Toward Clinically Applicable Highly-Accelerated SENSE

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Introduction

In images reconstructed by SENSE [1], a high acceleration factor can result in high local image noise level which often is equivalent to reduced diagnostic quality. For this reason, in clinical applications, the acceleration factor has to be restricted to values far lower than the theoretically achievable limit. To moderate this restriction, many advanced techniques [2~4] have been proposed to improve SENSE with high acceleration factors. It has been shown that the image quality can be dramatically improved by these methods when the SENSE acceleration factor is high. However, the success of these methods relies on long reconstruction time, and/or ideal acquisition scheme, and/or optimal regularization parameters. None of these requirements can be easily met clinically. Recently, we have proposed to use a mathematical tool, called variable splitting, to tackle these practical problems [5]. In this work, the application of this proposed method for imaging with regular Cartesian trajectory is demonstrated. Mathematical proof and experimental results show that the proposed method makes it possible to use highly-accelerated SENSE clinically because of low reconstruction error, fast reconstruction, and insensitivity to the choice of parameters.

Theory

The key idea of variable splitting is to decompose a complex problem into several easier sub-problems by introducing one or more auxiliary variables. By introducing an auxiliary variable $\hat{I}$, conventional sparsity constrained SENSE (Eq. (1)) [3,4] is transformed to the minimization problem in (2), which can be solved iteratively by minimizing (2) with respect to I and $\hat{I}$ individually while keeping the other one fixed. This results in two much easier sub-problems: (3) and (4). (3) is prior information ($\hat{I}$) regularized SENSE, which can be solved with the same reconstruction time as conventional SENSE with a pixel-by-pixel approach [5]. (4) is a well-studied image-denoising problem, which can be solved by a very efficient algorithm [6] whose most expensive computation is a set of fast Fourier transforms. To take advantage of spatially adaptive denoising, (4) is modified to be (5) without introducing any extra computational cost. *g* denotes the g-factor map. *mean(g)* denotes the mean of g-factor values. Notice there is ***no parameter*** in Eq. (5). We have mathematically proven the equivalence of Eq. (1) and the two sub-problems (Eqs. (3) and (5)) through the following two theorems. Theorem 1: For fixed $\alpha > 0$, the sequence $\left\{\left(I_n, \hat{I}_n\right)\right\}_n$ generated by alternately solving Eq. (3) and (5) from any starting point converges to $\left(I^\alpha, \hat{I}^\alpha\right)$, a solution of (2), and the convergence rate is linear. Theorem 2: As $\alpha \to \infty$, the sequence of $\left(I^\alpha, \hat{I}^\alpha\right)$ converges to a solution of (1).

$$\min_I E(I) = \sum_{j=1}^{Nch} \left\| F_p\left(S_j I\right) - k_j \right\|_2^2 + \lambda \left\| \nabla I \right\|_1 + \mu \left\| \Psi(I) \right\|_1 \quad (1)$$

$$\min_{I,\hat{I}} E\left(I, \hat{I}\right) = \sum_{j=1}^{Nch} \left\| F_p\left(S_j I\right) - k_j \right\|_2^2 + \lambda \left\| \nabla \hat{I} \right\|_1 + \mu \left\| \Psi\left(\hat{I}\right) \right\|_1 + \alpha \left\| I - \hat{I} \right\|_2^2 \quad (2)$$

$$\min_I E\left|\hat{I} = \sum_{j=1}^{Nch} \left\| F_p\left(S_j I\right) - k_j \right\|_2^2 + \alpha \left\| I - \hat{I} \right\|_2^2 \right. \quad (3)$$

$$\min_{\hat{I}} E\left|I = \lambda \left\| \nabla \hat{I} \right\|_1 + \mu \left\| \Psi\left(\hat{I}\right) \right\|_1 + \alpha \left\| I - \hat{I} \right\|_2^2 \right. \quad (4)$$

$$\min_{\hat{I}} E\left|I = 0.01 \times mean(g) \right\| (g-1) \nabla \hat{I} \Big\|_1 + \left\| I - \hat{I} \right\|_2^2 \quad (5)$$

