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Introduction

Large coil arrays with up to 64 or 128 elements have enabled parallel MRI at unprecedented speed [1-3]. Autocalibrating k-domain parallel MRI such as the GRAPPA methods is widely used in pMRI with conventional arrays but is rarely applied to large array systems [4,5]. This is primarily due to the computational challenge. In this work, we develop an efficient reconstruction method for k-domain parallel MRI with large arrays using array reduction. Experimental results show the new method can dramatically reduce processing time with minimal degradation of reconstruction quality.

Methods

To achieve improved data processing efficiency in large array systems, software compression (linear combination of channel data prior to reconstruction) or channel reduction (selecting a small set of most important channels) have been proposed [6-8]. However, the efficiency has to be achieved with somewhat reduced reconstruction quality.

In auto-calibrating k-domain methods, there is an additional degree of freedom – the choice of different set of channels to reconstruct each channel's k-space data. In large arrays, the coil element size tends to be small. As a result, the sensitivity of each element will be confined to a limited region. An important insight here is that not all channels provide significant information to the k-space data reconstruction of a particular channel. Indeed, only a small set of channels do. In this work, we developed an algorithm to adaptively select a set of relevant neighboring channels for each channel. Specifically, the cross-correlation coefficient between the m -th and the n -th channels is computed using $\rho(m, n) = \text{cov}(I_m, I_n) / (\sigma_m \sigma_n)$ where I_m and I_n are two calibration images and σ_m, σ_n are their standard deviations respectively. For the reconstruction of a particular channel, only these channels with a correlation coefficient larger than a predefined threshold α will be used. That is, for the m -th channel, only a reduced set of channels $\{n | \rho(m, n) > \alpha\}$ will be used to interpolate the missing k-space data. Assume that on average N channels were selected for each channel. The total computation and memory complexity will be reduced by a factor of $(N/C)^P$ where C is the total number of channels and P is a power number depending on whether directly matrix inversion or conjugate gradient method is used to calculate the interpolation coefficients.

The proposed method was tested using a phantom dataset acquired by a 64-channel linear array on a 4.7 T system with a uniform sphere shape and TR/TE/FOV=1500ms/25ms/140mm. To test the resolution, spin tagging was applied before the acquisition to create 2D orthogonal lines on the phantom. A 256×256 fully sampled data was acquired and retrospectively decimated. A 2×4 interpolation kernel and 32 ACS lines were used in the reconstruction. All processing was performed on a Dual-core 2.5 G computer with 2 GB memory in a Matlab software package without code optimization [9]. Different selections of threshold were used to test the effect of number of selected channels on the final reconstruction quality and running time.

Results

Figure 1 shows the reconstructed images using $N=31$, 15, 7 and 3 with a reduction factor (Rr) of 2 and 16. No obvious quality degradation can be observed with reduced channels numbers. Figure 2 is a set of 1D profiles at the highlighted locations in Fig. 1, which show the feature resolution was not compromised by the channel reduction neither. The SNR and running time for Rr=2 with different channel numbers (N) are shown in Table. 1. It is clear that the SNR of the reconstruction is not significantly affected by the channel reduction from 31 to 3. However, running time was drastically shortened by a factor of about 7.

Discussion

A method has been proposed for efficient auto-calibrated k-domain parallel imaging reconstruction in large array systems. By utilizing the channel correlations, array reduction was performed in a channel-by-channel fashion, which significantly reduces the computation and memory stress without degradation of reconstruction quality. The method can be combined with other complimentary fast GRAPPA reconstruction methods [10] to further improve the efficiency. With large arrays becoming important and popular, it is expected that the proposed method can significantly reduce processing time in practical application in such systems.

Table 1. SNR and running time v.s array reduction

References

N (channels)	31	15	7	3
SNR	21.2	20.8	20.3	19.8
Time (s)	96	31	18	14

- [1] M. McDougall,etc., MRM 54:386-392, 2005. [2] R. Lee, etc. Proc. ISMRM 2008, p. 440.
- [3] C. Hardy, etc., JMRI, 28:1219-1225, 2008. [4] Plussmann, etc. MRM 42:952-962, 1999.
- [5] M. Griswold, etc., MRM 47: 1202-10, 2002. [6] M. Doneva, etc., MAGMA. 21(3):187-96, 2008.
- [7] M. Buehrer, etc., MRM, 57:1131-1139, 2007. [8] F. Huang, etc., MRI, 26:133-141, 2008.
- [9] J. Ji, etc., Concepts Magn Reson (B) 31B: 24-36, 2007.
- [10] P.J. Beatty, etc., ISMRM 2007, p. 1749.

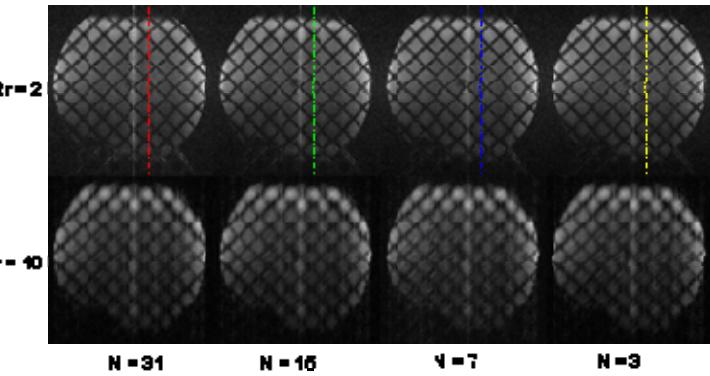


Fig.1 Reconstructions with different channel reduction Numbers.

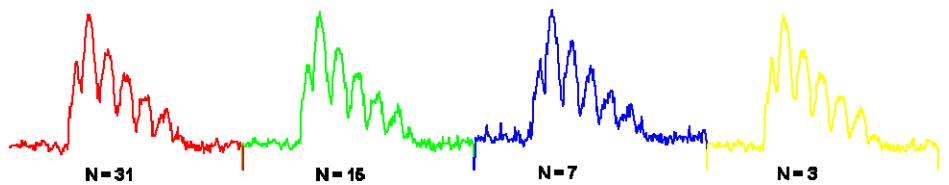


Fig.2 The 1-D profiles corresponding to the lines in Fig. 1. No resolution loss is observed.