Sensitivity Encoded Image Reconstruction Using Direct Regularization

F-H. Lin[1,2], F-N. Wang[1,3], T-Y. Huang[1,3], M. S. Hamalainen[1], K. K. Kwong[1], J. W. Belliveau[1], L. L. Wald[1]

[1]MGH-MIT-HMS Athinoula A. Martinos Center for Biomedical Imaging, Charlestown, MA, United States, [2]Harvard-MIT Divison of Health Sciences and Technology, Cambridge, MA, United States, [3]Dept. of Electrical Engineering, National Taiwan University, Taipei, Taiwan

Introduction

Parallel imaging technique has been proposed to utilize simultaneous data acquisition from multiple RF receivers to improve the spatiotemporal resolution of MRI (Sodickson and Manning 1997; Pruessmann, Weiger et al. 1999). Mathematically, the formation and the reconstruction of the parallel MRI, including image domain and k-space domain variants, have been formulated as linear equation (Sodickson and McKenzie 2001). Thus matrix inversion is a critical process in reconstructing a full-FOV image. Previously we showed that using the prior knowledge from the full-FOV reference scan can lead to reduced instability of SENSE unfolding (quantified by g-factors) (Lin, Kwong et al. 2002). Nevertheless, the major challenge of this automatic regularization is the time-consuming process to estimate the regularization parameter. Here we propose to estimate regularization parameter by partitioning the power spectrum of the singular values of the linear equation constituting the set of the aliased image pixels from multiple receivers based on the estimated SNR. Results including reconstructed images, g-factor maps and computational time are reported.

Methods

Given the receiver noise covariance Ψ, we use eigen decomposition to yield the whitened observation $\tilde{y}$: $\Psi = \boldsymbol{V}\Lambda\boldsymbol{V}^{\boldsymbol{H}}$, $\tilde{\boldsymbol{y}} \equiv \Lambda^{-1/2}\boldsymbol{V}^{\boldsymbol{H}}\vec{\boldsymbol{y}}$. The SNR of linear equation is then estimated as $\boldsymbol{SNR} \approx (\tilde{\boldsymbol{y}}^{\boldsymbol{H}}\tilde{\boldsymbol{y}})/\boldsymbol{n_c} - 1$, where $\boldsymbol{n_c}$ is the number of the array channel. Subsequently, we estimate the regularization parameter from the power spectrum of the singular values such that the square of the singular value with index $\boldsymbol{k}$ leads to the minimum of the cost function written as $\left\| \boldsymbol{SNR} - (\sum_{\boldsymbol{i}=1}^{\boldsymbol{k}} \boldsymbol{s}_{\boldsymbol{ii}}^2)/(\sum_{\boldsymbol{i}=\boldsymbol{k}+1}^{\boldsymbol{n_c}} \boldsymbol{s}_{\boldsymbol{ii}}^2) \right\|_2^2$, where $\boldsymbol{s_{ii}}$ is the $\boldsymbol{i}$-th entry of the singular value of the encoding matrix.

The *in vivo* anatomical images were acquired using a 3T scanner (Siemens Medical Solution, Inseln, NJ) with an 8-channel linear phased array coil. We used a FLASH 3D sequence to acquire *in vivo* brain images from a healthy subject. Parameters of FLASH sequence are TR=500 msec, TE=3.9 msec, flip angle=20 deg, slice thickness=3 mm with 1.5 mm gap, 48 slices, FOV=210 mm x 210 mm, image matrix=256 x 256. The same scan was repeated with the number of phase encode lines reduced to 50%, 37.5% and 25%.

Results and Discussion

Figure 1 shows the reconstructed images at 2.00-, 2.67- and 4.00-fold acceleration without regularization, with regularization parameter estimated from L-curve, and with regularization parameter estimated from SNR. By visual inspection, regularization decreased the noise level in basal ganglia in all three accelerations. The reconstructions of the 4.00-fold acceleration acquisition could not unfold the image successfully due to the lack of sufficient independent information from the array geometry. Table 1 listed the g-factor averages and standard deviations of the unregularized and regularized reconstructions in all three accelerations. Using regularization the g-factor is reduced. The averaged g-factor using SNR-based regularization is smaller than the averaged g-factor using the L-curve estimated regularization. Note that for 2.00-, 2.67- and4.00-fold accelerations, the time for regularization parameter calculation based on the estimated SNR can be reduced to 54%, 33% and 29% of the time used by the L-curve.

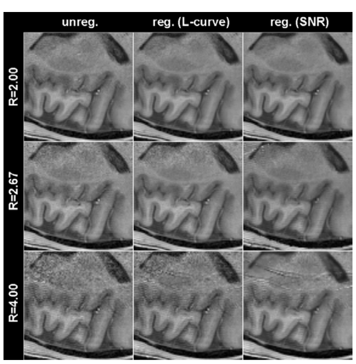

Figure 1. Reconstructed images at 2.00-, 2.67- and 4.00- fold accelerations without regularization or with regularization estimated from the L-curve.

accelerations	G unreg.	G reg. L-curve	G. reg. SNR	Time (sec) (L-curve)	Time (sec) (SNR)
2.00	1.08 (0.12)	0.71 (0.21)	0.41 (0.26)	5730	3159
2.67	1.23 (0.23)	0.82 (0.26)	0.44 (0.31)	3114	1041
4.00	1.82 (0.57)	1.09 (0.71)	0.49 (0.45)	2279	658

Table 1. The g-factors of reconstructed SENSE image at 2.00-, 2.67- and 4.00-fold accelerations using either no regularization, L-curve estimated regularization or SNR estimated regularization. The computational time for the regularization parameter for a 256-by-256 image is also listed.

References

Lin, F.-H., K. K. Kwong, et al. (2002). ISMRM 10th Scientific Meeting and Exhibition, Honolulu, Hawaii, USA.
Pruessmann, K. P., M. Weiger, et al. (1999). Magn Reson Med **42**(5): 952-62.
Sodickson, D. K. and W. J. Manning (1997). Magn Reson Med **38**(4): 591-603.
Sodickson, D. K. and C. A. McKenzie (2001). Med Phys **28**(8): 1629-43.