Methods

One set of brain data and one set of spine data were acquired on a 3.0T Achieva scanner (Philips, Best, Netherlands). Both are multi-slice 2-dimensional Cartesian data sets, acquired using an 8-channel head coil and a 16-channel CTL spine coil (Invivo Corp, Gainesville, FL) respectively . With the same FOV, pre-scan data for sensitivity maps were acquired with a matrix size of 64x64. The fully acquired data set was artificially under-sampled along one dimension with R = 4 (brain) and 6 (spine) to simulate the partially parallel acquisition. Eqs. (3) and (5) were used for image reconstruction by following the procedure shown in Fig. 1. The only parameter α was fixed to be 0.5 in all experiments. The acquired full *k*-space data sets were used to generate the reference images for root mean square error (RMSE) calculation.

Results

As shown by Fig. 1, the total calculation time for the proposed method is about two times of conventional SENSE. Low RMSE (4.3% and 7.8%) was achieved with high acceleration factors (4 and 6 along 1 dimension). For comparison, the RMSE was 6.4% (brain R=4) and 14% (spine R = 6) in conventional SENSE. In the five-times brightened error maps, no noticeable structure or edges can be observed. Hence the sparsity constrained reconstruction preserved the image spatial resolution well by using the fixed parameter α.

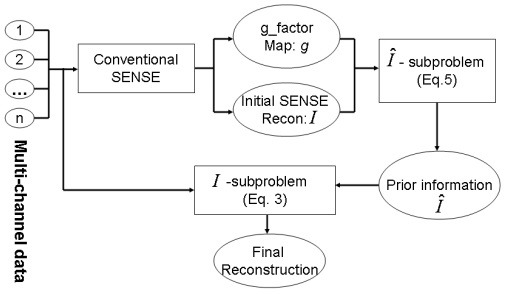

Fig. 1. Flowchart of the proposed method: self-feeding Sparse SENSE

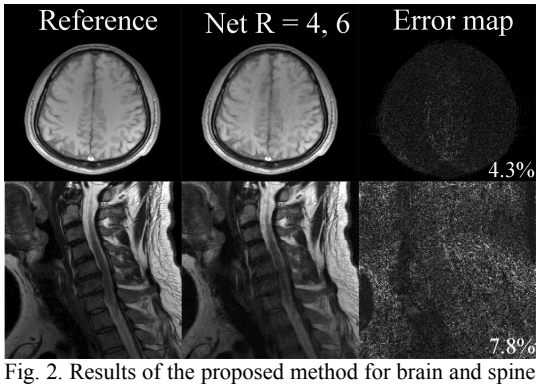

Fig. 2. Results of the proposed method for brain and spine data sets with net acceleration factor 4 and 6.

Conclusion

With ***regular Cartesian*** data trajectory, high acceleration factors were achieved by using the proposed method without adjusting any parameter. Compared to conventional SENSE, noise/artifact level was significantly reduced without noticeable impact on spatial resolution. The cost was only ***doubled reconstruction time***. In short, the proposed method improves the clinical applicability of highly accelerated SENSE through fast reconstruction speed, reduced sensitivity to the reconstruction parameters, and applicability to regular Cartesian trajectory.

References [1] Pruessmann K. P. et al. *Magn Reson Med* 1999; 42:952-962. [2] Ying L, Sheng J. *Magn Reson Med* 2007;57(6):1196-1202. [3] King KF. ISMRM 2008. p 1488 [4] Liang D, et.al. ISMRM 2009 p377 [5] Huang F, et al. 2009; the 3rd International Workshop on Parallel MRI. Santa Cruz, CA, USA. [6] Lin F-H, et.al. MRM 2004;51:559-567 [7] Yang J, et.al. TR08-27, CAAM, Rice Univ.; 2008