Parallel Compressed Sensing MRI Using Reweighted L1 Minimization

C-H. Chang[1]**, and J. Ji**[1]
[1]Texas A&M University, College Station, Texas, United States

Introduction: Integrating compressed sensing (CS) with multiple receiver coils has drawn great attentions because of its potential to significantly reduce imaging time in MRI [1-7]. The former is by incoherently sampling k-space and exploring the sparsity of MR images; the latter can reduce scan time by resorting to parallel MRI (pMRI). Several groups have applied CS to pMRI, such as integrating SENSE or SPACE-RIP [3-7]. In these work, CS is regarded as a regularization method and is integrated to take advantages of the sensitivity information from multiple receiver coils. In this abstract, we propose a reconstruction method that uses reweighted l_1 minimization to enhance the reconstruction of parallel CS MRI [9].

Methods: The system of pMRI can be formulated as a set of large-scale linear equations in the references [4, 8] as $\mathbf{y} = \mathbf{\Phi x}$, where $\mathbf{y}$ represents the acquired data vector at randomized k-space locations from all channels. $\mathbf{\Phi}$ represents the encoding matrix incorporating gradient-based and coil sensitivity-based encodings. The image $\mathbf{x}$ can be recovered by $\min TV(\mathbf{x})$ subject to $\|\mathbf{y} - \mathbf{\Phi x}\|_2 < \varepsilon$, where TV is the total variation and ε is a parameter proportional to the noise level. We proposed to use the reweighted nonlinear conjugate gradient solver to enhance the sparse solutions by minimizing $\|\mathbf{y} - \mathbf{\Phi x}\|_2^2 + \lambda \mathbf{w}^{(l)} TV(\mathbf{x})$, where the weights $w^{(l)}$ are inversely proportional to the total variation of $\mathbf{x}$ at each pixel location. Specifically, the image $\mathbf{x}$ is reconstructed as follows. First, set the iteration count l=0 and the initial weight $\mathbf{w}^{(0)} = \mathbf{1}$, and solve the minimization problem. Second, update the weight by $w^{(l+1)} = 1/(TV(x^{(l)}) + \delta)$, where δ is a small positive number to overcome the noise interference which is set to 0.1 for the normalized received data in this work. Finally, reiterate the previous steps until l attains a specified number.

To test the algorithm, both simulated and in-vivo data were used. A 4-channel k-space dataset was simulated using the 128×128 'Shepp-Logan' phantom and linear Gaussian sensitivities. The individual channel data were randomly under-sampled by a factor of R=6 along the phase encoding direction. In addition, a 4-channel 256×256 in-vivo brain MR dataset was acquired with the full field-of-view. Then, the random under-samping is simulated by a factor of R=4. The reconstructed image using the proposed method was compared with the sum-of-squares (SOS) from the fully-sampled data and with the reconstruction without reweighting.

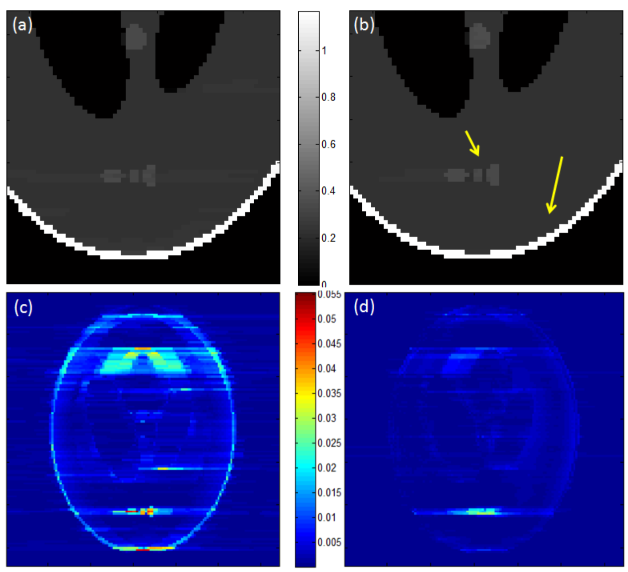

Figure.1 Reconstructed images: (a) without reweighting and (b) with the proposed reweighting method, (c)-(d) Respective reconstruction error images corresponding to (a)-(b).

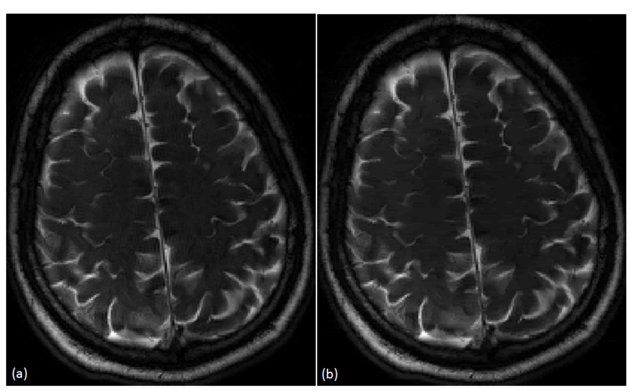

Figure.2 (a) SOS reconstruction from the fully-sampled 4-channel in-vivo data. (b) Reconstruction using the proposed method with R=4.

Results: Fig.1 (a) and (b) show the zoom-in parts of the reconstructed images without and with reweighting, respectively. (c) and (d) illustrate their corresponding reconstruction errors as compared to the SOS references. The normalized mean square error (NMSE) is 0.021 and 0.007, respectively. Fig. 2 (b) shows the reconstructed in-vivo image using the reweighted method, which recovered most details shown in the SOS reconstruction. The NMSE of this reconstruction is 0.056, which increases to 0.062 without reweighting.

Discussion and Conclusion: Iterative reweighting tends to estimate the locations of nonzero coefficients with higher accuracy. At the first iteration, larger signal magnitudes are most likely to be identified as nonzero. Subsequently, they are down-weighted in order to concentrate on the remaining small but nonzero entries. As a result, the reconstruction errors can be reduced. The reweighted nonlinear conjugate gradient method does slightly increase the computation complexity.

In summary, an improved reconstruction method is presented which uses reweighted l_1 minimization to solve the parallel compressed sensing MRI problem. Computer simulation and in-vivo experiments show that the new method can achieve improved image reconstructions quality with more details and sharper edges. This is important for MRI applications where recovering details is crucial such as high-resolution neuro- or cardiovascular imaging.

Reference:

[1] Candès EJ et al, IEEE Trans Inf Theory, 52: 489–509, 2006. [2] Lustig et al MRM 2007;58. [3] Liu B et al, ISMRM 2008; p:3154. [4] Zhao C et al, ISMRM 2008; p:1478. [5] Wu B et al, ISMRM 2008; p:1480. [6] King KF, ISMRM 2008; p:1488. [7]Liang D et al. Al MRM 2009; 62 [8]Kyriakos W et al MRM 2000;44. [9] Candès EJ et al, Journal of Fourier Analysis and Applications2008;14.