample factors (UF = 2, 4, 8, 16 and 32). Slices with clear ^{19}F signals were processed in the same manner and the SNR of reconstructed signal were normalized to SNR of the fully sampled signal. Matlab 2013 software (MathWorks, Natick, U.S.A) was used for all different CS reconstructions. Paired ANOVA test with Bonferroni correction was done using GraphPad PRISM 5 software (GraphPad Software, La Jolla, U.S.A) for statistical analysis. Time for reconstruction was also recorded for speed comparison.

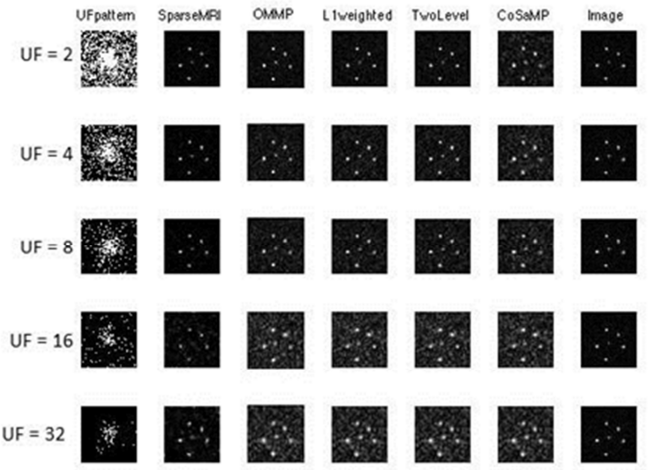

Fig.1 Reconstructed images by different algorithms under different UFs along with under-sampled pattern and fully-sampled image

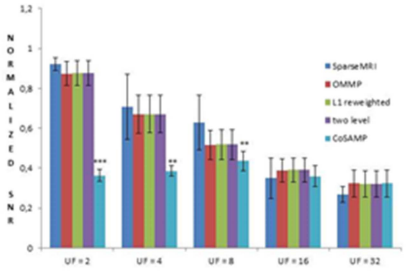

Fig.2 Normalized SNR values of reconstructed signal s of interest to the fully sampled image

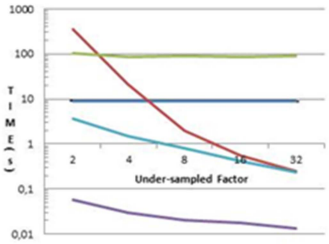

Fig.3 Average computational time of different algorithms under different UFs(standard deviation is too small to be visualized)

Results

At low UF (2-8), all algorithms except CoSaMP gave good and similar reconstructed image quality (fig.1 and fig.2), while for higher UF (16 and 32) the performance is degraded and there is no significant difference between different methods. Notably, while the standard deviation of the noise level is close resulting in similar SNR levels, the average noise level of the SparseMRI-based reconstructed image was lower than for the other methods. The two-level method is clearly the fastest method among all different algorithms while reweighted-L1 method is slowest without any significant improvement in image quality. The computational time (fig.3) decreased with increasing UF and was limited for most methods except for the OMMP method, which requires about 1500 times longer at UF of 2 vs. 32.

Conclusion and Discussion

To the best of our knowledge, this is the first time that different compressed sensing algorithms have been compared with regard to ^{19}F MRII applications. Despite the de-noise feature of SparseMRI giving better visualization of reconstructed images, we conclude that, except CoSAMP, all methods tested could generate images with a similar SNR. If one takes the computation time into account, the two-level method is the most efficiency algorithm. The dependency of these results on the under-sampling pattern and robustness to different types of 19F MRI applications needs to be further explored. Finally, the TV penalty[1] taken into account by SparseMRI can also be applied to the reweighted-L1 and two-level methods thereby further improving their performances.

References

1.Lustig M, et al. MRM 2007;58:1182-95; 2.Zhong J, et al. MRM 2013;69:1683-90; 3. Needell D, et al. Applied and Computational Harmonics Analysis 2009;26:301-21. 4. Liu E, et al. IEEE Trans 2012;58:2040-47. 5.Huang X, et al. accepted for publish in Signal Processing. 6. Candes EJ, et al. Journal of Fourier analysis and applications 2008;14:877-905