An improved approach in applying compressed sensing in parallel MR imaging

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Introduction Both parallel MRI (pMRI, [1]) and compressed sensing (CS, [2]) allow image reconstruction from an under-sampled data set. The former exploits data redundancy in a sparse transform domain representation whereas the latter exploits the redundancy in multiple receiver data sets. Some success has already been reported in combining the two methods directly [3]. We report a new approach in which conventional pMRI and CS are *cascaded* to better exploit the individual strengths of the two methods.

Theory The key difference between conventional pMRI (SENSE-like) reconstruction and that of CS recovery is that the former solely relies on the 2nd norm measurement of data consistency, whereas the latter further incorporates a 1st norm term to encourage the sparseness in the recovered data set, given that the underlying signal has a sparse nature. Thus

$$\tilde{x} = \arg\min_{x} \left(\| y - M x \|_2 \right) \qquad (1) \qquad\qquad \tilde{u} = \arg\min_{u} \left(\| y - M x \|_2 + \lambda \| u \|_1 \right) , \quad x = \Phi^{-1} u . \quad (2)$$

where y, x and M are respectively the partial data measurement, the underlying signal, and the pMRI encoding matrix; Φ is a transform used to enhance data sparsity. Equ. (1) represents the SENSE-like pMRI reconstruction while Equ. (2) represents the direct application of CS recovery with pMRI as in [3]. Successful CS recovery requires a non-uniform sampling pattern that produces a non-coherent aliasing pattern as described in [2]; on the other hand, a SENSE-like uniform sampling pattern is desirable for pMRI to improve the effectiveness of coil sensitivity encoding [1]. Hence employment of either type of sampling pattern reduces the overall effectiveness of Equ. (2).

To overcome the above constraint, we propose a two-step cascaded reconstruction. It is known that a SENSE-like pMRI reconstruction gives a 2nd norm optimal image estimation, but is impaired with reconstruction noise. On the other hand, CS recovery is noise stable, and use of a total variation (TV) constraint further suppress the intrinsic noise [2]; its drawback is the loss of image details (inaccurate image estimation). Hence the pros and cons of the two types of reconstruction complement each other. In our approach a SENSE reconstruction is first performed, and this is then incorporated as a prior estimation in the 2nd phase CS recovery with a TV constraint. Incorporation of the prior estimation in CS recovery can be achieved by performing a data sorting of the underlying image based on the prior estimation [4]. As has also been illustrated in [5], data sorting can be seen as a rearrangement of the elements in the underlying signal x and hence the corresponding columns in M. Thus we have:

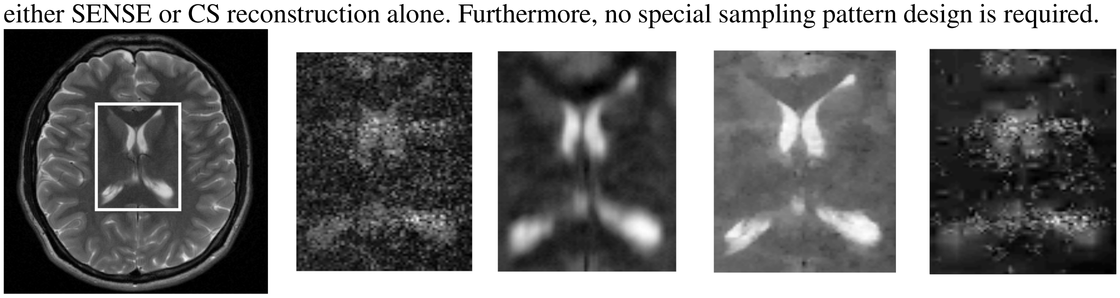
$$\tilde{v} = \arg\min_{v} \left(\| y - M_S \, x_S \|_2 + \lambda \| v \|_1 + \sigma TV(x) \right) , \; x_S = \Phi^{-1} v , \; x_S \xrightarrow{S^{-1}} x \quad (3)$$

where subscript 'S' denotes the sorting order that is obtained by sorting the SENSE reconstruction. Note that the TV constraint is applied to the 'unsorted' image. In Eqn. (3), coupled with the data consistency term, the CS operator preserves the image details from the SENSE reconstruction whereas the TV constraint suppresses the noise. For brevity, we refer to our method as SENSECS.

Method A 2D T2-weighted axial brain slice was obtained (256×256) using a 1.5T GE scanner equipped with an 8-channel head coil. Reconstructions using the muti-coil data sets were made using SENSE, CS and SENSECS at an acceleration factor of 6. A variable density sampling pattern was used in CS, whereas the SENSE-type uniform sampling pattern was used in SENSECS. CS reconstructions were performed based on a modification of the sparse MRI tool box by Lustig M., using a Daubechies wavelet transform. To further illustrate that the 2nd phase CS recovery in the new SENSECS is distinct from a filtering process, a wavelet shrinkage denoising [6] was performed on the SENSE reconstruction as a comparison.

Results and discussion Reconstructions of an axial brain slice using the different methods are shown in Fig 1. It is seen that at an acceleration factor of 6, SENSE reconstruction is severely corrupted by reconstruction noise, whereas the CS reconstruction shows blurring artifacts. The new SENSECS reconstruction preserves the image details while achieving a low noise profile. In comparison, wavelet denoising of the SENSE reconstruction is not successful due to the structured reconstruction noise.

Conclusion We have introduced a new method named SENSECS that achieves both good image fidelity and low noise level by exploiting the strengths of both SENSE reconstruction and CS reconstruction. It allows improved image reconstruction compared with either SENSE or CS reconstruction alone. Furthermore, no special sampling pattern design is required.



(a) full data acquisition (b) SENSE (c) CS (d) SENSECS (e) denoised SENSE

Figure 1: Reconstructions of an axial brain slice using different methods at an acceleration factor of 6. In (b)-(e), the boxed region in the reference image (a) are enlarged and compared. It is seen that the new SENSECS method gives the best reconstruction.

Reference [1] Pruessmann KP, *et al.* MRM, 1999 [2] Lustig M, *et al.* MRM, 2007 [3] Wu B. *et al.* Proc. ISMRM, 589, 2008 [4] Wu B, *et al.* SPIE, 7076, 2008 [5] Adluru G, *et al.* Proc. ISMRM, 3153, 2008 [6] Donoho D, IEEE Trans. Info. Theory, 1995